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Analysis on the Influencing Factors of the Anxiety and Depression Phenomenon of College Students' Employment Psychology Based on Immersive Online Gaming Analysis and Deep Learning

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Abstract. In order to explore the influencing factors of the anxiety and depression phenomenon of college students' employment psychology, this paper applies deep learning to the analysis of related factors. According to the characteristics of psychological factor data, this paper combines deep learning algorithm to propose a processing algorithm of employment psychology data based on deep learning. Moreover, this paper validates and analyzes the algorithm processing data flow and processing effect, and studies the influencing factors of the anxiety and depression phenomenon of college students' employment psychology in combination with survey interviews. In addition, this paper explores the impact of college graduates' psychological resilience and self-differentiation on employment anxiety, and the mediating role of self-differentiation between psychological resilience and employment anxiety. Finally, this paper verifies the effectiveness of this algorithm through experimental research.

Keywords: deep learning; college students; employment psychology; anxiety and depression
DOI: https://doi.org/10.14733/cadaps.2024.S5.120-137

1 INTRODUCTION

When studying the employment problem of college students, it is necessary to conduct a detailed analysis of the psychological problems of college students, and to have an in-depth understanding of some basic concepts and basic problems of college students' psychology. At the same time, it is necessary to provide counseling on the psychological problems of college students from the psychological state of college students and the reasons for the formation of these states [9]. The psychological problems of college students are of great significance to the cultivation of their outlook on employment, and they have different characteristics in different periods. Therefore, in the actual research process, relevant issues of college students should be discussed in depth. The employment psychology of college students can be simply understood as taking employment as the center and being formed under the interaction of other psychological phenomena. Moreover, its emergence, change and development process are because different types of schools and different grades of college students show different and complex characteristics [15]. The economic development and scientific and technological progress of countries in the world today mainly rely on high-quality talents. In particular, after China's accession to the World Trade Organization, a large number of high-level intellectuals are needed to build the country. If we want to cultivate high-quality talents, we must adhere to the party's educational policy, so that college students can achieve all-round development in morality, intelligence, physical fitness, and beauty, and improve their comprehensive quality. However, in the real society, some students only start from their own factors in the process of choosing a career, pursuing a single or narrower view of employment. They pay more attention to their own majors and believe that only when their work matches their own majors can they realize their own value. In addition, some graduates think that as long as they have certain specialties, it is easier to find a job, but the reality has brought certain problems to their employment [3].

Current graduates still have certain deviations in the process of professional selection, such as emphasizing liberal arts and neglecting science, paying more attention to science and technology subjects and ignoring humanities subjects. Such disciplinary deviations can easily cause certain deviations in their own qualities in various aspects, which are not compatible with the development of this era. Therefore, in the process of education reform, we must continuously strengthen the emphasis on quality education. While conducting professional training for students, we must also strengthen the training of our own qualities, promote the comprehensive development of students, and try to avoid the occurrence of serious problems. The phenomenon of partial essays makes students' own development more balanced. At the same time, it is necessary to cultivate students' own psychological resistance to stress in the university environment, and improve their psychological quality and moral and cultural level. the methodology for analysing the influencing factors of anxiety and depression among college students using immersive multimedia, deep learning techniques, and online gaming. It discusses the collection and preprocessing of data, the integration of immersive multimedia elements, the application of deep learning models, and the framework for online gaming-based investigation

In the process of job hunting, appropriate anxiety can help arouse graduates' sense of urgency and actively seek jobs. However, long-term and excessive anxiety will have a negative impact on the employment of graduates: on the one hand, it will inhibit the normal thinking of graduates and make graduates emotionally unstable, so that they cannot give full play to their talents and devote themselves to finding employment. At work, it affects graduates to find ideal jobs; on the other hand, when graduates are frustrated too many times in the process of looking for jobs, graduates will have a negative psychology of doubting themselves and society, and may cause serious psychological barriers. Or disease. Therefore, it is very necessary to explore effective ways to reduce the anxiety of graduates. According to previous studies, there are many factors that cause individual anxiety. Among them, social support, as an individual's external coping resource, has an important relationship with the individual's anxiety level in a specific situation; As an internal factor of the individual, knowledge evaluation plays a dominant role in the formation of anxiety. In the specific situation of employment, how social support and cognitive evaluation affect anxiety, there are few studies on this aspect. Therefore, this research attempts to explore the effective ways to reduce graduates' employment anxiety by exploring the mechanism of employment anxiety from external factors—social support and self-factors—cognitive evaluation in the employment process of college students, so as to enrich the past. Research on employment, and provide a psychological basis for colleges and universities to formulate employment-related measures.

This paper combines deep learning to analyze the employment psychology of college students, and studies the influencing factors of the anxiety phenomenon of college students' employment psychology, which provides theoretical references for subsequent employment guidance and student psychological counseling in colleges and universities.

