A Multi-feature and Time-aware-based Stress Evaluation Mechanism for Mental Status Adjustment

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With the rapid economic development, the prominent social competition has led to increasing psychological pressure of people felt from each aspect of life. Driven by the Internet of Things and artificial intelligence, intelligent psychological pressure detection systems based on deep learning and wearable devices have acquired some good results in practical application. However, existing studies argue that the psychological stress state is influenced by the current environment. They put much attention on the momentary features but ignore the dynamic change process of mental status in the time dimension. Besides, the lack of research in the general laws of psychological stress makes it difficult to quantitatively evaluate the stress status, resulting in the inability to perceive the stress state of users effectively. Thus, this article proposes an evaluation mechanism of psychological stress for adjusting the mental status of users. Specifically, we design a multi-dimensional feature space and a time-aware feature encoder, which integrate various stress features and capture time characteristics of stress state change. Moreover, a novel mental state model is proposed, which uses the pressure features with time characteristics to evaluate the pressure stress level. This model also quantifies the internal relationship between pressure features. Last, we establish a practicable testbed to demonstrate how to evaluate and adjust mental state of users by the proposed evaluation mechanism of psychological stress.

CCS Concepts: • **Applied computing → Health informatics;**

Additional Key Words and Phrases: Psychological pressure, multi-dimension feature, evaluation mechanism of stress, mental status adjustment

Min Chen and Wenjing Xiao contributed equally.

This work was supported by the Nature Science Foundation of China under Grant 61802139. Prof. Yixue Hao's work was supported by the Nature Science Foundation of China under Grant 61802138. The work was also supported by the Technology Innovation Project of Hubei Province of China under Grant 2019AHB061.

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1551-6857/2022/01-ART39 $15.00

https://doi.org/10.1145/3462763

ACM Reference format:
Min Chen, Wenjing Xiao, Miao Li, Yixue Hao, Long Hu, and Guangming Tao. 2022. A Multi-feature and Time-aware-based Stress Evaluation Mechanism for Mental Status Adjustment. *ACM Trans. Multimedia Comput. Commun. Appl.* 18, 1s, Article 39 (January 2022), 18 pages.
https://doi.org/10.1145/3462763

1 INTRODUCTION

Psychological pressure (also called psychological stress) is a cognitive and behavioral experience produced by the interaction of stress source and stress reaction. It has become a consensus that psychological stress will affect mental health [1]. According to the research [2], 60%–90% of human diseases are related to excessive psychological stress. Long-term suffering from heavy stress will have a detrimental effect on life and cause physical or mental illness. Thus, the reasonable pressure adjustment is significant to mental healthcare, individual life, and even social development.

Recently, researches on psychological pressure have been a hot topic in the fields of social psychology. It is an effective method to directly obtain user behavior portraits and subjective psychological evaluation reports through questionnaire surveys, which can analyze the correlation between user behavior characteristics and psychological states [3, 4]. When an individual suffers high psychological stress, some parts of his (or her) biological system may produce abnormal reactions, including heart rate [5], skin [6], and brain electricity [7, 8]. Besides, the comprehensive analysis between psychological stress and other mental diseases has attracted attention. For example, an interpretable relationship between depression, anxiety, and psychological stress has been proven [9–12]. Although these scholars have explored psychological pressure from different angles and have made a wealth of valuable achievements, there are two main challenges to this mental health evaluation task:

First, since the mental status is affected by the social environment, the analysis of psychological stress in the multi-modal environment is one of the mainstream research trends. However, these feature schemes only fuse features in the same dimension without considering the context influence between historical features and current features. More specifically, stress states are highly correlated with time, but the feature stitching methods ignore the dynamic change process of mental status in the time dimension, limiting the further improvement of the performance of psychological stress evaluation. So, an ideal method should analyze the time characteristics in multiple stress features.

Second, the data-label driven psychological stress analysis method is unexplainable and fails to capture the relation between the influence of psychological stress and the degrees of stress. The external performance of mental status is often slower than the generation of mental status, which makes the generation of data and label have time interval. Regardless of the context of stress characteristics, we only can infer the delayed mental status without time feature. So, it is unreasonable to evaluate psychological stress simply by relying on each subjective label. Therefore, there is an urgent need to study the general rules of psychological stress to improve the interpretability of the stress evaluation system before analyzing and adjusting the current mental status.

To address the above two challenges, this article proposes a **multi-feature and time-aware based evaluation mechanism of psychological stress (termed as MTEMPS)**. On the one hand, we consider complex stress sources to extract stress-related features and analyze the context information of stress features. On the other hand, we model the interpretable relation between multiple stress features and design a mental status function to evaluate psychological pressure state. The main contributions of this article are as follows:

- Based on the pressure formation process, the MTEMPS deploys a multi-dimension feature space and a time-aware feature encoder to extract multi-dimensional features and capture the time characteristics of feature space.
- Transferring the concept of stress from physics to psychological stress, a mental pressure state model is established to quantify individual performance in stressful situations as an evaluator of MTEMPS.
- A testbed is developed to demonstrate how to analyze the optimal stress state based on the evaluation mechanism of psychological stress and verify the effectiveness of the MTEMPS scheme.

The remainder of this article includes: First, we discuss the related works in Section 2, where we show state-of-the-art analysis methods of psychological stress. After that, we describe the architecture of MTEMPS in Section 3. Section 4 introduces the mental state model that is used as the evaluator in our system and conducts a theoretical analysis of the model. We build a testbed and demonstrate performance of our proposed method in Section 5. We make concluding remarks in Section 6.

2 RELATED WORK

The growing cultural needs in work, family, and academic culture have caused the problem of psychological stress to become more prominent. So far, there have been many research results on psychological stress, which have promoted the development of this field from all levels, and these studies have very important guiding significance for the work of this article.

2.1 Wearable Device for Psychological Pressure

With the development of wearable technology, intelligent Internet of things, and brain science technology, the intelligent automated psychological stress detection system, which integrates collection, processing, and analysis, has become an important component of the research in the field of psychological stress. SoDA combined with wearable medical sensors and established an automatic pressure detection and relief system to continuously monitor pressure levels and adjust excessive pressure [15]. **Electroencephalogram (EEG)** signal features are used to analyze the deep-level mental status of users. By simulating the working environment of the participants, Ahammed et al. [16] used the multi-scale entropy method to analyze the brain signals to evaluate the individual's psychological pressure. For office workers, an automatic, continuous, and non-attentive early pressure detection method was established [17]. In this method, stress detection is measured from three dimensions of psychology, physiology, and behavior pattern, and the stress detection system is designed based on multi-modal data.

