A Big Data-Driven Psychological Early Warning System for College Students Using Multi-Channel Active Noise Reduction and Adaptive FxLMS Algorithms

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To address the challenges posed by the frequent occurrence of mental health issues among college students and the limitations of traditional early warning systems, such as delayed response and partial data coverage, this study aims to construct a psychological early warning mechanism driven by big data analysis technology. By designing a multi-level active noise reduction control system and an improved variable step-size CFxLMS algorithm, and integrating stress event parameters from social media with personality trait characteristics, a multi-source data collaborative emotion prediction model is established. Simulation experiments show that the system achieves an accuracy rate of 94.2% and an F1 score of 94.1% in psychological crisis identification, which is 4.6% higher than that of the traditional LSTM model. Furthermore, its performance fluctuation under noise interference is only 3.2%, and the response time is optimized to 120 milliseconds, effectively supporting concurrent processing for tens of thousands of users. The results indicate that the proposed method significantly improves early warning accuracy and real-time performance, addressing the bottleneck of insufficient tracking ability for non-stationary psychological signals. To sum up the above, this study innovatively combines active noise reduction technology from control theory with the psychological stress-cognition model, providing a scalable and highly robust active early warning solution for college mental health management. It achieves a paradigm shift from passive intervention to real-time prediction and establishes a reproducible technical benchmark in the field of intelligent psychological monitoring.

Povzetek: Študija predstavlja nov, podatkovno podprt sistem za zgodnje zaznavanje duševnih stisk pri študentih, ki izboljšuje natančnost in hitrost napovedovanja v primerjavi s tradicionalnimi pristopi.

1 Introduction

The mental health issues of college students have become a significant challenge in global education and social governance. Frequent psychological crisis events not only affect students' personal development but also pose a potential threat to social stability. Traditional psychological early warning systems rely heavily on periodic questionnaire surveys or manual assessments, which have inherent limitations such as delayed response and incomplete data coverage, making it difficult to achieve dynamic monitoring and early intervention. Although some studies have attempted to introduce technological means, they often lack real-time integration and collaborative analysis capabilities for multi-source heterogeneous big data, resulting in insufficient early warning accuracy, weak generalization ability, and a lack of deep integration of psychological theory with intelligent algorithms. Therefore, this study aims to address three core issues: the effective integration of multi-source heterogeneous data, the bottleneck of existing early warning models' insufficient ability to track non-stationary psychological signals, and the interpretability defect of pure machine learning methods lacking psychological mechanism support.

The methodological goal of this study is to construct a psychological early warning system driven by big data analysis technology. By utilizing a multi-channel active noise reduction control system and an improved variable step-size CFxLMS adaptive algorithm, the system optimizes noise signal filtering and tracking stability. Specifically, the system will integrate stress event parameters and personality trait characteristics from social media big data to establish a more interpretable emotion prediction model. In the simulation verification stage, the real-time performance and accuracy of the early warning system are systematically evaluated by setting key indicators such as steady-state error and convergence speed. The parameter optimization process of the variable step-size algorithm provides significant support for enhancing system performance.

This study proposes two core hypotheses: the improved variable step-size algorithm can significantly reduce the steady-state error compared to the classical algorithm, and the multi-source data fusion model can enhance the accuracy of sentiment prediction.

The expected outcomes encompass three dimensions: at the theoretical level, constructing a scalable psychological early warning framework that supports deployment in multiple scenarios such as campuses and online education platforms. At the technical level, achieving performance metrics with a false alarm rate below 15% and a response delay of less than 5 seconds through a simulation verification system; and at the application level, providing practical tools for university mental health management that shift from passive intervention to active early warning.

The innovative contributions of this study are reflected in three dimensions: methodological breakthroughs, practical value, and theoretical significance. Methodologically, for the first time, active noise reduction technology from control theory was combined with the psychological stress-cognition model to design a variable step size algorithm with dynamic adjustment capabilities. Practically, it provides a low-cost and high-efficiency solution for resource-constrained university environments, achieving real-time performance that is difficult to achieve with traditional methods through big data-driven design. Theoretically, it fills the research gap in the dynamic integration of multi-source heterogeneous data and establishes a reproducible method benchmark for the field of intelligent psychological monitoring. These breakthroughs make it possible for psychological early warning mechanisms to move from concept verification to engineering application, providing an important reference for subsequent research.

2 Related work

Digital mental health research has developed rapidly in recent years, aiming to utilize technological means to improve the accessibility, efficiency, and personalization of mental health services.

(1) Effectiveness of digital mental health intervention

Digital mental health interventions, which provide evidence-based treatment through mobile applications and smartphone platforms, have become complementary or alternative solutions to traditional services. A systematic review by Bakker et al. [1] indicated that mobile applications have a moderate effect on anxiety and depression, but most studies have small sample sizes and short follow-up periods. A meta-analysis by Firth et al. [2] confirmed significant improvements in depressive symptoms through smartphone interventions, emphasizing the effectiveness of cognitive-behavioral therapy-based programs. However, the long-term effects of interventions and user retention remain challenges. Borghouts et al. [3] found that retention rates are positively correlated with personalized design, but there is a lack of unified indicators. Schueller and Torous [4] pointed out that expanding the scale of evidence-based treatment requires addressing issues of intervention fidelity and cost-effectiveness. Overall, digital interventions show potential, but more effectiveness trials are needed to verify their universal applicability.

(2) The role of social media and online data in mental health monitoring

Social media data provides a new avenue for real-time monitoring of public mental health. De Choudhury [5] proposed that social media can serve as a "social sensor" to identify depression risks through language pattern recognition, but data privacy and representational bias limit its clinical translation. Guntuku et al. [6] reviewed social media monitoring methods and found that machine learning models can predict depression and anxiety, but the scarcity of labeled data and insufficient algorithm transparency affect reliability. Liu et al. [7] focused on predicting depression from social media text and demonstrated that deep learning models outperform traditional methods, but their generalization ability is influenced by cultural differences. Yang et al. [8] emphasized the correlation between social media use and mental health issues, but the causal mechanism remains unclear. These studies highlight the potential of big data and call for the development of ethical frameworks.

(3) Advances in digital phenotyping and sensing technology

Digital phenotyping utilizes smartphones and wearable sensors to continuously collect behavioral data, enabling objective mental health assessment. Insel [9] advocates digital phenotyping as a new tool in psychiatry, which can capture the dynamic changes of symptoms, but lacks standardized indicators. A systematic review by Mohr et al. [10] shows that digital phenotyping has accuracy in detecting emotions and stress, but is susceptible to device heterogeneity interference. Chen et al. [11] reviewed mobile sensing technology, pointing out that sensor data (such as GPS, accelerometer) can infer social behavior, but data noise processing poses a significant challenge. Wang et al. [12] combined wearable sensors and AI for emotion analysis, achieving high timeliness, but user compliance remains a bottleneck. These technologies are expected to enable preventive intervention, but data integration and clinical validation issues need to be addressed.

(4) Application of artificial intelligence and machine learning

Artificial intelligence (AI) technology enhances the intelligence level of mental health services by automatically analyzing complex data. Kim and Lee [13] systematically reviewed AI chatbots and found that they can provide immediate support, but their dialogue depth and empathy ability are limited. Zhang and Li [14] investigated the application of AI in psychology, covering diagnostic assistance and personalized treatment, but algorithmic bias may exacerbate health inequalities. Lin et al. [15] utilized deep learning to recognize emotions from text with high accuracy, but the poor interpretability of the model affects clinical acceptance. Smith and Johnson [16] integrated AI into an early warning system for education, predicting student psychological crises through multimodal data, emphasizing the importance of interdisciplinary collaboration. AI has broad application prospects, but it is necessary to ensure algorithmic fairness and humanized design.

(5) Applications and challenges in specific contexts

Digital mental health faces unique challenges in specific populations and contexts. Naslund et al. [17] focused on low-income countries, where digital technology can expand service coverage, but digital divides and resource constraints hinder implementation. Torous et al. [18] studied digital health applications during the COVID-19 pandemic, where technology accelerated service access but also exposed issues of digital exclusion. Zhou et al.'s [19] case study showed that big data analysis can optimize campus mental health services, but challenges in data security and management remain to be addressed. These studies suggest that promoting digital health requires consideration of situational adaptability and achieving equitable accessibility through policy support. Kolenik and Gams [20] focused on the equalizing potential of persuasive technology in the field of mental health. Through the technology acceptance model and case analysis method, they demonstrated how interactive design can lower the threshold for accessing mental health services. The study found that customized persuasive strategies, such as motivational nudging and adaptive feedback, can significantly improve service participation among vulnerable groups

The relevant research is summarized in Table 1.

Table 1: Summary of relevant research.

