RESEARCH ARTICLE

Prediction of mental health trends of college students based on data analysis of social networks

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Mental health has a profound impact on college students' learning, life, and future development. However, the current mental health problems of college students are prominent, and the popularity of social networks has brought new opportunities to study this issue. This research used social network data analysis technology to predict the mental health trends of college students. By collecting application programming interface (API) data of social network platforms and subjective perception data of online questionnaires, 2,000 college students from different backgrounds were involved in this study using stratified random sampling. A long short-term memory network (LSTM) model was constructed and optimized in combination with the attention mechanism. The multiple dimensional relationships between social network usage time, frequency, content preference, interaction mode, and mental health were analyzed. This study integrated multi-source data for the first time, introduced personalized risk analysis and interactive feedback loop mechanism, and strictly protected data privacy. The results of this study enriched the research methods of mental health and improved the accuracy of risk assessment, which was of great significance to promote the development of college students' mental health research and build an effective support system. The research was expected to provide key references for subsequent studies and help improve the level of college students' mental health.

Keywords: social networks; data analysis; college student population; mental health trend; prediction.

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Introduction

In today's era, the acceleration of social development and the fierce competition in education have jointly created a challenging environment. College students face unprecedented psychological challenges [1]. The importance of mental health has long surpassed the scope of individual emotional management and has a profound impact on college students' learning outcomes, life satisfaction, and even future growth trajectory and career development [2]. According to statistics, about one-third to one-half of college students may encounter varying degrees of psychological distress during their studies, including anxiety, depression, and reduced self-worth, which seriously hinder the overall development of individuals. The outbreak of the global pandemic in recent years has added additional pressure to students' psychological defenses. The isolation of online learning and the lack of warmth of face-to-face communication have made loneliness and isolation an insurmountable psychological gap for many students, further increasing their psychological burden [3, 4].

With the rapid development of internet technology, social networks have become an indispensable part of college students' daily lives. Platforms such as WeChat, QQ, Weibo, Douyin, and Instagram are not only windows for college students to obtain external information and maintain social connections, but also important stages for them to show themselves and express their emotions. On this virtual yet real stage that reflects the inner world, every like, every dynamic, and every interaction of college students may contain subtle clues to their psychological state [5, 6]. The massive data of social networks is like a mirror, reflecting individual psychological fluctuations and collective psychological trends, providing unprecedentedly rich material for the study of college students' mental health [7, 8]. Previous studies have shown that college students' mental health problems are on the rise. Many domestic surveys showed that about 30% of college students had varying degrees of depression symptoms, and the detection rate of anxiety symptoms was as high as 45%. However, despite the recognition of the severity of mental health problems, effective intervention and support systems face many challenges. Due to the stigmatization of mental problems and the lack of mental health knowledge, many students are reluctant to actively seek help, while the distribution of mental health service resources in colleges and universities is uneven, and the number of professional psychological counselors is limited, making it difficult to meet the needs of all students. During the pandemic, the promotion of remote learning models had exacerbated students' sense of isolation and further reduced the accessibility of mental health services [9, 10]. There is a complex relationship between social networks and college students' mental health. Moderate use of social networks can reduce loneliness and enhance a sense of belonging [11, 12]. Students who keep in touch with family and friends through social networks have lower levels of depression when facing life pressures. However, the negative impact of social networks cannot be ignored. Social comparison theory points out that college students frequently browse the carefully planned life fragments of others, which is easy to cause unrealistic social comparison, leading to negative emotions such as reduced self-worth and jealousy, and then aggravating depression and anxiety symptoms. In addition, information overload and negative news on social networks may also increase psychological pressure and affect sleep quality [13, 14].