2.2 Artificial Intelligence for Psychological Pressure

In recent years, the use of artificial intelligence technology to study mental health has been a hot topic [18, 19]. The analysis of psychological stress is a complex task, and machine learning and deep learning methods have natural advantages in extracting high-dimensional features. Jung et al. [20] applied multi-modal biosensors to measure physiological changes. These physiological data are the input of the pressure evaluation model. They used fuzzy logic, support vector machines, decision trees, and random forests algorithms to quantify and classify the level of stress level through the expectation maximization method. Hwang et al. [21] proposed an end-to-end deep learning framework to identify stress states, using ultra-short-term original ECG signals without using any feature engineering methods. In the experiment, they calculated the best network architecture and convolution filter length. Besides, a pressure severity prediction system based on a convolutional neural network is established [22], and the neural network is used to learn the high-dimensional characteristics of pressure. Among them, the wireless sensor is used to collect various physiological indicators of the user and as the input of the depth model to complete high-precision pressure classification.

2.3 Evaluation Strategy of Psychological Pressure

Some scholars have designed new experimental paradigms for psychological stress and tried to study the methods such as inducing stress and relieving stress under the condition of meeting the moral standards. The results in these researches can provide references for the experimental design of psychological stress. Jeunet et al. [23] designed a stress-induction protocol able to independently vary the relevant types of psychophysiological activity and studied the feasibility of physiology-based load-invariant psychosocial stress-detection. In their experiments, stressful events were artificially increased to induce psychological stress among participants. Their mental status would reflect changes in physiological signals such as heart rate and skin conductance, which were then recorded by sensors. By controlling sensory input and physiological fluctuations, a singing-driven stress test experiment was established [24]. The author tried to induce the participants to produce stress by singing aloud at intervals. According to the experimental results, it is proved that "sing-a-song" method is a controllable method to induce mental stress. In addition, there are some surprising findings in some research results, which also show the open boundary of psychological research. Rashid et al. [25] innovatively analyzed the relationship between stress and learning style and used brain asymmetry to study learning style. The interesting finding here is that the correlation between stress and IQ has nearly 100%. Another study proposed meditation method to relieve stress, and **artificial neural networks (ANNs)** were used as the classifier to analyze the changes of psychological stress along time [26].

The above-mentioned researches explored the relation between the influence of psychological stress and the degrees of stress, which are important theories for adjusting the mental status and find the optimal stress value. And these also guided us to establish a feasible experiment to trigger psychological stress [28]. Different from the existing research topics, we propose a novel evaluation mechanism of psychological stress and establish a new evaluation paradigm of psychological pressure. The purpose of this article is to provide new attempts and expand new ideas for psychological stress research.

3 SYSTEM ARCHITECTURE

In this section, we introduce the evaluation mechanism of psychological pressure. The architecture of MTEMPS is shown in the Figure 1. This architecture includes three aspects: the multi-dimension feature space, the time-aware feature encoder, and the mental state model of stress. The multi-dimension feature space determines the complex feature of psychological stress in Section 3.1. Then, based on the various feature space, the time-aware feature encoder is used to capture the contextual relationship of pressure state changes in Section 3.2. And the mental state model uses the pressure features with time characteristics to evaluate the pressure stress level. In Section 3.3, we introduce the theoretical basis and function characteristics of the mental state model of stress.

3.1 The Multi-dimension Feature Space

From the perspective of stress formation, we determine the feature space of psychological stress from various features. Multiple stress feature sets include stress source, stress reaction, and stress resistance ability features. Specially, stress source features refer to certain situations or events that cause an individual to produce stress reactions, which is the input feature of the evaluation

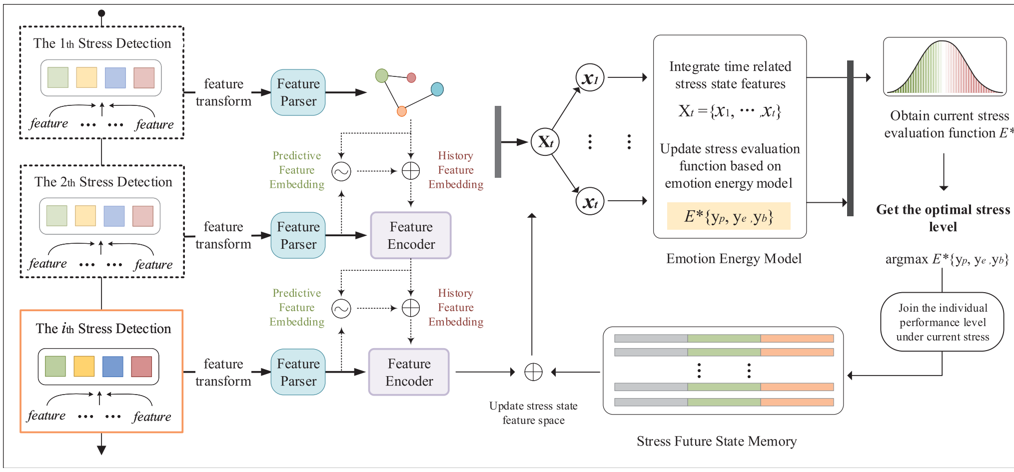


Fig. 1. The architecture of our proposed evaluation mechanism.

mechanism of psychological stress. In this article, we mainly select controllable stress source features caused by the surrounding environment, which come from society. Second, stress reaction feature refers to the external performance of individuals under psychological stress. Psychological stress system also mainly depends on the stress reaction feature to evaluate the user's stress level, and it is the feature data of this evaluation system. The stress reaction features are extracted from three aspects: physical expression, emotional expression, and behavioral expression. Sleep quality, appetite, fatigue state, physical symptoms are common physical expressions. Emotional expression includes basic emotions such as happiness, anger, sadness, and fear. Some compound emotions such as anxiety and depression are also considered. Behavioral expression refers to features that are more inclined to social behavior, excluding physical, and emotional performance. For stress resistance ability features, even in the face of the same stress event, users may have different stress reactions [31]. Therefore, in the analysis of individual stress, it is also necessary to consider the factors of individual cognitive competence, which is related to the individual's basic information, life background, and personality characteristics.

