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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 23 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i23.52877

PAPER

Leveraging Mobile Technology for Enhanced Mental Health Levels in University Students

Wei Li, Yan Lyu(✉), Qiuju Feng

North China University of Science and Technology, Tangshan, China

13733338682@163.com

ABSTRACT

With the advent of the digital era, the application of mobile technology in higher education has become increasingly prevalent, particularly in the management of students' mental health. University students face multiple pressures, including academic, social, and career-related challenges, which have led to a rise in mental health issues. As a result, the utilization of mobile technology to collect and analyze students' mental states and behavioral data in real-time has emerged as significant research focus. Current studies predominantly rely on traditional survey methods, which fail to capture students' dynamic mental states in real-time and often lack an in-depth understanding of complex behavioral patterns. Moreover, few existing studies have examined the integration of multi-source data, thereby limiting comprehensive analyses of mental health risks. This study proposes a dynamic mental behavior inference and mental health risk assessment framework for university students based on multi-source data integration. The framework aims to analyze students' mental health conditions comprehensively by integrating diverse data from mobile technology. Experimental results and analyses were presented to verify the framework's effectiveness and practicality, providing new insights for mental health management in higher education and laying the foundation for future research.

KEYWORDS

mobile technology, mental health, university students, data integration, risk assessment, improved Markov

1 INTRODUCTION

In the current digital era, the application of mobile technology in higher education has become increasingly prevalent, particularly in the management of students' mental health [1–4]. University students are confronted with multiple pressures, including academic demands, social challenges, and concerns about future employment, which have contributed to the growing prominence of mental health issues [5, 6]. Consequently, the collection and analysis of students' mental states and

Li, W., Lyu, Y., Feng, Q. (2024). Leveraging Mobile Technology for Enhanced Mental Health Levels in University Students. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(23), pp. 110–124. https://doi.org/10.3991/ijim.v18i23.52877

Article submitted 2024-09-14. Revision uploaded 2024-10-14. Final acceptance 2024-10-14.

behavioral data through mobile technology for the purpose of real-time monitoring and intervention has emerged as a significant research topic.

Exploring the application of mobile technology to improve students' mental health is of considerable research significance [7–10]. On the one hand, it assists higher education institutions in identifying and addressing mental health risks in a dynamic environment, thus contributing to the improvement of students' overall mental health. On the other hand, the integration and analysis of data from various sources can provide empirical support for the development of more scientifically informed management strategies, thereby enhancing students' mental health and learning experiences [11–15].

However, existing research methodologies tend to exhibit certain limitations and deficiencies. Many studies rely heavily on traditional survey methods, which are unable to capture students' dynamic mental states in a timely manner. The data analysis often remains at a quantitative level, lacking in-depth understanding of complex behavioral patterns [16–20]. Moreover, existing studies seldom incorporate the perspective of multi-source data integration, resulting in an underutilization of the wealth of available information when addressing mental health risks.

This study aims to propose a dynamic mental behavior inference and mental health risk assessment framework for university students based on multi-source data integration. By comprehensively analyzing diverse data derived from mobile technology, students' mental health conditions were explored in greater depth. Furthermore, experimental results and analyses were presented to validate the effectiveness and practicality of the proposed framework. This study not only provides new insights into the management of mental health in higher education but also lays the groundwork for future studies, offering significant theoretical and practical implications.

2 METHODOLOGY FOR INFERRING MENTAL BEHAVIOR AND ASSESSING MENTAL HEALTH RISKS AMONG UNIVERSITY STUDENTS

At present, the rapid development of mobile technology has enabled the real-time collection of diverse data regarding university students' behaviors and emotional states. These data sources include social media interactions, usage patterns on online learning platforms, and health monitoring applications. Through the integration of this multi-source data, a more comprehensive picture of students' mental health can be drawn. Compared with traditional survey methods, data obtained via mobile technology are more dynamic and real-time, reflecting students' genuine emotional and mental states in various contexts, thus enhancing the accuracy of predictive models. In this context, a method based on multi-source data integration for predicting university students' mental health levels and assessing risks was proposed.

The proposed method comprises five main modules. The psychological state description and reconstruction module is responsible for comprehensive modeling of the mental and behavioral states of university students. By integrating multi-source data obtained through mobile technology, such as social media activity, online learning behavior, and health monitoring information, a dynamic state space model was constructed. The particle filtering-based data assimilation module applies particle filtering techniques to assimilate the collected multi-source data, improving the accuracy of the system's state estimation. In the context of mental health risk assessment, particle filtering effectively integrates dynamic data, ensuring real-time monitoring and evaluation of students' mental behavior. By analyzing the distribution of particles, the state space model can be adjusted to reflect more accurate mental state changes. The improved Markov analysis model generation module focuses on constructing the foundational model for inferring mental behavior. This module generates a predictive model for analyzing students' mental behavior. This model is capable of capturing students' mental reactions in different contexts, providing theoretical support for subsequent risk assessments. The fourth module, the improved Markov search and analysis module, employs dynamic system scenario-based behavioral search and analysis methods to explore students' mental health data in greater depth. The mental health risk decision module consolidates the analysis results from the previous four modules, offering decision support for targeted intervention strategies. A detailed explanation of the five modules is provided below. The architecture of the model is shown in Figure 1.