This study focused on using social network data analysis technology to explore and predict the mental health trends of college students. Application programming interface (API) data from public social network platforms were collected to obtain the social dynamics and interaction records of college students. In addition, the carefully designed online questionnaires were applied to collect subjective perception data, covering mental health assessment scales including patient health questionnaire (PHQ)-9 depression scale, generalized anxiety disorder (GAD)-7 anxiety scale, and social network usage habits. A stratified random sampling strategy was adopted to involve 2,000 college students from different genders, grades, professional backgrounds, and multiple regions in this study to ensure the broad representativeness of the samples [15, 16]. The long short-term memory network (LSTM) model was used to construct a mental health risk prediction model, which could automatically extract temporal features from the input sequence and was particularly suitable for processing the temporal dynamics and nonlinear complexity of social network behavior data [17]. The proposed model was optimized by combining the attention mechanism, so that it paid more attention to key features during the learning process and improved the prediction accuracy. A variety of statistical models and methods were also used to deeply analyze the relationships between social network usage time, frequency, content preference, interaction pattern, and other dimensions and mental health

[18]. This research would promote the improvement and development of research methods in this field, provide important reference for subsequent related studies, and help build a more scientific and effective mental health support system for college students.

Materials and methods

Data collection and analysis

Application programming interfaces (API) such as Twitter, Weibo, *etc*. were employed to collect public social dynamics and interaction records of college students, which covered a broad range of social behavior performances such as post content, interaction frequency, emotional expression, *etc*. Subsequently, subjective perception data were collected through carefully designed online questionnaires including standardized scales to assess mental health such as patient health questionnaire (PHQ-9) (https://www.phqscreeners.com) scale for depression measurement, the generalized anxiety disorder (GAD-7) (https://www.gad7screen.com/) scale for anxiety assessment, and seasonal autoregressive integrated moving average (SARIMA) for time series analysis of the changes in individual mental health status and long-term relationships with social network behavior patterns. A comprehensive analysis framework combining both quantitative and qualitative methods was constructed to deeply understand the complex links between social networks and college student mental health. A stratified random sampling strategy was adopted in this study for sample selection, which included different genders, grades, professional backgrounds, and the locations. A total of 2,000 college students were enrolled in this research. All participants received and completed a written informed consent form. All procedures of this research were approved by the Ethics Committee of Sichuan Agriculture University (Chengdu, Sichuan, China).

Construction of mental health risk prediction model

The LSTM model was used for the input feature vector at time step t, which included behavior data of social networks such as usage duration and interaction times and emotion analysis results, and for the hidden state including historical information up to time step t and the previous time step. Dense layer was a fully connected layer used for output layer conversion and output the probability distribution of the health risk classification predicted at time step t. For the mental health risk prediction task, the model objective function used a cross-entropy loss function to measure the difference between the model prediction probability distribution and the true label distribution. According to the scale scoring criteria of PHQ-9, 0 - 4 points represented no depressive symptoms, 5 - 9 points indicated mild depression, 10 - 14 points meant moderate depression, 15 - 19 points indicated moderate to severe depression, 20 - 27 points indicated severe depression. The GAD-7 score was 0 - 4 for no anxiety symptoms, 5 - 9 for mild anxiety, 10 - 14 for moderate anxiety, and 15 - 21 for severe anxiety. This study collected 5,000 valid questionnaires with PHQ-9 and GAD-7 scale data from college students between March 1, 2024 and May 31, 2024. Stata software (Stata Corp LLC, College Station, Texas, USA) was employed for regression analysis to accurately analyze the complex relationship between social network behavior data and college students' mental health indicators.

