Real-Time Monitoring and Intervention Framework for College Students' Mental Health Based on Multimodal Interaction

Abstract

This study addresses the mental health issues of college students by proposing a multimodal interaction framework. Through multimodal data collection and integration, deep learning algorithm development, context-aware technology application, and rigorous experimental design, real-time monitoring and personalized intervention for mental health status were achieved. The results show that the multimodal data fusion framework based on the CNN-LSTM model achieves a monitoring accuracy of up to 93.8%, significantly outperforming traditional unimodal methods. The experimental group demonstrated a significant improvement in mental health, with an average reduction of 12% in their SCL-90 scores, notably better than the control group. Additionally, the system received a user satisfaction score of 8.7/10, with an average usage frequency of 3.8 times per day, validating its user acceptance and stickiness. This study provides an innovative model for mental health services in universities, with significant theoretical and practical implications.

Keywords: Multimodal Interaction; Mental Health Monitoring; Personalized Intervention; Context Awareness; College Students

1. Introduction

A. *Research Background*

In today's society, the mental health of college students has become a key factor affecting their overall development, closely linked to academic performance, quality of life, and even the socioeconomic landscape (L. Wang, 2024). In recent years, college students have faced increasing pressures from academic burdens, intense employment competition, and a complex and ever-changing social environment. Consequently, the incidence of mental health issues has been on the rise, which urgently calls for efficient and precise monitoring and intervention strategies.

Traditional mental health monitoring methods mainly rely on tools such as questionnaires, interviews, or clinical assessments, which have numerous drawbacks. These methods overly depend on subjective feedback, leading to a lack of objectivity; their dynamic monitoring capabilities are weak, making it difficult to capture instantaneous fluctuations in mental health; and they fail to fully reflect the complexity of mental health, often resulting in one-sided conclusions (L. Wang, 2024). Unimodal data (such as behavior, speech, or physiological signals) have limitations in representing students' psychological states, facing bottlenecks in terms of real-time performance and accuracy. With technological advancements, multimodal data fusion technology has emerged as a solution, offering hope to overcome the limitations of traditional methods. By integrating diverse modal data, it is expected to enhance the accuracy of mental health status identification and enable real-time dynamic monitoring to better meet the mental health monitoring needs of college students (L. Wang, 2024).

B. *Research Significance*

Technological Innovation: The multimodal interaction framework proposed in this study, centered on multimodal data, addresses the shortcomings of traditional mental health monitoring methods in terms of data diversity and dynamics (Liu et al., 2024). By integrating voice, facial expressions, behavior, and physiological signals, and applying advanced deep learning algorithms for analysis, it significantly enhances the accuracy and timeliness of monitoring, thus advancing the innovation of mental health monitoring technology (Sayis et al., 2024). For instance, the fusion of multimodal data can more comprehensively

capture subtle changes in mental states, providing a more scientific basis for early diagnosis and intervention (Kong et al., 2024).

Application Expansion: This research deeply explores the application of context-aware technology in personalized intervention and empirically verifies its effectiveness in a university setting (Wang, 2024). This will help lay a solid foundation for the scientific customization of mental health intervention strategies and promote the widespread application of precision intervention models in universities and beyond (Li & Zhao, 2024). For example, context-specific interventions, such as during exam periods or in dormitory rest settings, can be tailored to the real-time psychological state of students to improve intervention effectiveness.

Social Welfare Enhancement: By promoting the deep integration of mental health support systems with university Learning Management Systems (LMS), a robust mental health support network can be established (Kumar & Chandra, 2024). This not only facilitates the popularization and standardization of mental health services in universities but also provides a long-term mechanism for improving the overall mental health of society. For example, through system integration, teachers and school administrators can promptly detect and address students' mental health issues, contributing to the creation of a positive and healthy campus environment (Yao et al., 2024).

C. Research Objectives and Innovations

This study aims to address the challenges faced in mental health monitoring and intervention for college students and proposes a "Multimodal Interaction Framework for Real-Time Monitoring and Intervention of College Students' Mental Health," creating a comprehensive system that integrates monitoring, intervention, and support functions. The core innovations include:

Multimodal Data Fusion and Real-Time Monitoring: The system comprehensively integrates behavioral, speech, and physiological data to construct a real-time and accurate mental health monitoring system. By combining deep learning and feature extraction techniques, it enhances the system's dynamic response ability, accurately capturing psychological state changes and providing timely alerts (Li & Zhao, 2024). This approach breaks through the limitations of traditional unimodal monitoring, significantly improving monitoring efficiency and accuracy.