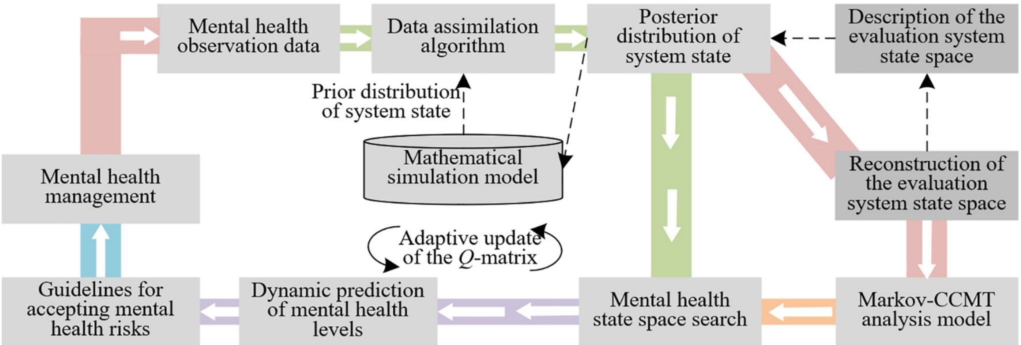

Fig. 1. The mental behavior inference and mental health risk assessment model for university students

a) Expanded psychological state space based on adjunct parameters: The expanded psychological state space consists of two parts: the real-time psychological state and the process variable states, along with their adjunct parameters. The adjunct parameters T' represent associated system parameters that influence changes in the psychological state T. Although these parameters are not directly coupled with the system's dynamic behavior, they provide crucial contextual information through their indirect impact on the psychological state T. This design allows the model to capture the diversity of students' mental states while reducing the complexity associated with considering multiple state parameters simultaneously, thereby improving analytical efficiency. The related process variables are also divided into two categories: key target process control parameters and adjunct parameters. The key target parameters directly affect students' mental health, such as academic pressure and the frequency of social activities. In contrast, adjunct parameters include factors such as social support and environmental conditions, which do not directly alter mental states but influence overall mental health by impacting key target parameters indirectly. Through this classification, the factors affecting university students' mental health can be identified and analyzed more clearly, offering a more systematic perspective for risk assessment.

The expanded psychological state vector can similarly be viewed as a composite state that encompasses both psychological states and their adjunct parameters. This expanded psychological state vector, denoted as $\{[z_1, z_2, z_3, z_4, cz_5, m_1], T'\}$, consists of three components: the physical component states of the system, the target control parameter states, and the adjunct parameters. The physical component state of the system is represented by parameters describing the mental behavior characteristics of students, denoted as $[z_1, z_2, z_3, z_4, cz_5, m_1]$. Each state parameter may correspond to different mental dimensions, such as emotional stability, learning motivation, and social interaction frequency. This component can also be referred to as the "student mental configuration," reflecting the overall mental state and behavioral patterns of the student. The target control parameter state is represented by m_1, which may include variables such as anxiety level or depression score. This parameter directly influences students' mental health and can provide real-time reflection of their mental state in specific situations. The adjunct parameters T' consist of environmental factors and social support information relevant to mental health. These adjunct parameters could include $T = [t_{\text{temperature}}, t_{\text{social support}}, t_{\text{academic pressure}}, t_{\text{family support}}]$. While these factors do not directly affect students' mental states, they influence overall mental health by indirectly affecting key target parameters, such as anxiety levels or depression scores. In the dynamic behavior inference, the psychological state evolution process begins with a green square, representing the initial mental state, and gradually transitions to other normal or degraded states. Ultimately, it may reach the red square, which indicates a mental health risk state. The state transitions occur between adjacent time steps and are determined by the system configuration, adjunct parameters, and the target process control parameters themselves.

b) Reconstruction of the psychological state space grid cells: The mental health status of university students is a highly dynamic and complex system, influenced by various factors, including individual mental states, social environments, and academic pressure. Due to the variability of these factors, traditional fixed state space divisions are often ineffective in capturing the true dynamics of students' mental states. To address this, a particle filtering-based method was employed to achieve dynamic adaptation and reconstruction of the psychological state space grid cells. This approach mitigates the analytical biases caused by fixed state space divisions and observation errors, thereby improving the accuracy of dynamic reliability analysis.

