A study on the application of neural networks to determine students' mental health status in school education

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Abstract

College students' studying and living environments have become more difficult as a result of modern society's growth, resulting in substantial psychological concerns. Most academics, on the other hand, are more interested in quantitative evaluations based on objective surveys and statistical analysis, or contrastive studies based on pre-designed intervention procedures. Few of them evaluate the combination of influencing elements when determining the severity of psychological distress. To address the issue, this research applies artificial neural networks (ANN) to the early detection and intervention of psychological crises among college students using physical education (PE). The psychological crises of college students was analysed with the structural equation, taking into account the interaction impact between affecting elements, using a suitable index system. Following that, a bidirectional long short-term memory (BiLSTM) network was built for the purpose of analysing college students' psychological crises, and the degree of psychological crisis was assessed using the emotional labelling attention mechanism. Finally, the impact of physical activity on the reduction of psychological stress in college students was thoroughly examined. Experiments confirmed the validity of the proposed approach.

Keywords: artificial neural network (ANN); psychological crisis among college and school students; early warning of psychological crisis; physical education (PE) intervention.

1. Introduction

In many parts of the world, there are limitations or bans on talking about mental health. This is due to a lack of understanding or knowledge. A study was conducted to determine whether students in a school setting had mental health issues, and if so what would help them solve these issues. The implementation of neural networks (NN) was one way that an experimenter looked at this problem. The other methods were exploratory factor analysis (EFA), pairwise comparisons between students, and logistic regression analyses. The other methods were exploratory factor analysis (EFA), pairwise comparisons between students, and logistic regression analyses. The results indicated that many students had mental health issues and that NN was successful in predicting which students had mental health issues. (Pramana et al., 2021)

Neural networks are a very good tool for determining which students have mental health issues because they can improve on accuracy in determining this information. NNs are collections of interconnected nodes that are set up to process and solve a task. An experimenter is trying to get a neural network to determine if there are students with mental health problems based on a list of criteria. School students' academic and living environments have become more difficult as contemporary civilization has progressed. Various stressful occurrences are induced by the complicated environment, which increases stress and bad emotions among School students. As a result, many School students have mental health issues such as irritation and anxiety (Guo et al., 2014; Hazarika et al., 2020; Kim et al., 2017; Wang, 2020). It is vital to manage and guide the psychological difficulties of School students through efficient early warning and intervention of psychological crises in order to assure their physical and mental growth (Cheng et al., 2014; Fang, 2021; Li, 2013; Li et al., 2013).

Traditional screening and early warning procedures for psychiatric crises in School students have substantial mistakes, low efficiency, and poor timeliness, according to clinical diagnostic scales (Deroche et al., 2012; Guo et al., 2018; Heazlewood et al., 2011; Nagelli et al., 2019; Sidong, 2013; Wu & Huang, 2012). Liu et al. studied the psychological crises of School students by anticipating and assessing their emotional changes, stressful situations, and personality factors using big data from social media (Liu et al., 2021). Jiang recommended proactive prevention, whole-process monitoring, and active intervention as countermeasures to the prediction of psychological crises among School students (Panqiu, 2018). Sadovnikova et al. investigated the psychological problems that School student's face as a result of travel difficulties, in the context of rising learning stress and the COVID epidemic. They applied the time view theory, which advocates a balanced view of time, to regular intervention of School students' psychological crises, and improved the intervention effect by developing a flexible mind to counter negative emotions (Sadovnikova et al., 2018).

School students' psychological crises are caused by a variety of factors. The usual intervention technique has glaring flaws, such as considerable delays and strong limits (Chang & Xinyi, 2017; Katou, 2013; Pacula et al., 2014; Xiong, 2020). Mindfulness-based cognitive

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therapy (MBCT) was used by Anagondahalli and Turner to avoid excessive actions in School students in psychiatric crisis, making the intervention more practicable and self-operable (Anagondahalli & Turner, 2012).

The psychological conditions of pupils have a significant impact on the development of physical education (PE) skills (Bauer & Kratschmar, 2015; Min-gang & Dan-dan, 2015; Tan, 2016). Beida and Bao categorised School students based on their sources, compared the psychological states of PE majors and other majors, and examined the psychological differences between School students of various majors, interpersonal relationships, employment prospects, emotions, family backgrounds, and economic conditions (Beida & Bao, 2011).

The majority of studies on the early detection and intervention of psychological crises in School students are carried out in pre-designed lab conditions. Quantitative evaluations based on objective surveys and statistical analysis, as well as contrastive studies based on predesigned intervention approaches, are the focus of the research. Few researchers take into account the combination of affecting elements (Hongjun et al., 2011; Huang, 2021). Some researchers even combine the psychological crisis early warning system with the psychological crisis intervention system, jeopardising the judgement for the severity of the psychological crisis.

This research presents artificial neural network (ANN) (Guo, 2020; Huang et al., 2020; Widyaningrum et al., 2020) to the early detection and PE intervention of psychological crises among School students based on the preceding analyses. Section 2 creates a suitable index system and uses it to examine the psychological crises of School students using the structural equation, taking into account the interaction impact of influencing elements. Section 3 builds a bidirectional long short-term memory (BiLSTM) network for analysing School students' psychological crises and discusses the flow of determining the degree of psychological crisis using the emotional labelling attention mechanism. Section 4 investigates the impact of physical activity on School students' psychological stress reduction. Experiments confirmed the validity of the proposed approach.

