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The mechanism and moderating effect of data-driven psychological service model on enhancing college students' stress coping efficacy

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SUMMARY: *This study explores the mechanism and moderating effect of data-driven psychological service models on enhancing college students' stress coping efficacy, providing methods for improving college students' mental health. This article collects data through a questionnaire survey and uses the cutting-edge Variational Mode Decomposition Residual Long Short Term Memory Network (VMD-TCN-LSTM) evaluation model to analyze the data, studying the relationship between college students' understanding of social support, stress coping efficacy, coping efficacy, and stress perception. At the same time, after modifying a certain feature value of the model, observe the degree of decrease in the evaluation effect, determine the key influencing factors, and compare the evaluation effect of the model with other algorithms. The experimental results show that the proposed VMD-TCN-LSTM model performs outstandingly in evaluating the stress coping efficacy of college students, with higher accuracy, G-mean, and F1 score than other benchmark algorithms. After shuffling each feature, the differences in consumption level and consumption behavior have a significant impact on the model's performance. Research has shown that the data-driven psychological service model can effectively enhance college students' sense of stress coping efficacy through mechanisms such as precise identification, personalized intervention, and dynamic monitoring, as well as effects such as social support, self-regulation of coping efficacy, and feedback regulation of psychological services.*

KEYWORDS: *data-driven; Psychological services; Coping with stress among college students; Sense of efficacy; Frontier decomposition; Residual network; Long Short Term Memory Network*

1 Introduction

With the development of society and the continuous enrichment of material life, people's pace of life is also getting faster and faster [1, 2]. The fierce competition in life has put enormous pressure on people. In recent years, the phenomenon of college students committing suicide has become increasingly serious. In response to this phenomenon, many universities have begun to equip professional psychologists and establish mental health counseling rooms to provide students with professional psychological counseling services [3]. Therefore, studying and exploring the perceived stress status of college students and proposing effective stress relief strategies is particularly important for the development of college students' mental health.

Perceived stress refers to a cognitive assessment of stress, in which an individual perceives external stimuli and evaluates their impact on themselves before deciding whether to classify them as a stressor. The level of stress among college students and the factors that affect their

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perception of stress are worth exploring. The "stress cognitive interaction theory" of stress perception suggests that individuals will evaluate the stressor, that is, the event itself, at two levels in their minds after encountering a crisis event. The first level is whether the event poses a threat to themselves, and the second level is how much resources they have available to solve the crisis [4]. Then individuals attempt to resolve the crisis event. Finally, make a stress response based on the outcome of the event handling. Understanding social support refers to the amount of emotional, material, informational, and other forms of support that individuals feel from the outside world. According to the theory of stress buffering mechanism of social support, it is known that social support plays an effective buffering role in individuals under stress. Theoretical research on mental health has always been a focus of attention, and understanding social support as a positive factor affecting mental health plays an important role in individuals' physical and mental well-being. College students' stress coping efficacy is a beneficial variable that regulates individual mental health, affecting the cognitive evaluation process of stress. Individuals with high levels of stress coping efficacy among college students are more likely to adopt effective strategies to cope with specific environmental requirements [5]. The stress buffering mechanism of social support indicates that social support can effectively buffer the stress that individuals bear under stress, supporting the direct effect of social support on stress. And understanding social support can have a beneficial impact on an individual's coping effectiveness. Therefore, this study introduces college students' stress coping efficacy and coping efficacy into the study of the relationship between perceived social support and stress perception, exploring the relationship between perceived social support, college students' stress coping efficacy, coping efficacy, and stress perception variables, which can improve the theory of how perceived social support affects stress perception. Both perceived social support and perceived stress can affect an individual's mental health [6]. This article investigates the mechanism by which perceived social support affects perceived stress, with the aim of providing methods for improving mental health. Social support affects an individual's cognitive evaluation process of stress, and high social support can lead to more stress adaptive behaviors, thereby reducing the negative impact of stressful events. The direct impact mechanism of perceived social support on stress perception is obvious, but the indirect effect of perceived social support on stress perception is worth exploring.

College students' sense of stress coping efficacy is an important factor affecting their individual mental health, influencing their cognitive evaluation of stress. Coping efficacy refers to an individual's self-efficacy when faced with emotional situations, which also affects their evaluation and response to stress. It is worth paying attention to whether understanding social support will indirectly affect stress perception by influencing college students' sense of coping efficacy and coping effectiveness. Therefore, this article will study the relationship between the four variables of college students' understanding of social support, college students' stress coping efficacy, coping efficacy, and stress perception, and collect data through questionnaire surveys. We use the VMD-TCN-LSTM evaluation model to analyze the data, in order to understand the current status of college students' understanding of social support, stress coping efficacy, coping efficacy, and stress perception.

