Hindawi
Scientific Programming
Volume 2022, Article ID 3755257, 9 pages
https://doi.org/10.1155/2022/3755257

Research Article

Analysis and Evaluation of the Relationship between Teaching Pressure and Self-Efficacy of College Teachers Based on Artificial Neural Network

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Received 20 January 2022; Revised 1 April 2022; Accepted 4 April 2022; Published 28 April 2022

Academic Editor: Ahmed Farouk

With the reform of the education system, the society today raises higher requirements for college teachers, which cause immense psychological stress among them. To enhance the quality of teachers, it is important to analyze the relationship between teaching pressure and self-efficacy. Therefore, this paper tries to analyze and evaluate the relationship between teaching pressure and self-efficacy of college teachers based on artificial neural network. Firstly, a grey correlation analysis (GRA) model was established for the teaching pressure and self-efficacy of college teachers, and the analysis procedure was detailed. Then, the possible multicollinearity of the GRA model was tested. In addition, a linear regression model was established based on Lasso variable selection model and ridge regression variable selection model, aiming to eliminate the multicollinearity between various teaching pressure factors in the GRA model. Finally, a multilabel learning algorithm was proposed based on neural network and label correlation. In this way, the correlations between the various teaching pressure factors and teachers' self-efficacy were mined automatically. The proposed model proved valid through experiments.

1. Introduction

With the reform of the education system, the society today raises higher requirements for college teachers: a college teacher needs to play multiple roles at the same time, namely, knowledge imparter, students' psychological tutor, class leader, and pioneer of advanced teaching method [1–5]. Many college teachers find it difficult to strike the balance between being an ordinary person and acting as a role model, and thus face an immense psychological stress [6–10]. Survey results show that college teachers of the same level, although faced with the same pressure in the same period, could be optimistic or pessimistic. When a teacher perceives a low teaching pressure, he/she will work actively, have a high self-efficacy, and improve his/her qualities rapidly. Therefore, it is important to analyze the relationship between teaching pressure and self-efficacy [11–13].

Chung and Chen [14] compared the self-efficacy, job satisfaction, and pressure of teachers in application-oriented colleges in Fujian and Taiwan and discussed the role of self-efficacy in this context. Considering the importance of science and educational psychology in education system, Kuo et al. [15] treated learning motivation as the predictor variable and self-efficacy as the evidence variable and tried to discover the important correlation of the learning motivation and self-efficacy of teachers and students with the principle of educational psychology. Hamedi [16] pointed out that education informatization is an inevitable trend of higher education reform; identified teachers as the key to advancing and applying information education; attributed the psychological stress of college teachers to subjective and objective sources under education informatization; and suggested that teachers should adjust their cognition, emotions, will, and behaviors to meet the needs of education. Wang and Wang [17] revised the technology acceptance model to focus on three individual differences (self-efficacy, personal innovation ability, and sensitivity to environmental pressure).

The above is a brief review of the research into the teaching pressure and self-efficacy of college teachers. It can be seen that the studies at home and abroad have achieved a lot of results, but some defects are yet to be solved. In terms of research contents, the relevant research is immature, failing to fully consider the various indices of teaching pressure. In terms of research methods, most studies rely on questionnaire survey and qualitative research. The scientific level and rigor must be improved by introducing artificial intelligence (AI) strategies. Therefore, this paper tries to analyze and evaluate the relationship between teaching pressure and self-efficacy of college teachers based on artificial neural network [18–20]. Section 2 establishes a grey correlation analysis (GRA) model for the teaching pressure and self-efficacy of college teachers and details the analysis procedure. Besides, the possible multicollinearity of the GRA model was tested with Pearson correlation coefficient and variance inflation factor (VIF). Then, a linear regression model was established based on Lasso variable selection model and ridge regression variable selection model, aiming to eliminate the multicollinearity between various teaching pressure factors in the GRA model. Section 3 proposes a multilabel learning algorithm based on neural network and label correlation and relies on the algorithm to automatically mine the correlations between the various teaching pressure factors and teachers' self-efficacy. The proposed model proved valid through experiments.

2. Multifactor Correlation Analysis Model

2.1. Model Construction. In recent years, domestic and foreign scholars have achieved fruitful results on the correlation analysis of different variables. The main tools used for correlation analysis are GRA, least squares regression, etc.