2. School Students' Psychological Crisis Analysis Based on Structural Equation and Interaction Effect

Figure 1 depicts the suggested psychological crisis evaluation index system for college students, which includes five criteria: causes, coping attitudes, stress reactions, impact interventions, and symptoms. Future pressure, significant emergencies, interpersonal strain, and economic pressure are all factors that contribute to psychological crisis among School students. School students' coping attitudes toward psychological distress are either negative, positive, or lax. School students' stress reactions to psychological crises may be categorised into four categories: mental, physiological, cognitive, and behavioural. College students in emotional distress can be helped from three sources: family, relatives, and friends, as well as the educational environment. School students often exhibit four symptoms during a psychological crisis: despair, anxiety, aggression, and paranoia.

Analyzing school students' psychological crises based on structural equation modeling (SEM) and interaction effects can provide valuable insights into the complex relationships between different psychological factors. Structural equation modeling is a statistical technique used to examine the relationships among multiple variables simultaneously and is particularly useful for understanding the underlying structures and causal relationships in complex systems

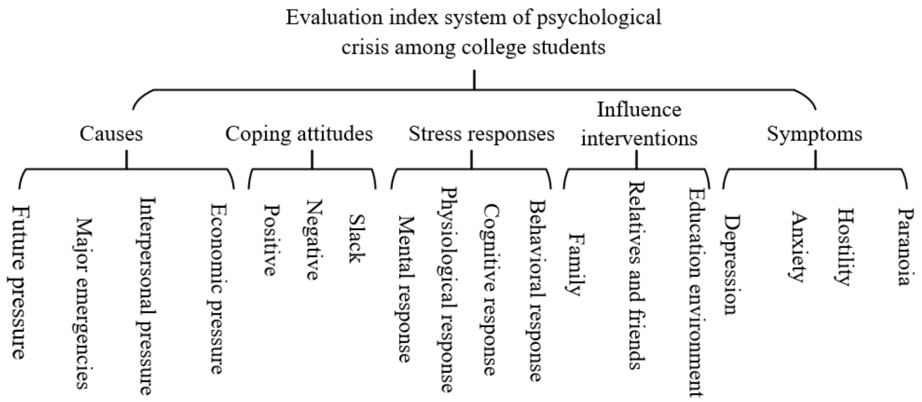

Figure 1. Evaluation index system of psychological crisis among college students

This study constructs a structural equation model (SEM) based on the aforementioned evaluation indices, which consists of a measurement equation and a structural equation. The indices were used as latent variables in an interaction effect analysis, setting the groundwork for a study of college students' psychological crises.

Let and be the error terms of exogenous variable a and endogenous variable b, respectively; and be the vectors made up of exogenous latent variables and endogenous latent variables, respectively; and be the link between an exogenous observable variable and an exogenous latent variable. Then vector A, which is made up of exogenous observable variables, may be written as follows:

$$A = \Gamma_a \delta + \varepsilon \tag{1}$$

Vector B composed of endogenous observable variables can be expressed as:

$$B = \Gamma_b \gamma + \sigma \tag{2}$$

Let Φ be the mutual influence between endogenous latent variables; Ψ be the influence of an exogenous latent variable on an endogenous latent variable. The unexplained part of the vector γ of endogenous latent variables in the structural equation was treated as the residual term of the equation, and combined into a vector η. Then, the relationship between latent variables can be described by a structural equation:

$$\gamma = \Phi\gamma + \Psi\delta + \eta \tag{3}$$

The SEM was defined under the following assumptions:

(1) The means of ε and σ are both 0, i.e., $MV(\varepsilon)=0$, and $MV(\sigma)=0$;

(2) The mean of η is 0, i.e., $MV(\eta)=0$;

(3) ε and σ are not correlated with δ and γ, and ε is not correlated with σ, i.e., $cov(\varepsilon, \delta)=0$, $cov(\sigma, \gamma)=0$, and $cov(\varepsilon, \sigma)=0$;

(4) η is not correlated with δ, ε, or σ, i.e., $cov(\eta, \delta)=0$, $cov(\eta, \varepsilon)=0$, and $cov(\eta, \sigma)=0$.

Let ψ be the covariance matrix between exogenous latent variables, i.e., $MV(\delta\delta')=\psi$; Ω_ε be the covariance matrix of ε, i.e., $MV(\varepsilon\varepsilon')=\Omega_\varepsilon$; Ω_σ be the covariance matrix of σ, i.e., $MV(\sigma\sigma')=\Omega_\sigma$; Θ be the covariance matrix of η, i.e., $MV(\eta\eta')=\Theta$. Solving the covariance on both sides of formula 1:

$$\begin{aligned} cov(a) &= MV\left((\Gamma_a\delta + \varepsilon)(\Gamma_a\delta + \varepsilon)'\right) \\ &= MV\left((\Gamma_a\delta + \varepsilon)(\delta'\Gamma_a' + \varepsilon')\right) \\ &= \Gamma_a MV(\delta\delta')\Gamma_a' + MV(\varepsilon\varepsilon') \\ &= \Gamma_a \psi \Gamma_a' + \Omega_\varepsilon \end{aligned} \tag{4}$$

The covariance matrix of exogenous variable a can be given by:

$$\textstyle\sum_{aa}(\varphi) = \Gamma_a MV(\gamma\gamma')\Gamma'_a + \Omega_\varepsilon \tag{5}$$

Similarly, the covariance matrix of endogenous variable b can be given by:

$$\textstyle\sum_{bb}(\varphi) = \Gamma_b MV(\gamma\gamma')\Gamma'_b + \Omega_\sigma \tag{6}$$

Suppose J-Φ is reversible. Formula 3 can be transposed into:

$$\gamma = (J - \Phi)^{-1}(\Psi\delta + \eta) = \hat{\Phi}(\Psi\delta + \eta) \tag{7}$$