2 Related research

Stress is a risk factor that affects the mental health of college students, and managing their stress coping efficacy is one of the important contents of mental health education. At present, there are still many difficulties and challenges that urgently need to be solved in the management of college students' stress coping efficacy [7]. In response to the new situations and problems that arise among college students, it is necessary to strengthen the education of college students' stress coping efficacy management, enhance their ability to effectively manage their own stress, which is not only of great significance for the growth and development of college students, but also conducive to improving the pertinence and effectiveness of ideological and political work in universities. This study starts with analyzing the current psychological pressure and management status of stress coping efficacy among college students. It classifies the sources of stress among college students, analyzes the problems and causes of stress coping efficacy management, and explores effective strategies to relieve their stress and improve their ability to manage stress coping efficacy.

2.1 Research on stress coping

Stress coping is the constantly changing cognitive and behavioral effort made by individuals to reduce and minimize internal and external demands when faced with pressures beyond their ability and resources in the environment. Individual mental health is not only closely related to stress levels, but also influenced by their coping styles and coping strategies. The study in reference [8] suggests that college students' coping strategies, in terms of frequency, are problem-solving, fantasy, rationalization, avoidance, and self blame. Reference [9] explores the overall characteristics of the development of coping strategies among college students from the perspectives of demographic and institutional background variables. Specifically, there is a clear trend of positive coping strategies, with multiple coping strategies being used in combination, and rare cases of using a single coping strategy. The coping styles of college students can be roughly divided into three types: positive coping style that tends to face problems directly, compound style that is in the process of exploration and uses both positive and negative methods, and negative action style that avoids and retreats. Pointing out that stress coping strategies are influenced by various internal and external factors, and starting from the campus experience of college students, analyzing the impact of campus integration and campus life efficacy on college students' coping strategies. Reference [10] studied the characteristics of stress coping efficacy among college students and found that as their grade level increases, their coping strategies tend to mature. Freshman students mainly seek help, suppress, and fantasize, while senior students tend to adopt more mature psychological regulation mechanisms. Reference [11] found that the coping strategies of college students are influenced by factors such as gender, grade level, major, and whether they are only children. Social support is an important factor affecting college students' sense of stress coping efficacy. When feeling cared for and supported by others, college students are more willing to cope with stress in a positive way; On the contrary, they tend to respond in a negative way. Research in reference [12] has shown that positive stress coping strategies have a buffering effect on the relationship between stressors and stress responses.

The above scholars' research on the coping efficacy of college students mainly includes the types of coping styles, grade characteristics of coping styles, and factors that affect coping styles. It is not difficult to see that college students generally have a more proactive coping style, but there are also negative coping styles such as avoidance and negative venting. And college students do not attach enough importance to seeking social support, such as seeking help from counselors, teachers, and professional psychological counselors. Friends, classmates, and other peers are the majority of students' choices when it comes to confiding and seeking help. Stress coping is an intermediate variable between stress and physical and mental health, and positive coping strategies are beneficial for the physical and mental health of college students.

2.2 Research on the Management of College Students' Stress Coping Efficacy

The management of college students' stress coping efficacy refers to the necessary intervention of foreseeable sources of stress before they occur, improving the efficiency of problem handling after stress occurs, and individuals actively adopting reasonable coping methods to alleviate or eliminate stress, maintain physical and mental health, and ensure the smooth achievement of learning and life goals. Essentially, this is a proactive and effective way of coping. Stress coping has post hoc and passive characteristics, while the management of stress coping efficacy among college students has a certain degree of initiative and positivity, which includes stress coping. Reference [13] suggests that effective holistic management of stress coping efficacy among college students should include the following four characteristics: (1) a clear understanding of physical responses under stress. (2) Have a clear understanding of factors related to stress. (3) Can use multiple effective coping techniques to address the causes of stress. (4) Regularly train relaxation techniques to maintain a harmonious balance in the body. The goal of managing college students' stress coping efficacy is not to eliminate all stress, but to minimize the negative effects of stress while ensuring quality of life and vitality. As the father of stress theory, Sally, said, "I cannot and should not eliminate my stress, but can only teach myself to enjoy it

Regarding the research on the management role of college students' stress coping efficacy, reference [14] suggests that training in stress coping efficacy management skills has a significant promoting effect on improving students' learning vitality and mental health. Reference [15] suggests that the management ability of college students' stress coping efficacy has a significant impact on their overall development, and effective management of college students' stress coping efficacy can promote their development. For the principles of managing college students' stress coping efficacy, reference [16] proposes the need to follow the principles of awareness, balance, handling, and mentality. The primary principle is awareness, which includes three levels: slightly excessive pressure triggers chaotic emotions; Excessive pressure can drive away various discomfort reactions; Excessive pressure leads to narrow consciousness, slow response to the environment, and the mind and body are on the brink of collapse. Scholars at home and abroad have proposed corresponding strategies for managing the stress coping efficacy of college students from different perspectives such as psychology, education, and management. Reference [17] suggests that social support is a way of helping people manage stress, and based on the theory of direct action, social support is primarily used as a means to prevent stress from occurring; Based on the theory of stress buffering, social support can help a person prevent negative consequences caused by a stressor. Reference [18] points out that the most important strategy for conquering stress is to pursue life goals. This life goal, or rather, the purpose with objections in life, is the foundation of individual health. Reference [19] suggests that group psychological counseling has a good effect on the management of college students' stress coping efficacy. Reference [20] suggests that it is necessary to increase the level of attention and strengthen the division of responsibilities among various entities; Building an academic support system and optimizing scholarship and assistance methods; Establish a tracking and monitoring mechanism to pay attention to individual differences; Improve mental health services and enhance students' self adjustment ability and psychological tolerance. Reference [21] suggests that the theory and practical application of "learned optimism" have had a significant positive impact on the psychological resilience and stress coping strategies of college students. It is proposed that the theory, methods, and application techniques of "learned optimism" can play a positive role in college students' mental health education, such as providing theoretical references for mental health education courses.