2 RELATED WORK

At present, research related to college students' social support mainly focuses on mental health. Moreover, many studies have confirmed the connection between social support and mental health. It is believed that social support is beneficial to the mental health of individuals, and the positive function of social support has been widely recognized. The literature [14] showed that the different social support of different important others perceived by college students is significantly negatively correlated with the level of trait anxiety. The literature [10] found that apart from the fact that there was no significant correlation between support utilization and anxiety, the total score of social support and other dimensions were significantly negatively correlated with anxiety. The literature [5] found that the total score of social support and its factors are significantly negatively correlated with the factors of the Symptom Self-Rating Scale. The literature [6] showed that the feeling of social support is significantly negatively correlated with the feeling of pressure. The literature [19] showed that there is a significant positive correlation between college students' learning adaptability and social support. Subjective well-being is a comprehensive evaluation of life satisfaction and individual emotional state, and it is an important indicator of individual mental health. The literature [9] showed that social support has a significant impact on subjective well-being. The literature [18] showed that social support, overall subjective well-being, life satisfaction, and positive affect are significantly positively correlated, while social support, self-esteem and negative affect are significantly negatively correlated. The literature [11] showed that the subscales of social support have a significant positive correlation with subjective well-being, and family support and friend support have a significant regression effect on subjective well-being. The literature [22] believed that social support has a negative side to individuals. The role of the social support system on an individual is quite complicated. If it is used improperly, it will even make the existing stressors more effective and increase the individual's tension. Therefore, starting from the social relationship, the deviation of the social support system of college students is summarized, and it is believed that there are certain deviations in the social support from the family, school and other institutions.

Literature [21] believes that the psychological dilemma of college students in employment is manifested in anxiety, cowardice, conformity, and arrogance. It advocates positive guidance for students who are not in employment psychological dilemma and remedy for college students who have been in employment psychological dilemma. The method of intervention combines individual cases, group work, and community work. Literature [8] believes that group work can be involved in the formation of different groups for specific groups. Facing college students who are in employment difficulties, they have advantages in improving their self-efficacy, acquiring ability, information, and mastering self-adjustment skills. Supportive help can be obtained in the intervening time, providing a new perspective for personalized intervention methods. By analyzing the social work intervention in the employment guidance system of colleges and universities, and discussing the solution to the psychological dilemma of college students' employment, the literature [2] believes that the current employment guidance of colleges and universities does not provide both prevention and correction for the psychological counseling of college students who encounter difficulties in job hunting. , And the value concept of social work believes that the client has the potential and strength for self-realization, and follows the principle of client self-determination. He systematically puts forward the specific application methods of individual, group, and community work in college employment guidance. The literature [13] believes that the main reason for the various difficulties is that the employment guidance work of colleges and universities has not formed a complete and mature system. Most of them still adopt the discipline methods such as psychology and human resource management. The form is relatively simple, and the system and content , Methods, and Team Explains the space of social work, proposes the way to intervene in case work for graduates' anxiety, and supports the further development of graduates through group work. Literature [12] compares the intervention methods of social work with ideological and political education, psychological counseling and counseling, and believes that traditional methods are no longer suitable for social development trends, while social work emphasizes dedication, acceptance, self-determination, individualization, etc., in specific practice and service There are unique advantages in intervention.

3 DATA PROCESSING ALGORITHM OF EMPLOYMENT PSYCHOLOGY BASED ON DEEP LEARNING

When solving unconstrained problems, one type of algorithm that is often used is the steepest descent method, which solves the model parameters of the adaptive algorithm. That is, for unconstrained optimization problems, Gradient Descent is one of the most commonly used methods, and another commonly used method is the least squares method. When solving the minimum value of the loss function, the gradient descent method can be used to iteratively solve step by step to obtain the minimized loss function and model parameter values.

The optimization model of the steepest descent method is minJ(w), where J is a continuously differentiable function of w. It is precisely because of the local iterative idea of the steepest descent method that makes it particularly suitable for a class of unconstrained optimization of adaptive algorithms. We assume that starting from a certain initial time w(O), we get a series of w(l), w(2),..., so that the function J(w) decreases in each iteration. And that is:

$$J\left(w\left(n+1\right)\right) < J\left(w\left(n\right)\right) \tag{1}$$

In the iterative process, the direction of the most rapid descent of the weight vector w is continuously adjusted to the negative gradient direction. And it is expressed as:

$$\hat{h} = \nabla J\left(w\right) = \frac{\partial J\left(w\right)}{\partial w} \tag{2}$$

Therefore, the steepest descent method can be summarized as:

$$w\left(n+1\right) = w\left(n\right) + \frac{1}{2}\mu\hat{h}\left(n\right) \tag{3}$$

Among them, n represents the iteration time, and μ is the step size factor.

The specific steps of the steepest descent method are as follows:

Step 1: The algorithm selects the initial point w(0), and the given accuracy requires $\tau > 0$.

Step 2: The algorithm calculates $\nabla J\left(w\left(n\right)\right)$. If $\left\|\nabla J\left(w\left(n\right)\right)\right\| < \tau$, the algorithm stops, otherwise, the algorithm gets n)=VJ(w(n)).

Step 3: The algorithm obtains the weight vector update formula, and then sets n=n+1, and returns to the second step.

During the update process, we must also pay great attention to the selection of the step size factor u. If the selection is improper, it is very likely that the adaptive algorithm will not converge, and eventually an ideal stable solution will not be obtained. I won't do a detailed introduction here for the time being, and we will analyze it further in the following chapters.