Solving formula 7:

$$\begin{aligned} MV(\gamma\gamma') &= MV\left[\left(\hat{\Phi}(\Psi\delta + \eta)\right)\left(\hat{\Phi}(\Psi\delta + \eta)\right)\right] \\ &= MV\left[\left(\hat{\Phi}(\Psi\delta + \eta)\right)\left(\hat{\Phi}(\Psi' + \eta)\right)\hat{\Phi}'\right] \\ &= \hat{\Phi}[\Psi MV(\delta\eta')\Psi' + MV(\delta\eta')]\hat{\Phi}' \\ &= \hat{\Phi}(\Psi\psi\Psi' + \Theta)\hat{\Phi}' \end{aligned} \tag{8}$$

Combining formula 8 with the covariance matrix of b:

$$\textstyle\sum_{bb}(\varphi) = \Gamma_b \tilde{\Phi}(\Psi\psi\Psi' + \Theta)\tilde{\Phi}'\Gamma_b' + \Omega_\sigma' \tag{9}$$

The covariance matrix of a and b can be expressed as:

$$\begin{aligned} \textstyle\sum_{ba}(\varphi) &= MV(ba') \\ &= MV[(\Gamma_b\gamma + \sigma)(\Gamma_a\delta + \varepsilon')] \\ &= MV[(\Gamma_b\gamma + \sigma)(\delta'\Gamma_a' + \varepsilon')] \\ &= \Gamma_b MV(\gamma\delta')\Gamma_a' + MV(\sigma\varepsilon') \\ &= \Gamma_b MV(\gamma\delta')\Gamma_a' \\ &= \Gamma_b MV\left(\hat{\Phi}(\Psi\delta + \eta)\delta'\right)\Gamma_a' \\ &= \Gamma_b \hat{\Phi}\Psi MV(\delta\delta')\Gamma_a' \\ &= \Gamma_b \hat{\Phi}\Psi\psi\Gamma_a' \end{aligned} \tag{10}$$

Similarly, it can be deduced that:

$$\textstyle\sum_{ab}(\varphi) = MV(ab') = \Gamma_a \psi \Psi \hat{\Phi} \Gamma_b' \tag{11}$$

The covariance matrix of $(b', a')'$ can be expressed as:

$$\begin{aligned} \textstyle\sum(\varphi) &= \begin{pmatrix} \sum_{bb}(\varphi) & \sum_{ba}(\varphi) \\ \sum_{ab}(\varphi) & \sum_{aa}(\varphi) \end{pmatrix} \\ &= \begin{pmatrix} \Gamma_b\hat{\Phi}(\Psi\psi\Psi' + \Phi)\hat{\Phi}'\Gamma_b' + \Omega_\sigma & \Gamma_b\hat{\Phi}\Psi\psi\Gamma_a' \\ \Gamma_a\psi\Psi'\hat{\Phi}'\Gamma_b' & \Gamma_a\psi\Gamma_a' + \Omega_\varepsilon \end{pmatrix} \end{aligned} \tag{12}$$

Formula 12 shows that the SEM of the degree of psychological crisis among college students involves parameter matrices like Γ_a, Γ_b, Φ, Ψ, ψ, Θ, Ω_ε and Ω_σ. Solving the model is equivalent to the estimation of these parameters.

Suppose δ_1 is an exogenous latent variable containing four observable variables a1, a2, a3 and a4, δ2 is an exogenous latent variable containing three observable variables a5, a6 and a7, δ3 is an exogenous latent variable containing four observable variables a8, a9, a10 and a11, δ4 is an exogenous latent variable containing three observable variables a12, a13 and a14, δ5 is an exogenous latent variable containing four observable variables a_{15}, a_{16}, a_{17} and a_{18}, and γ is an endogenous latent variable containing four observable variables b_1, b_2, b_3 and b_4. It is assumed that δ_1, δ_2, δ_3, δ_4 and δ_5 interact with each other, and their independent and interaction terms both affect γ. The 10 interaction terms can be obtained by product operation of the five independent terms of δ_1, δ_2, δ_3, δ_4 and δ_5.

Assuming that all indices have been decentralized, the observable variable corresponding to each secondary index can be measured by:

$$\begin{cases} a_1 = \delta_1 + \varepsilon_1 \\ a_2 = \mu_2\delta_1 + \varepsilon_2 \\ a_3 = \mu_3\delta_1 + \varepsilon_3 \\ a_4 = \mu_4\delta_1 + \varepsilon_4 \end{cases} \tag{13}$$

$$\begin{cases} a_5 = \delta_2 + \varepsilon_5 \\ a_6 = \mu_6\delta_2 + \varepsilon_6 \\ a_7 = \mu_7\delta_2 + \varepsilon_7 \end{cases} \tag{14}$$

$$\begin{cases} a_8 = \delta_3 + \varepsilon_8 \\ a_9 = \mu_9\delta_3 + \varepsilon_9 \\ a_{10} = \mu_{10}\delta_3 + \varepsilon_{10} \\ a_{11} = \mu_{11}\delta_3 + \varepsilon_{11} \end{cases} \tag{15}$$

$$\begin{cases} a_{12} = \delta_4 + \varepsilon_{12} \\ a_{13} = \mu_{13}\delta_4 + \varepsilon_{13} \\ a_{14} = \mu_{14}\delta_4 + \varepsilon_{14} \end{cases} \tag{16}$$

$$\begin{cases} a_{15} = \delta_5 + \varepsilon_{15} \\ a_{16} = \mu_{16}\delta_5 + \varepsilon_{16} \\ a_{17} = \mu_{17}\delta_5 + \varepsilon_{17} \\ a_{18} = \mu_{18}\delta_5 + \varepsilon_{18} \end{cases} \tag{17}$$