Particle filtering, a sample-based Bayesian filter, approximates the probability density function of the psychological state by propagating a set of randomly weighted particles through the state space. This method is particularly suitable for handling nonlinear and non-Gaussian systems, which are common in mental health monitoring, as students' mental states are influenced by multiple complex factors, often displaying significant dynamism and uncertainty. The basic process of particle filtering consists of two steps: prediction and update. During the prediction phase, the state of each particle is updated using a dynamic model, simulating the evolution of students' mental states over time. In the update phase, the particles are weighted based on observed data, adjusting their distribution within the state space accordingly. By applying weights to each particle, the system corrects previous predictions using real-time multi-source data.

Specifically, let the posterior probability density distribution of the psychological state be represented by $o\left(a_j \middle| c_{1:j}\right)$, where the state value of the u-th particle is denoted by a_j^u, the weight of particle i is denoted by q_j^u, the state variable at time j is represented by a_j, and the sequence of observations from the initial time to time j is denoted by $C_{1:j}$. If V particles can be independently obtained from $o\left(a_j \middle| c_{1:j}\right)$, the posterior probability distribution of the psychological state can be obtained using the following expression:

$$o\left(a_j \middle| c_{1:j}\right) \approx q_j^u \sum_{u=1}^{V} \sigma\left(a_j - a_j^u\right) \tag{1}$$

If the particle set can be extracted from the importance distribution of $w\left(a_j^u \middle| a_{j-1}^u, c_j\right)$ the formula for calculating particle weights is given as follows:

$$q_j^u = q_{j-1}^u \frac{o\left(c_j \middle| a_j^u\right) o\left(a_j^u \middle| a_{j-1}^u\right)}{w\left(a_j^u \middle| a_{j-1}^u, c_j\right)} \tag{2}$$

In this study, the prior distribution function of the state variable was chosen as the importance distribution function $\left(w\left(a_j^u \middle| a_{j-1}^u, c_j\right) = o\left(a_j^u \middle| a_{j-1}^u\right)\right)$ to simplify the computation. The simplified formula for calculating particle weights is given as follows:

$$q_j^u = q_{j-1}^u o\left(c_j^u \middle| a_j^u\right) \tag{3}$$

By normalizing the particle weights $q_j^u = q_j^u / \left(\sum_{u=1}^{V} q_j^u\right)$, the posterior estimate of the psychological state can be approximated by the following formula:

$$\hat{a}_j = \sum_{u=1}^{V} a_j^u \tilde{q}_j^u \tag{4}$$

To avoid the particle degeneracy issue caused by sequential importance sampling, a resampling process was introduced in this study. During the normalization of the particle weights, a cumulative weight function D_u was constructed, as shown in the following formula:

$$D_u = \sum_{k=1}^{u} \tilde{q}_s^k \tag{5}$$

The total weight of all V sampled particles is 1. Furthermore, D_u, calculated by adding particles one by one to the subset $u(u = 1, 2, ..., V)$, divides the interval [0, 1] into V non-overlapping subintervals: $[0, 1] = \{ | 1\ [0, D_1] | \cup | 1\ [D_2, D_1] |\ ... \cup | u\ [D_{u-1}, D_u] | \cup ... \cup | V\ [D_{V-1}, D_V] | \}$. Assuming that i_u is a uniformly distributed random variable within the interval [0, 1], V points were sampled. During the resampling process, the particles were copied and updated using $V_u(u = 1,2, ..., L)$ based on the number of randomly sampled points falling into different intervals. $| V1\ [0, D_1] | \cup | V2\ [D_2, D_1] |\ ... \cup | V_u[D_{u-1}, D_u] | \cup ... \cup | V_V\ [D_{V-1}, D_V] | \}$, resulting in $q_j^u = 1/V$. The implementation steps for the dynamic adaptive reconstruction of the psychological state space grid cells based on particle filtering are as follows:

Step 1: Initialization of particles: Based on the existing spatiotemporal coupled model of the psychological state and in combination with the input or assumptions of the initial state, the psychological state at the initial time $T_0(s_0)$ and its adjunct parameters $T_0'(s_0)$ were determined. For instance, in the context of university students' mental health assessment, initial states may be set using previous mental evaluation data or results from self-report questionnaires, reflecting students' mental characteristics. A Gaussian sampling method with variance δ was then applied for N times to generate an initial particle set $T_{tt}(s_0)$ and adjunct parameters $T'_{tt}(s_0)$. Each particle in this context represents a set of values from an expanded psychological state vector, comprising multiple parameters related to mental health.

Step 2: Obtaining prior estimates at time s_u: In the second step, the initial particle sets $T_{tt}(s_0)$ and $T'_{tt}(s_0)$ were input into the system simulation model or state space model to calculate state predictions for subsequent time steps s_u. During this process, particles were used to represent the mental health state at future moments. By propagating and evolving each particle within the previously established model, the predicted values of V particles with equal weights at each time step s_u, denoted as $\left[T_{tr}(s_u), T'_{tr}(s_u)\right]$, were obtained. These predictions not only reflect the dynamic changes in students' mental states but also capture the impact of real-time mental measurements obtained through mobile technology on state estimation.