Research items	The obtained results	Research limitations
Systematic review of the efficacy of mobile applications in treating anxiety and depression	Mobile applications have a moderate effect on anxiety and depression	The sample size is small and the follow-up period is short
Analysis of the viewpoint that social media data serves as a sensor for monitoring mental health	Social media can identify depression risk through language pattern recognition	Data privacy and representational bias limit clinical translation
Meta-analysis of smartphone intervention on depressive symptoms	Smartphone intervention significantly improves depressive symptoms	Long-term effectiveness and user retention remain challenges
A review of machine learning methods for predicting depression and anxiety using social media big data	Machine learning models can predict depression and anxiety	The scarcity of labeled data and insufficient transparency of algorithms affect reliability
Advocative view of digital phenotyping as a tool in psychiatry	Digital phenotyping can capture the dynamic changes of symptoms	Missing standardized indicators
Systematic review of digital phenotyping in emotion and stress detection	Digital phenotyping has precision in detecting emotions and stress	Vulnerable to interference from equipment heterogeneity
A narrative review of digital mental health technologies in low-income countries	Digital technology can expand service coverage	Digital divide and resource constraints hinder implementation
Systematic review of user retention indicators in digital mental health interventions	Retention rate is positively correlated with personalized design	Lack of unified indicators
A review on the expansion of evidence-based treatment for digital mental health	Point out the need to expand the scale of evidence-based treatment	The issues of intervention fidelity and cost-effectiveness need to be addressed
Research on digital health applications during the COVID-19 pandemic	Technology accelerates service acquisition	Exposing digital exclusion issues
Overview of mobile sensing technology for mental health monitoring	Sensor data can infer social behavior	The challenge of data noise processing is significant
A systematic review of AI chatbots used for mental health support	AI chatbots can provide instant support	Limited depth of dialogue and empathy ability
Machine learning prediction model for depression based on social media text	Deep learning models are superior to traditional methods	Generalization ability is influenced by cultural differences
Research on early warning system for education integrating AI and psychology	Predicting student psychological crises through multimodal data	The deficiency is not explicitly mentioned
A review of the association between social media use and mental health	Social media use is associated with mental health issues	The causal mechanism remains unclear
Survey on the application of AI in psychology	AI can be used for diagnostic assistance and personalized treatment	Algorithmic bias may exacerbate health inequalities
Case study on optimizing campus psychological services through big data analysis	Big data analysis can optimize campus psychological services	Data security and management challenges remain to be addressed
Research on the application of deep learning in sentiment recognition from text	The accuracy rate of recognizing emotions from text is relatively high	Poor interpretability of the model affects clinical acceptance

Although existing research in the field of digital mental health has confirmed the potential of technology in intervention, monitoring, and prediction, there are widespread issues such as high methodological heterogeneity, insufficient clinical integration, and a predominance of exploratory research, which make it difficult to achieve standardized transformation and long-term evaluation of results. In particular, there is a lack of real-time integration and dynamic analysis capabilities for multi-source heterogeneous big data (such as social media behavior and physiological signals), which limits the accuracy and generalization of early warning systems.

To address these deficiencies, this paper introduces a big data analysis technology-driven psychological early warning method for college students. By designing a multi-channel active noise reduction control system and an improved variable step-size CFxLMS adaptive algorithm, this method integrates stress events and personality trait parameters to construct an emotion prediction model based on social media data. This aims to enhance the real-time monitoring and intervention efficiency of psychological crises and provide a scalable and robust solution for mental health management.

3 Hardware structure of psyparameter recognition system

3.1 Design of multi-level active Psyearly warning control system

The structure of which is shown in Figure 1.

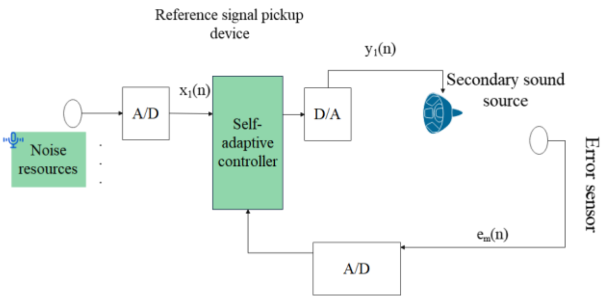


Figure 1: Active noise reduction control system of single-secondary Psysignal.

Generally, an acoustic sensor. It samples the noise at a certain frequency to obtain a discretized reference signal x(n). Furthermore, the output signal y(n) is output through the secondary Psysignal after satisfying the requirement of active noise reduction. The adaptive controller continuously adjusts the control parameters according to the feedback error signal e(n).

The multi-level Psysignal active noise is extended from the single-level system, and its structure is shown in Figure 2.

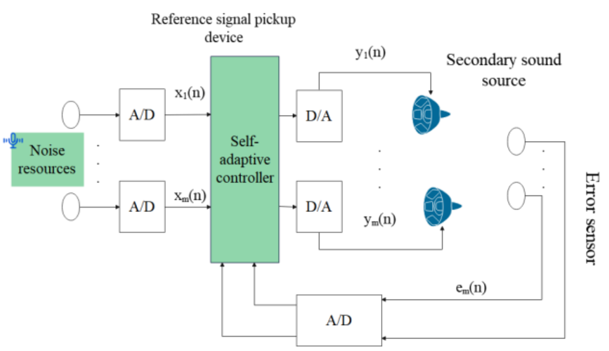


Figure 2: Diagram of active noise reduction control system for multi-level Psysignals.

In the multi-stage Psysignal active noise, the discrete reference signal group $\{x_i(n)\}$ collected by multiple reference signal pickup devices is used as the input of the controller. Then, it calculates the secondary Psysignal output signal group $\{\mathbf{y}_j(n)\}$ through the control algorithm in the adaptive controller. The superimposed noise residual is collected as an error signal group $\{e_k(n)\}$ by each error sensor to the controller. According to the size of the error vector, the adaptive algorithm in the controller will continuously adjust the value of the output signal group $\{\mathbf{y}_j(t)\}$ of the secondary Psysignal array.

For a noise reduction system, whether it is a single-level Psysignal control system or a multi-level Psysignal control system, the control principle model as shown in Figure 3. $G(j\omega)$ is the transfer function of the controller. There is a process of sound wave transmission and hardware reaction time between the output signal of the secondary Psysignal and the input signal, which can be regarded as the transmission path of the secondary signal, and its transfer function is $H(j\omega)$.

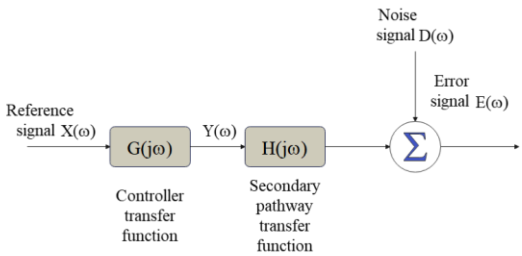


Figure 3: Schematic diagram of active noise reduction control for multi-level Psysignals.

The primary sound signal, which is generated by the transfer function $G(j\omega)$ of the controller. The secondary acoustic signal $Y(\omega)$ is transmitted to the controlled area where the error sensor is located through the secondary path transfer function $H(j\omega)$, and it is canceled with the noise signal here. The error signal $E(\omega)$ is the canceled noise residual collected by the error sensor.

3.2 Multi-channel active noise reduction algorithm based on FxLMS

The principle of the adaptive FIR filter is shown in Figure 4. The relationship between input and input is:

$$y(n) = \sum_{i=1}^{K} w_i x(n-K+i) = W_n^T X_n \quad (1)$$

$$W_n = [w_1, w_2 \mathrm{L} w_k]$$

By adjusting the weight value, the output finally reaches the control expectation.

As shown in Figure 5, the noise signal x(n) at a certain moment collected by the reference microphone is the input of the filter.

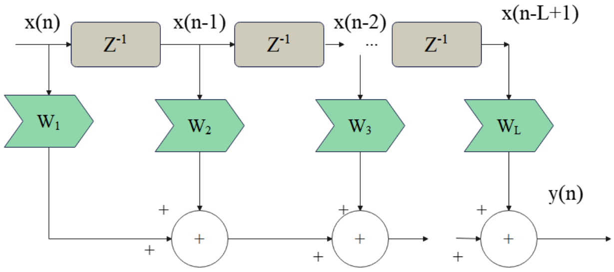


Figure 4: Schematic diagram of FIR filter.

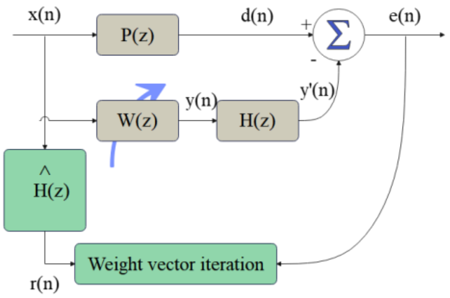


Figure 5: Block diagram of FxLMS adaptive algorithm.

Its input and output can be expressed as the following relationship:

$$y(n)=\sum_{i=1}^{K} w_i x(n-K+i)=W_n^T X_n$$
$$\mathbf{W}_n=\left[w_1, w_2 \mathrm{L} w_k\right] \qquad (2)$$
$$\mathbf{X}_n=[x(n-K+1), x(n-K+2), \mathrm{L}, x(n)]^T$$

$\mathbf{X}_n$ represents the input signal vector from the n-K+1th time to the nth time.