The foreign research of self-efficacy began with the American psychologist Albert Bandura, who created the concept of self-efficacy in 1977. Seven years later, he defined self-efficacy from the angle of social cognitive theory as an individual's belief in their capacity to execute behaviors necessary to produce specific performance attainments. The self-efficacy is mainly influenced by six factors: performance experience, vicarious experience, imaginal experience, social persuasion, physical arousal, and psychological state. To derive the correlation between college teachers' teaching pressure and self-efficacy, it is important to exclude the unimportant factors and sort the influencing factors by the degree of correlation. For this purpose, the study constructs a GRA model. The analysis procedure of the proposed model is as follows.

Step 1. To reflect the systematic correlations and fully consider the possible multicollinearity, it is necessary to set up the reference series and comparative series for correlation analysis. This paper takes the quantified self-efficacy of teachers as the reference series Q and the quantified values of teaching pressure factors as the comparative series W_i. Let l be the calculation moment and i be the number of rows of influencing factors. Then, the reference series and comparative series can be, respectively, expressed as

$$\begin{cases} Q = Q(l)\, l = 1, 2, \ldots, m, \\ W = W_i(l)\, l = 1, 2, \ldots, m, i = 1, 2, \ldots n. \end{cases} \tag{1}$$

Step 2. Preprocess the collected sample data; i.e., take the average of the series data of each teaching pressure factor:

$$w_i(l)' = \frac{w_i(l)}{\overline{w_i}}. \tag{2}$$

Let $\tau \in [0, 1]$ be the resolution coefficient that determines the difference of correlation coefficients. Then, the correlation coefficient between self-efficacy of college teachers and each teaching pressure factor can be calculated by

$$\delta_i(l) = \frac{(\min/i)(\min/l)\left|w_0(l) - w_i(l)\right| + \tau(\max/i)(\max/l)\left|w_0(l) - w_i(l)\right|}{\left|w_0(l) - w_i(l)\right| + \tau(\max/\mathrm{i})(\max/l)\left|w_0(l) - w_i(l)\right|}. \tag{3}$$

Step 3. Compute the correlation degree between self-efficacy of college teachers and each teaching pressure factor. Here, correlation coefficient is introduced to measure the degree of correlation between the two concepts. The correlation coefficient has various values, which correspond to the influencing factors. To reduce the effects of dispersion of sample data on overall correlation comparison, this paper takes the average of the correlation coefficients corresponding to different influencing factors at different moments. The correlation degree can be calculated by

$$e_i = \frac{1}{n}\sum_{l=1}^{n} \delta_i(l). \tag{4}$$

When the correlation degree e falls in [0, 0.25], teachers' self-efficacy has a low correlation with teaching pressure factors. When e falls in [0.25, 0.5], teachers' self-efficacy has a medium correlation with teaching pressure factors. When e falls in [0.5, 0.75], teachers' self-efficacy has a relatively strong correlation with teaching pressure factors. When e falls in [0.75, 1], teachers' self-efficacy has a highly strong correlation with teaching pressure factors.

Step 4. After computing the correlation degree of each teaching pressure factor, rank the various factors by the correlation degree with teachers' self-efficacy.

To test the possible multicollinearity of the GRA model, the teaching pressure factors selected by the model were tested based on Pearson correlation coefficient.

The author firstly calculated the covariance $XF(w, q) = HO(W,Q)\text{-}HO(W)HO(Q)$ between each influencing factor and teachers' self-efficacy and then computed the standard deviation ε_w of the influencing factors and that ε_q of teachers' self-efficacy. Let HO be the expectation. Then, the Pearson correlation coefficient φ_{wq} between each teaching pressure factor and teachers' self-efficacy can be calculated by