The above scholars have conducted research from different disciplinary perspectives such as psychology, education, and management, seeking strategies for managing college students' stress coping efficacy from both internal and external dimensions. They have made contributions to promoting the physical and mental health development of college students and the research on managing college students' stress coping efficacy.

2.3 Causes of Pressure Generation

Reference [22] analyzed four factors that contribute to the sources of stress: students themselves, their families, society, and schools. Reference [23] also explored the influencing factors of graduate students' psychological stress from four aspects: personal, school, family, and society. Reference [24] studied the impact of changes in family structure on depression, anxiety, and stress symptoms in college students, and found that the occurrence of depression, anxiety, and stress symptoms in college students is related to the type of family structure and factors of change. Reference [25] suggests that conflicts between individuals and themselves, individuals and others, individuals and the environment, and values are the main causes of psychological stress among college students. Reference [26] analyzes the reasons for college students' stress from the perspective of stress environment. Starting from three aspects: the high-pressure environment (social environment), the high-pressure environment (school education environment), and the low-pressure environment (family environment, classroom and dormitory environment on campus, and subjective environment), it is concluded that the educational environment is an important factor affecting the stress of college students.

Based on the research of the aforementioned scholars, the causes of stress among college students have been analyzed mainly from the perspectives of subjective and objective factors, as well as the pressure environment. It is also possible to analyze the causes of stress from the perspective of the dimensions of stress sources, and further research can be conducted on the substantive influencing factors of stress on college students and the social roots behind stress.

3 VMD-TCN-LSTM evaluation model for college students' stress coping efficacy

3.1 Variational Mode Decomposition

This paper proposes a cutting-edge data decomposition residual long short-term memory network (VMD-TCN-LSTM) evaluation model for assessing the stress coping efficacy of college students. VMD is a cutting-edge data decomposition method designed specifically for adaptive and non recursive data decomposition [27]. Its core lies in achieving frequency band separation of data through the overall construction and solution of variational problems. This method has significant advantages in quickly extracting intrinsic sub modal components of data from time series. VMD can decompose highly correlated eigenvalues into an equal number of sub modal components. This decomposition method not only simplifies the data structure, but also provides a solid foundation for further feature reconstruction. In this way, the non stationarity of the time series is reduced. The specific expression for VMD is:

$$f = \min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left\{ \left[\delta(t) + \frac{\mathrm{j}}{\pi t} \right] * u_k(t) \right\} \mathrm{e}^{-\mathrm{j}\omega_k t} \right\|_2^2 \right\} \tag{1}$$

where, k is the number of VMDs; u_k is the k-th mode decomposed; ω_k is the corresponding center frequency.

The specific steps of VMD include the following key steps: (1) It is necessary to collect and prepare time series data on college students' stress coping efficacy to ensure the completeness and accuracy of the data; (2) Using VMD algorithm to separate the frequency bands of college students' stress coping efficacy data and extract inherent sub modal components; (3) Based on the sub modal components obtained from decomposition, feature reconstruction is carried out to provide strong support for subsequent experiments and analysis of college students' stress coping efficacy data.

3.2 TCN Network Model

The core idea of TCN is to obtain short-term and long-term features of time series through causal convolution and dilated convolution. The grid input length of TCN network needs to be consistent with the output length, and there is a certain mapping relationship. For time series input $X=[x_1,x_2,\cdots,x_T]$ and one-dimensional convolution output $Y=[y_1,y_2,\cdots,y_T]$, the formula is:

$$y_t=\sum_{i=0}^{k-1}\omega_i\cdot x_{t-i} \tag{2}$$

where, *k* is the size of the convolution kernel; ω_i is the convolution kernel weight; *t* is the current time step.

Dilated convolution is the key to TCN, used to expand the receptive field of the network. Expansion convolution introduces an expansion factor *d* on the basis of causal convolution, and its output is defined as:

$$y_t=\sum_{i=0}^{k-1}\omega_i\cdot x_{t-i\cdot d} \tag{3}$$

where, *d* is the expansion factor, which is the jump distance between adjacent elements in the convolution kernel; $t-i\cdot d\geq 0$ ensures the causality of causal convolution.

The core of residual connections is residual blocks, as shown in Figure 1.