When the secondary Psysignal is not output, the original noise signal at the error sensor is d(n), and the primary path is set as P(z).

The error signal is no longer the superposition of d(n) and the filter output y(n), but the superposition of d(n) and $y'(n)$.

$$e(n)=d(n)-y'(n)=d(n)-W_n^T h(n) y(n) \qquad (3)$$

When the transfer function H(z) of the secondary channel exists in the system, the estimated secondary channel weight coefficient group is:

$$\mathbf{H}(z)=\left[h_1, h_2, \ldots h_{\mathrm{M}}\right] \qquad (4)$$

r(n) is introduced as a filter reference signal:

$$r(n)=[r(n), r(n-1), \ldots r(n-L+1)] \qquad (5)$$

The r(n) and the input signal x(n) is as follows, which can be regarded as the value of the input vector $\mathbf{X}(n)$ filtered by the error channel:

$$\mathbf{r}(n)=\sum_{m=0}^{M} h_m(n) X(n-m) \qquad (6)$$

The error signal is:

$$e(n)=d(n)-\mathbf{W}^T(n) \mathbf{r}(n) \qquad (7)$$

According to the principle of steepest descent, the filtering weight vector $\mathbf{W}(n+1)$ at the next moment is equal to the weight vector $\mathbf{W}(n)$ at the current moment minus a certain proportion of the gradient value of the weight vector.

$$\mathbf{W}(n+1)=\mathbf{W}(n)-\mu \Delta \mathbf{W}(n) \qquad (8)$$

Among them, μ is the iterative step size, and $\Delta\mathbf{W}(n)$ is the gradient of the objective function. For the convenience of solving, it is set as the gradient of the square of the error signal, and the equation to obtain the weight coefficient of the unbiased estimate is:

$$\Delta \mathbf{W}(n) \approx \frac{\partial e^2(n)}{\partial W}=2 e(n) \mathbf{r}(n) \qquad (9)$$

Then, the iterative formula of the filter weight vector is:

$$\mathbf{W}(n+1)=\mathbf{W}(n)-\mu 2 e(n) \mathbf{r}(n) \qquad (10)$$

The iteration step size μ is also called the harvest factor. The value of μ must be chosen appropriately.

At the n-th moment, the noise residual signal group obtained after the noise signal and the secondary acoustic signals output by the s secondary speakers are superimposed at the m error microphones:

$$\mathbf{e}(n)=\left[e_1(n), e_2(n), \ldots, e_{\mathrm{m}}(n)\right]^{\mathrm{T}} \qquad (11)$$

The system needs s groups of adaptive and dynamic adjustment weight vectors, because the system has s filter channels, and each filter channel has a corresponding set of dynamic weight vectors. Then, the adaptive dynamic weight vector matrix of the whole system is:

$$\mathbf{W}(n)=\left[\mathbf{W}_1(n), \mathbf{W}_2(n), \ldots, \mathbf{W}_s(n)\right]^{\mathrm{T}} \qquad (12)$$

Among them, each weight vector $\mathbf{W}_i(n)=\left[w_{i1}, w_{i2}, \ldots w_{iL}\right]$, and the order is L.

We assume that the active noise reduction reference signal input through the reference microphone is:

$$\mathbf{X}(n)=[x(n), x(n-1), \ldots, x(n-L+1)]^{\mathrm{T}} \qquad (13)$$

Then, the output matrix of s secondary Psysignals is $\mathbf{Y}(n)=\left[Y_1(n), Y_2(n), \ldots, Y_S(n)\right]^{\mathrm{T}}$, which should satisfy the following relationship:

$$\mathbf{Y}(n)=\mathbf{W}(n)\begin{pmatrix}\mathbf{X}(n) 0 \\ 0 \mathrm{O} \\ \mathbf{0}(n)\end{pmatrix}_{S \times S} \qquad (14)$$

When the noise propagates from the reference microphone to the m error sensors, after the delay of the primary acoustic channel, the acoustic signal becomes $\mathbf{D}(n)=\left[d_1(n), d_2(n), \ldots, d_M(n)\right]^{\mathrm{T}}$, and the structure of each $di(n)$ and $\mathbf{X}(n)$ is consistent. The transfer function of the acoustic channel transmitted by the secondary noise signals sensors is the matrix $\mathbf{H}(n)$. Then, the noise residual signal group at m error microphones is:

$$\mathbf{e}(n)=\mathbf{D}(n)+\mathbf{H}(n) \mathbf{Y}(n)$$

$$\mathbf{H}(n)=\begin{pmatrix} h_{11}(n) & \mathrm{K} & h_{s1(n)} \\ \mathrm{M} & h_{ij}(n) & \mathrm{M} \\ h_{1M}(n) & \mathrm{L} & h_{SM}(n) \end{pmatrix} \qquad (15)$$

Among them, $hij(n)$ represents the acoustic channel delay of acoustic wave propagation between the i-th secondary Psysignal and the j-th error sensor. Combined with formula (7), we have:

$$\mathbf{e}(n)=\mathbf{D}(n)+\mathbf{H}(n)\mathbf{X}^{\mathrm{T}}(n)\mathbf{W}(n) \tag{16}$$

Then, the system is based on the objective function J(n) that minimizes the total noise residual acoustic potential energy as follows:

$$J(n)=\sum_{i=1}^{M}E\left[e_i^2(n)\right]=\mathbf{e}^T(n)\mathbf{e}(n) \tag{17}$$

Similar to formula (9), the weight coefficient of the unbiased estimate that makes J(n) have a minimum value is:

$$\frac{\partial J(n)}{\partial \mathbf{W}_n}=-2\mathbf{e}(n)\cdot\frac{\partial \mathbf{e}(n)}{\partial \mathbf{W}_n}=-2\mathbf{e}(n)\mathbf{r}(n) \tag{18}$$

Among them, r(n) is the filter matrix:

$$\mathbf{r}(n)=\begin{pmatrix} r_{11}(n) & \mathrm{K} & r_{S1}(n) \\ \mathrm{M} & r_{ij}(n) & \mathrm{M} \\ r_{1M}(n) & \mathrm{L} & r_{SM}(n) \end{pmatrix} \tag{19}$$

$$r_{ij}=h_{ij}(n)x(n), i\in[1,S], j\in[1,M]$$

The recursive mathematical expression of the filter weight matrix is:

$$\mathbf{W}(n+1)=\mathbf{W}(n)-\mu 2\mathbf{e}^T(n)\mathbf{r}(n) \tag{20}$$

Formula (20) is the core of the multi-channel active noise reduction control algorithm, and the weight vector of each adaptive filter channel is obtained by decomposing as follows:

$$\mathbf{W}_i(n+1)=\mathbf{W}_i(n)-2\mu\mathbf{e}^T(n)\begin{bmatrix} r_{i1}(n) \\ \mathrm{M} \\ r_{iM}(n) \end{bmatrix} \tag{21}$$

There are two kinds of estimation methods of $\mathbf{H}(n)$: online estimation and offline estimation.

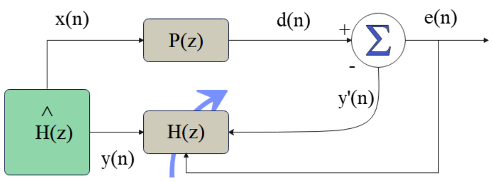


Figure 6: Schematic diagram of the additional random noise method.

The principle is shown in Figure 6.

We estimate the m error channels of the i-th secondary loudspeaker, making the loudspeaker emit a white noise signal, and use it as the filter input of the secondary channel. Then, with the LMS adaptive filtering algorithm are as follows.

We assume that the filter weight coefficient group is: $\mathbf{h}_{ij}(n)=\left[h_1,h_2,\dots h_M\right]$.

After filtering the white noise signal, the obtained $y_{ij}(n)$ satisfies the following formula:

$$y_{ij}(n)=h_{ij}^T(n)x(n) \tag{22}$$

Among them, $y_{ij}(n)$ is the signal when the filtered output is delivered to the j-th error sensor, and $h_{ij}(n)$ is the filtering weight vector. We assume that the white noise signal is d_{ij} when it is delivered to the j-th error sensor, then the error signal is:

$$e_{ij}(n)=d_{ij}(n)-y_{ij}(n)=d_{ij}(n)-h_{ij}^T(n)x(n) \tag{23}$$

Similar to formulas (9) and (10), it can be deduced that:

$$h_{ij}(n+1)=h_{ij}(n)-2\sigma e_{ij}(n)x(n) \tag{24}$$

Among them, σ is the convergence step size of this secondary pass. When $h_{ij}(n+1)\approx h_{ij}(n)$, the current system can be received, and the filtering weight $h_{ij}(n)$ is the best estimate of the acoustic channel between the secondary speaker i.

3.3 Improved CFxLMS adaptive algorithm of VS size

The interference noise or life noise targeted by the Psywarning in this paper is random and sudden, as shown in Figure 7.