The four observable variables b_1, b_2, b_3 and b_4 of the degree of psychological crisis among college students can be measured by:

$$\begin{cases} b_1 = \upsilon_{b1} + \gamma + \sigma_1 \\ b_2 = \upsilon_{b2} + \mu_{b2}\gamma + \sigma_2 \\ b_3 = \upsilon_{b3} + \mu_{b3}\gamma + \sigma_3 \\ b_4 = \upsilon_{b4} + \mu_{b4}\gamma + \sigma_4 \end{cases} \tag{18}$$

Let Σ be the sum of interaction terms; β_1, β_2, β_3, β_4 and β_5 be the main effect coefficients; β_6 be the interaction effect coefficient. Then, the structural equation can be established as:

$$\gamma = \beta_1\delta_1 + \beta_2\delta_2 + \beta_3\delta_3 + \beta_4\delta_4 + \beta_5\delta_5 + \beta_6 \sum_{i,j=1,i\neq j}^{5} \left(\delta_i\delta_j\right) + \eta \tag{19}$$

If the SEM has no mean, then the four observable variables b_1, b_2, b_3 and b_4 can be measured by:

$$\begin{cases} b_1 = \gamma + \sigma_1 \\ b_2 = \mu_{b2}\gamma + \sigma_2 \\ b_3 = \mu_{b3}\gamma + \sigma_3 \\ b_4 = \mu_{b4}\gamma + \sigma_4 \end{cases} \tag{20}$$

The corresponding structural equation can be given by:

$$\gamma = \beta_1\delta_1 + \beta_2\delta_2 + \beta_3\delta_3 + \beta_4\delta_4 + \beta_5\delta_5 + \beta_6 \sum_{i,j=1,i\neq j}^{5} \left(\delta_i\delta_j - MV\left(\delta_i\delta_j\right)\right) + \eta \tag{21}$$

3. BiLSTM-Based Analysis of Psychological Crisis among College Students

The LSTM controls the index information flow of the current network with one memory cell MU, and three gates, namely, an input gate EN, a forget gate YW, and an output gate EX. Let $g_{\tau-1}$ be the state of the memory cell at the previous moment; EN_τ be the input of the index information; Q_{YW} be the matrix multiplication of the forget gate; r_{YW} be the bias of the forget gate function; ζ be the sigmoid function. Then, the forget gate of the LSTM can operate by the following mechanism:

$$YW_\tau = \zeta\left(Q_{YW}\left[g_{\tau-1}EN_\tau\right] + r_{YW}\right) \tag{22}$$

Let T be tanh function; Q_{MU} be the matrix multiplication of the input gate; r_{MU} be the bias of the input gate function. Then, the input gate of the LSTM can operate by the following mechanism:

$$I_\tau = \zeta\left(Q_I\left[g_{\tau-1}EN_\tau\right] + r_I\right) \tag{23}$$

$$MU_\tau = T\left(Q_{MU}\left[g_{\tau-1}EN_\tau\right] + r_{MU}\right) \tag{24}$$

$$MU_\tau^{*} = YW_\tau * MU_{\tau-1}^{*} + I_\tau * MU_\tau \tag{25}$$

Let Q_{EX} be the matrix multiplication of the output gate; r_{EX} be the bias of the output gate function. Then, the output gate of the LSTM can operate by the following mechanism:

$$EX_\tau = \zeta\left(Q_{EX}\left[g_{\tau-1}EN_\tau\right] + r_{EX}\right) \tag{26}$$

$$g_\tau = EX_\tau * T\left(MU_\tau\right) \tag{27}$$

Our research and experimental dataset not only contains the data of psychological crisis evaluation for college students, but also covers the texts on the interviews and comments on motional confession of college students about their psychological stress and emotions (hereinafter referred to as the IC texts for short). The sentence vectors of the above texts constitute an unlabeled training set, which is suitable for training large, unlabeled corpus. Figure 2 provides the structure of psychological crisis analysis model for college students.