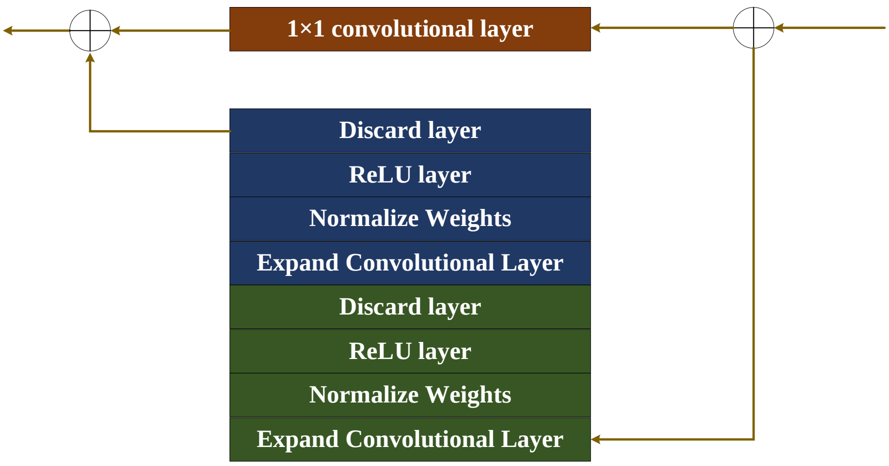

Figure 1: TCN residual block

3.3 Long Short Term Memory Network

LSTM is a variant of Recurrent Neural Network (RNN) that adds a unit state structure to RNN, which gives LSTM a unique memory and forget mode. This memory and forgetting mode enables LSTM to store and process long-term dependent information, thus better capturing and memorizing historical information when processing lithium battery related feature input values, thereby improving the accuracy of predicting college students' stress coping efficacy [28].

The model architecture of LSTM is presented in Figure 2, and its core structure mainly includes several key parts: input gate, forget gate, output gate, and cell state. Specifically, the input gate is responsible for regulating the flow of new information, acting as an information filter that determines which new data can enter the model; The forget gate is responsible for identifying existing information, determining which information should be discarded, and avoiding unnecessary or redundant information from interfering with the model; The output gate plays a role in controlling the output of information, precisely controlling what information can be output from the model for subsequent analysis and use. The unit state, as the memory core of LSTM, is like an information repository that can store historical information for a long time.

The definition and calculation process of each part of the LSTM model structure are as follows:

(1) Forget the door. The forget gate determines which information about college students' stress coping efficacy needs to be forgotten in the memory unit state of the previous time step. The calculation form is:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, X_t] + b_f\right) \tag{4}$$

where, f_t is the output of the forget gate; h_{t-1} is the output of the previous unit; σ is the Sigmoid activation function; W_f and b_f are weight matrices and biases.

(2) Enter the door. How much new information about the time step of current college students' stress coping efficacy needs to be written into the memory unit state for input gate control? The calculation form is:

$$\begin{cases} i_t = \sigma\left(W_i \times [h_{t-1}, X_t] + b_i\right) \\ \tilde{c}_t = \tanh\left(W_c \times [h_{t-1}, X_t] + b_c\right) \end{cases} \tag{5}$$

where, W_c and b_c are the weight matrix and bias of the current unit; W_i and b_i are the weight matrix and bias of the input gate.

(3) Output gate. Determine which college students' stress coping efficacy data features to output using Sigmoid, and then multiply them with tanh to determine the final output. The calculation form is:

$$\begin{cases} c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\ o_t = \sigma\left(W_o \times [h_{t-1}, X_t] + b_o\right) \\ h_t = o_t \odot \tanh\left(c_t\right) \end{cases} \tag{6}$$

where, W_o and b_o are the weight matrix and bias of the output gate.

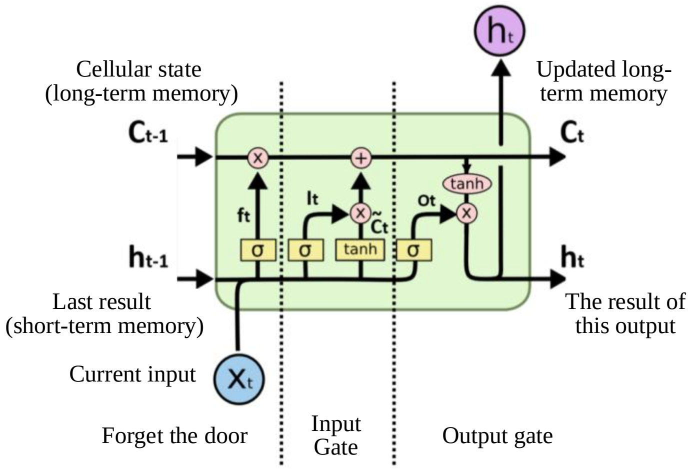

Figure 2: Model Structure of LSTM

3.4 Algorithm steps

The TCN-LSTM model consists of TCN layer, LSTM layer, Dropout layer, and Dense layer. The TCN layer receives the stress coping efficacy related features of college students constructed earlier and completes feature extraction. Then, the feature results extracted by TCN are input into the LSTM model for secondary feature extraction, achieving the purpose of feature fusion. Finally, the output is obtained through the Dropout layer and Dense layer. At the same time, this model adopts Bayesian hyperparameter tuning to obtain the optimal batch_2, learning rate, iteration times, etc., and then sets the model hyperparameters using the optimized hyperparameters.