In order to better understand the steepest descent method, here we enumerate a visual example to illustrate. We assume that the filter length is 2, and the unconstrained linear optimization problem can be expressed as[4]:

$$J\left(w_0,w_1\right)=0.9-2\left[0.5,-0.4\right]\begin{bmatrix}w_0\\w_1\end{bmatrix}+\left[w_0,w_1\right]\begin{bmatrix}1&0.5\\0.5&1\end{bmatrix}\begin{bmatrix}w_0\\w_1\end{bmatrix} \tag{4}$$

Then we can get the three-dimensional diagram of the function $J\left(w_0,w_1\right)$ in Figure 1 with the tap weights w0 and w1 as variables

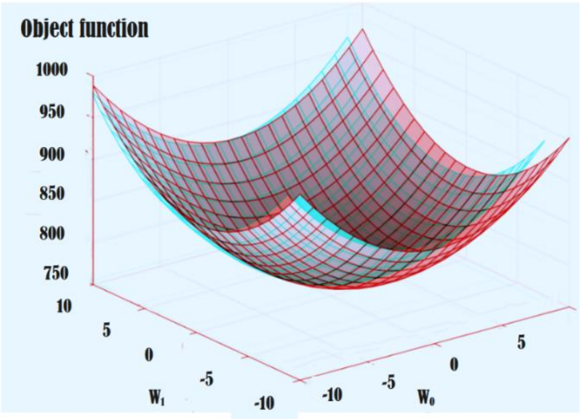

Figure 1: Error performance surface of two-tap transversal filter.

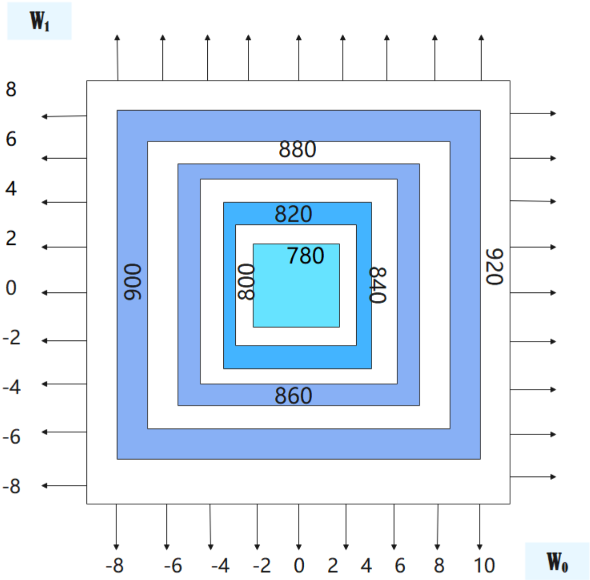

Figure 2: The contour map of the performance surface described in Figure 1.

Figure 2 is a contour map of the change of the objective function J as the tap weights w0 and w1. It can be seen from the figure that the trajectory of the two weights is an ellipse. Their trajectories shrink as the objective function J gradually approaches the minimum. When J=.Jmin, the trajectory shrinks to a point (this is not shown in the figure above), and the weight at this time is the optimal solution.

Among the adaptive filtering algorithms, the most commonly used method is the steepest descent method, which has been introduced in detail above. Another commonly used method is the least squares method. The idea of recursive least squares, which is common in adaptive filtering algorithms, comes from this :

$$d(n) = x^T(n) w_0 + \varepsilon(n) \tag{5}$$

Among them, $\varepsilon(n)$ usually represents white noise with a mean value of 0 and a variance of σ^2. And it is used to illustrate the imprecision of the model.

The output signal (n) of the filter can be expressed as:

$$y(n) = x^T(n) w(n) \tag{6}$$

The error signal is expressed as:

$$e(n) = d(n) - y(n) \tag{7}$$

In the least squares method, the selection of the tap weights should minimize the square method and e2(n) of the error. That is, the first derivative of the algorithm to e2(n) is equal to zero, and we get[16]:

$$d(n)x(n) - x^T(n)x(n)w(n) = 0 \tag{8}$$

Among them, R_{sd} can be used to represent the cross-correlation matrix d(n)x(n), and R_{xx} to represent the autocorrelation matrix $x^T(n)x(n)$, and the optimal solution of the weight vector can be obtained as:

$$w_{opt} = R_{xx}^{-1} R_{xd} \tag{9}$$

The least-mean-square algorithm takes the expected $E\left(\left|e(n)\right|^2\right)$ of the square of the error signal as the cost function, and the error signal comes from the difference between the expected signal and the output signal of the filter, as shown in (7). From the idea of the stochastic gradient descent method, it can be derived:

$$\begin{aligned} \nabla J(n) &= -2d(n)x(n) + 2x^T(n)w(n)x(n) \\ &= -2e(n)x(n) \end{aligned} \tag{10}$$

Next, the weight vector update formula of the LMS algorithm can be obtained[20]:

$$w(n+1)=w(m)+\frac{1}{2}\mu\nabla J(n)$$
$$=w(n)+\mu e(n)x(n) \quad (11)$$

Among them, the step factor μ is a key factor that affects the speed of the algorithm iteration. The smaller the μ, the slower the algorithm iteration speed, but at the same time it has a smaller steady-state error. The larger the μ, the faster the algorithm iteration speed, but the larger the steady-state error. Moreover, when the μ value is too large to exceed the value range, the algorithm will not converge. The value range of the step factor μ can be expressed as:

$$0<\mu<1/\lambda_{\max} \quad (12)$$

Among them, $\lambda_{\max}$ is the maximum eigenvalue of the autocorrelation matrix of the input signal.