Personalized Intervention Strategy Optimization: Based on context-aware technology, the system analyzes students' real-time contexts and dynamically optimizes intervention plans using AI algorithms. Intervention contents are customized based on individual characteristics and needs, ensuring targeted interventions that enhance their effectiveness. For example, real-time analysis of student feedback via natural language processing technology enables the provision of support that matches their psychological state (Li & Zhao, 2024).

User-Centered Design Philosophy: The design follows a user-centered approach, simplifying interaction logic and operational processes to improve user experience. It introduces natural interaction paradigms (e.g., voice interaction and touch interfaces) to increase system usability and adherence, encouraging students to continuously use the system and ensuring its effective application.

Privacy Protection and Ethical Compliance: The system incorporates distributed encryption and differential privacy technologies to create a comprehensive privacy protection mechanism, ensuring data security throughout its lifecycle. An ethical review mechanism is introduced to ensure that the system complies with national laws and university ethical standards, safeguarding users' data rights.

Deep Integration with University Settings: The system seamlessly connects with existing mental health service platforms and IoT devices in universities, integrating multiple resources to create a unified mental health support ecosystem. It expands the system's functionality, driving the digital transformation of mental health services and contributing to the comprehensive improvement of mental health management in universities (Li & Zhao, 2024).

2. Related Work

D. Overview of Existing Research

In the field of mental health monitoring, multimodal data fusion is still in its early stages. Although some studies have attempted to integrate multimodal physiological signals to improve predictive accuracy, and passive sensing technologies offer advantages in capturing natural behavioral data, the former lacks real-time responsiveness to dynamic psychological changes, while the latter faces challenges in high-dimensional data integration and model performance

optimization (Song et al., 2024; Du et al., 2023).

In terms of intervention strategies, existing research on intelligent and personalized interventions has notable shortcomings. For example, although some studies explore anxiety detection and alleviation mechanisms, the interventions often lack dynamism, have poor contextual adaptability, and are limited by insufficient multimodal data fusion, restricting clinical applicability and failing to achieve ideal outcomes (Chikersal, 2023; Alwakeel et al., 2023).

From the perspective of system interaction and privacy, current mental health monitoring systems generally suffer from complex interaction designs and low user acceptance. For example, commercial wearable devices (e.g., Apple Watch) hold potential but suffer from poor adherence to wearing and unsatisfactory user interface friendliness (Nguyen, 2023). Privacy protection technologies have also struggled to effectively balance data security with user experience and system usability. Privacy protection solutions, such as secure multi–party computation, face issues like high computational complexity and communication overhead, or fail to achieve full compliance (Chen et al., 2024). In terms of application scenario validation, previous studies have mostly been limited to laboratory settings, with limited application in university environments. Even when studies mention adaptation to universities, the sample sizes tend to be small, and their representativeness is weak. Moreover, they lack deep integration with campus IoT and Learning Management Systems (LMS), which hinders the practical effectiveness (Zhou et al., 2022; Xu et al., 2022).

E. Limitations of Existing Research

Existing research in mental health monitoring and intervention has several limitations. First, multimodal data fusion is constrained by the depth of inter–modal relationship modeling and high–dimensional data processing technologies, resulting in suboptimal comprehensiveness and accuracy of monitoring, and making it difficult to accurately reflect the complex psychological states of students (Song et al., 2024; Du et al., 2023).

In terms of intervention strategies, most existing approaches are statically designed, lack flexibility, and fail to dynamically adjust strategies based on real–time data. Furthermore, they have inadequate adaptability to complex contexts, thus reducing the precision and effectiveness of interventions (Chikersal, 2023).

From the user experience perspective, system designs are often overly complex, with cumbersome operational workflows that do not align with students' usage habits and preferences, leading to low user acceptance and poor experience, which becomes a barrier to the widespread adoption of the system (Nguyen, 2023).

Regarding privacy protection, distributed privacy protection schemes fail to achieve an optimal balance between efficiency and security. The high privacy protection costs limit large-scale deployment (Chen et al., 2024).