Predicting college students' stress coping efficacy strategies based on the fusion method of VMD and deep learning. The specific steps are as follows: (1) Perform VMD decomposition on the original sequence data, decomposing the time series with strong non-stationary properties into a series of stationary modal components; (2) Normalize the decomposed multiple components; (3) Reconstruct the predicted sequence and train it in the TCN-LSTM model for prediction; ④ Reconstruct the prediction values of each sub modal model to obtain the final prediction results of college students' stress coping efficacy, and evaluate the predictive performance of college students' stress coping efficacy. The prediction process of college students' stress coping efficacy is shown in Figure 3.

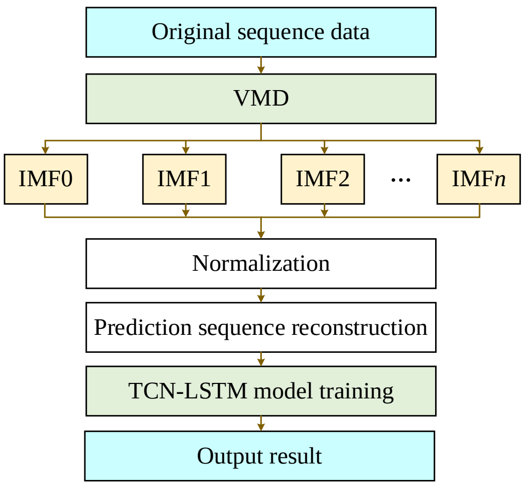

Figure 3: Prediction Process

4 Analysis of Student Psychological Stress Assessment Results

4.1 Experimental setup

To further investigate the effectiveness of the two machine learning algorithms used in this experiment in evaluating the stress coping ability of college students compared to other algorithms, we specifically selected representative algorithms such as Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), and Random Forest (RF) as benchmark references. When evaluating the performance of the psychological stress assessment algorithm, this article used a 10 fold cross validation method to complete the training and testing of the model. In the field of machine learning, the application of this method is extremely common. Especially when faced with small datasets, this method demonstrates unique advantages as it ensures that every sample in the dataset has the opportunity to participate in the training and testing process. This feature makes it highly compatible with the sample set we have constructed for college students' stress coping effectiveness. In the specific operation of dividing the training set and the testing set, we adopt an ordered extraction method, that is, extracting one tenth of each set of data according to category size as the testing set, and the remaining data as the training set. This process needs to be repeated ten times, in order to construct ten training and testing sets of stress coping effectiveness data for college students with different levels of stress coping effectiveness. Subsequently, we trained the model using each of these ten training sets and tested its performance on the corresponding test set. Finally, the average of the performance results obtained from these ten tests is taken as the final performance indicator of the model. It is worth mentioning that in the actual experimental process, the data results we recorded were the average of the ten fold cross validation obtained.

In this experiment, we carefully selected a series of core evaluation indicators to comprehensively evaluate the experimental effect, which specifically include accuracy ACC, accuracy P, recall R, F1 score, accuracy of real classroom situations ACC+, accuracy of real non classroom situations ACC -, and G-means. The specific calculation model for these indicators is presented as follows:

$$\mathrm{ACC} = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

$$\mathrm{P} = \frac{TP}{TP + FP} \tag{8}$$

$$\mathrm{R} = \frac{TP}{TP + FN} \tag{9}$$

$$F1\text{-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{10}$$

$$ACC_{+} = \frac{TP}{TP + FN} \tag{11}$$

$$ACC_{-} = \frac{TN}{TN + FP} \tag{12}$$

$$\text{G-mean} = \sqrt{ACC_{-} \times ACC_{+}} \tag{13}$$

4.2 Result Analysis

In this experiment, to achieve the optimization goal of parameter selection, we compared and analyzed the model constructed by residual long short-term memory network (VMD-TCN-LSTM) and anomaly detection (LOF) algorithm with a series of benchmark models. These benchmark models include Naive Bayes (NB) algorithm, Support Vector Machine (SVM) algorithm, Decision Tree (DT) algorithm, and Random Forest (RF) algorithm. Among them, Naive Bayes (NB), Support Vector Machines (SVM), and Decision Trees (DT) all belong to relatively simple model types; The Random Forest (RF) algorithm belongs to the category of ensemble learning models. There is research confirming that when the number of weak classifiers is set to n=1, a single neural network can exhibit specific effects. When evaluating model performance for benchmark comparison, we mainly select accuracy (ACC), G-means, and F1 score as key evaluation indicators. The specific comparison results of various algorithm effects are shown in Table 1.