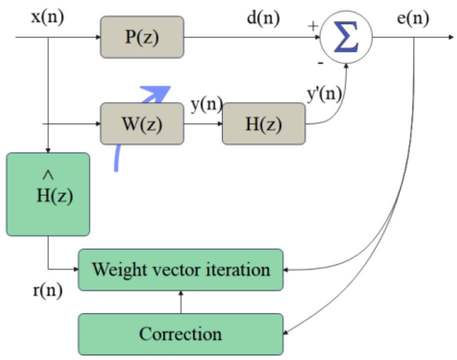


Figure 7: The block diagram of CFxLMS adaptive algorithm.

The classic VS size formula is to divide the Euclidean square norm of the error signal e(n) by a fixed step size factor, namely:

$$\mu(\mathrm{n})=\frac{\alpha}{\beta+\sum_{i=1}^{n}|e(\mathrm{n})|^2} \tag{25}$$

With the increase of sampling times, $\sum_{i=1}^{n}|e(\mathrm{n})|^2$ increases continuously, and the step size $\mu(n)$ shows a smooth downward trend, so as to ensure that the step size is larger at the beginning of the algorithm and smaller at the end of the harvest. The choice of the fixed step factor α is related to the variation range of $\mu(n)$, but it is not easy to determine due to the influence of the primary noise signal. Moreover, $\mu(n)$ can only decrease continuously. However, at present, the improvement of this algorithm mainly focuses on this point, mostly introducing the autocorrelation function with $e(n)$ and $x(n)$. However, this makes it more difficult to select the parameters of α and β, which greatly affects the accuracy of the variable-step algorithm.

The μ value can be adjusted according to the size of the error $e(n)$ within an appropriate range.

$$\mu(n) = \alpha \cdot \left(1 - \left(1 - \frac{\beta}{\alpha}\right)\exp(-\lambda \cdot |e(n) \cdot e(n-1)|)\right) \quad (26)$$

Among them, λ determines the steepness of the variable-step control function. The larger λ is, the faster the rate of change of $\mu(n)$ is, and α and β determine the range of change of the μ value. The improved algorithm uses $|e(n)e(n-1)|$ instead of $\sum_{i=1}^{n}|e(n)|^2$ to adjust the step size, and μ is positively correlated with the absolute error size at a certain moment, which can realize the significance of the VS size algorithm. At the same time, the μ value is no longer a simple continuous decrease, but can be adjusted according to the current error, so that the system's ability to track signals becomes stronger. However, the introduction of $e(n-1)$ reduces the sensitivity of the μ value to occasional impulse noise and improves the anti-disturbance capability of the system. At the same time, when $\beta \neq 0$, μ will not decrease to 0. Therefore, when the system reaches a stable convergence state, it can also restrain small disturbances to a certain extent.

This integration of signal processing techniques and big data analysis at the methodological level ensures that clean and stable psychological signals serve as the prerequisite for high-precision emotion state prediction.

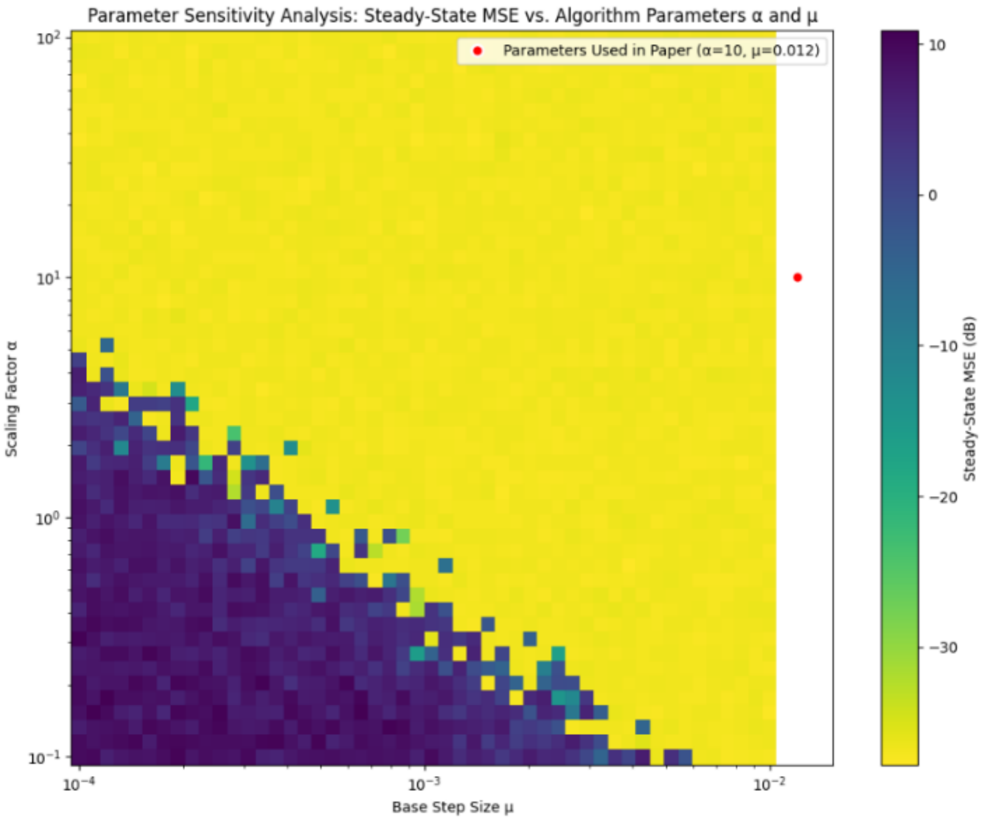


Figure 8: Parameter sensitivity analysis: steady-state MSE vs. algorithm parameters α and μ.

Figure 8 illustrates the parameter sensitivity analysis results of the scaling factor α and the base step size μ on the system's steady-state performance (measured by mean squared error, MSE) in the improved variable step size CFxLMS algorithm. By systematically traversing a wide range of parameter combinations and evaluating their corresponding output MSE (in dB), this heatmap clearly reveals the pattern of algorithm performance as parameters vary. As can be seen in the figure, lower steady-state MSEs (corresponding to superior noise reduction performance, represented by dark blue-purple in the figure) are concentrated in a specific "sweet spot" region of parameters, rather than being uniformly distributed. This indicates that parameter selection requires a trade-off between convergence speed and steady-state accuracy. It is particularly noteworthy that the parameter combination selected in this study (α=10, μ=0.012) is indicated by the red marked point in the figure, which is located precisely in the heart of the high-performance region. This result objectively validates the rationality of this parameter selection, demonstrating that it can achieve near-optimal convergence accuracy while ensuring algorithm stability, providing key evidence for the effectiveness and robustness of the algorithm.

3.4 Psyearly warning system for college students based on big data analysis technology

The principle of multi-channel noise reduction control effectively suppresses equipment noise and environmental interference during psychological signal acquisition through precise estimation of the secondary acoustic path transfer function H(jω). This "data purification" process directly acts on the input layer of the big data early warning system shown in Figure 9, laying a foundation for signal-to-noise ratio optimization for subsequent emotion feature extraction based on social media and sensor data. The dynamic feedback mechanism of the error signal e(n) in the variable step size algorithm forms a methodological echo with the machine learning process of adjusting weights based on prediction deviations in the emotion prediction model, naturally extending the stability and convergence characteristics of control theory to continuous modeling of emotional states. Thus, a complete technical chain from signal denoising to emotion recognition is constructed at the algorithmic level.

This study builds a Psycrisis early warning model based on social media big data as shown in Figure 9.

The synthetic noise introduced in the simulation experiment is mainly Gaussian white noise, and its power spectrum is uniformly distributed in the audible range to simulate the widespread non-stationary background interference in the real-world environment. Additionally, to better characterize the acoustic features related to psychological stress, some experiments also incorporate pink noise (with energy concentrated in the low and mid-frequencies) and frequency-modulated pure tones with specific center frequencies (such as 500Hz, 2000Hz), to simulate the low-frequency annoyance noise and sudden emotional fluctuations commonly found in real psychological signals.