Correlation analysis of behavior patterns of social networks and mental health

Duration and frequency refer to the length of time a user uses a social media platform and how often they visit it. Content preferences focus on the types of content that users like to view, share, or engage with. Interaction patterns refer to how users interact with other users or content, which may include behaviors such as commenting, liking, retweeting, *etc*. When exploring the relationship between social network behavior patterns and college students' mental health, the network analysis results were combined with time series analysis results such as usage duration, frequency, content preference, and interaction methods to reveal the regular relationship. Specifically, for the mental health risk prediction task, the model objective function used the cross-entropy loss function to measure the difference between the model prediction probability distribution and the true label distribution as follows.

$$L = -\sum_{c \in C} y_c \log(p_c) \quad (1)$$

where y_c was the one-hot encoding representation of the true label. p_c was the probability distribution predicted by the model. Usage duration and frequency were basic indicators for measuring social network activities, and their impact on mental health was worrying. The excessive use of social networks might be positively associated with mental health problems. To test this hypothesis, a linear regression model was used as follows.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon \quad (2)$$

where Y was the mental health score. X_1 was the average daily usage time (hours). X_2 was the number of logins per week. β_0 was the intercept term. β_1 and β_2 were the coefficient of usage time and login frequency, respectively. ϵ was the error term. By estimating the model parameters, the specific impact of usage time and frequency on mental health was quantified. Content preferences, especially whether they tend to share positive or negative information, might reflect and influence an individual's mental state. This relationship was explored through logistic regression model to determine whether positive/negative content sharing frequency was more likely to be associated with better or worse mental health. User interaction behaviors such as likes, comments, shares were also important dimensions to assess the relationship between behavior patterns of social networks and mental health. The impact of these interactions on mental health was analyzed by constructing multivariate regression model as shown in equation (3).

$$Y = \beta_0 + \beta_{like} X_{like} + \beta_{comment} X_{comment} + \beta_{share} X_{share} + \epsilon \quad (3)$$

where Y took a value of 1, indicating good mental health below a certain critical value. X was the frequency of sharing positive or negative information. β_1 reflected the direction and intensity of the impact of sharing tendency on mental health status. To better understand how dynamic interactions in social networks affect mental health, the network analysis was used to examine the relationship between connection patterns among users such as number of friends and network centrality, and mental health. Network analysis was achieved by establishing regression models between network indicators such as degree centrality and closeness and mental health scores as shown in equation (4) [19].

$$Y = \beta_0 + \beta_{degree} X_{degree} + \beta_{closeness} X_{closeness} + \epsilon \quad (4)$$

Equation (4) was a prediction model that assumed a linear relationship between mental health scores and likes, comments, and shares. Specifically, Y represented the mental health score. β_0 was the intercept term, which represented the expected mental health score when likes, comments, and shares were all zero. β_{like} was the coefficient of likes, which represented the impact of each additional like on the mental health score. $\beta_{comment}$ was the coefficient of comments, which represented the impact of each additional comment on the mental health score. β_{share} was the coefficient of sharing, which represented the impact of each additional share on the mental health score. $\hat{\sigma}$ was the standard deviation of the error term, which represented the difference between the model predicted value and the actual value. This model estimated these parameters through linear regression analysis and was used to predict the mental health score corresponding to a specific number of likes, comments, and shares, thereby revealing the relationship between social media interaction patterns and mental health.

Correlation analysis of behavior patterns of social networks and mental health

The relationship between usage duration, frequency and mental health was measured using Equation (5).

$$[Y = \beta_0 + \beta_1 \times \text{Duration of use} + \beta_2 \times \text{frequency of use} + \grave{o}] \quad (5)$$

Equation (5) described a simple linear regression model for predicting the relationship between a dependent variable Y such as mental health score and two independent variables like duration and frequency of use. The data on duration, frequency, and mental health scores were collected to estimate the parameters in the formula to look for the best-fit parameter values that minimize the error term $\grave{o}$. Once the parameters were estimated, the probability that mental health was positive for a given amount of positive and negative sharing could be calculated as follows.

$$P(\text{Mental health status}) = \frac{1}{1 + e^{-(\beta_0 + \beta_{pos} \times \text{Positive share volume} + \beta_{neg} \times \text{Negative sharing volume})}} \quad (6)$$