Table 1: Comparison of the Effectiveness of Various Algorithms in Evaluating College Students' Stress Coping Efficacy

Algorithm model	Accuracy ACC	G-mean	F1-score
VMD-TCN-LSTM	0.978	0.926	0.893
LOF	0.917	0.811	0.617
SVM	0.915	0	0
NB	0.703	0.650	0.441
DT	0.674	0.475	0.305
RF	0.731	0.725	0.520

According to the data in Table 1, from the perspective of accuracy ACC, the VMD-TCN-LSTM model exhibits significant advantages, with an accuracy of up to 0.978. Compared to it, the accuracy of the LOF algorithm is 0.917, which is still at a relatively high level, but there is still a certain gap compared to the VMD-TCN-LSTM model. The accuracy of SVM is 0.915, which is close to the LOF algorithm. However, the accuracy of simple models NB and DT is relatively low, at 0.703 and 0.674, respectively. This indicates that when dealing with complex data such as college students' stress coping efficacy, simple models may not be able to fully capture key features in the data, resulting in limited classification accuracy. The accuracy of the ensemble learning model RF is 0.731, which is better than some simple models, but still has significant room for improvement compared to the VMD-TCN-LSTM model. This indicates that the VMD-TCN-LSTM model has stronger capabilities in data feature extraction and classification prediction, and can more accurately identify the categories of stress coping efficacy among college students.

On the G-mean metric, the VMD-TCN-LSTM model also performed well, reaching 0.926. The G-mean of the LOF algorithm is 0.811, which is relatively low. It is worth noting that the G-mean of SVM is 0, which means that the SVM model may have serious imbalances in processing data, resulting in extremely poor recognition ability for certain categories. The G-means of NB and DT models are 0.650 and 0.475, respectively, highlighting once again the limitations of simple models in handling complex data. The G-mean of the RF model is 0.725, which is better than some simple models, but still significantly different from the VMD-TCN-LSTM model. This further demonstrates the outstanding performance of the VMD-TCN-LSTM model in balancing the classification effects of different categories.

Looking at F1 score again, the VMD-TCN-LSTM model achieved a score of 0.893. The F1 score of the LOF algorithm is 0.617, which is significantly different from the VMD-TCN-

LSTM model. Due to the G-mean being 0, SVM's F1 score has also been severely affected. The F1 scores of NB and DT models are 0.441 and 0.305, respectively, indicating that they perform poorly in balancing accuracy and recall. The F1 score of the RF model is 0.520, which is slightly improved but still inferior to the VMD-TCN-LSTM model. F1 score combines precision and recall, and the excellent performance of VMD-TCN-LSTM model on this indicator indicates that it can effectively recall samples from various categories while ensuring classification accuracy.

Based on the above three evaluation indicators, the VMD-TCN-LSTM model performs the most outstandingly in assessing the stress coping efficacy of college students. This is thanks to its unique model structure, which can better handle complex components in data through VMD data decomposition. The combination of TCN and LSTM fully utilizes the characteristics of time series data, enabling the model to more accurately capture the dynamic changes and inherent patterns of college students' stress coping efficacy. In contrast, other models have limitations to varying degrees. Simple models are difficult to handle complex data, while some models perform poorly in balancing classification performance and overall performance.

Modify the experimental VMD-TCN-LSTM model by modifying a certain feature value, and then observe the degree of decline in the evaluation effect of the model on college students' stress coping efficacy. It is believed that which feature causes a more significant decline in the model's effectiveness and which feature has a greater impact on the model's psychological stress assessment results. The specific operation method is as follows: first, retain the trained model and each feature value, but each time a feature value is studied, randomly shuffle the corresponding feature value of its test sample, then re score the model performance, calculate the evaluation index, and repeat this shuffling and scoring operation multiple times to obtain the average value.

VMD-TCN-LSTM (- Fhf) is used to represent the model for shuffling the economic characteristics Fhf of students' families, VMD-TCN-LSTM (- Fsc) is used to represent the model for shuffling the consumption behavior characteristics Fsc of students, VMD-TCN-LSTM (- Fsa) is used to represent the model for shuffling the learning ability characteristics Fsa of students, and VMD-TCN-LSTM (- Fsd) is used to represent the model for shuffling the consumption level difference characteristics Fsd of students. ACC, G-mean, and F1 score are used as evaluation criteria, and their specific model effects are shown in Table 2.

Table 2: Comparison of the Effects of Various Features on VMD-TCN-LSTM Algorithm

Algorithm model	ACC	G-mean	F1-score
VMD-TCN-LSTM	0.802	0.808	0.563
VMD-TCN-LSTM (- Fhf)	0.743	0.765	0.502
VMD-TCN-LSTM(- Fsc)	0.667	0.659	0.407
VMD-TCN-LSTM(-Fsa)	0.706	0.701	0.458
VMD-TCN-LSTM(-Fsd)	0.625	0.549	0.303

According to the data presented in Table 2, the original VMD-TCN-LSTM model achieved an accuracy ACC of 0.802, a G-mean of 0.808, and an F1 score of 0.563 in evaluating the stress coping efficacy of college students. This indicates that the model has a certain level of evaluation ability and accuracy overall. When we shuffle the economic characteristics of students' families Fhf and obtain the VMD-TCN-LSTM (- Fhf) model, its accuracy ACC decreases to 0.743, G-mean decreases to 0.765, and F1 score becomes 0.502. Compared with the original model, all indicators have shown a certain degree of decline. This indicates that the economic characteristics of students' families play a certain role in the model evaluation process. Family economic status may affect students' living environment, resource acquisition, and other aspects, thereby exerting a certain impact on their stress coping efficacy.