Step 3: Particle weight update calculation: In the third step, the weight of each particle was updated to reflect the Euclidean distance between the simulator's predicted values $\left[T_{tr}(s_u), T'_{tr}(s_u)\right]$ and the actual observed values $\left[T_l(s_u), T'_l(s_u)\right]$. Specifically, the difference between the predicted particle set and the actual sensor data was calculated, and the square root of the sum of squared differences was used to estimate the particle weights. Particles closer to the observed data were assigned higher weights, visually represented as larger black or grey spheres, indicating their importance in the state estimation. In contrast, particles further from the observed values were assigned lower weights, displayed as smaller spheres. Assuming that the covariance matrix of the expanded psychological state vector $\left[T_{tr}(s_u), T'_{tr}(s_u)\right]$ is denoted by O^{-1}, the weight q_v of each particle can be calculated using the following formula:

$$q_v = \frac{1}{\sqrt{2\tau}} r^{-\frac{\left[T_{tr}(s_u), T'_{tr}(s_u)\right]^S \cdot (O^{-1}) \cdot \left[T_l(s_u), T'_l(s_u)\right]}{2}} \tag{6}$$

Step 4: Particle resampling: In the fourth step, resampling was performed based on the updated particle weights to generate a posterior distribution particle set for the psychological state. The resampling process focuses on replicating particles with higher weights, while particles with very low weights are less likely to be replicated and may eventually be eliminated. After resampling, the total number of particles remained unchanged, and the weight of each particle was re-normalized to $1/V$, ensuring that all particles have equal starting weights for the next iteration. This resampling process dynamically adjusts the psychological state estimation based on the latest observation data. For example, when significant changes occur in some students' mental states, resampling ensures that these changes are better captured and reflected. Ultimately, the resampled particle set $\left[T_e(s_u), T'_e(s_u)\right]$ serves as the new initial particle set for the next iteration, forming a new prior estimate of the expanded psychological state. This iterative mechanism continues until the predictive analysis of the system is completed, providing ongoing support for monitoring and assessing university students' mental health. Figure 2 illustrates the process of reconstructing the psychological state space.

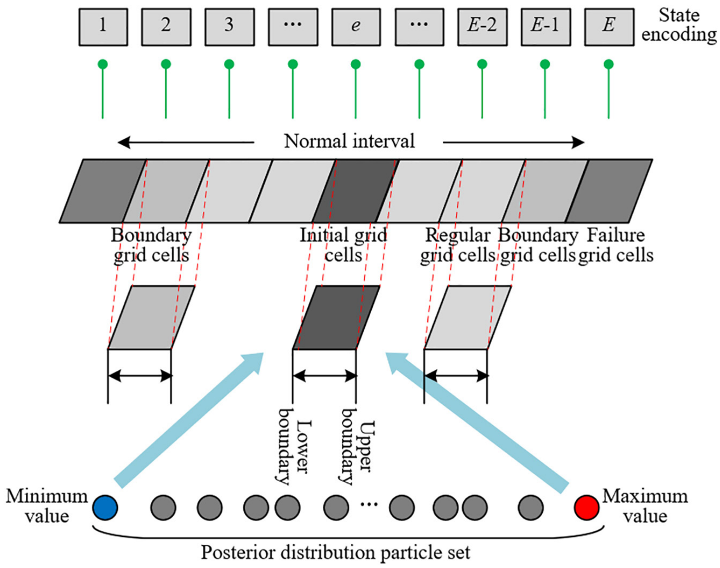

Fig. 2. Reconstruction process of the psychological state space

c) Generation of the synchronous improved Markov analysis model: This analysis model lies in obtaining the probability mapping relationships between grid cells during psychological state transitions. However, in the context of complex dynamic nonlinear systems, particularly in the field of university students' mental health, acquiring precise analytical solutions is often extremely challenging. To address this difficulty, a simulation-based sampling method was proposed in this study, using the Monte Carlo method to perform random sampling on the probability distribution of the psychological state, thereby achieving an accurate approximation of the system's state. This approach allows the dynamic characteristics of state transitions to be effectively captured without relying on strict analytical solutions.

The main concept behind implementing this model is to treat the assimilated psychological state as the initial state of the system and dynamically generate the *G*-matrix using an equally weighted point product method. Initially, equidistant points were selected from the system grid cells to ensure that the chosen state points comprehensively cover the potential state changes that may occur in the mental health assessment. These psychological states and configurations were then input into the simulation model for simulation and trajectory tracking to observe how the mental states of university students evolve over time under different initial conditions. By analyzing the simulation results, the dynamic characteristics of state changes were captured, providing data support for subsequent evaluations. Finally, statistical analysis was conducted based on the system simulation test results to obtain approximate system condition state transition probabilities. Specifically, assuming I points are uniformly sampled from a grid cell k', the number of sampled points that transition from the starting grid cell k' to grid cell k is denoted as $i\left(k\middle|k'\right)$, with the total number of samples represented by I. The following formula describes the relationship between the time step Δs and the system configuration l':

$$H\left(k\middle|k', l', \Delta s\right) = \frac{i\left(k\middle|k'\right)}{I} \tag{7}$$