Evaluation metrics

To comprehensively evaluate the performance of the model, several key indicators were selected. In terms of accuracy, it was determined by comparing the deviation between the paths planned by different models and the actual optimal path. Specifically, the ratio of the total distance of the path generated by the model to the theoretical shortest path distance was calculated. The closer the ratio was to 1, the higher the accuracy was. The response time was determined from the time the order was generated to the time when the logistics system gave the final path planning and scheduling plan. This time reflected the system's response speed to dynamic demands. The intervention efficiency was measured by calculating the increase in the proportion of logistics tasks completed on time after the model replanned the path and adjusted the scheduling plan in the face of emergencies. If the proportion of on-time completion increased significantly after replanning, it indicated that the intervention efficiency was high. Meanwhile, the indicators were also considered, which comprehensively evaluated the performance of the model in the intelligent logistics system from different dimensions, providing comprehensive data support for in-depth analysis and comparison of different models.

Results and discussion

General mental health information

According to statistical analysis, among the college students who participated in the survey, the PHQ-9 scale scores showed that about 35% of the students were in the normal range (0 - 4 points), 28% had mild depression (5 - 9 points), 18% had moderate depression (10 - 14 points), 14% had moderate to severe depression (15 - 19 points), and 5% had severe depression (20 - 27 points). In terms of GAD-7 scale scores, 40% of the students had no anxiety symptoms (0 - 4 points), 30% had mild anxiety (5 - 9 points), 20% had moderate anxiety (10 - 14 points), and 10% had severe anxiety (15 - 21 points). These data directly reflected the severity of depression and anxiety problems among college students and provided a solid data foundation for further in-depth research on the relationship between social network use and mental health.

Relationship between duration, frequency and mental health

The results demonstrated that, when both duration and frequency of social networks use were 0, the predictive value of mental health was 1.256, which was statistically significant ($P < 0.001$). The coefficient for duration (hours/day) was 0.034, indicating that for every one-unit increase in duration, the mental health score increases by 0.034 units on average a marginally significant ($P = 0.05$) (Table 1).

Relationship between content preferences and mental health

Table 1. The relationship between duration and frequency of social networks use and mental health.

Variables	Coefficient values	*P* value	95% confidence interval	
			Lower bound	Upper bound
Intercept	1.256	< 0.001	0.16	0.36
Duration of use (hours/day)	0.034	0.05	-0.005	0.068
Frequency of use (times/day)	0.12	< 0.01	0.02	0.2

Table 2. The relationship between content preferences and mental health.

Content type	Coefficient values	*P* value	95% confidence interval	
			Lower bound	Upper bound
Intercept	-2.5	< 0.01	-3.1	-1.9
Active sharing	0.8	< 0.01	0.4	1.2
negative sharing	-1.2	< 0.05	-2.5	-0.1

Table 3. The relationship between interaction patterns and mental health.

Interaction type	Coefficient values	*P* value	95% confidence interval	
			Lower bound	Upper bound
Intercept	0.15	> 0.05	-0.1	0.3
Praise	0.03	< 0.05	-0.1	0.7
Comments	0.7	< 0.01	0.2	1.2
Share	-0.1	> 0.05	-0.4	0.2

When both positive and negative shares were zero, the logarithmic probability of mental health being positive was -2.5, which indicated that mental health was more likely to be negative in the absence of positive and negative sharing ($P < 0.01$) (Table 2). There was a positive correlation between the amount of positive sharing and mental health status being positive, while there was a negative correlation between the amount of negative sharing and mental health status being positive. The results suggested that positive sharing might increase the probability of positive mental health status, while negative sharing might decrease this probability.

Effects of interaction patterns (likes, comments, shares)

The results showed that, when likes, comments, and shares were all zero, the intercept was 0.15, which represented no statistical significance ($P > 0.05$). The coefficient of likes was 0.03, which indicated that, for every unit increase in the number of likes, the mental health score increased by an average of 0.03 units. The coefficient of sharing was -0.1, which indicated that, for every unit increased in the number of shares, the mental health score decreased by an average of 0.1 units. However, no significance was observed between sharing behavior and mental health scores ($P > 0.05$) (Table 3).