3.2 The Time-aware Feature Encoder

For this module, we formally describe the time-aware feature encoder of MTEMPS based on the multi-dimension feature space. Figure 2 shows the analysis process of the multi-dimension feature space and the time-aware feature encoder. Stress source features are expressed as $X^t = x_1^t, x_2^t, \ldots, x_n^t$, where n represents the number of feature types of the stress source, that is, $|X| = n$, where $|\cdot|$ represents the number of features in the set, x_i^t is the ith stress source feature at timestamp t. And $Y^t = y_p^t, y_e^t, y_b^t$ denotes stress reaction feature from timestep $t-1$ to t, where y_p^t, y_e^t, and y_b^t correspond to physical expression, emotional expression, and behavioral expression. Besides, we assume that E is the stress resistance ability feature set denoted as $E = \varepsilon_d^+, \varepsilon_d^-, \varepsilon_s^+, \varepsilon_s^-$, and the stress resistance ability of an individual can be explained from two aspects. The first aspect is judgment of the competence of coping with stressful events, expressed as ε_d^+ and ε_d^-, which refer to the positive and negative coping attitudes of an individual, respectively. The second aspect is the sense of social identity, expressed as ε_s^+ and ε_s^-, which, respectively, represent the degree of support from family and society, mainly based on the subject feeling of an individual. And it is

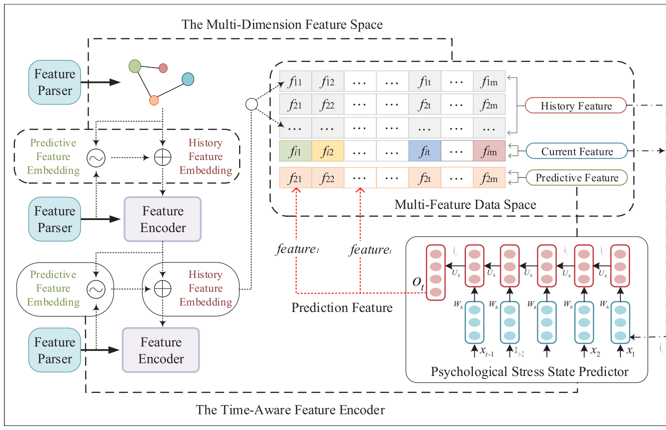


Fig. 2. Multi-dimension feature space module and time-aware feature encoder module.

assumed that the predicted stress source feature and stress reaction feature in the next timestamp $t+1$ are expressed as $\widehat{x^t}$ and $\widehat{y^t}$, respectively. Based the historical and current stress feature, the time-aware feature encoder can aware the change of stress feature in time dimension by predicting the stress state at the next time $t+1$. The predictor of stress state actually is a sequence model. At time $t-1$, this encoder maps x^{t-1} to $h^{t-1} = F(h^{t-1}, x^{t-1})$, h^{t-1} represents the state of the encoder hidden layer at time $t-1$, and F is a nonlinear activation function. Here, we select **GRU (Gated Recurrent Neural)** network as F. So, the output of the encoder network is the predicted pressure state at time t. Combining historical state, present state, and predicted state data, we obtained the final feature vector, which includes time characteristics of psychological pressure.

3.3 The Mental State Model

After obtaining stress features with time characteristic, how to establish the mapping relationship between stress state features and pressure performance is a major problem. However, because there is no definite quantitative evaluation standard for mental disorders, that becomes more difficult to evaluate psychological stress than other evaluation system of non-psychological fields. According to related psychology hypotheses, the view of activation theory [29] is that every individual has an **optimal activation level (OAL)**. Besides, the peak effect of time pressure [30] believes that there is an optimal time pressure point where the individual happiness index is the highest. When time pressure is too high or too low, the individual's happiness experience will decline. Thus, based on the support of the above theory and experimental research, we transferred the concept of stress from physics to psychological stress and propose a mental state model of stress. First, we suppose that there is an inverted U-curve relationship between stress and individual performance, that is, when the pressure value is within an appropriate range, the individual will have the best performance. If it is lower or higher than the optimal stress level, then the individual's performance will be inferior to the optimal individual's performance. Each individual has the best stress state (also called pressure level) in a specific social environment. Under the pressure state, people will achieve the best individual performance. In other words, it is a new scientific problem to model the relation between pressure source and pressure reaction. On the basis of this hypothesis, we introduce the mental state model of stress in Section 4, which is an expression of psychological stress and personal performance, to find the optimal stress level where the user's individual performance is at its best.

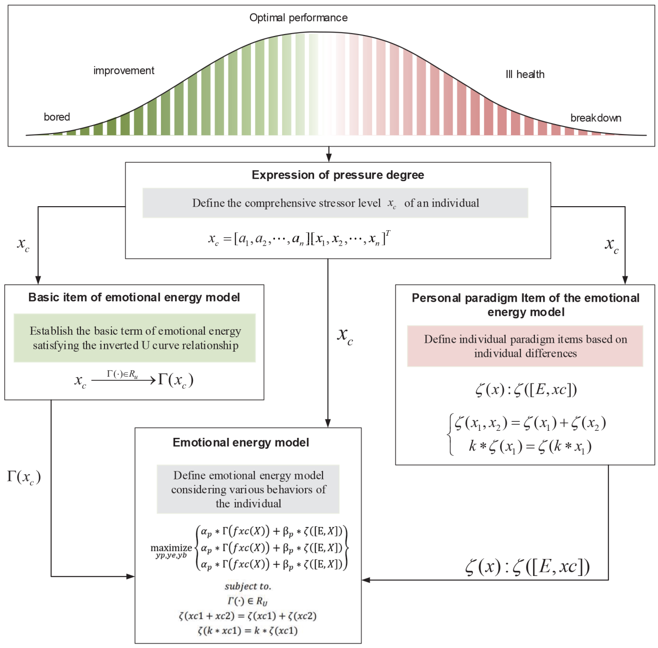


Fig. 3. The flow of building the mental state model.

4 METHODOLOGY

The mental state model used to evaluate psychological pressure state is introduced in this section, On the one hand, the stress source and the stress reaction are regarded as the independent and dependent variables, respectively. On the other hand, this model considers that stress state is also related to individual cognitive ability and quantifies the relationship between multidimensional stress features. Figure 3 shows the process of establishing the mental state model.

4.1 Model Description

Expression of comprehensive stress event: Based on the definition of multi-dimensional feature in Section 3.1, it is assumed that each individual has all the stress source features, that is, each individual corresponds to an X. If the individual does not experience an event or situation caused by a certain type of stress source, then $x_i = 0$. Because the value of x_i is the degree of the ith kind of stress source, and $x_i \in \mathbb{R}_0^+$, the comprehensive level of stress imposed on the individual can be expressed as x_c:

$$f(x_c) : x_c = [w_1, \ldots, w_n] \cdot [x_1, \ldots, x_n]^T, \tag{1}$$

where, $[w_1, \ldots, w_n]$ is the weight vector of the stress source features, and $w_1 + w_2 + \cdots + w_n = 1$, $w_i \in \mathbb{R}_0^+$. a_i denotes the influence degree of the stress source x_i on individual performance. If $w_i > w_j$, the impact of the x_i-type stress source has higher impact than the x_j-type on the individual. Similarly, if $w_i = 0$, then the x_i-type stress source will not result in a stress reaction from the individual. Since $w_i \in \mathbb{R}_0^+$ and $x_i \in \mathbb{R}_0^+$, the comprehensive level of stress source (x_c) of the individual satisfies $x_c \in \mathbb{R}_0^+$.