When simulating the trajectory of psychological states, attention must be paid to the distribution of particles within different spatial grid cells. This distribution is crucial for understanding system dynamics, as it reflects the relationship between changes in mental health status and the corresponding adjunct parameters. Variations in adjunct parameters can influence the assessment of mental states, making it necessary to construct a unique *G*-matrix for each extended psychological state. This approach ensures the distinctiveness and adaptability of each state, preventing misjudgment caused by parameter changes. Another key consideration is that even with the same psychological state, different adjunct parameters can lead to significant differences in the trajectories of sampled points. This indicates that the model must be flexible enough to accommodate changes in adjunct parameters. In practical applications, the mean value of the adjunct parameters can be calculated by taking the ratio of the sum of adjunct parameter values for particles that fall into a specific grid cell to the number of corresponding particles. Assuming the number of particles falling into grid cell k is denoted by V_k, and the adjunct parameters corresponding to the particle set in grid cell k are represented by $T'_k\left(k|k'\right)$, the adjunct parameters of the psychological state at the next search time step are represented by T_k, and the calculation formula is given as follows:

$$\bar{T}_k = \frac{\sum_{i(k|k')} T'_k\left(k|k'\right)}{V_k} \tag{8}$$

The transition probabilities $\left(H\left(m\,|\,m', j', \Delta t\right)\right)\left(G\left(l\,|\,l', k', \Delta s\right)\right)$ of the system configuration were updated synchronously. The transition probability of the state change of a single component was simply estimated as the product of the failure rate and a very small-time interval Δts. Multiplying matrix *GH* by matrix *HG* allows the improved Markov analysis model to be synchronously generated. Therefore, given the initial psychological state and configuration, the model adopts a sparse sub-matrix form $Q\left(m, j\,|\,m', j', \Delta t\right)W\left(l, k\,|\,l', k', \Delta s\right)$, rather than a full probability mapping scheme of the psychological state transition probability (*QW*), to achieve more efficient analysis of system evolution.

d) Dynamic mental health risk sequence prediction algorithm: The dynamic mental health risk sequence prediction model relies on the synchronous improved Markov analysis model generated by data assimilation techniques, combined with system trajectory simulation, to provide comprehensive dynamic predictions and risk assessments of university students' mental health. The basic framework of this model begins with the current assimilated initial psychological state T_z, which is derived from dynamic monitoring through multi-source data integration, ensuring that the model reflects the most up-to-date mental health information. Subsequently, the evolution of the psychological state was predicted through a state transition model. This process involves initializing several parameters, including the search depth J, the initial psychological state probability O_0, and the system configuration l'.

In the proposed model, system evolution analysis was enhanced by using a sub-matrix search $w\left(l, k\,|\,l', k', \Delta s\right)$, which improves analytical efficiency, significantly reducing the complexity of the search process when facing complex state transitions, and enhancing the model's real-time response to system dynamics. By setting the state transition probabilities of the current psychological state and configuration to zero, the model generates a sparse matrix, which not only reduces unnecessary computation but also focuses on probable state transition relationships. Compared to traditional methods, this model adopts a simulation-based equally weighted point product method to synchronously update the *G*-matrix for each psychological state node, ensuring the accuracy and real-time performance of state mapping. This method improves the model's ability to handle complex mental states, ensuring that each state transition is based on the most current system information. Assuming that the probability of the merged psychological state at the previous time step is represented by O_h^{j-1}, the occurrence probability of the sequence path at search depth J is given as follows:

$$O^j = O_h^{j-1} \cdot W^j \tag{9}$$

This model traverses multi-source data, encompassing information such as social media activity, academic performance, and lifestyle habits to construct a dynamic psychological state space. Based on this, each psychological state represents a snapshot of a university student's mental state at a specific point in time. The model treats these states as nodes and illustrates the evolution of students' mental states over time through state transition branches. As data continuously updates, psychological state transition branches with the same final state are merged. The merged psychological state represents a set of similar mental states, and its occurrence probability is equal to the sum of the transition probabilities of all branches leading to the same state.

$$O_h^j = \sum_{SE} O^j \tag{10}$$

Next, the model evaluates and ranks the merged psychological states, taking into account the likelihood of system degradation. By calculating the merged average adjunct parameter $T_t^{-\prime}$, the model assigns an adjunct parameter to each new parent node, reflecting the sensitivity of students' mental states to external changes. Assuming that the number of psychological states with the same transition is denoted by v_t, the formula is given as follows:

$$\bar{T}_T' = \frac{\sum_{SE} \bar{T}_k'}{v_t} \tag{11}$$

Finally, based on this dynamic risk sequence prediction model, educators and mental health professionals are able to conduct real-time monitoring and intervention of students' mental behavior. This not only helps students receive timely mental support but also fosters the development of a collective mental health environment on campus. Through deep integration and analysis of multi-source data, this method provides an innovative and actionable solution for assessing the mental health risks of university students.