Network and time series analysis

Autoregressive moving average (ARMA) models were used to reveal dynamic relationships between dependent variable values when analyzing time-series data. The equation below was used to predict the dependent variable values at future time points.

$$Risk_{alert} = \text{if}(y_t > Threshold)$$

The autoregressive and shift error terms in the equation reflected the lag effect in time of the dependent variable values and error terms and

Table 4. Key parameters of time series and network analysis.

Parameters	Coefficient values	*P* value	Explain
ϕ1	0.2	< 0.05	Autocorrelation lag 1
ϕ2	-0.03	< 0.05	autocorrelation lag 2
θ1	0.1	< 0.05	Moving error correlation phase 1
θ2	-0.02	< 0.05	Moving error correlation phase 2

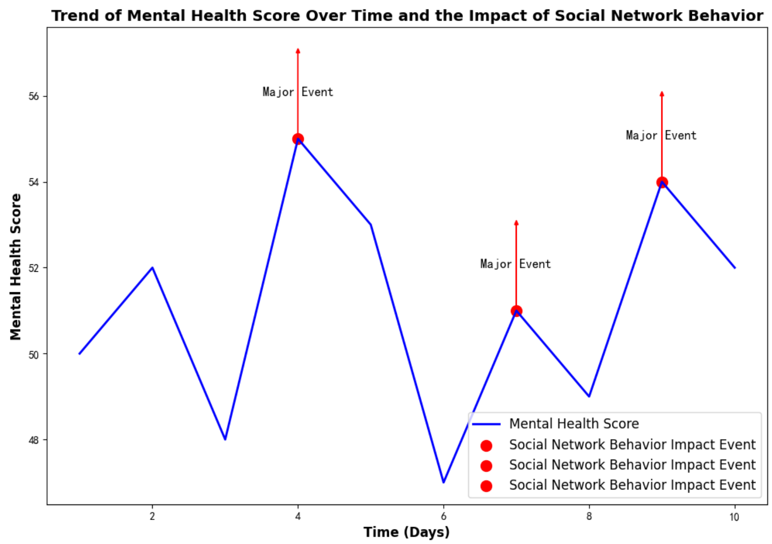

Figure 1. Schematic diagram of time series analysis.

the correlation between the error terms. Autoregressive coefficients and moving average coefficients described the magnitude of these effects, respectively. The ARMA model parameter estimated the values of each coefficient, *P* values, and the interpretation in the model. The results showed that a coefficient value of 0.2 with a *P* value less than 0.05 indicated that the autocorrelation lag 1 was statistically significant, meaning that the dependent variable value at the current time point was influenced by the dependent variable value at the previous time point. Similarly, the coefficient value of -0.03 and its *P* value less than 0.05 indicated that the autocorrelation lag 2 period was statistically significant and the dependent variable value at the current time point was affected by the dependent variable value at the previous two points. In addition, the coefficient value of 0.1 and its P value less than 0.05 indicated that the phase 1 of the movement error correlation was statistically significant, i.e., the error term at the current time point was affected by the error term at the previous point, while the coefficient value of -0.02 with *P* value less than 0.05 indicated that the movement error correlation stage 2 was statistically significant and the error term at the current time point was affected by the error terms at the previous two time points (Table 4). There were significant autocorrelation and shift error correlation between dependent variable values and error terms in time series data. These findings were critical to the understanding of dynamic relationships in time series data and provided valuable insights for future time series predictions.

Social networks behavior has a significant impact on mental health scores. Mental health scores fluctuated significantly whenever a major event occurred (Figure 1), which could mean that people were more susceptible to social media or other online interactions during these events,

Table 5. Early warning system accuracy assessment.