Basic component of the mental state model: Based on theoretical support from previous literature [32], we postulate in this study the existence of an inverted U-curve relationship between stress event and stress reaction, which is the basic property of our mental stress model. Assuming that this model satisfies the inverted U-curve relationship (marked as R_U), we define a basic component to limit that mental status function satisfies the above-mentioned relationship. Assume that $\Gamma(\cdot)$ represents a type of function that conforms to the trend of the inverted U-curve. The comprehensive stress level x_c in this article is an independent variable, so the basic component $\Gamma(x)$ of the mental state model can be expressed as:

$$\begin{aligned} \Gamma(x_c) &\to \Gamma(f_{x_c}(x_1, \ldots, x_n)) \\ st.x_c &\xrightarrow{\Gamma(\cdot)\in R_U} \Gamma(x_c), \end{aligned} \tag{2}$$

where we restrict that $\Gamma(\cdot)$ satisfies the inverted U-curve relationship.

Personal paradigm component of the mental state model: It is generally known that the stress-resistant ability varies according to each individual, due to different backgrounds of life and personality. Therefore, it is necessary for the mental state model to consider the differences of individuals' personality. Therefore, we import a personal paradigm component (marked as $\zeta(x_c)$) in our model and analyze the meaning of the personal paradigm component. First, the stress-resistant ability varies according to the individual and will show different performances. Next, individuals face different stress sources, and their corresponding performances are also different. So, the personal paradigm component is affected by the stress-resistant ability and the stress source type. Thus, both E and x_c (in $\zeta(x_c)$) were designed and the personal paradigm component of is expressed as:

$$\zeta(x) \to \zeta(E, x_c) \to \zeta([\varepsilon_d^+, \varepsilon_d^-, \varepsilon_s^+, \varepsilon_s^-, x_c]). \tag{3}$$

It is noted that for a specific individual, E is an unchangeable constant vector. Consequently, the personal paradigm component $\zeta(x)$ has only one independent variable, x_c. There are the other two requirements on the personal paradigm component. On the one hand, the impact on the personal paradigm for each individual increases with increasing source of pressure. In other words, when the stressor level is magnified by k times, the corresponding personal paradigm function term is also magnified by k times. On the other hand, in this model, we consider the fact that multiple pressures have double effects on individuals. Therefore, we define that the function value of the personal paradigm term follows superposition relationship, under the superposition of the stress source level. $\zeta(x)$ satisfies two conditions: one is that x_c maintains vector addition in the definitional domain of $\zeta(\cdot)$, the other is that x_c satisfies the principle of scalar multiplication. The mathematical formula can be expressed as follows:

$$\begin{aligned} \zeta(x_{c1} + x_{c2}) &= \zeta(x_{c1}) + \zeta(x_{c2}), \\ \zeta(k * x_{c1}) &= k * \zeta(x_{c1}), \end{aligned} \tag{4}$$

where $x_{c1}, x_{c2} \in I_\zeta$ and k is a scalar and $k \in K$. I_ζ is the definitional domain of x_c on $\zeta(\cdot)$, and $\zeta(\cdot)$ is defined as a derivable and differentiable function.

Mental State Model: In real life, the psychological stress reaction is presented in multiple levels and is very difficult to quantify the overall mental status. In this regard, this stress reaction is described by three aspects of expression. Based on the stress reaction feature described in Section 3.1, the model is defined as a one-dimensional vector, $Y = y_p, y_e, y_b$, where y_p,y_e,y_b correspond to physical expression, emotional expression, and behavioral expression. The stress reaction $y_c, c = p, e, b$ at single aspect is a superposition expression of the basic components and the personal paradigm components:

$$
\begin{aligned}
&Y = \{y_p, y_e, y_b\} \\
&\begin{bmatrix} y_p \\ y_e \\ y_b \end{bmatrix} = \begin{bmatrix} \alpha_p, \beta_p \\ \alpha_e, \beta_e \\ \alpha_b, \beta_b \end{bmatrix} * [\Gamma(f(x_c)), \zeta([E, x_c])],
\end{aligned}
\tag{5}
$$

where α_p,α_e,α_b represent the parameter factors of physical expression, emotional expression, and behavioral expression, respectively, and β_p, β_e, β_b represent the parameter factors of the personal paradigm component, respectively. Moreover, the y_p,y_e,y_b, and x_c still follow the inverted U relationship.

To sum up, the mathematical expression of mental state model is as follows:

$$
\begin{aligned}
&\underset{y_p, y_e, y_b}{maximize} E = \\
&\qquad \begin{Bmatrix} \alpha_p * \Gamma(f(x_c)) + \beta_p * \zeta([E, x_c]) \\ \alpha_e * \Gamma(f(x_c)) + \beta_e * \zeta([E, x_c]) \\ \alpha_b * \Gamma(f(x_c)) + \beta_b * \zeta([E, x_c]) \end{Bmatrix} \\
&subject \quad to \\
&\qquad \Gamma(\cdot) \in R_U \\
&\qquad \zeta(x_{c1} + x_{c2}) = \zeta(x_{c1}) + \zeta(x_{c2}) \\
&\qquad \zeta(k * x_{c1}) = k * \zeta(x_{c1}),
\end{aligned}
\tag{6}
$$

where the independent variable is x_c, E represents the target item for adjusting pressure state.

4.2 Model Analysis

In this subsection, we analyze above-mentioned model and prove its convergence, that is, the existence of an optimal stress level for an individual in a specific environment. Since the inverted U-curve relationship in mental stress model is not derivable, we first define an extensive functional form of the inverted U-curve relation. Then, in conjunction with the extensive functional form and the personal paradigm components, we deduce that the optimization problem of mental status adjustment of psychological stress is solvable.