3 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Comprehensive evaluation results

Sample No.	Mobile App Data	Wearable Device Data	Social Media Data	Geographic Location Data	Final Evaluation
1	0.221	0.1952	0.2015	0.2951	Excellent
2	0.1658	0.1245	0.1562	0.0784	Good
3	0.0715	0.2985	0.2415	0.2315	Pass
4	0.421	0.2325	0.2031	0.1562	Pass

(Continued)

Table 1. Comprehensive evaluation results *(Continued)*

Sample No.	Mobile App Data	Wearable Device Data	Social Media Data	Geographic Location Data	Final Evaluation
5	0.132	0.1652	0.1958	0.2329	Excellent
6	0.2456	0.1954	0.2321	0.2325	Fail
7	0.1895	0.1231	0.1625	0.2985	Excellent
8	0.1852	0.2985	0.2715	0.2325	Good
9	0.3215	0.2232	0.2236	0.0784	Good
10	0.0489	0.1658	0.1026	0.1562	Excellent
11	0.4023	0.2145	0.2154	0.2315	Pass
12	0.2515	0.1326	0.151	0.2315	Pass

The comprehensive evaluation results shown in Table 1 reveal significant differences across sample evaluations. Samples rated as "excellent" (e.g., Samples 1, 5, 7, and 10) exhibit high scores in mobile app data and social media data, indicating that active social interaction and mobile app usage have a positive impact on mental health. In contrast, samples rated as "fail" (e.g., Sample 6), despite having relatively high wearable device data scores, show lower overall scores, suggesting a potential disconnect between physiological data and mental health. Furthermore, "pass" samples (e.g., Samples 3, 4, 11, and 12) demonstrate relatively balanced data but still score lower than the "excellent" or "good" samples, reflecting the challenges these students may face in maintaining optimal mental health. From the analysis, it is evident that the comprehensive evaluation of mental health levels is influenced by multiple data sources. Active communication and social media engagement appear to enhance mental health, while lower-scoring samples suggest that reliance solely on wearable device data may not fully capture students' mental states. It is recommended that personalized mental health interventions be implemented for "fail" and "pass" samples, with a focus on increasing social interaction and mobile app engagement to improve overall mental health.

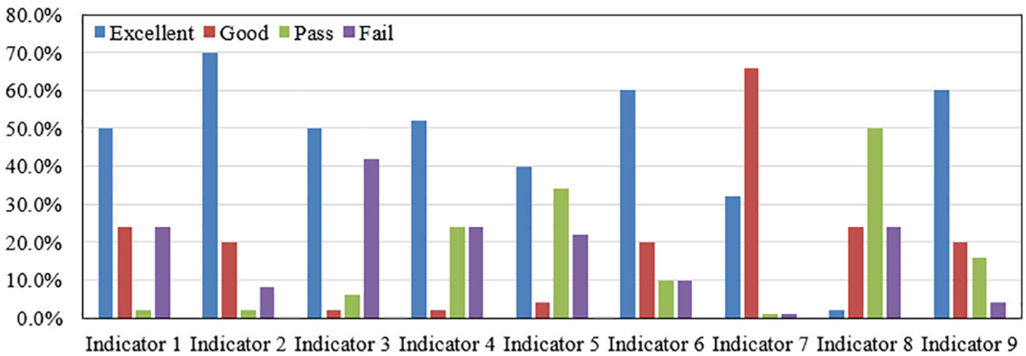

Fig. 3. Comprehensive evaluation probability of university students' mental health levels based on mobile app dataset

The nine indicators in Figure 3 are as follows: 1) Emotional state score; 2) Frequency of mental health self-assessment; 3) Level of social interaction; 4) Emotional fluctuation index; 5) Frequency of positive emotional experiences; 6) Frequency of negative emotional experiences; 7) Stress level assessment; 8) Sleep quality score;

and 9) Physical and mental health behavior records. In the "excellent" samples shown in Figure 3, indicators such as Indicator 1 (emotional state score), Indicator 2 (frequency of mental health self-assessment), and Indicator 3 (level of social interaction) exhibit high proportions (50% and above), indicating that these students maintain good overall mental health. In particular, the balance between social interaction levels and the frequency of negative emotional experiences (Indicator 6) in the "excellent" samples highlights the positive influence of a supportive social environment on mental health. In contrast, the "fail" samples display elevated values in multiple indicators (e.g., Indicators 3 and 7), indicating higher levels of negative emotional experiences and stress, suggesting that these students may be experiencing considerable mental pressure and social isolation. In summary, by combining multi-source data integration with particle filtering theory, the model can effectively identify and predict changes in students' mental health. A high proportion of "excellent" and "good" evaluations is associated with positive emotional experiences and social interactions, while the "fail" samples underscore mental health risks that require intervention. Therefore, implementing personalized interventions, particularly focusing on social interaction and emotional management, is essential to improving students' mental health.