The LMS algorithm is the most basic and also the most widely used adaptive filtering algorithm. However, in some practical situations, for example, when the output signal is large, the LMS algorithm will encounter the problem of noise amplification.

The Normalized Least Mean Square (NLMS) algorithm is similar to the LMS algorithm, except that the weight update formula is slightly different.

$$w(n+1)=w(n)+\frac{\mu}{\left\|x(n)\right\|^2}x(n)e(n) \quad (13)$$

It is worth noting that while the NLMS algorithm overcomes the problems of the LMS algorithm, it still has some problems. If the input signal x(n) is too small, it may cause numerical calculation difficulties. Therefore, we introduce a constant factor in the denominator to obtain the weight update formula of the new NLMS algorithm, as shown in the following formula:

$$w(n+1)=w(n)+\frac{\mu}{\delta+\left\|x(n)\right\|}x(n)e(n) \quad (14)$$

Among them, $\delta>0$.

Regardless of whether it is for uncorrelated signals or related signals, the NLMS algorithm exhibits a faster convergence rate than the LMS algorithm.

The optimization problem of Recursive Least Square (RL.S) can be expressed as follows[17]:

$$\min J(n)=\sum_{i=0}^{n}\lambda^{n-i}\left|e(i)\right|^2=\sum_{i=0}^{n}\lambda^{n-i}\left|y(i)-x^T(i)w(n)\right|^2 \quad (15)$$

Among them, $0\le\lambda\le1$ is the forgetting factor. The algorithm finds the first derivative of formula (15), and we can get:

$$\frac{\partial J(n)}{\partial w(n)} = \frac{\partial}{\partial w(n)} \sum_{i=0}^{n} \lambda^{n-i} \left| y(i) - w^T(n) x(i) \right|^2$$
$$= R(n) w(n) - r(n) \tag{16}$$

Thus, we get the optimal solution:

$$w_{opt} = R^{-1}(n) r(n) \tag{17}$$

Among them, there are:

$$R(n) = \sum_{i=0}^{n} \lambda^{n-i} x(i) x^T(i) \tag{18}$$

$$r(n) = \sum_{i=0}^{n} \lambda^{n-i} y(i) x(i) \tag{19}$$

The iterative steps of the RLS algorithm are as follows:

We define the inverse matrix Q(n) = R -1(n), we can get:

$$Q(n) = \frac{1}{\theta}\left[Q(n-1) - \frac{Q(n-1)x(n)x^T(n)Q(n-1)}{\lambda + x^T(n)Q(n-1)x(n)} \right]$$
$$= \frac{1}{\theta}\left[Q(n-1) - k(n)x^T(n)Q(n-1) \right] \tag{20}$$

Among them, k(n) is the gain vector, and the expression is as follows:

$$k(n) = \frac{Q(n-1)x(n)}{\lambda + x^T(n)Q(n-1)x(n)} \tag{21}$$

the following update formula can be obtained:

$$R(n) = \lambda R(n-1) + x(n)x^T(n) \tag{22}$$

$$r(n) = \lambda r(n-1) + x(n)y(n) \tag{23}$$

The final weight vector update formula is:

$$w(n) = w(n-1) + k(n)e(n) \tag{24}$$

When the input signal is a colored signal, the effects of the aforementioned algorithms will become relatively poor. In order to solve this problem, related scholars have proposed a new adaptive algorithm called Affine Projection Algorithm (AP). This algorithm can be seen as an evolution of the LMS algorithm. The input signal is no longer the input vector u(n) of Lx1, but is expanded in the time domain to obtain the input matrix U(n) of LxP, and its expression is as follows:

$$U(n)=\left[u(n),u(n-1),...,u(n-P+1)\right] \tag{25}$$

Among them, P is the order of affine projection.

At the same time, the expected vector and output vector can be expressed as:

$$d(n)=\left[d(n),d(n-1),...,d(n-P+1)\right]^T \tag{26}$$

$$t(n)=U^T(n)w(n)=\left[y(n),y(n-1),...,y(n-P+1)\right]^T \tag{27}$$

Then the error vector can be expressed as:

$$e(n)=d(n)-y(n)=\left[e(n),e(n-1),...,e(n-P+1)\right]^T \tag{28}$$

The goal of the APA algorithm is to minimize the formula (29) under the constraint of $d(n)-U^T(n)w(n)=0$.

$$\left\|w(n)-w(n-1)\right\|^2 \tag{29}$$

At this point, we can use the Lagrangian multiplier method to obtain the update formula of the APA algorithm, as shown in the following formula:

$$w(n)=w(n-1)+\mu U(n)\left[U^T(n)U(n)+\delta I_p\right]^{-1}e(n) \tag{30}$$

After the affine projection algorithm was proposed, scholars Lee and Gan proposed a new adaptive filtering algorithm for processing colored signals. That is, the normalized subband adaptive algorithm (Normlized Subband Adaptive Filter, NSAF). The algorithm uses a subband adaptive filter to achieve the convergence of the algorithm. The filter is based on a multi-rate digital filter and includes two parts: an analysis filter (Figure 3) and a synthesis filter (Figure 5).