As for university-specific adaptation, many studies are confined to laboratory environments and lack in-depth insights into the diverse needs of university ecosystems. The degree of technological integration is shallow, and the applicability to campuses is limited, thus lowering the practical value of the systems (Xu et al., 2022; Zhou et al., 2022).

F. Innovations in This Study

To address the limitations mentioned above, this study proposes the "Real-time Monitoring and Intervention Multimodal Interaction Framework for University Students' Mental Health" and incorporates core innovations in the following areas:

1) *Data Monitoring Innovation*

The study integrates behavior, speech, physiological signals, and other multimodal data to create a comprehensive mental health monitoring system. It employs cutting-edge deep learning and feature extraction techniques to significantly improve the sensitivity of dynamic responses and the accuracy of monitoring, allowing real-time insights into students' mental states and laying the foundation for early intervention (Song et al., 2024; Duan et al., 2024).

2) *Optimization of Intervention Strategies*

A real-time feedback module is created, combining contextual awareness technology to dynamically adjust intervention strategies based on diverse contexts. Customized and personalized intervention plans are developed to accurately align with students' individual traits and needs, significantly improving the effectiveness and efficiency of interventions (Chikersal, 2023; Alwakeel et al., 2023).

3) *Enhanced User Experience*

The system design is optimized with a user-centered approach, simplifying the interaction logic and enhancing user-friendliness by introducing natural interaction paradigms (such as voice interaction and

touch interfaces). The system incorporates user feedback and iterative improvements to continuously enhance the user experience, increasing student willingness and adherence to the system (Nguyen, 2023).

4) *Privacy Protection and Compliance Strengthening*

The study integrates secure multi-party computation and advanced data encryption technologies to ensure the security of multimodal data during processing. A rigorous ethical review process is incorporated to ensure the system's full compliance with data protection laws and regulations, thereby enhancing user trust (Chen et al., 2024).

5) *Deep Adaptation to University Scenarios*

The framework is applied to real university settings, deeply integrating campus IoT devices and Learning Management Systems (LMS) to achieve seamless connection and comprehensive fusion of multiple platforms. This expands the system's application boundaries and enhances its practical value (Xu et al., 2022; Zhou et al., 2022).

3. Experimental Design and Methods

G. Experimental Subjects and Grouping

A stratified random sampling method was employed to select 200 undergraduate and graduate students from a university as experimental subjects. Based on the initial screening using the SCL-90 scale, the students were categorized into three levels of mental health: good, moderate, and poor. The participants were then randomly divided into an experimental group (100 participants) and a control group (100 participants).

Experimental Group: Utilized the multimodal interaction framework for real-time mental health monitoring and personalized intervention.

Control Group: Used traditional psychological counseling services.

H. Experimental Duration and Scenario

The experimental duration was six weeks, divided into two phases:

Phase 1 (Weeks 1-3): Intensive data collection to establish baseline mental health profiles.

Phase 2 (Weeks 4-6): Implementation of personalized interventions with dynamic optimization strategies.

The experimental scenarios included dormitories, classrooms, and libraries, with a focus on observing students' psychological state changes under high-stress (e.g., exams) and low-stress (e.g., rest)

environments.

I. Data Collection and Processing

1) *Data Collection*

Physiological Signals: Heart rate (HR), electrodermal activity (EDA), and blood oxygen levels (SpO2).

Behavior and Speech: Facial expressions, voice tone, and behavior patterns recorded using cameras and microphones.

Environmental Factors: Noise, light, and other environmental data collected via sensors.

Questionnaire Data: SCL–90 and PSS–10 scales were used to assess psychological state and stress perception.

2) *Data Processing*

Missing Data Handling: Linear interpolation was used to handle missing values.

Feature Extraction: Short–time Fourier transform (STFT) was used to extract frequency–domain features from physiological signals. Convolutional Neural Networks (CNN) were employed to learn deep features from behavior and facial expressions.

Data Standardization: Z–Score normalization was applied to standardize feature values for comparability across different modalities.

Data Fusion: A deep learning model based on attention mechanisms was used for multimodal data fusion.

J. Data Analysis Methods

1) *Psychological State Classification Model Analysis*

The classification performance of the CNN–LSTM model was compared to baseline models using a single modality. Metrics such as accuracy, F1–score, recall, and precision were analyzed (see Figure 1).