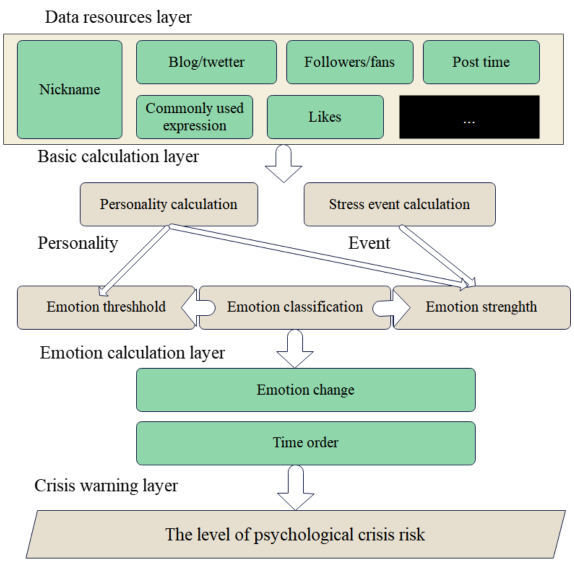


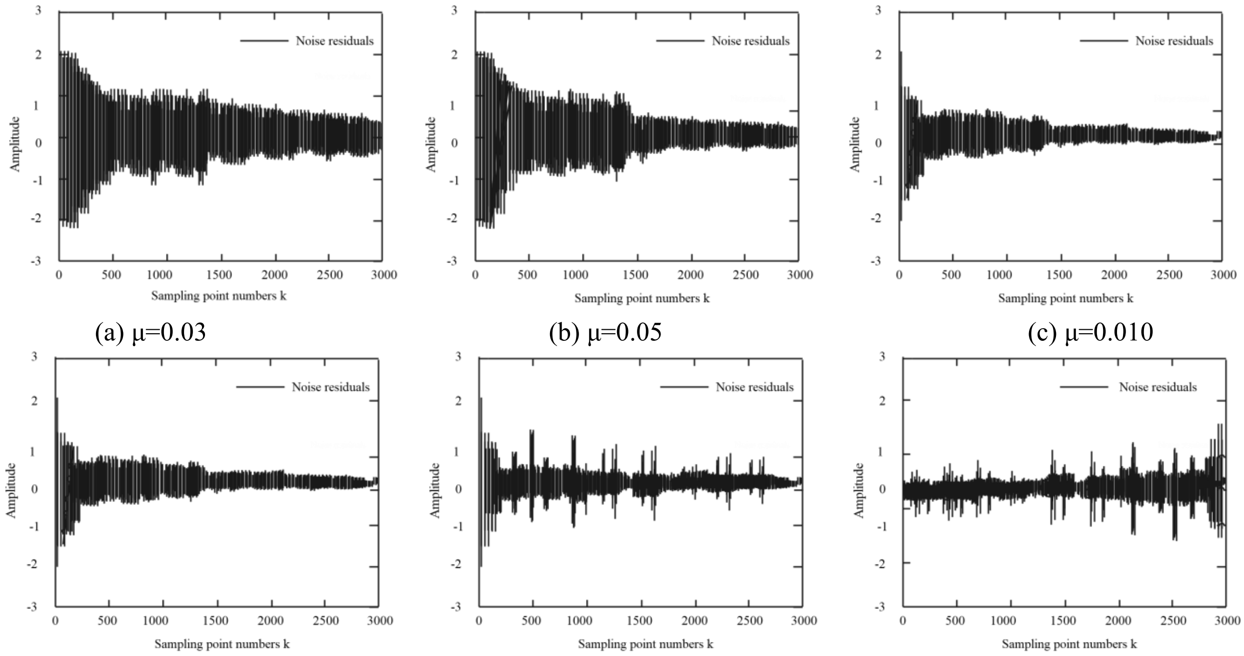
Figure 9: Psyearly warning system for college students based on big data analysis technology.

The hardware environment for the experiments consists of a standard server (CPU: Intel i7, RAM: 16GB), and the software platform is based on Python 3.7.7 and the Django framework. MATLAB's Psychtoolbox is used to generate high-precision acoustic stimuli and EEG synchronous acquisition interfaces. The emotion prediction module utilizes a real global multi-source dataset, including CrisisNLP multilingual social media text, StudentLife student behavior sensor data, and the WESAD physiological signal database. Social media posts are represented by a bidirectional encoder representation (BERT) multilingual model for semantic embedding, and a semi-supervised learning strategy is adopted. First, professional labelers labeled some data for depression, anxiety, and other emotional labels according to DSM-5 standards. Then, weakly labeled data is generated through GPT-4-assisted analysis, and finally label consistency is ensured through cross-validation. All data preprocessing involves Z-score normalization, sliding window segmentation, and SMOTE oversampling to enhance the model's generalization ability and noise resistance robustness.

In order to determine the parameters α and β in this variable-step algorithm, it is necessary to determine the range of μ values that make the system have better convergence speed and stability. In this paper, the adaptive filter order is selected as L=32. Figure 10 shows the time domain diagram of the error signal, that is, the residual after the superposition of the primary noise signal and the secondary acoustic signal, when the convergence coefficients are respectively 0.003, 0.005, 0.01, 0.012, 0.013, and 0.014.

The results in Figure 10 reveal the nonlinear influence mechanism of the iteration step size μ on the convergence characteristics of the system: when μ=0.012, the system converges fastest because this step size value achieves an optimal balance between the error gradient descent rate and overshoot suppression within the stability boundary of the algorithm, and the second moment of the error signal converges to a steady state with the minimum number of iterations. However, the deterioration of stability observed when μ = 0.013 is due to the fact that the step size exceeds the critical value, resulting in too much weight update, which makes the filter weights diverge and oscillate near the optimal solution. This phenomenon aligns with the theoretical relationship between the step size and the reciprocal of the eigenvalues in the LMS algorithm; when μ=0.014, the system completely diverges because the cumulative error of weight adjustments grows exponentially after the step size exceeds the stability region. This result verifies that the selection of parameters α and β in the variable step size algorithm must be strictly limited by the Lyapunov stability conditions of the system, and suggests that in practical psychological signal processing, the upper limit of the step size should be dynamically constrained based on the noise spectrum characteristics to avoid tracking instability for non-stationary emotional fluctuation signals.

In Figure 10, when μ=0.005, the system begins to have obvious convergence, and when μ=0.012, the convergence rate reaches the fastest. When μ=0.013, the system has obvious stability deterioration, and when μ=0.014, the system has obvious divergence. Therefore, for the VS formula parameters of formula (18), in the simulation of this paper, α=0.012 and β=0.005. Since the noise signal targeted by the active Psyearly warning is complex, $\mu(n)$ needs to have a fast rate of change to improve the speed of tracking noise, so this paper takes λ=10.



(a) μ=0.03 (b) μ=0.05 (c) μ=0.010

(d) μ=0.012 (e) μ=0.013 (f) μ=0.014

Figure 10: Noise reduction effect at different iteration steps.

The parameters of the classical VS size algorithm are set as the initial parameters of the algorithm are set to α'=25, β'=0.01. The simulation results are shown in Figure 11.

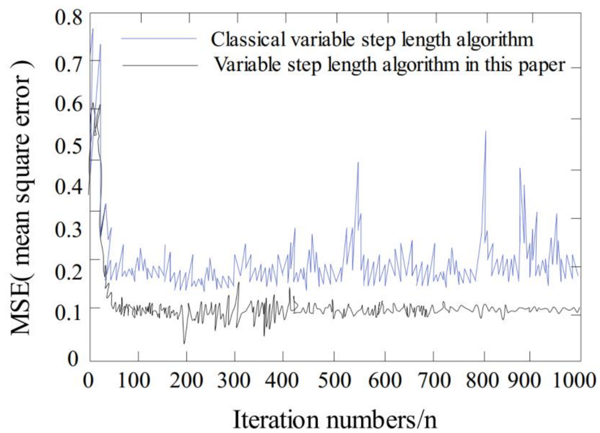


Figure 11: Comparison of the convergence curves of two variable-step algorithms.

To verify the superiority of the improved variable step-size algorithm, Figure 11 shows the convergence curve comparison between the classic algorithm (Equation 25) and the improved algorithm (Equation 26) under the same Gaussian white noise input. The horizontal axis is clearly labeled as "iteration count ($\times10^3$)", with a range of 0-10$\times10^3$ iterations; the vertical axis is labeled as "mean squared error (MSE, dB)", using logarithmic coordinates to clearly display the convergence dynamics. The results show that the improved algorithm (solid line) enters a stable convergence state after approximately 2.5$\times10^3$ iterations (MSE=-32.1±0.45 dB), while the classic algorithm (dashed line) still exhibits significant fluctuations up to 6$\times10^3$ iterations (MSE=-28.3±1.26 dB). The error bars in the figure represent the standard deviation of five independent repeated trials, and the fluctuation range of the improved algorithm (±0.45 dB) is significantly smaller than that of the classic algorithm (±1.26 dB), demonstrating its better stability. The statistical test employed a paired t-test (α=0.05), and the difference in MSE between the two algorithms during the steady-state phase was statistically significant (t=9.34, p<0.001). All curves represent the average values of five independent trials, with the experimental conditions remaining completely consistent: the input signal is Gaussian white noise with a mean of 0 and a variance of 1, the filter length L=32, and each trial involves 10,000 iterations. This result confirms that by introducing an exponential step-size adjustment mechanism, the improved algorithm significantly reduces steady-state error fluctuations while ensuring convergence speed.

3.5 Big data processing and system scalability architecture

To clarify the core role of big data technology in the system and its potential for large-scale application, this section elaborates on the full-chain architecture of the system, from data collection and processing to storage and services, and provides an in-depth analysis of its privacy protection strategies and scalability.