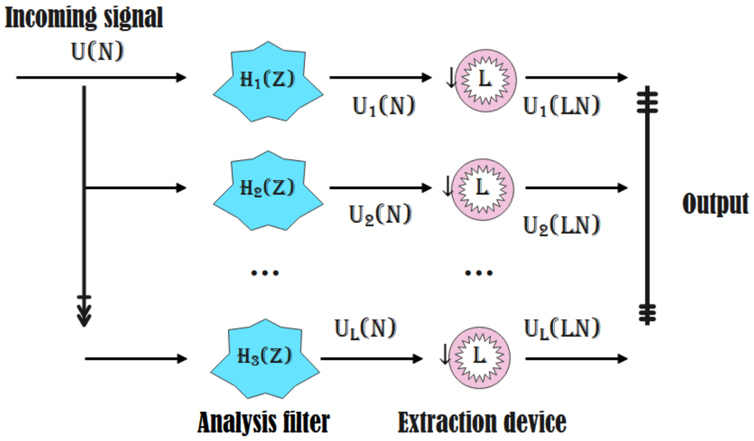

Figure 3: Analysis filter.

As shown in Figure 3, the analysis filter bank is composed of digital filters of length L with a common output. We use H,(z),H.(=)...H,(z) to represent the transfer function of the analysis filter. The input signal u(n) is divided into a group of sub-band signals represented by {u(n) light. The decimator group in the figure performs down-decimation on the subband signal. And the k-th L multiple decimator uses the subband signal u,(m) to generate the following output signal, as shown in the following formula:

$$u_{k,D}(n)=u_k(Ln), k=1,2,...,L \tag{31}$$

In order to better illustrate the extraction process, we set L=3, and the original sequence and extraction sequence can be obtained as follows:

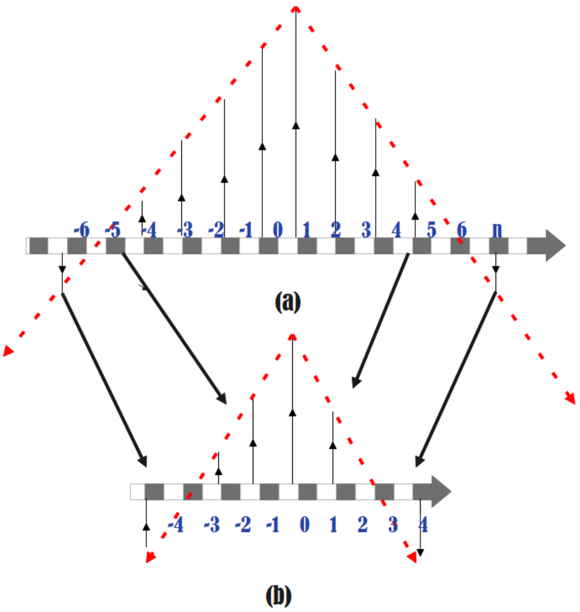

Figure 4: (a) Original sequence (b) Extracted sequence.

The integrated filter in Figure 5 includes two parts: an expander and an integrated filter bank. The work done by the expander is just the opposite of the decimator, which is to extract the input signal. And its expression is as follows:

$$v_{k,E}=\begin{cases} v_k(n/L), if\ n\ is\ a\ multiple\ of\ L \\ 0, other \end{cases} \tag{32}$$

The integrated filter bank is composed of a group of L digital filters with common output in parallel. $F_1(z), F_2(z),..., F_L(z)$ in the figure represents the transfer function of the integrated filter, and v(n) represents its output result.

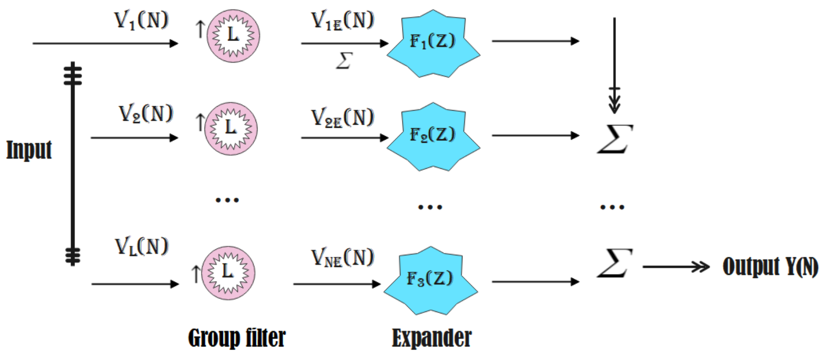

Figure 5: Synthesis filter.

Again, we set up L=3, and use Figure 6 to show the expansion process of the integrated filter.