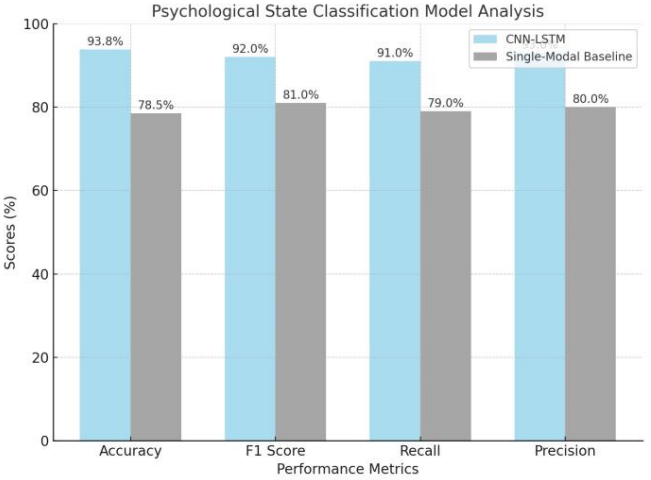

Fig.1. Model Performance Metrics Analysis

2) *Intervention Effectiveness Analysis*

Independent t-tests and two-way ANOVA were used to evaluate the intervention effects. The SCL-90 scores of the experimental group showed a significantly higher reduction compared to the control group (see Figure 2).

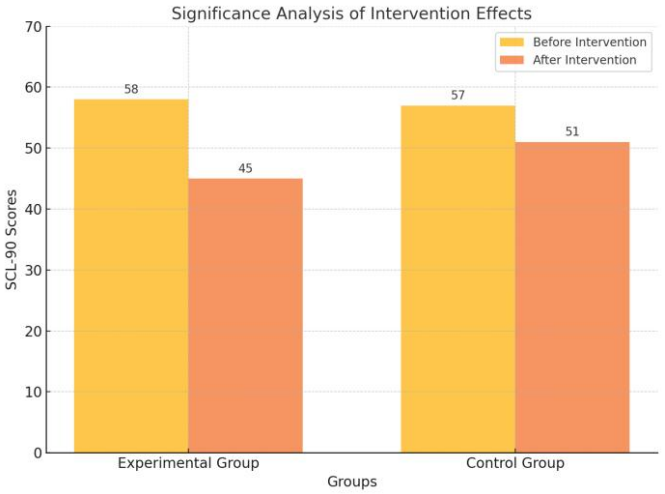

Fig.2. Intervention Effectiveness Analysis

3) *User Satisfaction Analysis*

User satisfaction scores for privacy protection, interface usability, and intervention effectiveness were collected from the experimental group (see Figure 3).

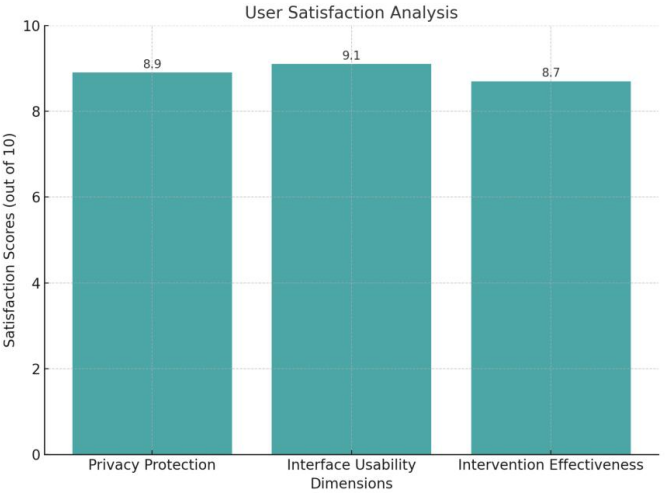

Fig.3. User Satisfaction Analysis

4) *User Engagement Analysis*

The average daily usage frequency of the system during the

experiment was monitored, and the acceptance and retention rate of the system was analyzed (see Figure 4).