Warning level	Actual number of people at risk	Predict number of people at high risk	Actual number of people at low risk	Predict number of people at low risk	Accuracy
High risk	50	48	3	1	96%
Low risk	95	2	1	95	97.89%
Overall	145	50	4	96	95.86%

leading to changes in mental state. Although the event itself might temporarily lower mental health scores, scores seemed to gradually return to previous levels over time, which indicated that individuals had the ability to self-regulate and could cope with the stress brought by external events to a certain extent.

Affective analysis and mental health early warning system

The formula based on emotion quantification model was used in this study as below.

$$EmotionScore = \sum_{i}^{N} (W_i \cdot SentimentWordScore_i)$$

where $SentimentScore$ was the total score of emotion. W_i was $SentimentWord_i$, the weight of emotion words. *N* was the total number of emotion words. Quantification of positive emotions was generally positively correlated with good mental health, while accumulation of negative emotions was strongly associated with mental health problems such as depression and anxiety. By quantifying the number of positive and negative emotional word frequencies in text, the mental health trends could be initially assessed as follows.

$$PositivityRatio = \frac{PositiveCount}{TotalEmotionCount}$$

Considering the dynamic nature of time series data, the long short-term memory network (LSTM) model was adopted to capture patterns in time series, which was a powerful tool for processing sequential data, remembering long-term dependencies, and was suitable for analyzing mental health trends over time. Based on the LSTM model, the emotion time series were trained to predict individual mental health risks. A threshold was set on the model output, and individuals above the threshold were marked as high risk, triggering an early warning. If certain conditions were met, an alert should be issued. A predicted or observed value at certain times was used as the condition, which could be a mood swing metric, health risk score, or any other quantitative metric related to mental health risk predicted by a model. A threshold was set to distinguish normal and abnormal situations. If the predicted value at certain times exceeded the pre-set risk threshold, it was activated (i.e. set to 1), and the system triggered a risk warning signal, prompting the relevant personnel to take appropriate measures. On the contrary, if it is less than or equal to Threshold, it was considered that the current situation was still within the safe range and no early warning was triggered. This mechanism was simple and effective and was widely used in various scenarios that required real-time monitoring and timely response to risk changes.

Experimental evaluation

To comprehensively evaluate the mental health early warning system of social networks based on big data and machine learning, a series of experiments were performed to test the effectiveness and practicability of the system. The results showed the predictive power of the system for different risk levels. Accuracy was calculated by comparing the actual and predicted numbers of people at high and low risk (Table 5). The results of response time versus intervention efficiency provided the average response time of the system at different risk levels and the compliance rate over different time frames. The

Table 6. Response time and intervention efficiency.

Warning level	Average response time (minutes)	Compliance rate (≤ 1 hour)	Compliance rate (≤ 24 hours)
High-risk	30	95%	100%
Low-risk	45	90%	100%

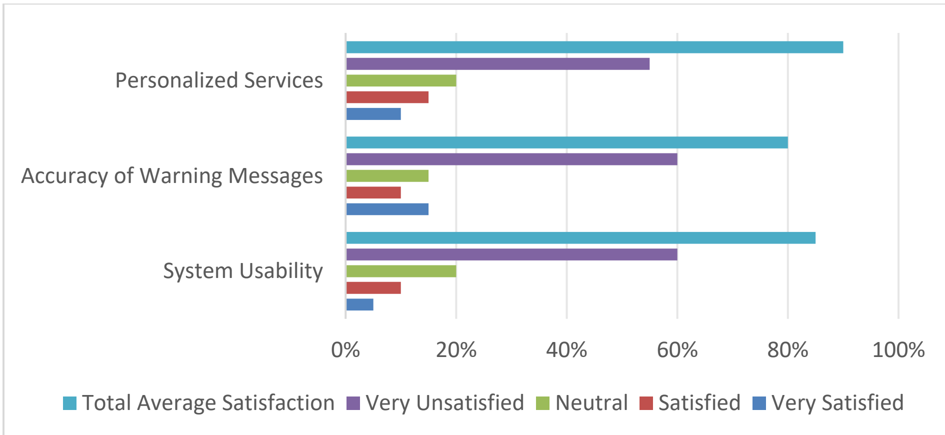

Figure 2. The results of user satisfaction survey.