Looking at the VMD-TCN-LSTM (- FSC) model after shuffling the student consumption behavior characteristics Fsc, its accuracy ACC significantly decreased to 0.667, G-mean decreased to 0.659, and F1 score was only 0.407. Compared with the original model, the decrease is more significant. This indicates that the consumption behavior characteristics of students have a significant impact on the evaluation results of the model. Consumer behavior often reflects students' lifestyle habits, consumption concepts, and other factors, which may be closely related to their psychological state and stress coping strategies. For example, excessive or insufficient consumption may reflect students' different coping strategies and psychological states when facing pressure. After shuffling the learning ability feature Fsa of students, the VMD-TCN-LSTM (- Fasa) model showed a decrease in accuracy ACC to 0.706, G-mean to 0.701, and F1 score to 0.458. Learning ability, as an important aspect of students' growth process, also has a certain impact on their sense of stress coping efficacy. Students with strong learning abilities may have more confidence and methods when facing academic pressure, while students with weaker learning abilities may be more prone to anxiety and stress. In terms of the degree of data decline, its impact falls between the characteristics of household economy and consumption behavior.

Finally, the VMD-TCN-LSTM (- Fsd) model with the feature Fsd of poor student consumption level was shuffled, and the accuracy ACC decreased to 0.625, the G-mean decreased to 0.549, and the F1 score was only 0.303, which was the most significant decrease in model performance after shuffling all features. Poor consumption levels may involve economic differences and differences in consumption levels among students, which may lead to social and psychological stress among students, thereby affecting their sense of stress coping efficacy. The significant impact of this feature on the model evaluation results suggests that poor consumption level may be a key factor in the formation and coping process of psychological stress among college students.

Based on the comparative analysis of the model performance after shuffling various features, we can clearly see the degree of influence of different features on the evaluation of college students' stress coping efficacy using the VMD-TCN-LSTM model. The impact of consumption level differences and consumption behavior characteristics on the model performance is relatively significant, while the impact of household economic characteristics and learning ability characteristics is relatively small. This research result provides important basis for us to deeply understand the influencing factors of college students' stress coping efficacy, and also points out the direction for further optimizing the model and improving the accuracy of evaluation in the future.

5 Discussion on the Mechanism of Enhancing College Students' Stress Coping Efficacy

5.1 Mechanism of data-driven psychological service model

(1) Data driven precise identification of stressors and coping patterns. The data-driven psychological service model utilizes advanced algorithm models, such as the VMD-TCN-LSTM model in this study, to accurately identify key factors that affect college students' stress coping efficacy from massive student data. From the analysis of the model performance after shuffling each feature, it can be seen that the characteristics of poor consumption level and consumption behavior have a significant impact on the evaluation results of the model. This means that under data-driven approaches, psychological services can more accurately focus on these key sources of stress. For example, psychological services can provide targeted guidance

on economic management and reasonable consumption for students with high levels of consumption pressure, helping them adjust their consumption concepts and alleviate the psychological pressure caused by economic differences. Meanwhile, by analyzing the characteristics of consumer behavior, we can understand the correlation between students' consumption habits and stress coping strategies, and guide them to form healthy consumption behaviors and positive stress coping patterns.

(2) The development of personalized psychological intervention strategies. Based on data-driven results, the psychological service model can develop personalized psychological intervention strategies for college students with different characteristics. Different students have differences in family economics, consumption behavior, learning ability, and consumption level, which lead to varying levels of coping efficacy when facing pressure. For students whose family economic characteristics have a significant impact, psychological services can provide more resources on economic assistance information and psychological support, helping them alleviate the negative impact of economic pressure on their psychology. For students whose learning ability characteristics have a significant impact, targeted learning methods and time management training can be carried out to improve their learning ability and enhance their sense of efficacy in coping with academic pressure. Through personalized psychological intervention strategies, students' actual needs can be more effectively met and their ability to cope with stress can be improved.

(3) Dynamically monitor and adjust psychological services. The data-driven psychological service model has the advantage of dynamic monitoring. As students' living environment and psychological state change, their sources of stress and coping strategies may also change. By continuously collecting and analyzing relevant data from students, psychological services can provide real-time insights into changes in students' stress coping efficacy. For example, when a student's consumption behavior characteristics are found to have undergone significant changes, which may lead to a decrease in stress coping efficacy, psychological services can adjust intervention strategies in a timely manner and provide corresponding support and guidance. This dynamic monitoring and adjustment can ensure that psychological services always match the actual needs of students, improving the effectiveness and pertinence of psychological services.