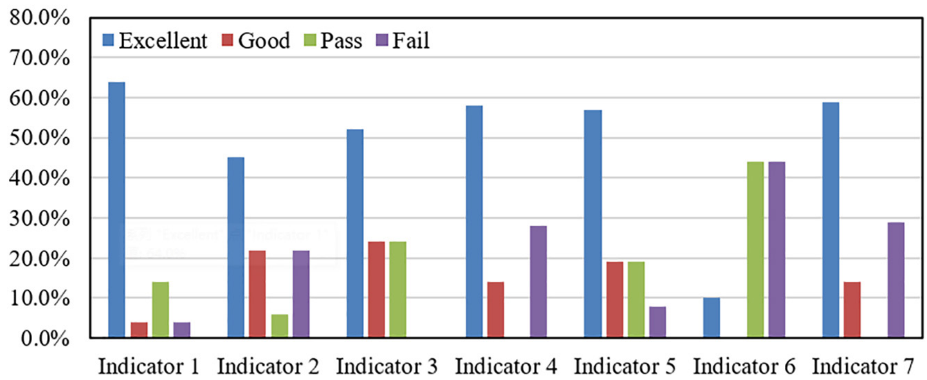

Fig. 4. Comprehensive evaluation probability of university students' mental health levels based on a wearable device dataset

The seven indicators in Figure 4 are as follows: 1) Heart rate variability; 2) Sleep quality; 3) Exercise volume; 4) Activity level; 5) Stress level; 6) Body temperature variation; and 7) Life regularity. According to the comprehensive evaluation results based on the wearable device dataset shown in Figure 4, the "excellent" samples display high proportions in heart rate variability (64%) and life regularity (59%), suggesting that these students maintain relatively stable physiological states, contributing to good mental health. Evaluations of sleep quality and exercise volume also show high rates of 58% and 52%, respectively, further highlighting the positive correlation between physical health and mental well-being. In contrast, the "good" samples exhibit relatively lower scores in several indicators (e.g., exercise volume and sleep quality), at only 24% and 22%, respectively, implying that these students may be at a potential risk for mental health challenges. Additionally, the "pass" and "fail" samples show lower scores in stress level and life regularity, with percentages of 44% and 29%, respectively, indicating substantial room for improvement in these areas. From the analysis, the research method combining multi-source data integration and particle filtering theory proves effective in identifying and monitoring dynamic changes in students' mental health. The strong physiological indicators in the "excellent" samples suggest a close link between their stable physiological state and good mental health, while the "fail" samples emphasize the importance of stress management and life regularity, indicating a need for targeted interventions.

The four indicators in Figure 5 are as follows: 1) Frequency of social interaction; 2) Sentiment analysis; 3) Frequency of negative emotional expression; and 4) Topic relevance score. According to the comprehensive evaluation results shown in Figure 5 based on the social media dataset, the "excellent" samples display a high proportion in both the frequency of social interaction (50%) and sentiment analysis (60%), indicating that these students are actively engaged in social activities and tend to express positive emotions. At the same time, the proportion of negative emotional expression is relatively low (31%), suggesting that the "excellent" students are more likely to maintain a positive emotional state. In contrast, the "fail" samples exhibit a higher frequency of negative emotional expression, reaching 37%, indicating that these students may face significant challenges in emotional regulation. Additionally, the "good" and "pass" samples perform relatively weaker across the indicators, particularly in sentiment analysis and frequency of social interaction, implying that their social activities and emotional expression may be limited. From the analysis, the method combining multi-source data integration and particle filtering theory provides strong support for monitoring and predicting students' mental health. The high proportion of social interaction and positive sentiment in the "excellent" samples underscores the importance of active social engagement in mental health, while the elevated negative emotional expression in the "fail" samples highlights the urgent need for mental intervention.

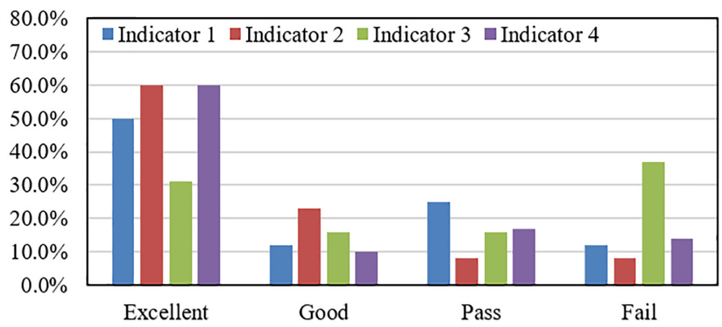

Fig. 5. Comprehensive evaluation probability of university students' mental health levels based on social media dataset