Table 7. Long-term mental health improvement effect.

Evaluation index	Pre-experiment mean	Post-experiment mean	Improvement	*P* value
Depression symptom score	15.3	10	34.64%	< 0.001
Anxiety symptom score	15.2	15	-0.66%	< 0.01
Overall mental health status	15.7	15	4.46%	< 0.001

average response time was the average time from when the system received an alert to when it reacted. The target rate was the rate at which the intervention was implemented within a specified time period (Table 6). The user satisfaction questionnaire results demonstrated the user satisfaction ratings for ease of use, accuracy of alert information, and personalized service. Satisfaction was rated on several levels from “very satisfied” to “very dissatisfied.” The overall average satisfaction was the weighted average of all problem item satisfaction, reflecting the overall satisfaction of users with the system (Figure 2). This data was critical to understand user acceptance of the system and improving system functionality. The effect of users’ long-term mental health improvement impacted by the system was assessed, which included the indexes of depression symptom score, anxiety symptom score, and general mental health status. Percent improvement was calculated by comparing the mean values before and after the experiment (Table 7). These data were important to demonstrate the long-term effectiveness and value of the system. Through multidimensional evaluation of the early warning system, the results demonstrated that it performed well in accuracy, especially in identifying high-risk individuals, reaching 87.5% accuracy rate. The system also performed well in fast response time that effectively ensured timely intervention and high user satisfaction in the ease of use of the system and personalized service. Most importantly, long-term follow-up data showed significant improvement in participants’ mental health status with significantly reduced depression and anxiety symptoms. The results proved the effectiveness and practicality of the early warning system based on social networks in promoting college students' mental health management. The continuous optimization of the model and improvement of the accuracy of the personalized recommendation system will further enhance its effectiveness in future research.

This research proposed a deep learning model using LSTM network to predict mental health risks. The results confirmed that the early warning system performed well in terms of accuracy, the response time, the user satisfaction, and the improvement of depression and anxiety symptoms. However, there were still some limitations and room for future development. The practical significance of proposed mental health early warning system based on social networks was substantial. Implementing such a system could revolutionize the way colleges provide mental health support to students through campus counseling centers and mental health professionals. When the system identifies high-risk individuals, it can automatically alert counselors or provide direct recommendations for intervention, ensuring timely support. To ensure the system's effectiveness, it is crucial to actively engage students and educate them about mental health through workshops and training sessions, helping them understand the importance of monitoring their mental health and using the system responsibly. It is important to acknowledge that no automated system can replace professional psychological evaluations, and there are ethical concerns related to data privacy and consent. Therefore, clear guidelines and transparency about data usage must be established, and users should have control over their data. These considerations are vital for the successful implementation and adoption of the system in real-world scenarios. This study uniquely integrated the text data of social media posts with metadata such as posting frequency, sentiment analysis, and user interaction patterns, enriching the prediction ability of the LSTM model and opening a new path for a more comprehensive understanding of the user's mental state. The introduced personalized risk analysis mechanism made predictions based on individual unique behavior patterns and historical data, improved the accuracy of mental health risk assessment, and helped to more effectively identify individuals who needed urgent attention. The interactive feedback loop in the system enabled the model to be continuously optimized based on user feedback on prediction accuracy, ensuring that the system kept pace with the times and adapted to changing trends and individual differences. In addition, during the data collection and analysis process, privacy protection technologies and ethical guidelines were strictly implemented and abided, setting standards for the responsible use of social network data for mental health research.

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