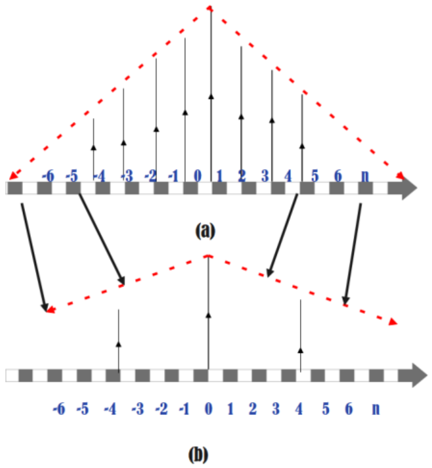

Figure 6: (a) Original sequence (b) Extended sequence.

In the subband adaptive algorithm, we can define the error signal of the kth subband as:

$$e_{k,D}(n)=d_{k,D}(n)-y_{k,D}(n)=d_{k,D}(n)-u_k^T w(n) \tag{33}$$

Among them, $u_k(n)=\left[u_k(Ln),u_k(Ln-1),\dots,u_k(Ln-M+1)\right], d_{k,D}(n)=d_k(Ln)$, and L is the number of subbands, and M is the filter length.

Under the constraint of $d_{k,D}(n)-u_k^T(n)w(n)=0$, the goal of the NSAF algorithm is to minimize the formula (34).

$$\left\|w(n+1)-w(n)\right\|^2 \tag{34}$$

Using the Lagrange multiplier method, the weight vector update formula is obtained as:

$$w(n+1)=w(n)+\mu\sum_{k=0}^{n-1}\frac{u_k(n)e_{k,D}(n)}{u_k^T(n)u_k(n)} \tag{35}$$

Under the basic adaptive algorithm model based on the truncated regression model, the output response d(n) is considered to be unsatisfactory and cannot be fully observed. In this case, we can measure the output data d(n) correctly only when the output data d(n) is in an interval (c-, c+). The distorted output response d(n) can be expressed by $\hat{d}(n)$ as:

$$\hat{d}(n)=\begin{cases} c^+, d(n)\ge c^+ \\ d(n), c^- < d(n) < c^+ \\ c^-, d(n)\le c^- \end{cases} \tag{36}$$

An effective adaptive truncated regression algorithm is based on Heckman's two-step strategy. The algorithm first obtains the estimated value of $\beta = w_0/\sigma_0$ by solving the Probit regression problem, then replaces the truncated regression model with a linear regression model, and then uses the estimated value of w_0 obtained by the ordinary least square method. The basic algorithm recursion of adaptive truncated regression is as follows (for details, please refer to the literature):

$$\hat{\beta}(n)=\hat{\beta}(n-1)+\mu\frac{\partial\Gamma_n(\beta)}{\partial\beta}\Big|_{\beta-\hat{\beta}(n-1)} \tag{37}$$

$$w(n)=w(n-1)-\frac{\mu}{2}\frac{\partial e\left(w,\hat{\beta}(n)\right)}{\partial w}\Big|_{w=w(n-1)} \tag{38}$$

There are:

$$\Gamma(n)=I_{\{c^-<\hat{d}(n)<c^+\}}\log\left(\Phi_n^+(\beta)-\Phi_n^-(\beta)\right)+\left(1-I_{\{c^-<\hat{d}(n)<c^+\}}\right)\log\left(1-\Phi_n^+(\beta)+\Phi_n^-(\beta)\right) \tag{39}$$

$$\begin{aligned} e_n\left(w,\hat{\beta}(n)\right)&=\hat{d}(n)-\left(\Phi_n^+(\beta)-\Phi_n^-(\beta)\right)x^T(n)w+\sigma_0\left(\varphi_n^+\left(\hat{\beta}(n)\right)-\varphi_n^-\left(\hat{\beta}(n)\right)\right) \\ &-\left(c^+/\sigma_0-x^T(n)\hat{\beta}(n)\right)\left(1-\Phi_n^+\left(\hat{\beta}(n)\right)\right)+\left(c^-/\sigma_0-x^T(n)\hat{\beta}(n)\right)\Phi_n^-\left(\hat{\beta}(n)\right) \end{aligned} \tag{40}$$

Among them, there are:

$$\begin{cases} \Phi_n^+\left(\hat{\beta}(n)\right)=\Phi\left(c^+/\sigma_0-x^T(n)\hat{\beta}(n)\right) \\ \Phi_n^-\left(\hat{\beta}(n)\right)=\Phi\left(c^-/\sigma_0-x^T(n)\hat{\beta}(n)\right) \\ \varphi_n^+\left(\hat{\beta}(n)\right)=\varphi\left(c^+/\sigma_0-x^T(n)\hat{\beta}(n)\right) \\ \varphi_n^-\left(\hat{\beta}(n)\right)=\varphi\left(c^-/\sigma_0-x^T(n)\tilde{\beta}(n)\right) \end{cases} \tag{41}$$

$\Phi(\cdot)$ and $\varphi(\cdot)$ represent the distribution function and probability density function, respectively. In addition, the expression of I_A in formula (39) is:

$$I_A = \begin{cases} 1, \text{Event A occurred} \\ 0, other \end{cases} \tag{42}$$