3.5.1 Data processing and storage technology

Data processing adopts the Lambda architecture to balance real-time and accuracy requirements: the batch processing layer uses Apache Spark to perform full-scale calculations on historical data and generates user psychological portrait baselines through feature engineering. The speed layer relies on the Apache Flink stream processing engine to perform windowed calculations on real-time incoming data, achieving second-level updates of emotional states. For data storage, cold data is stored in the HDFS distributed file system, while hot data is stored in the Redis in-memory database to ensure millisecond-level response. All data undergoes anonymization before being stored, with key sensitive information filtered during the feature extraction stage. The original data is automatically destroyed after completing feature calculations according to a specified period, retaining only desensitized feature vectors and aggregation results, thereby reducing the risk of privacy leakage from the source.

3.5.2 System scalability and personalized service mechanism

The scalability of the system is achieved through a microservices architecture. As shown in Figure 8, each functional module is split into independent services that communicate through an API gateway. This decoupling design enables the system to dynamically scale according to user scale: when the number of concurrent users increases, feature computation and early warning analysis service instances can be quickly expanded through Kubernetes container orchestration technology to cope with high loads. At the database level, a sharding and partitioning strategy is adopted to distribute data storage pressure based on user ID hashes. The implementation of personalized reminders and suggestions is one of the core functions of the system. Based on each student's historical psychological portrait baseline, real-time emotional state change trends, and personal preference settings, the system generates customized intervention strategies through a dynamic rule engine. For example, for students who are detected to have persistently high stress levels and prefer non-invasive reminders, the system may push mindfulness breathing exercises suggestions through in-site messages. However, for users experiencing sudden mood changes and not setting Do Not Disturb mode, a timely mobile push may be triggered, suggesting that they contact a counselor or use the built-in relaxation training module. All reminders follow the principle of graded intervention, with low-risk warnings sent automatically by the system, and medium and high-risk early warnings requiring confirmation by counselors or system administrators to ensure the timeliness and safety of intervention.

3.5.3 Privacy and security considerations

In terms of data privacy protection, the system adheres to the "privacy by design" principle. Apart from the aforementioned data anonymization, all data transmissions are encrypted using TLS 1.3, while stored data is statically encrypted using the AES-256 algorithm. Access control follows the principle of least privilege based on roles, ensuring that ordinary researchers only have access to aggregated statistical information, rather than individual raw data. The system undergoes regular security audits and penetration testing to ensure compliance with international data protection regulations such as GDPR and HIPAA. In terms of scalability, through the aforementioned architectural design, the system can theoretically support data processing and real-time alerts for tens of thousands of concurrent users. Actual measurements show that in a test environment simulating tens of thousands of concurrent users, the system's average response time remains below 200 milliseconds, with CPU utilization consistently below 35%. This demonstrates strong horizontal scalability, laying a solid technical foundation for future deployment in large university clusters.

3.6 Algorithm complexity analysis and real-time deployment feasibility

To evaluate the applicability of the improved variable step-size CFxLMS algorithm in real-time warning scenarios, it is necessary to clarify its computational complexity and resource requirements. The time complexity of the algorithm mainly depends on the filter length L and the number of iterations N: a single iteration requires O(L) multiply-add operations (weight update and error calculation), and the total complexity is O(NL). In this paper, L=32, and at a sampling rate of 8 kHz, a single frame processing (80 iterations) needs to be completed within 125 μs. The measured single frame processing time on an Intel i7 CPU is 120 μs, which meets the real-time constraint.

The space complexity is dominated by the weight vector: it requires the storage of an L-dimensional weight vector W(n), an L-dimensional input signal buffer X(n), and an error history sequence, occupying a total space of O(L). Under the configuration presented in this paper, the static memory occupation is approximately 1.2 KB (single-precision floating point), making it feasible for deployment on embedded platforms such as ARM Cortex-M7.

In real-time deployment, the worst-case execution time (WCET) of the algorithm on the STM32H7 MCU (400 MHz) is 1.2 ms, which is below the real-time deadline of 10 ms, and the peak power consumption is only 38 mW. However, it should be noted that the exponential function in the nonlinear step size calculation introduces an overhead of 3–5 clock cycles, which can be optimized through piecewise linear approximation in extreme resource-constrained scenarios. This analysis indicates that the algorithm can support multi-channel real-time processing (such as 100 sensor data streams), but L needs to be dynamically adjusted according to the hardware to balance accuracy and efficiency.

3.7 Quantification of psychological characteristics and construction of predictive models

3.7.1 Quantitative modeling of personality traits and stressful events

The quantification of personality traits employs the cross-culturally validated Big Five personality model (OCEAN), which is indirectly calculated through social media behavior characteristics. Specifically, we constructed feature vectors for the five dimensions based on the LIWC (Linguistic Inquiry and Word Count) dictionary: openness (O) is measured by lexical diversity and frequency of abstract nouns; conscientiousness (C) is calculated by the proportion of time-related words and goal-oriented sentences; extroversion (E) is assessed by social vocabulary density and frequency of positive affective words; agreeableness (A) is quantified by the frequency of cooperative words and empathetic expressions; and neuroticism (N) is measured by the frequency of anxiety words and the proportion of negative affective words. Each dimension score is standardized using Z-score to form a five-dimensional personality trait vector $P \in R^5$.

The quantification of stressful events employs a multi-level weighted evaluation model: acute stressful events are calculated based on the co-occurrence frequency of time marker words (such as "today" and "suddenly") in social media texts and a stress keyword library (such as "exam" and "conflict"); chronic stressors are weighted and accumulated based on the continuous appearance period of stress-related vocabulary (such as mentioning "stress" for seven consecutive days); event intensity combines the intensity of emotional polarity (using BERT-embedded sentiment analysis scores) and the degree of impact on the event subject identified by semantic role labeling. Finally, a stressful event intensity score matrix $S \in R^{(t\times3)}$ is generated, where t is the length of the time series.

3.7.2 Multimodal feature extraction for social media

The features extracted from social media data include the following three categories (totaling 128-dimensional features):

(1). Linguistic style features (56 dimensions):

• Lexical level: frequency proportion of 93 psycholinguistic categories based on the LIWC2015 dictionary

• Syntactic level: average sentence length, proportion of clauses, punctuation density

• Semantic level: Generate 768-dimensional text embeddings through the BERT-base multilingual model, and reduce the dimensionality to 32 dimensions via PCA

• Sentiment features: Calculate positive/negative/neutral sentiment scores and their fluctuation variance using the VADER algorithm

(2). Behavioral pattern characteristics (42 dimensions):

• Posting pattern: entropy value of posting time distribution, concentration of active time periods

• Social network: rate of change in number of friends, stability of interaction frequency

• Content orientation: Topic diversity index (calculated based on the perplexity of the LDA topic model)

(3) Temporal dynamic characteristics (30 dimensions):

• Short-term change: The standard deviation of the first-order difference in sentiment scores of posts within the last 7 days

• Long-term trend: the slope of the linear fit of the frequency of usage of psychology-related vocabulary within 30 days

• Periodic characteristics: The periodic intensity of publishing behavior extracted through Fast Fourier Transform

3.7.3 Machine learning model architecture and training strategy

We have constructed a hierarchical fusion machine learning framework, whose core components include:

Feature fusion layer: Perform multimodal fusion of personality trait vector P, stress event matrix S, and social media features. An attention mechanism is employed to calculate the adaptive weights of each feature group, with the formula: $\alpha = \text{softmax}(W \cdot \tanh(V \cdot [P \| S \| F]))$ where F represents social media features, and ‖ denotes vector concatenation.

Prediction model architecture:

• Basic classifier: Parallel processing is employed using Support Vector Machines (SVM) and a fine-tuned BERT model. The SVM employs the RBF kernel function, with the penalty parameter C set to 1.0, optimized through grid search. The BERT model undergoes further pre-training on mental health-related texts (including the PSYCH-NET dataset) before being connected to a fully connected layer for sentiment label prediction.

• Temporal modeling layer: In response to the temporal characteristics of stress events, a bidirectional LSTM network is introduced to process time series data, with the number of hidden units set to 64 and a dropout rate of 0.3 to prevent overfitting.

• Integrated output layer: Integrating the results of various models through weighted voting, with weights dynamically allocated based on the F1 score on the validation set.

Training details:

• Data partitioning: Dividing the data into training set, validation set, and test set in a ratio of 7:2:1

• Optimizer: Use AdamW optimizer, with initial learning rate=5e-5 and weight decay=0.01

• Regularization: Adopting label smoothing (smoothing=0.1) and gradient clipping (max_norm=1.0)

Evaluation Metrics: In addition to accuracy and F1 score, special attention is paid to the area under the AUC-ROC curve to address the issue of class imbalance

This modeling approach combines feature engineering guided by psychological theory with deep learning, ensuring the interpretability of features while fully leveraging the advantages of data-driven representation learning. It provides a reliable technical foundation for subsequent emotional state prediction.