4.2.1 Extensive Functional Formula of Inverted U-Curve Relation. Based on Kuznets's theory [33], the inverted U-curve is used to explain practical problems in a relationship-based society. Thus, we set this curve in the first quadrant of the $x - y$ coordinate system. Assume that $\tilde{x}$, $\tilde{y}$ are the independent and dependent variables of this curve, respectively. We describe the inverted-U curve phenomenon in two stages. According to the inverted U-shape hypothesis [34], "At the beginning, when the arousal level increases, the performance will improve until it has reached the optimal arousal level." In this first stage (marked as $\tilde{x} \le \theta_{\tilde{x}}$), $\tilde{y}$ increases with the increase of $\tilde{x}$. Thus, when $\tilde{x} \le \theta_{\tilde{x}}$, the relationship between $\tilde{x}$ and $\tilde{y}$ can be expressed as $\tilde{x} \to f_i(\cdot)$, where $f_i(\cdot)$ is an increasing function. As $\tilde{x}$ increases, the increment of $\tilde{\Gamma}(\tilde{x})$ decreases. In the second stage (marked as $\tilde{x} > \theta_{\tilde{x}}$), the inverted U phenomenon is described as, "When the arousal level further enhances, the performance decreases." At this time, further increase of $\tilde{x}$ will cause $\tilde{y}$ to decrease. Thus, when $\tilde{x} > \theta_{\tilde{x}}$, the relationship between $\tilde{x}$ and $\tilde{y}$ can be expressed as $\tilde{x} \to f_d(\tilde{x})$, where $f_d(\cdot)$ is a deceasing function and $\tilde{\Gamma}(\tilde{x})$ decreases more rapidly. So far, the extensive functional form of the inverted U-curve (marked as $\tilde{\Gamma}(\cdot)$) can be expressed as:

$$
\tilde{\Gamma}(\tilde{x}) = \begin{cases} f_u(\tilde{x}), & \tilde{x} \le \theta_{\tilde{x}} \\ f_d(\tilde{x}), & \tilde{x} > \theta_{\tilde{x}}. \end{cases}
\tag{7}
$$

It is necessary to note that the function $\tilde{\Gamma}(\tilde{x})$ is continuous, that is to say, $\tilde{\Gamma}(\theta_{\tilde{x}})$ is differentiable when $\tilde{x} = \theta_{\tilde{x}}$.

4.2.2 Verification of Mental State Adjustment. Next, $\forall \tilde{x}_1, \tilde{x}_2 \in (0, \theta_{\tilde{x}}]$ in function $\tilde{\Gamma}(\cdot)$, we know that $f_i(\tilde{x}_1) \leq f_i(\theta_{\tilde{x}})$, because $f_i(\cdot)$ is an increasing function and $\tilde{x}_1 \leq \theta_{\tilde{x}}$. For $\forall \tilde{x}_1, \tilde{x}_2 \in (\theta_{\tilde{x}}, \bowtie]$, we can get $f_d(\tilde{x}_2) \leq f_i(\theta_{\tilde{x}})$ based on $f_d(\cdot)$ as a decreasing function and $\tilde{x}_2 \geq \theta_{\tilde{x}}$, Thus, $\forall \tilde{x} in I$, I denotes domain of definition, can get $\tilde{\Gamma}(\tilde{x}) \leq f_i(\theta_{\tilde{x}})$. Therefore, $\Gamma(\cdot)$ has its max value at $\tilde{x} = \theta_{\tilde{x}}$. Then, we differentiate the function $\tilde{\Gamma}(\tilde{x})$:

$$\frac{\mathrm{d}\tilde{\Gamma}}{\mathrm{d}\tilde{x}} = \frac{\mathrm{d}}{\mathrm{d}\tilde{x}}\tilde{\Gamma}(\tilde{x}) = \tilde{\Gamma}'(\tilde{x}). \tag{8}$$

When $\tilde{x} = \theta_{\tilde{x}}$, $\tilde{\Gamma}'(\tilde{x}) = 0$. Thus, for $\tilde{x} \leq \theta_{\tilde{x}}$, $\tilde{\Gamma}'(\tilde{x}) > 0$ and monotonously decreasing. For $\tilde{x} > \theta_{\tilde{x}}$, $\tilde{\Gamma}(\tilde{x})$ decreases faster, so $\tilde{\Gamma}'(\tilde{x}) = 0$ is also monotonously decreasing for $\tilde{x} > \theta_{\tilde{x}}$. To sum up, $\tilde{\Gamma}'(\tilde{x})$ is a monotonically decreasing function in the domain of definition. Here, assume that when $\tilde{x} \rightarrow \bowtie$, $\tilde{\Gamma}'(\tilde{x})$ is divergent.

Next, we discuss the personal paradigm component of the emotion energy $\zeta(x_c)$ to analyze its derivative property. Because $\zeta(x_c)$ is derivable and differentiable, we can derive $\zeta(x_c)$ on $\tilde{x}$, as follows:

$$\frac{\mathrm{d}}{\mathrm{d}\tilde{x}}\zeta = \lim_{\triangle x \to 0} \frac{\zeta(\tilde{x} + \triangle x) - \zeta(\tilde{x})}{(\tilde{x} + \triangle x) - \tilde{x}}. \tag{9}$$

According to Equation (4), when $k = -1$, we can get $-\zeta(\tilde{x}) = \zeta(-\tilde{x})$. So,

$$\zeta(\tilde{x} + x) - \zeta(\tilde{x}) = \zeta(\tilde{x} + x) + \zeta(-\tilde{x}) \tag{10}$$

$$= \zeta(\tilde{x} + x - \tilde{x}) = \zeta(x). \tag{11}$$

Based on the aforesaid, we can get that $\zeta'(\tilde{x}) = \zeta'(0), \tilde{x} \in I$, and $\zeta'(0)$ is a constant (marked as C). Next, we analyze the three expression functions, which integrates the overall function characteristics including basic components and the personal paradigm components. Since y_p,y_e,y_b have the same functional forms, we take the physical expression $y_p = \alpha_p * \Gamma(f(x_c)) + \beta_p * \zeta([E, x_c])$ as an example for analysis. If it is proved that y_p has and only has one maximum point, then $maximize\{y_p\}$ is solvable. Thus, we derived y_p, using the following mathematical expression:

$$\frac{\mathrm{d}}{\mathrm{d}x_c} y_p = \alpha_p \zeta'(x_c) + \beta_p \zeta'(x_c) = 0. \tag{12}$$

According to Equation (3), $y_p'(x_c)$ is a monotonically decreasing function in the domain of definition. So, there is only one point (marked as $\theta_{\tilde{x}_p}$) that makes $y_p'(x_c) = 0$, that is $\alpha_p \zeta'(\theta_{\tilde{x}_p}) + \beta_p \zeta'(\theta_{\tilde{x}_p}) = 0$. Moreover, when $x_c < \theta_{\tilde{x}_p}$, then $y_p'(x_c) > 0$ and if $x_c > \theta_{\tilde{x}_p}$, then $y_p'(x_c) \leq 0$. So, we can prove that $maximize\{y_p\}$ has a solution. Correspondingly, it can be proved that models y_e and y_b are solvable. We conclude that the optimization problem of mental status adjustment has optimal solutions.