The recursive least squares method (CR-RLS) based on the censored regression model first re-estimates the expected signal. If $\hat{d}(n) = c^+$, the expected output under Gaussian background noise is re-estimated as:

$$\bar{d}(n) = x^T(n) w(n-1) + \sigma_0 \Omega\left(\frac{x^T w(n-1) - c^+}{\sigma_0}\right) \tag{43}$$

If $\hat{d}(n) = c^-$, then there is:

$$\bar{d}(n) = x^T(n) w(n-1) - \sigma_0 \Omega\left(\frac{c^- - x^T(n) w(n-1)}{\sigma_0}\right) \tag{44}$$

In addition, if $c^- < \hat{d}(n) < c^+$, then there is:

$$\bar{d}(n) = \hat{d}(n) \tag{45}$$

Therefore, the update steps of the weight vector of the CR-RLS algorithm are:

$$Q(n) = \frac{1}{\lambda}\left(Q(n) - \frac{Q(n-1) x(n) x^T(n) Q(n-1)}{\lambda + x^T(n) Q(n-1) x(n)}\right) \tag{46}$$

$$e(n) = \bar{d}(n) - x^T(n) w(n-1) \tag{47}$$

$$w(n-1) = w(n-1) + e(n) Q(n) x(n) \tag{48}$$

4 ANALYSIS ON THE INFLUENCING FACTORS OF THE ANXIETY AND DEPRESSION PHENOMENON OF COLLEGE STUDENTS' EMPLOYMENT PSYCHOLOGY BASED ON DEEP LEARNING

In order to further investigate the impact of psychological resilience on college graduates' employment anxiety and its various dimensions, this paper uses the five dimensions of psychological resilience, self-efficacy, organizational style, social ability, family cohesion and social resources as independent variables to analyze the employment anxiety of college graduates and its various dimensions. The regression method adopted is the stepwise entry method. We use the dimensions of psychological resilience as independent variables and the employment anxiety of university graduates as dependent variables. Finally, we count the effects of the above factors on the psychological anxiety and depression of college students, and obtain the results shown in Table 1 to Table 5.

NO	*Relevance*	*NO*	*Relevance*	*NO*	*Relevance*	*NO*	*Relevance*
1	*21.41*	*14*	*28.57*	*27*	*23.48*	*40*	*22.76*
2	*23.87*	*15*	*28.64*	*28*	*19.65*	*41*	*20.38*
3	*25.88*	*16*	*30.25*	*29*	*20.06*	*42*	*28.13*
4	*23.78*	*17*	*23.13*	*30*	*25.20*	*43*	*24.53*
5	*28.37*	*18*	*24.39*	*31*	*20.19*	*44*	*24.04*
6	*25.12*	*19*	*26.40*	*32*	*22.12*	*45*	*22.03*
7	*20.30*	*20*	*28.86*	*33*	*27.23*	*46*	*19.59*
8	*22.38*	*21*	*23.40*	*34*	*19.17*	*47*	*23.43*
9	*27.58*	*22*	*25.41*	*35*	*20.94*	*48*	*30.00*
10	*26.90*	*23*	*24.39*	*36*	*27.21*	*49*	*24.71*
11	*21.19*	*24*	*23.91*	*37*	*23.06*	*50*	*20.35*
12	*29.64*	*25*	*27.78*	*38*	*24.90*	*51*	*25.06*
13	*23.74*	*26*	*25.54*	*39*	*24.13*	*52*	*1.01*

Table 1: The correlation between self-efficacy and employment anxiety of college students.

NO	*Relevance*	*NO*	*Relevance*	*NO*	*Relevance*	*NO*	*Relevance*
1	*15.09*	*14*	*13.20*	*27*	*16.77*	*40*	*10.42*
2	*15.19*	*15*	*9.78*	*28*	*16.58*	*41*	*16.82*
3	*11.71*	*16*	*18.02*	*29*	*19.75*	*42*	*18.91*
4	*9.33*	*17*	*17.11*	*30*	*10.46*	*43*	*13.41*
5	*20.78*	*18*	*14.81*	*31*	*20.53*	*44*	*14.57*
6	*10.45*	*19*	*11.33*	*32*	*20.15*	*45*	*18.12*
7	*15.51*	*20*	*17.41*	*33*	*11.70*	*46*	*20.14*
8	*18.55*	*21*	*20.07*	*34*	*16.73*	*47*	*14.93*
9	*9.77*	*22*	*10.69*	*35*	*20.27*	*48*	*20.52*
10	*11.91*	*23*	*11.83*	*36*	*14.12*	*49*	*19.26*
11	*20.04*	*24*	*11.03*	*37*	*15.37*	*50*	*14.68*
12	*9.59*	*25*	*19.74*	*38*	*10.61*	*51*	*18.45*
13	*9.80*	*26*	*13.60*	*39*	*9.80*	*52*	*16.05*

Table 2: The correlation between organizational style and employment anxiety of college students.