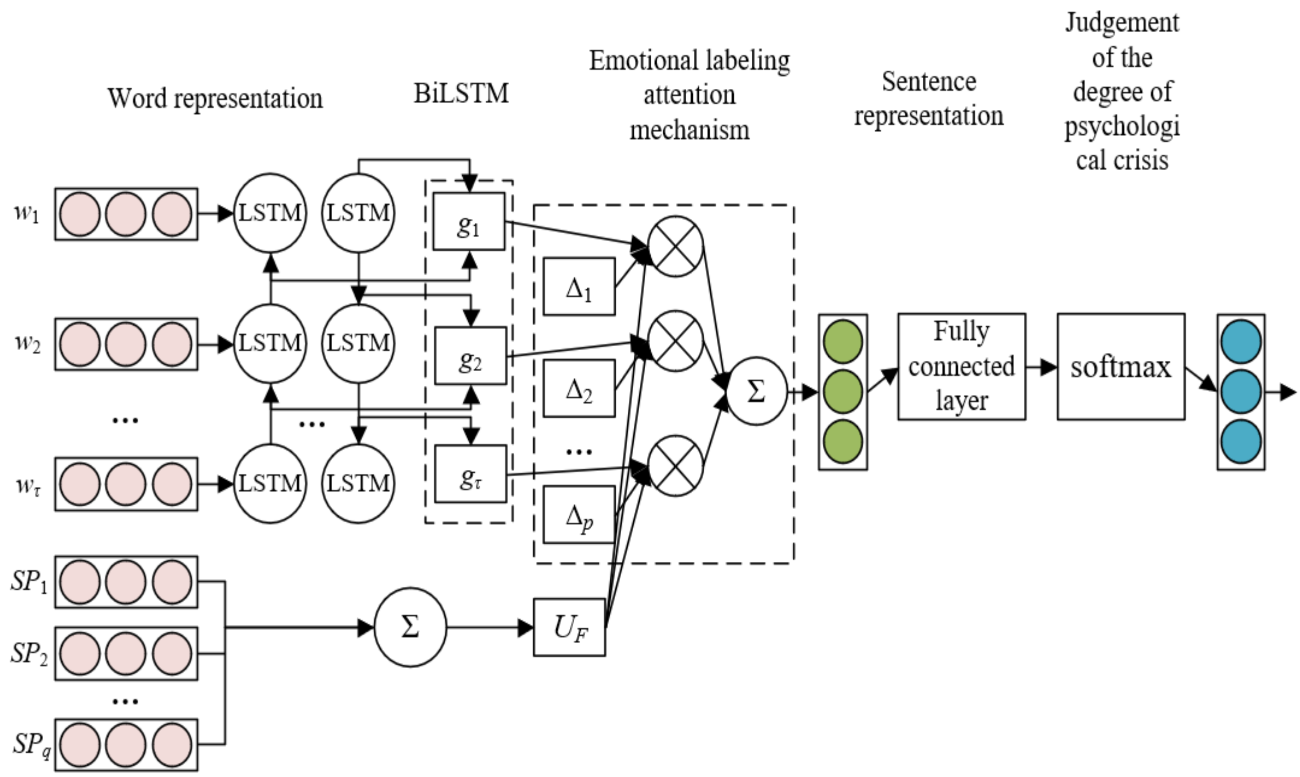

Figure 2. Structure of psychological crisis analysis model for college students

Suppose the longest IC text has m semantic units, which are converted into a series of word vectors w_l after neural network training. There are many emotional labels in the set of training sentence vectors. Each emotional label has a unique semantic code. During neural network training, the code is defined as a special word vector SP_i. Then, the word vector matrix GD^Q of an IC text obeying sequential distribution can be expressed as:

$$GD^Q = w_1 \oplus w_2 \oplus \ldots \oplus w_l \tag{28}$$

Similarly, the emotional labels can be stitched into an emotional space matrix GD^F of the same dimensions as GD^Q, that is, $[SP_1, SP_2, \ldots, SP_q]$:

$$GD^F = SP_1 \oplus SP_2 \oplus \ldots \oplus SP_q \tag{29}$$

If the text has fewer than m semantic units, full zero vectors of different lengths can be added to the end of GD^Q to ensure the dimensional consistency between all word vector matrices. GD^Q and GD^F can be connected into a complete IC text vector matrix GD:

$$GD = GD^F + GD^Q \tag{30}$$

Our research focuses on the effect of emotional labels on text. Therefore, the emotional features were extracted from the target text, and added to the emotional label attention mechanism. Then, GD^Q was used to replace GD as the input of the proposed neural network for the extraction of psychological stress and emotional eigenvectors of college students.

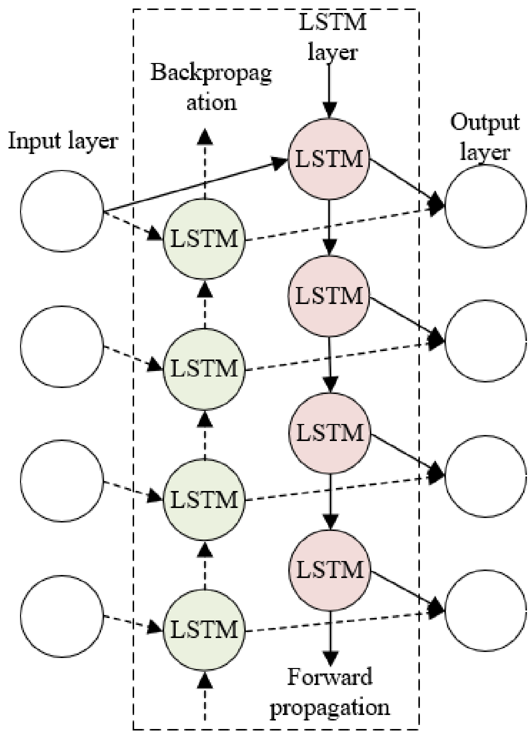

Figure 3. Structure of BiLSTM

In our psychological crisis analysis model for college students, the LSTM obtains GD^Q information from two opposite directions (forward and reverse directions), and keeps the inputs in the two directions consistent. Figure 3 shows the structure of the designed BiLSTM.

The final output of the network is the deep word vector feature DH of the class for the degree of psychological crisis among college students:

$$DH = \begin{pmatrix} DH_1 \\ DH_2 \\ \vdots \\ DH_n \end{pmatrix} \tag{31}$$

The word vector U_F with emotional label can be defined as:

$$U_F = \sum_{p=1}^{i} SP_p \tag{32}$$

Text sentence combined with emotional label can be expressed as:

$$HQ = \sum_{p=1}^{l} \Delta_p DH_p \tag{33}$$

where, Δp is the degree of importance of the p-th word in the emotional labeled text sentence to the judgement of the degree of psychological crisis among college students, i.e., the attention weight of the p-th word in the text sentence. This index helps to accurately determine whether emotional label enhances or weakens the emotion. The weight of emotional label can be calculated by:

$$\Delta_p = \frac{e^{IM(DH_p, U_F)}}{\sum_{j=1}^{l} e^{IM(DH_p, U_F)}} \tag{34}$$

Let ω_R and ω_D be weight matrices; r be the bias. The degree of importance of a word in the emotional labeled text can be measured by:

$$IM(g_p, U_F) = U^T T(\omega_R g_p + \omega_D U_F + r) \tag{35}$$

Formula 35 shows that, during the processing of emotional label attention mechanism, the final output vector HQ of the emotional label attention mechanism layer can be derived from Δp.