5 EXPERIMENTS AND RESULT ANALYSIS

In this section, we design stress test experimental platform for psychological stress to analyze the mental status adjustment and evaluate the proposed model. The purpose of this section is to demonstrate the feasibility of the proposed mental state model for stress adjustment. There are two key issues. On the one hand, how to design an experimental scene close to real life. On the other hand, it is necessary to deduce the model, that is, to transform it into a specific mathematical function.

5.1 Materials Design and Collection

First, an experimental scheme is set up to demonstrate the viewpoints of mental status optimization to illustrate the research and application on psychological pressure problem. We recruited college student volunteers as the subjects for psychological stress test. The questionnaire confirmed that none of them had a mental disorder or had recently taken psychotropic drugs. All the volunteers signed an informed consent form before conducting the experiment. And the identity of the participants was kept confidential.

The test scenario for the experiment chooses real student exam events. In each experiment, we used the questionnaire to collect volunteers' stress source and stress reaction feature. Since stress resistance ability feature is formed by long-term historical experience, all experiments of each volunteer only conduct one stress resistance ability test, and the corresponding questionnaire scales are **Trait Coping Style Questionnaire (TCSQ)** [35] and **Multidimensional Perceived Social Support Scale (MPSSS)** [36]. The experiment details for volunteers to participate in a stress test are as follows. The volunteers fill in the **EEQ (Exam Events Questionnaire)**-(a) questionnaire to inquire about their psychological state before exam test. The survey items in the EEQ scale only contain objective questions and will not induce emotions in the volunteers to affect the performance of the test. And after the exam, the volunteers filled in the EEQ-(b), which supplement the difficulty and time of the exam. The EEQ-(a) and EEQ-(b) scales completed the collection of stress source features. Then, the volunteers filled in the **Stress Reaction Questionnaire (SRQ)** [37], which recorded the current stress status of the volunteers in the three aspects (physical expression, emotional expression, and behavior expression). In addition, the score of each exam test is also a stress reaction feature. The design of this experiment is a real scene faced by volunteers rather than an inductive experiment. Therefore, the collected features or data truly reflect the volunteer's psychological stress state. It should be noted that EEQ is a stress event evaluation questionnaire specially designed for this experiment (refer to the attachment for details). Therefore, it can be seen that each exam test corresponds to a psychological stress sample. Therefore, each volunteer will have a set of sample data in each exam.

In the physiology stress experiment, to make a good comparison, we chose volunteers who had the same curriculum and exam arrangement. Finally, students from the school of computer science of Huazhong University of Science and Technology were selected as experimental subjects. A total of 30 volunteers (20 women, 10 men) participated in the experiment. Their age ranges from 19 to 28 with the average age of 23 years. Since the choice of courses varies from person to person, we choose volunteer compulsory courses as the experimental test scene with a total of 19 compulsory courses.

5.2 Experiments Setting

Based on the above introduction, each volunteer first filled out the TCSQ [35] to evaluate their stress resistance ability. For the ith compulsory course exam, they filled in the EEQ(a), EEQ(b), and SRQ [37]. The following is the specific process for obtaining the features of psychological stress:

- Stress resistance ability feature: The scores for positive competence and negative competence in handling events, corresponding to the two values of ε_d^+ and ε_d^- in the model were obtained through the TCSQ [35]. Besides, the degrees of the "support from family" and of the "support from the society," namely, ε_d^+ and ε_d^- were obtained through the MPSSS [36].
- Stress source feature: The EEQ is a stress event scale specially designed for the experiment in our research, referring to the **Life Events Questionnaire (LEQ)** [38]. The EEQ focuses on the common psychological stress events of college students, including the impacts of family,

Table 1. Solve-for Parameters of the Mental State Model for an Individual

Related expressions	Unknown parameter
$\begin{bmatrix} \alpha_p, \beta_p \\ \alpha_e, \beta_e \\ \alpha_b, \beta_b \end{bmatrix} * [\Gamma(f(x_c)), \zeta([E, x_c])]$	$\alpha_p, \beta_p, \alpha_e, \beta_e, \alpha_b, \beta_b$
$\Gamma(x_c) = a * x_c^2 + b * x_c + c$	a, b, c
$\zeta(x_c) = D * E * x_c + e$	d, e

study and exam, interpersonal relationships, affection, and daily life. These impact features are expressed as $\{x_1^i, x_2^i, x_3^i, x_4^i, x_5^i\}$, respectively. Each volunteer sets the proportion of different pressure sources according to their own requirement, that is, the self-defining weight vector $[w_1, w_2, w_3, w_4, w_5]$. Finally, with Equation (1), we get the comprehensive impact value x_c^i of each volunteer on stress events.

- Under the influence of the stress event in the ith exam period, the students have stress reactions in three aspects: emotional, physical, and behavioral. According to SRQ and the exam scores, we can evaluate the performance state of the volunteers under the stress of exam. And the stress reaction degree of emotional expression, physical expression, and behavioral expression are expressed as y_p^i, y_e^i, and y_b^i, respectively.

Through the above process, EEQ and SRQ are filled by each student to obtain a sample data (stress source feature and stress reaction feature) in each exam test. And after certain number of exam tests, multiple data samples of each student were obtained.

The mental state model established in Section 4 is a universal form of mental state model of psychological stress, so only when this model is concreted into a definite function formula can it be carried out mathematical analysis. Therefore, we use an example analysis method to discuss the use case of the model to verify the feasibility for adjusting psychological stress.

Because the quadratic function has a wide range of applications, this experiment embodies the basic term as a quadratic linear function of x_c, expressed as $\Gamma(x_c) = a * x_c^2 + b * x_c + c$, where $-b/(2a) > 0, a < 0$. Then the personal paradigm component is embodied as a linear function, expressed as $\zeta(x_c) = D * E * x_c + e$. It is easy to prove that the specific functional forms $\Delta(x_c)$ and $\zeta(x_c)$ meet the definition requirements of basic terms and personal paradigm component, respectively.

5.3 Experiment Result

According to the experiments setting, we analyze the unknown parameters that need to be calculated in the mental state model of the student. Table 1 shows the 11 unknown parameters (mentioned as the solve-for parameters) required to be solved. According to the experiments setting, each student needs to calculate this set of solve-for parameters to obtain his model. Therefore, the optimization problem is transformed into how to obtain these 11 unknown parameters.