NO	Relevance	NO	Relevance	NO	Relevance	NO	Relevance
1	32.28	14	34.84	27	26.42	40	34.52
2	23.57	15	23.81	28	31.99	41	23.66
3	27.22	16	30.02	29	29.31	42	32.68
4	25.57	17	31.52	30	33.74	43	29.87
5	34.13	18	23.23	31	34.98	44	28.55
6	33.34	19	31.06	32	34.28	45	24.23
7	32.83	20	33.73	33	31.95	46	24.07
8	25.92	21	26.80	34	32.62	47	23.39
9	24.36	22	28.76	35	26.30	48	29.34
10	33.30	23	30.52	36	33.89	49	23.59
11	25.27	24	29.89	37	26.01	50	31.22
12	27.00	25	23.95	38	31.63	51	25.99
13	32.87	26	31.47	39	23.56	52	31.00

Table 3: The correlation between social skills and employment anxiety of college students.

NO	Relevance	NO	Relevance	NO	Relevance	NO	Relevance
1	15.96	14	9.57	27	15.30	40	8.96
2	16.83	15	7.14	28	14.98	41	12.59
3	15.36	16	13.68	29	16.28	42	11.83
4	8.62	17	12.49	30	15.71	43	8.41
5	12.38	18	12.32	31	16.51	44	14.06
6	16.50	19	12.47	32	10.93	45	10.02
7	14.09	20	8.31	33	17.08	46	8.63
8	8.71	21	13.95	34	15.47	47	16.75
9	16.55	22	14.13	35	7.94	48	12.37
10	14.90	23	9.25	36	13.90	49	11.94
11	9.06	24	9.22	37	15.64	50	13.74
12	14.13	25	17.24	38	11.75	51	10.28
13	8.87	26	10.29	39	16.33	52	13.86

Table 4: The correlation between family cohesion and employment anxiety of college students.

NO	Relevance	NO	Relevance	NO	Relevance	NO	Relevance
1	39.47	14	34.13	27	41.06	40	38.14
2	29.17	15	34.13	28	38.88	41	32.32
3	41.83	16	38.57	29	35.92	42	39.71
4	38.06	17	39.94	30	42.56	43	39.21
5	40.41	18	38.53	31	42.93	44	33.59
6	30.14	19	38.56	32	29.66	45	37.73
7	38.89	20	29.46	33	33.72	46	34.26
8	36.24	21	42.00	34	34.42	47	42.06
9	38.33	22	38.48	35	32.30	48	30.76
10	35.39	23	40.12	36	31.27	49	34.30
11	34.11	24	35.61	37	34.03	50	30.73
12	40.81	25	34.51	38	32.77	51	33.42
13	34.36	26	35.45	39	35.14	52	32.67

Table 5: The correlation between social resources and employment anxiety of college students.

This study uses statistical methods to test the differences in the demographic variables of college graduates' employment anxiety. In general, there is no significant difference in employment anxiety among college graduates of different genders. Moreover, college graduates from different places of origin have significant differences in their future work tensions. Graduates from key universities and non-key universities have significant differences in the dimensions of lack of confidence in employment and future job stress. The graduates with job intention and graduates with the intention to enter the postgraduate entrance examination have significant differences in the physiological response of employment anxiety, the dimensions of future job stress and the total score of employment anxiety. There is a significant difference in employment confidence between graduates who have served as student leaders and those who have not served as student leaders. In addition, there are significant differences between graduates who have received employment guidance and those who have not received employment guidance in the physiological response to employment anxiety, the dimension of lack of self-confidence, and the total score of employment anxiety. Graduates with different part-time experience have significant differences in their physiological responses to employment anxiety and future job stress. The following is the reason analysis and opinions.

The level of employment anxiety of college graduates showed significant differences in the variables of graduation intention and whether they had received employment guidance. The physiological response to employment anxiety is significantly different in the variables of graduation intention, whether to receive employment guidance and part-time experience. The lack of self-confidence in employment has significant differences in the variables of school type, whether or not they have served as student leaders, whether they have received employment guidance and part-time experience. There are significant differences in future job tensions in student source, school category, graduation intention and part-time experience. The psychological resilience of college graduates is significantly negatively correlated with employment anxiety, self-differentiation is significantly negatively correlated with employment anxiety, and psychological resilience is significantly positively correlated with self-differentiation. The self-differentiation of college graduates plays an intermediary role between psychological resilience and employment anxiety, that is, psychological resilience affects employment anxiety through self-differentiation.

5 CONCLUSION

Psychological resilience plays a decisive role in the development of people in stressful situations, and is closely related to people's physical and mental health. College graduates are faced with a stressful situation of job hunting and decision-making. Under this circumstance, psychological resilience is closely related to the employment anxiety of college graduates, and plays an important role in the mental health and future development of college graduates. In the context of the information age, this research mainly explores the impact of college graduates' psychological resilience and self-differentiation on employment anxiety, and the mediating role of self-differentiation between psychological resilience and employment anxiety. This paper combines deep learning to analyze the influencing factors of the anxiety and depression phenomenon of college students' employment psychology. Moreover, this paper introduces the self-differentiation variable to study the mechanism of the relationship between the psychological elasticity of self-differentiation as an intermediary and employment anxiety. Finally, this paper verifies the influencing factors of the anxiety and depression phenomenon of college students' employment psychology through research and analysis.

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