Figure 4 explains the evaluation flow of psychological crisis among college students under emotional labeling attention mechanism.

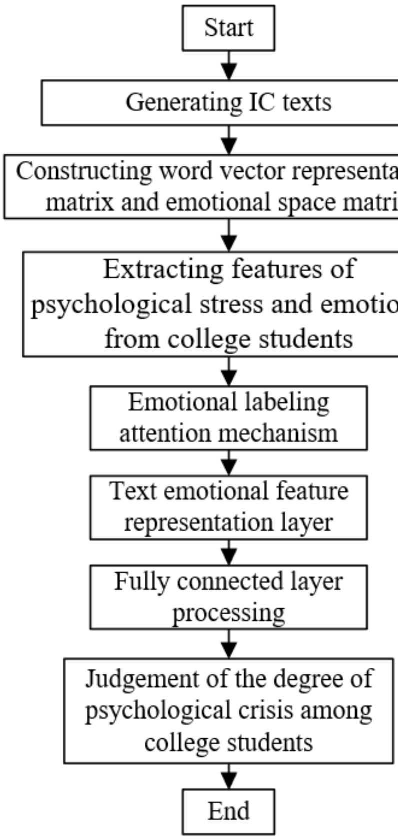

Figure 4. Evaluation flow of psychological crisis among college students under emotional labeling attention mechanism

Four target classes b_i were designed for the psychological crisis among college students: healthy, poor, disorderly, and ill. This paper classifies the degree of psychological crisis with the normalized index function softmax, which maps each element in HQ to (0, 1), and classifies the elements according to the probabilities of belonging to the four target classes.Let i be the number of actual classes of objects. Then, the probability distribution of membership can be calculated by:

$$GV_i(b) = \frac{e^{b_i}}{\sum_{j=1}^{l} e^{b_i}}, i = 1,2,3,\ldots,l \tag{36}$$

To ensure the accurate classification of the degree of psychological crisis among college students, the error between the predicted and actual probabilities for an object to belong to a class can be measured by the cross-entropy loss function:

$$K = -\sum_{e \in E} \sum_{s=1}^{S} GV_s^H(e) \log(GV_s(e)) \quad (37)$$

4. Effect of PE Intervention on Psychological Stress Easement of College Students

To further explore the relationship between psychological stress easement and PE intervention, a stochastic effect model was adopted to test the longitudinal time effect of PE intervention on psychological stress.

The stochastic effect model was constructed to observe and describe the changes in psychological stress of the college students. On the first layer of the model, the independent variable is PE intervention intensity (PEI), and the dependent variable is the psychological stress easement (PSE):

$$PSE = \alpha_0 + \alpha_1(TIME) + \alpha_2(PEI) + \theta \quad (38)$$

Suppose α_0, α_1 and α_2 consist of a fixed effect θ_0, θ_1 and θ_2, and a random effect λ_0, λ_1 and λ_2, respectively. Taking time as the control variable, the second layer of the model can be constructed as:

$$\alpha_0 = \theta_0 + \lambda_0 \quad (39)$$

$$\alpha_1 = \theta_1 + \lambda_1 \quad (40)$$

$$\alpha_2 = \theta_2 + \lambda_2 \quad (41)$$

To explain the difference in the emotional trend of psychological stress easement among college students, the low-level or high-level explained variable of PEI could be introduced to the second layer of the model. Suppose PE intervention intensity PEI_L is the independent variable, and psychological stress easement PSE_L is the dependent variable of the first layer. Under the regulation of low PEI, the model can be constructed as:

$$PSE_L = \alpha_{L-0} + \alpha_{L-1}(TIME_L) + \alpha_{L-2}(PEI_L) + \theta_L \quad (42)$$

where,

$$\alpha_{L-0} = \theta_{L-0} + \theta'_{L-0}(PEI_L) + \lambda_{L-0} \quad (43)$$

$$\alpha_{L-1} = \theta_{L-1} + \lambda_{L-1} \quad (44)$$

$$\alpha_{L-2} = \theta_{L-2} + \theta'_{L-2}(PEI_L) + \lambda_{L-2} \quad (45)$$

Under the regulation of high PEI_L, the model can be constructed as:

$$PSE_H = \alpha_{H-0} + \alpha_{H-1}(TIME_H) + \alpha_{H-2}(PEI_H) + \theta_H \quad (46)$$

where,

$$\alpha_{H-0} = \theta_{H-0} + \theta'_{H-0}(PEI_H) + \lambda_{H-0} \quad (43)$$

$$\alpha_{H-1} = \theta_{H-1} + \lambda_{H-1} \quad (44)$$

$$\alpha_{H-2} = \theta_{H-2} + \theta'_{H-2}(PEI_H) + \lambda_{H-2} \quad (45)$$

5. Experiments and Results Analysis

Table 1 presents the correlation coefficients between the five primary indices for psychological crisis among college students, namely, causes, coping attitudes, stress responses, influence interventions, and symptoms. The correlation coefficients between the indices fell in 0.345-0.562, a sign of medium correlation. The correlation coefficients between each index and total score fell in 0.613-0.785, indicating high correlations. Therefore, our evaluation index system has high structural validity.