5.2 Moderation effect of data-driven psychological service model

(1) The regulatory role of the social support system. Social support plays an important regulatory role in the data-driven psychological service model to enhance the stress coping efficacy of college students. Understanding social support as a positive factor affecting mental health can buffer the stress that individuals experience under stressful conditions. Driven by data, psychological services can better understand the social support received by students. For students with limited social support, psychological services can increase their social support network through organizing club activities, establishing mutual aid groups, and other means. At the same time, guide students to have a correct understanding and utilize social support, and enhance their ability to obtain resources and strength from social support. For example, when students face pressure from poor consumption levels, social support can provide economic assistance and psychological encouragement, regulate their stress response, and enhance their sense of stress coping efficacy.

(2) The self-regulation effect of coping efficacy. The coping effectiveness of college students also plays a self-regulation role in the data-driven psychological service model. Coping efficacy refers to an individual's self-efficacy when faced with emotional situations, which affects their evaluation and response to stress. Through data-driven analysis, students can gain a clearer understanding of their coping effectiveness in different stress situations. When

students find that their coping efficiency is low in a certain aspect, they can improve it through self-learning and training. For example, for students whose learning ability characteristics affect their sense of coping with stress, they can improve their learning ability and enhance their sense of coping with academic pressure by participating in learning skills training courses, seeking advice from teachers and classmates, and so on. This self-regulation effect can make students more proactive in coping with stress and improve the long-term effectiveness of psychological services.

(3) The feedback regulation effect of psychological service mode. The data-driven psychological service model itself also has a feedback regulation function. By analyzing the evaluation data of the effectiveness of psychological services, we can understand the effectiveness and shortcomings of the psychological service model. For example, if it is found that psychological intervention strategies targeting a specific characteristic of students are ineffective, the intervention methods and content can be adjusted in a timely manner. At the same time, feedback results will be provided to students to help them understand their progress and areas for improvement, further stimulating their enthusiasm and initiative to participate in psychological services. This feedback regulation effect can continuously optimize the psychological service model and improve its ability to enhance college students' stress coping efficacy.

In summary, the data-driven psychological service model can effectively enhance college students' sense of stress coping efficacy by accurately identifying stressors and coping patterns, developing personalized psychological intervention strategies, dynamically monitoring and adjusting psychological services, as well as social support systems, self-regulation of coping efficacy, and feedback regulation of psychological service models. Future research can further explore how to better integrate data resources, optimize algorithm models, and strengthen the integration of psychological service models with other educational processes, providing stronger support for the mental health of college students.

6 Conclusion

This study will focus on the impact and regulatory effects of data-driven psychological service models on enhancing college students' stress coping efficacy, with the aim of providing practical strategies for optimizing the mental health status of college students. The study used questionnaire survey method to obtain relevant data, and applied advanced variational mode decomposition residual long short-term memory network (VMD-TCN-LSTM) evaluation model to deeply analyze the collected data, in order to explore the complex relationship between the four variables of college students' understanding of social support, stress coping efficacy, coping efficacy, and stress perception. In the specific research process, on the one hand, we adjust a certain feature parameter of the model and observe the magnitude of the decrease in evaluation effect, in order to determine the key influencing factors; On the other hand, a comparative analysis will be conducted between the proposed VMD-TCN-LSTM model and other algorithms. The experimental results show that the VMD-TCN-LSTM model exhibits excellent performance in evaluating the stress coping efficacy of college students. Its accuracy, G-mean, F1 score, and other indicators are significantly better than other benchmark algorithms. After randomly shuffling each feature, it was found that the differences in consumption level and consumption behavior had a significant impact on the model's performance. This provides important clues for us to further explore the influencing factors of college students' stress coping efficacy. The research ultimately concluded that the data-driven psychological service model operates through a series of mechanisms, such as accurately identifying stressors and coping patterns, developing personalized psychological intervention plans, and dynamically monitoring and adjusting psychological services; By utilizing the social support system, self-regulation of coping efficacy, and feedback regulation of psychological services, the sense of stress coping efficacy of college students can be effectively enhanced. This research achievement has opened up new paths and methods for mental health education in universities, which helps to more accurately identify students' stress problems, provide personalized psychological assistance, and promote the mental health development of college students.

There are still some areas for improvement in this study. For example, there may be certain limitations in the coverage area and sample size selected for data acquisition, which may affect the universality and generalizability of research conclusions. Moreover, the constructed model may still have some imperfections when dealing with some complex situations. In response to the above situation, subsequent research can be promoted from the following dimensions: firstly, broaden the boundaries of data collection, increase the sample size, and include college students from different regions and types of universities in the research scope, in order to enhance the universality and practical application value of research conclusions; Secondly, deeply optimize the algorithm model, fully integrate more cutting-edge technological means and methods, enhance the model's ability to analyze complex data and the accuracy of prediction; Thirdly, we will delve into the organic integration path between data-driven psychological service models and other educational sectors, such as closely integrating psychological services with curriculum teaching activities, campus culture construction, etc., to build a comprehensive and systematic framework for mental health education, thereby providing more solid and powerful guarantees for the mental health of college students.

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