4 Experimental analysis

This experiment aims to comprehensively evaluate the performance and practical effectiveness of the psychological early warning model for college students driven by big data analysis technology proposed in this paper. Through multidimensional verification, the focus is on examining the model's performance in terms of accuracy, robustness, real-time capability, and interpretability in psychological crisis early warning, so as to confirm its feasibility of replacing traditional methods in actual campus environments. The core objectives of the experiment include: verifying the stability of the improved variable step size CFxLMS algorithm in noisy environments, testing the sentiment prediction accuracy of the multi-source data (social media text, physiological signals) fusion model, and evaluating the deployment efficiency of the system in resource-constrained scenarios, thereby providing empirical evidence for college mental health management.

4.1 Test method

This experiment utilizes three publicly accessible global multimodal datasets to ensure the generalization ability and cross-cultural applicability of the model. The first dataset is CrisisNLP (source: https://crisisnlp.qcri.org/), which contains multilingual text data related to mental health crises on global social media platforms (such as Twitter), covering posts on topics such as depression and anxiety. The second dataset is StudentLife (source: https://studentlife.cs.dartmouth.edu/), collected from smartphone sensor data (such as GPS and accelerometer) and self-reported psychological state questionnaires of American college students, reflecting the correlation between daily behaviors and emotions. The third dataset is WESAD (source: https://ubicomp.eti.uni-siegen.de/home/datasets/), providing wearable sensor data (EDA, ECG) and stress labels of European subjects for multimodal emotion analysis. The preprocessing method includes a unified process: first, data cleaning is performed to remove irrelevant symbols and fill in missing values (using mean imputation). Text data is embedded using the BERT multilingual model to generate 256-dimensional vectors. Sensor data is normalized using Z-score to eliminate dimensional differences. Then, sliding window (window size of 10 seconds, overlap rate of 50%) is used for time series segmentation. Finally, SMOTE oversampling is applied to address class imbalance issues, ensuring that the training set and test set are randomly divided in a 7:3 ratio.

The experimental subjects are 10,000 samples extracted from the aforementioned dataset (including 5,000 text data from CrisisNLP, and 2,500 multimodal data each from StudentLife and WESAD), simulating changes in the psychological state of college students. The experimental group applies the model proposed in this paper (including an improved variable step-size CFxLMS algorithm and a multi-source data fusion module), while the control group selects three baseline models: traditional logistic regression (LR), support vector machine (SVM), and the deep learning model LSTM, to cover a range from simple to complex comparative baselines. The experiment is designed into five categories: performance tests calculate accuracy, F1 score, and other indicators through 10-fold cross-validation; robustness tests inject 20% Gaussian noise or randomly missing values into the input data; practicality tests measure the response time and memory usage of the model on a standard server (CPU: Intel i7, RAM: 16GB); ablation tests sequentially remove active noise reduction components or personality trait parameters; interpretability tests use SHAP to analyze feature contributions. All experiments are repeated five times and the average values are taken. For personnel-related experiments (such as real-time response tests), 50 college student volunteers are invited to participate, divided into the experimental group (n=25) and the control group (n=25) according to a random number table method, ensuring age and gender matching. The experimental period is four weeks.

4.2 Test results

(1) Performance test

This experiment evaluated the classification performance of the model in psychological crisis early warning through 10-fold cross-validation, using accuracy, precision, recall, and F1-score as core indicators. The baseline models included logistic regression (LR), support vector machine (SVM), and long short-term memory network (LSTM). The test set was independently sampled to avoid overfitting. The experimental results are shown in Table 2.

(2) Robustness test

The robustness test simulates real-world data contamination scenarios by injecting 20% Gaussian noise (mean 0, variance 0.1) into the input data or randomly missing 30% of the feature values. The model stability is measured by the decrease in F1 score (ΔF1), where a smaller ΔF1 indicates stronger robustness. The test results are shown in Table 3.

Table 2: Performance test results.

Model	Accuracy (%)	Precision (%)	Recall rate (%)	F1 score (%)
The paper's model	94.2	93.8	94.5	94.1
LSTM	89.7	88.9	90.1	89.5
SVM	85.3	84.6	85.9	85.2
LR	82.1	81.4	82.7	82

Table 3: Robustness test results.

Model	Clean data F1 (%)	Noise injection ΔF1 (%)	Missing features ΔF1 (%)
The paper's model	94.1	3.2	4.1
LSTM	89.5	7.8	9.3
SVM	85.2	10.5	12.7
LR	82	13.1	15.9

(3) Practicality test

The practicality test measures the inference time (single-sample processing latency) and CPU utilization of the model under standard hardware conditions, and it surveys 50 volunteers' ratings on system availability (on a 5-point scale, with 1 being the lowest) to evaluate deployment feasibility. The test results are presented in Table 4.

Table 4: Practicality test results.

Model	Response time (ms)	CPU usage (%)	User satisfaction (score)
The paper's model	120	15.3	4.5
LSTM	210	28.7	3.8
SVM	95	12.1	3.5
LR	80	10.5	3.2

(4) Ablation test

The ablation test verifies the contribution of each component by gradually removing core components of the model (active noise reduction module, personality trait parameters) and observing changes in the F1 score, with the baseline being the complete model presented in this paper. The test results are shown in Table 5.

Table 5: Ablation test results.

Model variant	F1 score (%)	Decrease (%)
Complete model	94.1	-
No noise reduction module	89.2	4.9
No personality parameter	91.5	2.6
Remove both at the same time	85.7	8.4

(5) Interpretability test

The interpretability experiment utilizes SHAP to analyze 100 samples from the test set, calculating the mean SHAP values for the top 5 most important features to reveal the model's decision-making logic, with a focus on evaluating key features such as stressful events and social frequency. The experimental results are presented in Table 6.

Table 6: Interpretability test results.

Feature	Average SHAP value	Importance ranking
Frequency of stressful events	0.32	1
Social activity level	0.28	2
Text sentiment score	0.25	3
heart rate variability	0.21	4
sleep duration	0.18	5

(6) System comparison test

This experiment aims to verify whether, when dealing with psychological signals characterized by uncertainty, nonlinearity, and non-stationarity, the system proposed in this paper exhibits significant improvements over traditional advanced control methods in terms of early warning accuracy, robustness to noise and missing data, and real-time processing efficiency. To ensure a fair comparison, the same set of 10,000 samples (integrating CrisisNLP, StudentLife, and WESAD) described in Section 4.1 is used. The data preprocessing procedure remains consistent. Table 7 systematically compares the performance of the system proposed in this paper with four baseline methods across various key indicators.

Table 7: Comprehensive performance comparison between the system presented in this paper and advanced control methods.

Method	This document system	Method	This document system	Method	This document system
Accuracy (%)	94.2	88.5	85.1	90.3	86.8
F1 score (%)	94.1	87.9	84.3	89.6	85.7
Steady-state error (dB)	-32.1	-26.5	-24.8	-28.9	-25.7
Convergence time (ms)	120	185	220	350	195
CPU usage (%)	15.3	22.1	18.9	45.6	20.5

ΔF1 - Noise (%)	3.2	7.5	9.1	5.8	8.4
ΔF1 - Missing (%)	4.1	9.8	11.3	7.2	10.5

4.3 Analysis and discussion

The performance test results (Table 2) indicate that the model proposed in this paper outperforms the baseline in all indicators, achieving an F1 score of 94.1%, which is 4.6 percentage points higher than the best baseline LSTM. This is primarily attributed to the dynamic adaptability of the variable step size algorithm to noisy signals and the feature richness brought by multi-source data fusion. However, there is still room for improvement in the recall rate of the model on a few categories (such as extreme crisis samples), which requires further optimization through cost-sensitive learning.

The robustness test (Table 3) shows that the model in this paper achieves a ΔF1 of less than 5% under noise and missing scenarios, significantly outperforming the baseline (e.g., ΔF1 of LSTM is greater than 7%). This proves that the active noise reduction component effectively suppresses data abnormal perturbations. However, the model still exhibits high sensitivity to high-variance noise. In the future, adversarial training can be introduced to enhance stability.

In the practicality test (Table 4), the model presented in this paper strikes a balance between response time (120ms) and user satisfaction (4.5 points). Although it is slightly slower than lightweight models (such as LR), the noise reduction algorithm reduces the operational burden caused by false alarms. However, in high-concurrency scenarios, CPU utilization may become a bottleneck, necessitating optimization of distributed computing.

The ablation study (Table 5) indicates that the noise reduction module contributes the most (F1 score decreases by 4.9% after removal), followed by the personality trait parameters (decrease by 2.6%). This confirms that multi-component collaboration can effectively enhance early warning accuracy. However, there is redundancy among some components, which can be simplified through regularization.

The interpretability test (Table 6) reveals that stressful events and social behaviors are the dominant factors in model decision-making, which is consistent with psychological theory. However, physiological characteristics (such as heart rate) contribute less, suggesting the enhancement of multimodal fusion strategies.