Table 1. *Correlation coefficients between primary indices*

Latent variable	δ_1	δ_2	δ_3	δ_4	δ_5	Total score
δ_1	1.000					
δ_2	0.562	1.000				
δ_3	0.507	0.543	1.000			
δ_4	0.376	0.371	0.476	1.000		
δ_5	0.345	0.413	0.462	0.475	1.000	
Total score	0.785	0.753	0.735	0.657	0.613	1.000

Table 2. *Recognition of psychological crisis among college students before and after the introduction of emotional labeling attention mechanism*

System	Level of psychological crisis	*P* (%)	*R* (%)	*F* (%)
Pre-introduction	Healthy	74.62	78.91	75.41
	Poor	77.93	77.86	75.72
	Disorderly	75.87	78.37	72.37
	Ill	81.87	80.37	79.37
Post-introduction	Healthy	85.21	86.49	86.63
	Poor	85.76	81.28	87.09
	Disorderly	82.09	85.74	83.25
	Ill	81.23	80.34	81.32

Table 2 compares the recognized levels of psychological crisis among college students before and after the introduction of emotional labeling attention mechanism. The comparison reveals that the recognition accuracy of psychological crisis varied with the emotional labels. Before the mechanism was introduced, the ill-level psychological crisis was recognized relatively accurately (80%). After the mechanism was introduced, all four classes of psychological crisis were recognized with an accuracy surpassing 80%. Therefore, our psychological crisis analysis model, which integrates emotional labeling attention mechanism, performs better than the ordinary psychological crisis analysis model, which does not consider emotional labels. The inclusion of emotional labels in the analysis model appears to have played a crucial role in this improvement. By incorporating emotional information, the model gains a deeper understanding of the psychological crisis, enabling it to make more precise and accurate classifications for different classes. The enhanced recognition accuracy across all classes of psychological crises suggests that the emotional labeling attention mechanism has successfully captured relevant emotional cues, allowing the model to better distinguish and differentiate between different types of psychological crises. Overall, the introduction of the emotional labeling attention mechanism has proven to be beneficial, leading to a more robust and effective psychological crisis analysis model with improved performance in recognizing and categorizing various psychological crisis types

Table 3. *Index scores of target college students and Chinese college student norm*

Latent variables	Target college students	Norm	*t*	*p*
δ_1	2.31±0.57	2.09±0.54	4.572	0.000
δ_2	2.02±0.65	1.82±0.65	1.237	0.231
δ_3	1.93±0.67	1.82±0.65	3.723	0.000
δ_4	1.87±0.60	1.79±0.65	4.256	0.000
δ_5	1.80±0.53	1.82±0.65	4.429	0.804

Table 3 compares the index scores of target college students with those of Chinese college student norm. It can be seen that the target college students received high scores on causes, coping attitudes, and stress responses, suggesting that they are very likely to have psychological crisis in these three aspects. The target college students differed greatly in coping attitudes and stress responses from the norm, that is, they face more severe psychological crisis than the national average in these two aspects.

Table 4. *Index scores of college students in different grades*

Latent variables	Grade 1	Grade 2	Grade 3	*t*	*p*
δ_1	1.32±0.32	1.50±0.39	1.22±0.39	3.651	0.027
δ_2	2.25±0.78	2.30±0.27	2.25±0.47	1.023	0.364
δ_3	2.01±0.63	2.02±0.63	2.01±0.63	0.067	0.932
δ_4	1.97±0.65	1.96±0.62	1.84±0.65	0.834	0.431
δ_5	1.81±0.50	1.87±0.50	1.79±0.53	1.036	0.356
Total score	17.32±4.65	16.54±4.46	16.69±4.66	0.842	0.439

Table 4 compares the index scores of college students in different grades. Except for causes, there was no significant difference in any other index between college students in different grades.

Whichever the grade, the college students scored high on coping attitudes, stress responses, and influence intervention.

Therefore, the college students tend to suffer from psychological crisis in these three aspects. The total score indicates that psychological crisis is most likely to occur among grade 1 students, followed in turn by grade 3 students, and grade 2 students.

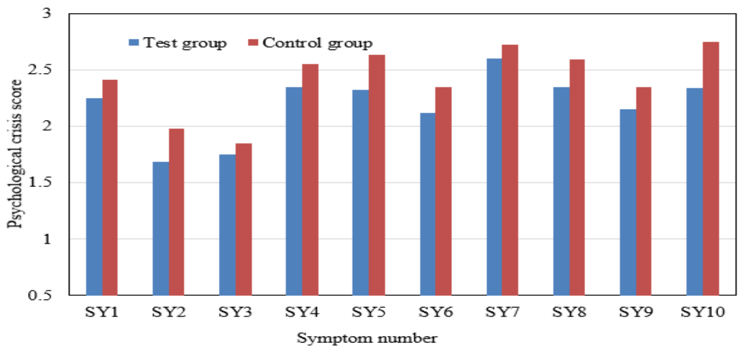

Figure 5. Psychological crisis scores of test group and control group

The target college students were divided into a test group (receiving PE intervention) and a control group. Their psychological crisis level was evaluated against 10 symptoms, namely, depression, anxiety, and hostility. Figure 5 compares the psychological crisis scores of test group and control group. Table 5 compares the scores of each criterion between the two groups.