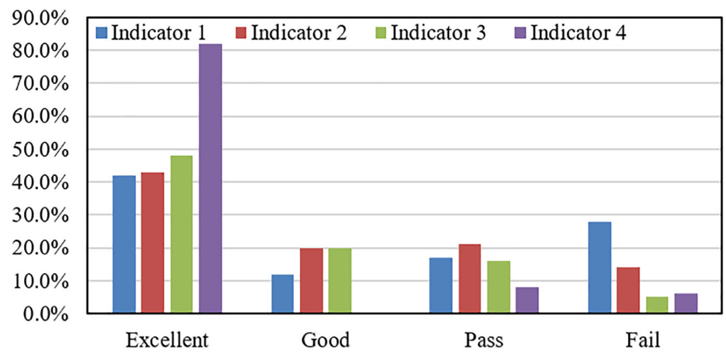

Fig. 6. Comprehensive evaluation probability of university students' mental health levels based on geographic location dataset

The four indicators in Figure 6 are as follows: 1) Activity range; 2) Number of frequently visited locations; 3) Travel frequency; 4) Diversity of social activity locations. According to the comprehensive evaluation results based on the geographic location dataset shown in Figure 6, the “excellent” samples display high proportions in both activity range (42%), and number of frequently visited locations (43%), suggesting that these students engage in a wide range of daily activities and participate in diverse social and cultural events. Furthermore, the diversity of social activity locations reaches as high as 82%, indicating that the “excellent” students actively explore different environments and social venues during their interactions. In contrast, the “fail” samples show significantly lower percentages in both activity range and number of frequently visited locations, at 28% and 14%, respectively. This may indicate that these students maintain a more confined social circle, limiting their potential for improving mental health. From the analysis, the method combining multi-source data integration and particle filtering theory proves effective in monitoring and predicting students’ mental health levels. The broad activity range and high frequency of diverse social activity locations in the “excellent” samples suggest good mental health, closely associated with an active social environment. On the other hand, the low levels of activity and social diversity among the “fail” samples indicate that interventions focused on expanding social activities and increasing travel frequency may be needed to enhance their mental health.

4 CONCLUSION

A method for predicting the mental health levels of university students and assessing the risks based on multi-source data integration was proposed in this study. This approach, utilizing particle filtering-based data assimilation theory, effectively processes data from various channels, including mobile applications, wearable devices, social media, geographic locations, and communication applications. The core of this method lies in dynamically adjusting the predictive model to adapt in real time to changes in students’ mental health, thereby enhancing the accuracy and timeliness of mental health monitoring. Through the effective integration and analysis of multi-source data, potential mental health risks were successfully identified, and targeted intervention measures were provided to universities. The experimental results demonstrate that the comprehensive evaluation probabilities of each dataset reflect the mental health levels of students. Among them, the predictive capabilities of the mobile application and wearable device datasets were particularly notable, providing valuable references for universities in daily management. The combination of social media and geographic location data also provided a more comprehensive perspective for mental health assessments, reflecting students’ mental states in different environments.

The innovation of this study lies in its forward-looking predictive capability, which is particularly crucial in a rapidly changing social environment. The findings indicate that through the dynamic integration of multi-source data, a proactive approach to mental health management can be provided to universities, enabling them to take effective measures before issues escalate, thus ensuring students’ mental health. This comprehensive evaluation method lays the foundation for establishing a more scientific mental health intervention system. The value of this study is reflected in its provision of a scientific, dynamic assessment tool for mental health management in universities, thereby enhancing the precision and effectiveness of intervention measures. However, the study has certain limitations. For instance, the diversity of data sources may introduce some bias during integration, potentially affecting the final assessment results. Moreover, while the study demonstrates strong predictive capabilities, further validation is required to assess the specific impact of different datasets on mental health evaluation to improve the model's reliability. Future research can expand in several directions. First, more diverse data sources and algorithms could be explored to improve the accuracy of the predictive model. Second, research on mental health interventions could be integrated to evaluate the effectiveness of various intervention strategies, thereby continuously optimizing mental health management practices in universities. Additionally, with the advancement of technology, leveraging artificial intelligence and machine learning methods to enhance data analysis capabilities will be a key area of exploration. These efforts will contribute to providing more comprehensive and scientific support for the mental health of university students.

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6 AUTHORS

Wei Li, a doctoral graduate from Eternal University in the Philippines, is currently employed at Jitang College of North China University of Science and Technology, focusing on research in Education (E-mail: aqgzc1@ncst.edu.cn).

Yan Lyu, a master’s graduate from Hebei Normal University, is currently employed at North China University of Science and Technology, with a primary research focus in Education (E-mail: 13733338682@163.com).

Qiuju Feng, a master’s graduate from Hebei Union University, is currently employed at Jitang College of North China University of Science and Technology, focusing on research in ideological and political education (E-mail: xslh_17@163.com).