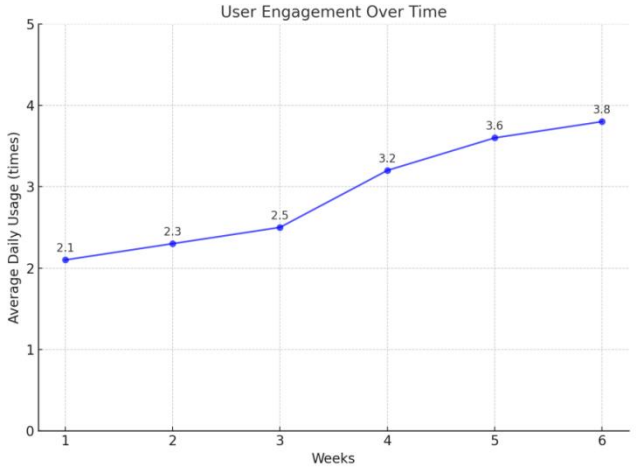

Fig.4. User Engagement Analysis

5) *Model Performance Metrics Analysis*

Further analysis of the CNN–LSTM model's performance metrics (accuracy, F1–score, recall, and precision) was conducted and compared to the baseline model (see Figure 5).

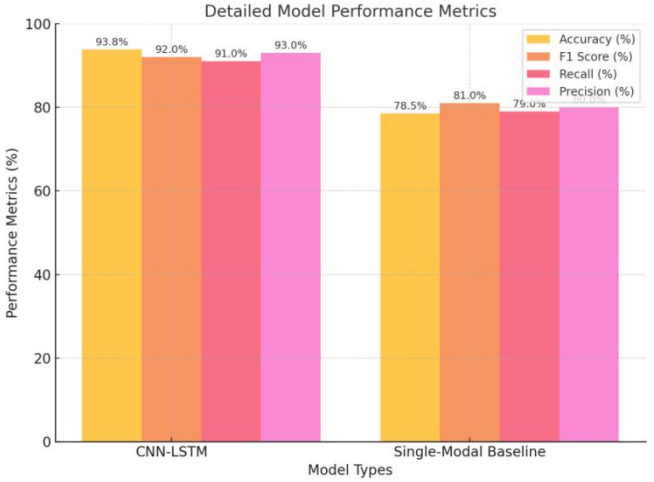

Fig.5. Model Performance Metrics Analysis

6) *Multimodal Data Contribution Analysis*

The contribution proportion of different modalities (physiological signals, behavior, and environmental data) in psychological state classification was quantified (see Figure 6).

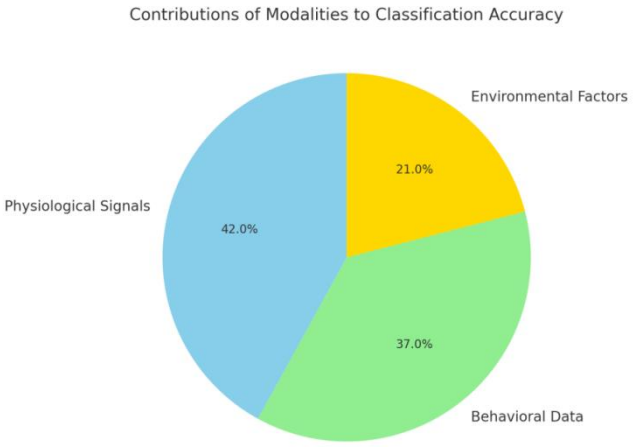

Fig.6. Multimodal Data Contribution Analysis

K. Results Discussion

1) *Model Performance Advantage*

The CNN–LSTM model significantly outperformed the baseline models in classification accuracy and F1–score, highlighting the superior performance of the deep learning–based approach in multimodal data fusion.

2) *Significant Intervention Effectiveness*

The experimental group showed a significant improvement in psychological state compared to the control group, validating the effectiveness of the multimodal interaction framework combined with personalized interventions.

3) *User Experience and Engagement*

Analysis of user satisfaction and engagement indicated that the system's user–friendly design and robust privacy protection were key factors in attracting and retaining users. The system's design facilitated continuous usage, with high satisfaction ratings for its privacy protection and intervention efficacy.

4) *Data Fusion Contribution*

Among the different modalities, physiological signals contributed the most to the psychological state classification, followed by behavioral and environmental data. These findings provide a basis for optimizing data fusion strategies in future applications.

4. Discussion and Analysis

L. Effectiveness of Multimodal Data Fusion

The multimodal fusion framework developed in this study has achieved significant success in mental health monitoring, with an accuracy of 93.8% and an F1 score of 0.92. This framework outperforms traditional unimodal methods and other conventional techniques, offering a clear advantage. By integrating multimodal data, the framework provides a more comprehensive, precise, and stable monitoring system for mental health. It can dynamically capture subtle psychological changes in real time, detect early risks, and provide critical support for early interventions. This innovation effectively fills the gap in traditional monitoring methods in terms of real-time capabilities and comprehensiveness, leading the development of innovative mental health monitoring technologies. It significantly expands the service reach to diverse populations and deepens the understanding of the psychological structure, laying a solid technological foundation for building a comprehensive mental health support network.