Table 5. *Criteria level scores of test group and control group*

Latent variables	Target college students	Norm	*p*	Latent variables	Target college students	Norm	*p*
a_1	1.73±0.43	1.65±0.56	0.427	a_{10}	1.32±0.48	1.43±0.56	0.511
a_2	1.54±0.42	1.52±0.47	1.000	a_{11}	1.56±0.44	1.58±0.49	0.416
a_3	2.07±0.76	2.04±0.81	0.763	a_{12}	2.17±0.78	2.11±0.04	0.673
a_4	1.84±0.52	1.79±0.57	0.386	a_{13}	1.46±0.53	1.42±0.56	0.311
a_5	1.75±0.51	1.62±0.63	0.375	a_{14}	1.88±0.55	1.64±0.68	0.453
a_6	1.72±0.53	1.68±0.72	0.637	a_{15}	1.71±0.56	1.62±0.77	0.533
a_7	1.71±0.42	1.42±0.67	0.784	a_{16}	1.74±0.44	1.53±0.61	0.241
a_8	1.57±0.48	1.71±0.53	0.752	a_{17}	1.67±0.48	1.79±0.11	0.236
a_9	1.74±0.56	1.72±0.62	0.863	a_{18}	1.75±0.51	1.81±0.63	0.866

As shown in Figure 5 and Table 5, statistical t-test confirms the significant differences between the test group and the control group on all 10 psychological crisis symptoms. Therefore, the test group greatly outshines the control group in psychological stress easement, after taking four more physical exercises per week (a total of 120min). This means PE intervention simultaneously promotes physical and mental health, improve body functions, stimulate the secretion of endorphin, and enhance subjective physiological comfort, thereby accelerating the recovery from psychological crisis.

After the PE intervention, great changes took place in the total score, and the criterial level scores of psychological crisis evaluation. On the distribution of symptom scores, 4 and 5 college students in the test group had poor to disorderly symptoms, while 11 and 8 in the control group had these two symptoms. Hence, the psychological crisis scores of the test group are generally lower than those of the control group. In addition, the test group differed significantly from the control group in mean psychological health score, anxiety, and somatization, and very significantly in hostility. Therefore, it is clearly demonstrated that the test group significantly outperforms the control group in overall psychological health, anxiety, somatization, and hostility, thanks to the four additional physical exercises per week (a total of 120min).

Table 6. Influence of PE intervention on psychological crisis of college students

Dependent variable	Fixed effects				Random effects		
		Coefficient	Standard error SE	T value		Variance SD	Chi-square x^2
Psychological stress easement of college students	θ_0	1.75	0.08	35.62	λ_0	0.07	267.35
	θ_1	0.00	0.03	-0.13	λ_1	0.00	152.93
	θ_2	0.37	0.05	5.36	λ_2	0.09	202.76

Table 6 shows the influence of PE intervention on psychological crisis of college students. On the fixed effects, the PE intervention intensity significantly promoted the psychological stress easement of college students, while the time variable had no impact on the latter factor.

Therefore, the psychological stress easement of college students does not change linearly with the elapse of time, but increases with the PE intervention intensity. On the random effects.

The intercepts of different college students change significantly, which signifies the prominent individual difference in psychological stress easement of college students under the same intensity of PE intervention. Thus, it is necessary to find the causes of the individual difference.

Table 7. *Regulation of low PEI on psychological crisis of college students*

Dependent variable	Fixed effects				Random effects		
		Coefficient	Standard error SE	T value		Variance SD	Chi-square x^2
Psychological stress easement of college students	$\theta_{L\text{-}0}$	1.72	0.02	38.54	$\mu_{L\text{-}0}$	0.07	245.84
	$\theta'_{L\text{-}0}$	-0.24	0.03	-6.72			
	$\theta_{L\text{-}2}$	0.35	0.04	5.43	$\mu_{L\text{-}2}$	0.06	194.38
	$\theta'_{L\text{-}2}$	-0.13	0.05	-1.15			

Next, the PE intervention intensity PEI was introduced to create new random effects models. Table 7 illustrates the regulation of low PEI on psychological crisis of college students. The results show that a low PEI had no significant effect on the psychological stress easement of college students. Every unit of increment in low PEI led to 0.19 unit of decrease in psychological stress among college students, that is, the influence curve of low PEI on psychological stress easement has a small slope. The introduction of low PEI changed the residual variation of the intercept from 0.069 to 0.031. Therefore, low PEI does not significantly regulate the influence of PE intervention on the psychological stress easement of college students.

Table 8: *Regulation of high PEI on psychological crisis of college students*

Dependent variable	Fixed effects				Random effects		
		Coefficient	Standard error SE	T value		Variance SD	Chi-square x^2
Negative emotions	$\theta_{H\text{-}0}$	1.75	0.02	38.72	$\mu_{H\text{-}0}$	0.07	247.05
	$\theta'_{H\text{-}0}$	-0.16	0.03	-4.89			
	$\theta_{H\text{-}2}$	0.37	0.05	5.27	$\mu_{H\text{-}2}$	0.06	192.37
	$\theta'_{H\text{-}2}$	-0.24	0.06	-2.31			

Table 8 displays how high PEI regulates psychological crisis of college students. It can be seen that the high PEI negatively predicted the psychological stress easement of college students. Every unit of increment in high PEI led to 0.25 unit of decrease in psychological stress among college students, that is, the influence curve of high PEI on psychological stress easement has a large slope.

The introduction of high PEI changed the residual variation of the intercept from 0.085 to 0.042. Therefore, high PEI does significantly regulate the influence of PE intervention on the psychological stress easement of college students.

5. Conclusions

This paper introduces the ANN to the early warning and PE intervention of psychological crisis among college students. Firstly, an evaluation index system was established for psychological crisis among college students, and used to construct the structural equation for psychological crisis analysis. The interaction effect between influencing factors was analyzed in details. Next, a BiLSTM was proposed, the judgement flow of psychological crisis level was clarified, based on emotional labeling attention mechanism. Finally, the authors analyzed the influence of PE intervention on psychological stress easement of college students. Through experiments, the correlation coefficients between the selected evaluation indices were summarized, which reflects the good structural validity of the proposed evaluation index system. Further, the psychological crisis scores and criteria level cores were compared between the test group and the control group. The comparison confirms that PE intervention promotes the psychological stress easement of college students, and the high PEI significantly regulates the influence of PE intervention on the psychological stress easement of college students.

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