For each student, we use his 19 sets of data samples to fit his mental state model to obtain the 11 unknown parameters mentioned above. In this article, the parameter-solving problem is transformed into an optimization problem, and the optimization algorithm is used to solve it. The following introduces the specific process of solving the unknown parameters in the model, taking volunteer A as an example.

Table 2. Stress Test Results of Volunteer A

Number	X_c	Y_e	Y_b	Y_p
1	9.26	28.55	47.10	23.42
2	10.80	27.82	44.14	22.27
3	12.80	24.38	34.82	20.75
4	10.60	26.01	51.33	23.06
5	10.70	27.68	48.30	21.00
6	10.30	26.07	48.48	22.59
7	7.07	24.52	45.56	21.15
8	10.60	29.61	46.43	24.61
9	9.74	29.05	47.70	22.40
10	13.20	21.07	27.28	18.57
11	11.80	27.37	37.56	20.91
12	5.13	19.58	38.03	18.17
13	8.80	26.96	50.20	24.76
14	9.34	28.15	43.19	23.09
15	6.45	25.92	42.02	19.81
16	12.70	22.83	34.20	20.06
17	5.79	24.62	40.04	19.67
18	5.71	23.08	39.42	19.81
19	11.80	27.09	50.14	22.36

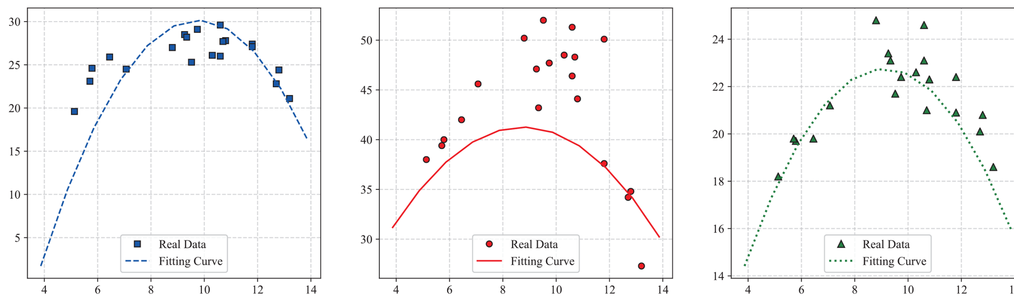
Data Preparation. For each volunteer, they have 19 sets of data sample in the whole experiment, which is a two-dimensional vector with a size of 19×4. Every column vector of this vector consists of a comprehensive psychological stress value x_c and three psychological stress reaction values y_p, y_e, y_b, in Table 2.

Fitness Function Definition. After obtaining a complete data samples $(X_c, Y) = \{(x_c^i, y_p^i, y_e^i, y_b^i)|i \in [1, 19]\}$ of volunteer A, the next goal is to calculate the optimal solve-for parameters, expressed as $P = \{p_1, p_2, \ldots, p_{11}\}$. So, the decision variable of this optimization problem is P. And the fitness function of this problem is to minimize the difference between the real performance value (denoted as y_p^i, y_e^i, and y_b^i, respectively) and the calculated performance value (denoted as $\hat{y}_p^i$, $\hat{y}_e^i$, and $\hat{y}_b^i$, respectively) of emotion energy model, the performance is as follows:

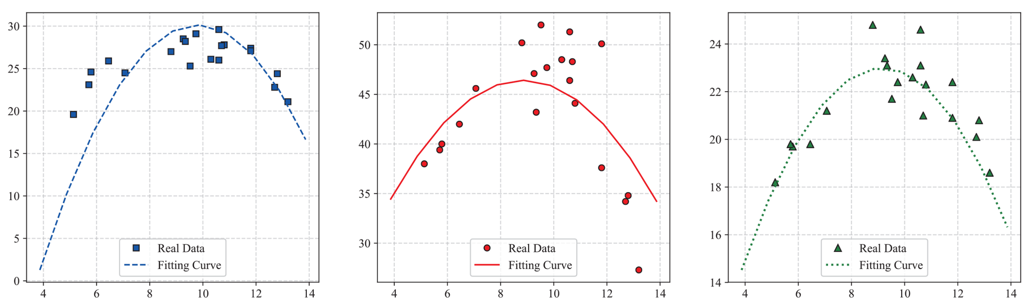
$$\begin{cases} fit_p = \frac{1}{n}\sum_{i=1}^{n}(y_p^i - \hat{y}_p^i)^2 \\ fit_e = \frac{1}{n}\sum_{i=1}^{n}(y_e^i - \hat{y}_e^i)^2 \\ fit_b = \frac{1}{n}\sum_{i=1}^{n}(y_b^i - \hat{y}_b^i)^2, \end{cases} \tag{13}$$

where we choose the **MSE (Mean Squared Error)** function as the loss function to calculate the difference between y_p^i, y_e^i, and y_b^i and $\hat{y}_p^i$, $\hat{y}_e^i$, and $\hat{y}_b^i$. Besides, $n = 19$. It can be seen that the unknown parameter solution of the emotion energy model is a multi-objective optimization problem, that is, try to minimize fit_p, fit_e, and fit_b.

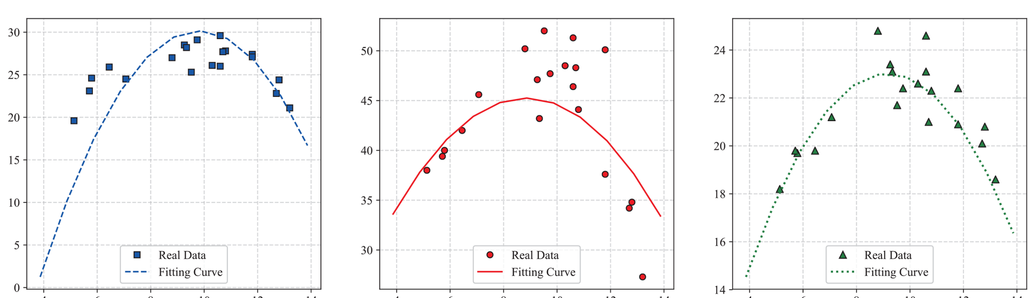
Parameter Solving Process. Based on the fitness function (Equation (13)), we use **NSGA-II (Fast and elitist Non-Dominated Sorting Genetic Algorithm)** to solve this multi-objective problem. Since the decision variable are continuous variables, the decision variables are transformed into number sequence using the real coding method in solving process. For NSGA-II algorithm setting, the population size of variable exploration factor is set as 91, and the number of



(a) The fitting effect of the 8^{th} group of non inferior solution parameters.