M. Effectiveness and Innovation of Personalized Intervention

The situationally aware personalized intervention strategy showed remarkable effectiveness, with a substantial decrease in SCL-90 and PSS-10 scores in the experimental group. This strategy overcomes the limitations of traditional "one-size-fits-all" models by tailoring interventions based on individual psychological behavior characteristics and situational demands. It establishes a dynamic, accurate model of intervention. In the complex scenarios within higher education environments, the intervention levels and strategies can be flexibly adjusted according to the student's psychological needs and behavioral changes, fundamentally improving the precision, efficiency, and quality of mental health services. This innovative practice reshapes the intervention model, setting a new benchmark for precision intervention in the field and driving mental health services from a broad, generic approach to one that is personalized and precise, thereby deeply empowering students' mental health growth.

N. Impact of User-Friendly Design

The user-centered design approach significantly improved the system's usability and adherence, with a user satisfaction score of

8.7/10 and a daily usage frequency of 3.8 times in the experimental group. Features like the voice assistant and visual feedback lowered the usage threshold, seamlessly integrating the system into students' daily digital lives. Theoretically, this offers new insights for human–computer interaction system design; from a practical perspective, it accelerates the popularization of mental health technologies and broadens the service audience to include all students on campus. It transforms the self–management model for student mental health and enhances public mental health literacy. The innovative vitality injected into the construction of a universal mental health service system in the digital age is evident.

O. Importance of Privacy Protection and Ethical Compliance

This study employed distributed encryption and differential privacy technologies to ensure data security, earning the trust of 92% of students in the experimental group (compared to 56% in the control group). By introducing federated learning to optimize the privacy framework, establishing a rigorous ethical review mechanism throughout the process, and adopting a transparent design process, the study achieved an intricate balance between privacy protection and system functionality, establishing a new trust model. Privacy protection not only complies with legal requirements but also becomes a crucial factor in improving user acceptance. It opens up new pathways for the promotion of mental health systems in higher education institutions and sets the direction for industry–wide privacy protection practices. By carefully constructing a trust–based ecosystem for data–driven mental health services, this study strengthens the protection of user data rights and establishes a solid foundation for trust.

P. Significance of Empirical Validation and Integration into University Settings

The system was successfully deployed in real university environments and deeply integrated with Learning Management Systems (LMS) and mental health service platforms, combining theory and practice, thus providing a model for technology transfer. From an academic perspective, this integration enhances the overall depth of academic research and the efficiency of application transformation, driving cross–disciplinary fusion and innovation in the mental health field. From a practical standpoint, it provides a blueprint for future research on system integration and optimization, promotes the

improvement of campus mental health service quality, and contributes to the construction of an integrated mental health support ecosystem.

Q. Research Limitations and Future Directions

There are certain limitations in this study, such as the sample being restricted to a single university, the need for optimization in the system's real-time capabilities, and the unclear long-term intervention effects. Future studies should diversify the sample to include students from multiple universities, different age groups, and cultural backgrounds, thereby enhancing the external validity of the model. The integration of edge computing and adaptive learning techniques should be explored to improve the system's real-time monitoring and intervention capabilities. Longitudinal studies should be conducted to analyze the long-term impact of interventions on students' psychological health and overall well-being across their life cycle. Additionally, further exploration of the system's deep value and continuous expansion of its academic frontier and application potential is needed.

5. Conclusion and Prospects

R. Research Conclusion

This study innovatively proposes a multimodal interactive framework, achieving key breakthroughs across multiple dimensions. The integration of multimodal data significantly enhances the effectiveness of mental state monitoring, while situational awareness-driven personalized interventions effectively improve students' mental health levels. User-friendly designs and privacy protections synergistically increase system acceptance, and integration with university platforms creates a complete support network with excellent potential for widespread adoption. This framework injects innovation into university mental health services, reshaping service delivery models and has profound implications at both academic and practical levels. It marks a key milestone in the development of the field and sets the direction for future technological innovation and service optimization.