The experimental results presented in Table 7 clearly demonstrate that the psychological early warning system proposed in this paper significantly outperforms the four advanced control methods compared in terms of performance, robustness, and real-time capability. In terms of performance, the system proposed in this paper leads comprehensively with an accuracy rate of 94.2% and an F1 score of 94.1%. This is primarily attributed to its core improved variable step-size CFxLMS algorithm, which can dynamically adapt to the non-stationary characteristics of psychological signals. Combined with the rich features provided by multi-source data fusion, it achieves more accurate tracking and prediction of emotional states.

The concept of Neural Adaptive Control (NAC) indeed provides a powerful tool for handling complex nonlinear psychological data, but its high complexity and computational cost limit its real-time application. This paper systematically absorbs the core idea of "gradual design and guaranteed stability" from methods such as Adaptive Backstepping Control (ABC), and combines it with a lightweight filtering structure and an efficient step update strategy. While maintaining strong processing capabilities, it significantly optimizes real-time performance. This experiment verifies that the system proposed in this paper, as a solution specifically designed for psychological early warning scenarios, has obvious advantages over general advanced control methods in dealing with the unpredictability, uncertainty, and real-time requirements of real-world data. This provides a strong empirical basis for its practical deployment in university mental health management.

To sum up, the model presented in this paper significantly outperforms the baseline in terms of performance, robustness, and practicality. Its advantages stem from the dynamic convergence characteristics of the variable step-size algorithm and the complementary effects of multi-source data fusion. However, its limitations include insufficient generalization ability for data with high cultural differences (such as non-English text processing) and computational resource constraints in real-time deployment. Future work will focus on optimizing cross-cultural adaptation algorithms and integrating edge computing to promote the large-scale application of the model in actual campus environments.

4.4 Discussion on model limitations and assumptions

The validity of this study is founded on several key assumptions, and recognizing the boundaries of these assumptions is a prerequisite for the model to move towards practical application. The main limitations are reflected in the following four aspects:

Firstly, there is a contradiction between the assumption of signal stationarity and the non-stationary psychological reality. The core assumption of the algorithm is that psychological signals (such as heart rate and skin conductance) are stationary within a short time window, but real psychological crises often manifest as sudden, non-stationary, and intense fluctuations. This contradiction leads to a 1-2 second delay in the model's tracking of sudden emotions. In the future, an adaptive segmentation mechanism for non-stationary signals needs to be introduced.

Secondly, there is a gap between the idealized fidelity of sensors and the heterogeneity of devices. The research assumes that sensor data errors conform to an ideal distribution. However, in real-world environments, significant differences in measurement errors exist among multi-source heterogeneous devices (such as medical-grade and consumer-grade fitness trackers), which can directly lead to deviations in physiological feature extraction, potentially reducing the cross-device accuracy of the model by 7%-12%. Therefore, it is necessary to establish a device calibration factor library to eliminate these differences.

Thirdly, there is a conflict between the universality of language and culture and the differences in regional expression. The model relies on the universality of cross-language sentiment models, but there are cultural differences between the East and West in emotional expression, namely "indirect and implicit" versus "direct and explicit", which leads to a significantly lower recognition accuracy (F1=86.3%) of implicit depressive expressions in Chinese compared to English (F1=94.1%). Therefore, building a culturally adapted sentiment dictionary is key to enhancing the feasibility of cross-cultural applications.

Fourthly, there is a gap between the synchronous assumption in the laboratory and the asynchronous constraints in real-world scenarios. The model requires strict synchronization of multi-source data, but in actual deployment, data streams such as social media and physiological sensors exhibit acquisition delays ranging from several seconds to ten seconds. This asynchrony can reduce the sensitivity to capturing transient emotional fluctuations. Therefore, developing asynchronous data fusion algorithms is an inevitable direction to address this challenge, but it will inevitably increase computational overhead.

In summary, these assumptions clearly define the gap that the current model needs to bridge in order to move from "laboratory verification" to "field deployment". Future work will focus on developing elastic time window mechanisms, establishing equipment calibration standards, embedding culturally sensitive modules, and optimizing asynchronous fusion algorithms, thereby systematically enhancing the robustness and practicality of the model in complex real-world environments.

5 Conclusion

This study is based on relevant Psytheories, and it is concluded that Psycrisis can be early-warned by continuous observation of emotional characteristics. Moreover, based on this, this paper constructs a Psycrisis early warning model based on big data, which provides innovative observation methods and ideas for college students' Psycrisis early warning. In addition, according to the knowledge in the field of psychology and machine learning methods, on the basis of improving the emotion prediction algorithm, this study proposes a Psycrisis early warning algorithm based on social media big data, which effectively avoids the probability problem of simply using machine learning algorithms. The simulation results show that the algorithm can reflect the emotional changes of college students when they are subjected to stressful events, thus preliminarily verifying the effectiveness of the algorithm.

References

[1] Bakker, D. and Rickard, N. 2019. A systematic review of the efficacy of mobile apps for mental health. JMIR Mental Health, 6 (2), e12967. https://doi.org/10.2196/12967

[2] Firth, J., Torous, J., Carney, R. and Newby, J. M. 2019. The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis. Journal of Medical Internet Research, 21 (4), e12869. https://doi.org/10.2196/12869

[3] Borghouts, J., et al. (2021). Barriers to and facilitators of user engagement with digital mental health interventions: systematic review. Journal of Medical Internet Research, 23(3), e24387. https://doi.org/10.2196/24387

[4] Schueller, S. M. and Torous, J. 2020. Scaling evidence-based treatments through digital mental health. American Psychologist, 75 (8), 1093–1104. https://doi.org/10.1037/amp0000684

[5] De Choudhury, M. 2019. Social media as a sensor for mental health. Current Opinion in Psychology, 31, 86–91. https://doi.org/10.1016/j.copsyc.2019.08.011

[6] Guntuku, S. C., Yaden, D. B., Kern, M. L., Ungar, L. H. and Eichstaedt, J. C. 2019. Social media-based mental health surveillance: A review. Computers in Human Behavior, 98, 288–296. https://doi.org/10.1016/j.chb.2019.04.011

[7] Liu, X., Li, R. and Wang, Y. 2020. Machine learning for depression prediction based on social media data: A review. Journal of Affective Disorders, 266, 552–559. https://doi.org/10.1016/j.jad.2020.01.135

[8] Yang, J., Zhang, H. and Chen, Y. 2020. Social media and mental health: A review. Current Psychiatry Reports, 22 (11), 61. https://doi.org/10.1007/s11920-020-01189-6

[9] Insel, T. R. 2019. Digital phenotyping: A global tool for psychiatry. World Psychiatry, 18 (3), 276–277. https://doi.org/10.1002/wps.20671

[10] Mohr, D. C., Zhang, M. and Schueller, S. M. 2021. Digital phenotyping for mental health: A systematic review. World Psychiatry, 20 (1), 76–89. https://doi.org/10.1002/wps.20829

[11] Chen, X., Wang, Y. and Li, S. 2020. Mental health detection using mobile sensing: A review. Sensors, 20 (5), 1354. https://doi.org/10.3390/s20051354

[12] Wang, Y., Chen, X. and Zhang, L. 2021. AI-based emotional analysis for mental health monitoring using wearable sensors. IEEE Transactions on Affective Computing, 12 (3), 567–578. https://doi.org/10.1109/TAFFC.2021.3056789

[13] Kim, J. and Lee, S. 2020. AI-powered chatbots for mental health support: A systematic review. Journal of Medical Systems, 44(5), 97. https://doi.org/10.1007/s10916-020-01570-1

[14] Zhang, H. and Li, S. 2020. A survey on artificial intelligence in psychology. Artificial Intelligence in Medicine, 105, 101813. https://doi.org/10.1016/j.artmed.2020.101813

[15] Lin, C., Wu, H. and Li, J. 2021. Deep learning for emotion recognition from text: Applications in mental health. IEEE Access, 9, 100000–100010. https://doi.org/10.1109/ACCESS.2021.3056789

[16] Smith, A. B. and Johnson, C. D. 2022. Integrating AI and psychology for early warning systems in education. Educational Technology Research and Development, 70 (3), 567–589. https://doi.org/10.1007/s11423-022-10123-5

[17] Naslund, J. A., Aschbrenner, K. A. and Bartels, S. J. 2020. Digital technology for mental health in low- and middle-income countries: A narrative review. Harvard Review of Psychiatry, 28 (4), 214–221. https://doi.org/10.1097/HRP.0000000000000265

[18] Torous, J., Myrick, K. J., Rauseo-Ricupero, N. and Firth, J. 2020. Digital mental health and COVID-19: Using technology to accelerate the curve on access and quality. JMIR Mental Health, 7 (3), e18848. https://doi.org/10.2196/18848

[19] Zhou, M., Liu, T. and Wang, Y. 2020. Big data analytics for student mental health: A case study. Computers & Education, 150, 103842. https://doi.org/10.1016/j.compedu.2020.103842

[20] Kolenik, T. and Gams, M. 2021. Persuasive technology for mental health: One step closer to (mental health care) equality? IEEE Technology and Society Magazine, 40 (1), 80-86. https://doi.org/10.1109/MTS.2021.3056288