(b) The fitting effect of the 52^{th} group of non inferior solution parameters.



(c) The fitting effect of the 89^{th} group of non inferior solution parameters.

Fig. 4. Non-inferior results of the 8th, 52nd, and 89th group of parameters.

iterations of the algorithm is 500. Besides, the probability of mating two individuals is 1.0, and the probability of mutating an individual is 0.091. Under the above settings, the Approximation Non-inferior Set [39] for this multi-objective problem is obtained.

Final Scheme Confirmation. Through the solving process, the Pareto-optimal solution of P of volunteer A is obtained. Then, based on the three-dimensional space distance of fit_p, fit_e, and fit_b, we selected certain number of parameter solutions that have larger space distance. Table 3 shows the parameter solutions and the fitness function value. Since $\alpha_p, \beta_p, \alpha_e, \beta_e, \alpha_b, \beta_b, c, d$ (respectively, 1.23, -2.21, 0.45, 0.01, -5.82, and -0.47) have the same parameter values in different solutions, Table 3 does not show these parameters. Different parameter solutions pay different attention to the three sub-objective functions (fit_p, fit_e, and fit_b). For example, Figure 4 shows the fitting effect of the 8th, 52nd, and 89th parameter solutions. The volunteer A can decide which parameter solution to use as his own mental state model in the near term according to his own preferences.

Table 3. Non-inferior Solutions of Emotion Energy Model Parameters

Group No.	α_e	β_e	a	b	c	fit_p	fit_e	fit_b
8	0.64	0.68	−0.66	12.14	18.43	51.30	109.32	17.77
52	0.73	0.69	−0.66	12.20	18.75	52.11	69.92	15.08
91	0.71	0.67	−0.66	12.21	18.77	52.20	72.17	14.87

Table 4. The Parameters of y_p, y_e, and y_b

Type	Function model
y_p	$-0.82 * x_c^2 + 16.09 * x_c - 48.99$
y_e	$-0.48 * x_c^2 + 8.52 * x_c + 8.76$
y_b	$-0.30 * x_c^2 + 5.54 * x_c - 2.36$

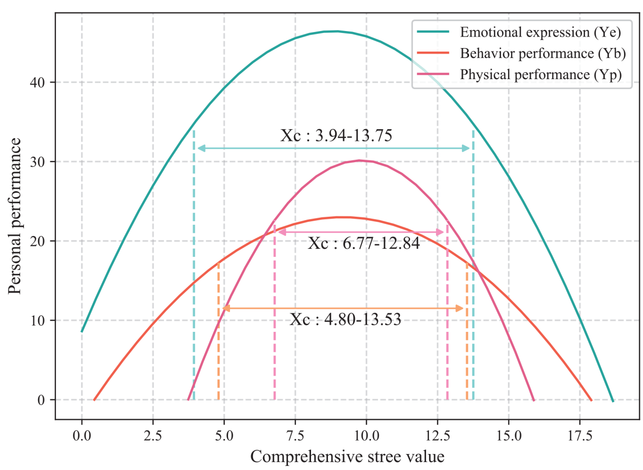


Fig. 5. The stress performance for y_p, y_e, y_b of volunteer A.

Assuming that volunteer A pays more attention to physical performance, the 8th parameter solution is more appropriate. If he (or she) is more concerned about emotion or behavioral performance, then volunteer A can choose the 52nd or 89th parameter solution.

So far, we can get the emotion energy model of volunteer A with known parameters. In this article, we choose the 52nd parameter solution as his emotion energy model. Table 4 shows the corresponding y_p, y_e, and y_b functions.

Correspondingly, Figure 5 shows the stress reaction state (that is at the performance function y_p, y_e, and y_b) of volunteer A. It can be seen that his physical performance state is good when the stress value ranges between 7–13, while the emotion performance state is good when the stress value ranges between 4 and 13.5 and the best behavioral performance corresponds to a pressure value range of 5–13.5. Thus, when the stress value ranges from 7 to 13, volunteer A reaches the optimal state in physical, emotional, and behavioral performance. So, we can roughly determine that the optimal stress value in the recent period ranged from 7 to 13 and they will show good performance when the stress value varies in this range. In other words, he (or she) might have great study efficiency or obtain excellent exam results or have a satisfying state of life.

5.4 Performance Evaluation and Analysis

In summary, using the methods described above, we can calculate the mental state model of different individuals and find their optimal psychological pressure level. Since the individual's mental status will not change much in a short term, the mental state model can be used as a reference and guidance for individual mental health regulation. In this way, teachers or parents can build a short-term emotion energy model according to the individual's recent physical and psychological state. Then, the approximate optimal stress level range of stress level can be calculated according to the emotion energy model, termed as $x_c^{up} - x_c^{down}$, so individuals can actively change the current events and environment to adjust the psychological pressure state.

For instance, if pressure level of the student is very small and learning performance is not relatively positive, then you can put more pressure on the students to adjust the psychological pressure value to x_c^{up}, such as setting a deadline for a task. Assuming that excessive stress is applied on the student, the teacher can talk to them or extend the plan appropriately to regulate the stress value of the student to to x_c^{up} or above. Assuming that the student is currently in a state of excessive psychological stress, the teacher can talk to the student or adjust the study plan appropriately to release the student's psychological pressure, so the psychological pressure level is lower than x_c^{down}.

Psychological pressure itself is not an objective thing; it is rather the subjective interpretation of an individual toward a specific event. So, this pattern of mental status needs to be adjusted slowly. Through the viewpoints of this article, we can continuously establish specific expressions for short-term individual psychological pressure to guide them to adjust the pressure level and try to keep the individual in a positive pressure state and promote the mental status of the individual to have a better performance.

6 CONCLUSION

This article discussed the relationship between psychological stresses and personal performance based on existing researches and theories. And we assume that each individual has their optimal psychological stress in a specific social environment. Based on previous research results, we propose a multi-feature and time-aware based evaluation mechanism of psychological stress for mental status adjustment. The architecture of the evaluation mechanism of psychological stress includes multi-dimension feature space, time-aware feature encoder, and a novel mental state model.

And the multi-dimension feature space considers the complicated stress sources, stress reaction, and stress-resistance feature. The time-aware feature encoder captures time characteristics of stress state change. The novel mental state model uses the pressure features with time characteristics to evaluate the pressure stress level. To this end, we build the experimental testbed and recruited the college student volunteers to conduct psychological stress experiments, in view of the optimal pressure problem described herein. In the experiment, we demonstrate how to turn the mental state model with unknown parameters into an individual mental state model and how to optimize psychological state of students through this model.

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Received December 2020; revised April 2021; accepted April 2021