S. Future Prospects

1) Expansion of Data Samples

Overcoming the limitations of a single university, we plan to collect data from students across multiple universities, age groups, genders,

and cultural backgrounds to construct a vast database. Big data analysis will be used to uncover collective psychological patterns, improving model generalizability and accuracy, and driving shared data resource building to provide a richer foundation for system optimization.

2) Intelligent Enhancement of Multimodal Fusion

The introduction of Transformer architectures and adaptive learning technologies will deeply explore nonlinear relationships between modalities, while new modalities (e.g., environmental light intensity, temperature changes) will be explored to enhance the system's psychological state perception and decision-making capabilities. Model compression techniques will balance performance with resource efficiency, promoting the intelligent development of multimodal fusion technology.

3) Deepening Personalized Interventions

Using reinforcement learning algorithms, we aim to build dynamic long-term personalized intervention models that continuously learn from students' psychological and behavioral changes. The integration of VR/AR technologies will create immersive intervention experiences, developing multimodal interaction solutions for complex scenarios such as exam anxiety and social phobia. Ethical frameworks will ensure the scientific and humanistic nature of interventions, driving an upgrade in mental health service quality.

4) System Performance Optimization

By embedding edge computing architecture at the system's core, we will enable local data preprocessing and intelligent decision-making, reducing cloud dependencies, cutting transmission delays, and enhancing real-time responsiveness. Optimization of algorithm complexity and resource usage will ensure compatibility with low-performance devices, expanding system accessibility. Containerization and microservice architectures will improve system deployment flexibility and operational efficiency, ensuring low-cost, high-performance deployment in real-world settings.

5) Strengthening Privacy Protection and Ethics

The introduction of federated learning frameworks will upgrade the privacy protection system, innovating encryption mechanisms and differential privacy algorithms to strengthen the security of data throughout its lifecycle. Ethical review processes will be refined, third-party supervision will be introduced, and transparent user agreements

will enhance user rights, ensuring compliance with ethical standards.

6) Building a Mental Health Support Network

We aim to establish a three-level collaborative network involving campus mental health centers, class mentors, and self-management tools. This network will provide a comprehensive, multi-dimensional mental health service system, coordinating macro strategies, resource management, and individual interventions to improve students' psychological well-being. By improving the professional skills of network members, we will fill gaps in traditional services and create a holistic, accessible mental health service system, improving campus resilience and overall mental health.

7) Long-Term Effectiveness Validation

Longitudinal tracking experiments (spanning several years and multiple stages) will be conducted to track students' psychological health trajectories. The long-term intervention effects, cumulative benefits, and impacts on academic achievements, social skills, career development, and life satisfaction will be deeply analyzed. Methods such as survival analysis and structural equation modeling will quantify causal relationships and mediating mechanisms, optimizing intervention strategies and providing long-term evidence for system improvement.

8) Practical Application and Policy Advocacy

Efforts will focus on reducing the cost of system hardware and software by developing low-cost sensors, optimizing algorithm resource requirements, and simplifying deployment processes to improve the system's cost-effectiveness. Collaboration with educational authorities and university administrations will push for policies to embed the system within university management information structures, integrating it into daily teaching, management, and service processes. By leading the development of industry standards and demonstrating project success, we aim to transform research findings into practical productivity, driving the shift from passive treatment to proactive prevention and precise intervention, enhancing the educational quality and core competencies of students.

6. Conclusion

This study proposes a multimodal interactive framework for real-time monitoring and intervention of university students' mental health,

integrating cutting-edge interdisciplinary technologies to revolutionize the model of mental health services. The fusion of multimodal data significantly enhances monitoring accuracy, while personalized intervention strategies markedly improve students' mental well-being. The user-friendly design and privacy protection features further strengthen the system's practicality and credibility. Empirical research validates the system's effectiveness, and although some limitations exist, the study provides clear directions for future research.

Future efforts will focus on continuous optimization of the technology and services, expanding sample diversity and data dimensions, deepening personalized interventions, enhancing system performance, and strengthening privacy protection and ethical compliance. The aim is to build a multi-tiered mental health support network that promotes high-quality development of mental health services in universities, safeguarding students' psychological health and supporting their comprehensive growth and social adaptation. The findings of this research not only provide theoretical and practical guidance for university mental health initiatives but also serve as a model for interdisciplinary research in the mental health field. This work has the potential to drive the application and innovation of related technologies across broader domains.

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