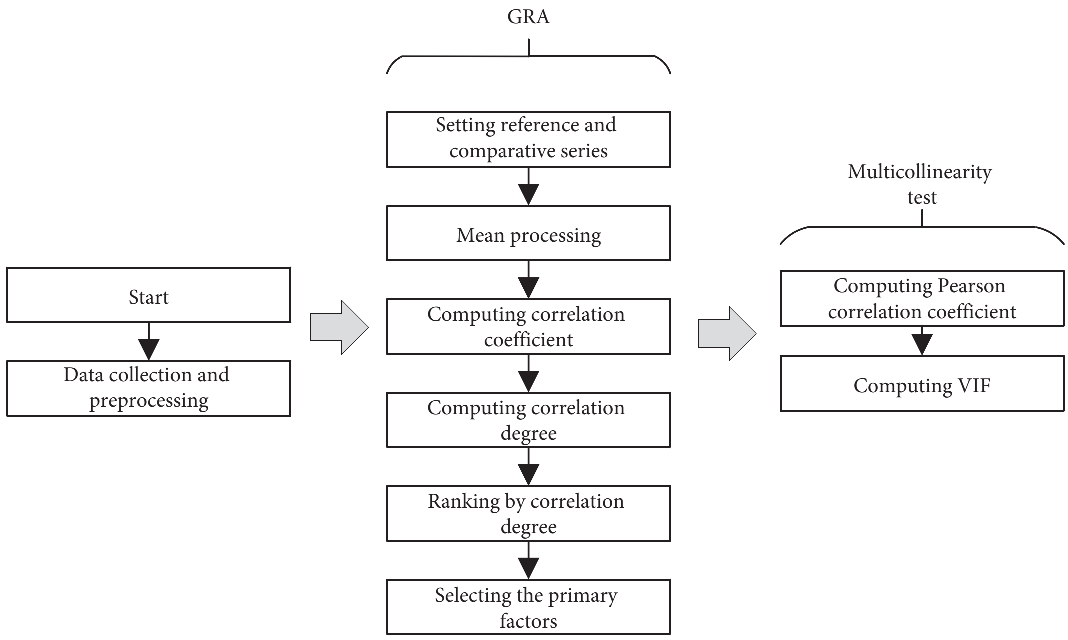

Figure 1: Model flow.

$$\varphi_{wq} = \frac{XF(w,q)}{\varepsilon_w \varepsilon_q} = \frac{HO\left[(w-\lambda_w)(q-\lambda_q)\right]}{\varepsilon_w \varepsilon_q}. \tag{5}$$

If $\varphi_{wq} = 0$, the teaching pressure factor is not linearly correlated with teachers' self-efficacy; if $\varphi_{wq} > 0$, the two have a positively correlation; if $\varphi_{wq} < 0$, the two have a negative correlation; if $\varphi_{wq} > 0.8$, the two have a very strong linear correlation.

Next, the VIFs were calculated for the teaching pressure factors. The first step is to compute the coefficient of multiple determination E_i^2 of the current teaching pressure factor relative to the other influencing factors. The VIF can be calculated by

$$\mathrm{VIF} = \frac{1}{1-E_i^2}. \tag{6}$$

If the VIF > 100, the GRA model faces a severe multicollinearity between the various teaching pressure factors. If the VIF is greater than 10 and smaller than 100, the model factors have a relatively strong multicollinearity. If the VIF is greater than 0 and smaller than 10, the model factors have a negligible multicollinearity. Figure 1 shows the execution flow of the multifactor correlation analysis model, which consists of model construction and multicollinearity test.

2.2. Variable Selection. Our regression model was constructed based on Lasso variable selection model, aiming to eliminate the multicollinearity between the various teaching pressure factors of the GRA model.

Let Q be teachers' self-efficacy, W be the matrix of teaching pressure factors, α be the parameter to be estimated, and σ be the error term. For a general linear regression model, there is $Q = W\alpha + \sigma$. After centralizing Q and normalizing W, the least squares estimation can be expressed as

$$\min\left[\sum_{i=1}^{m}\left(q_i - \sum_{j=1}^{n}\alpha w_{ij}\right)^2\right]. \tag{7}$$

The parameter to be estimated satisfies

$$\widehat{\alpha}_{LAS} = \left(W^T W\right)^{-1} W^T q. \tag{8}$$

Under the constraint $\sum^n |\alpha| \le p$, the Lasso regression can be derived from formula (7):

$$\begin{cases} \widehat{\alpha}_{\text{lasso}} = \operatorname{argmin}\left[\displaystyle\sum_{i=1}^{m}\left(q_i - \sum_{j=1}^{n}\alpha w_{ij}\right)^2\right], \\ \text{s.t. } \displaystyle\sum_{j=1}^{n}|\alpha| \le p. \end{cases} \tag{9}$$

Let μ be a positive penalty parameter controlling the number of influencing factors. The value of this parameter can be computed through cross validation. Based on Lagrangian duality, the above formula can be converted into

$$\widehat{\alpha}_{\text{lasso}} = \operatorname{argmin}\left[\sum_{i=1}^{m}\left(q_i - \sum_{j=1}^{n}\beta w_{ij}\right)^2 + \mu\sum_{j=1}^{n}|\alpha|\right]. \tag{10}$$

The greater than penalty parameter, the closer the regression coefficient of teaching pressure parameters to zero.

This paper also constructs a ridge regression variable selection model, aiming to eliminate the multicollinearity between influencing factors and form a contrast against Lasso variable selection model. For a general linear regression model, there is

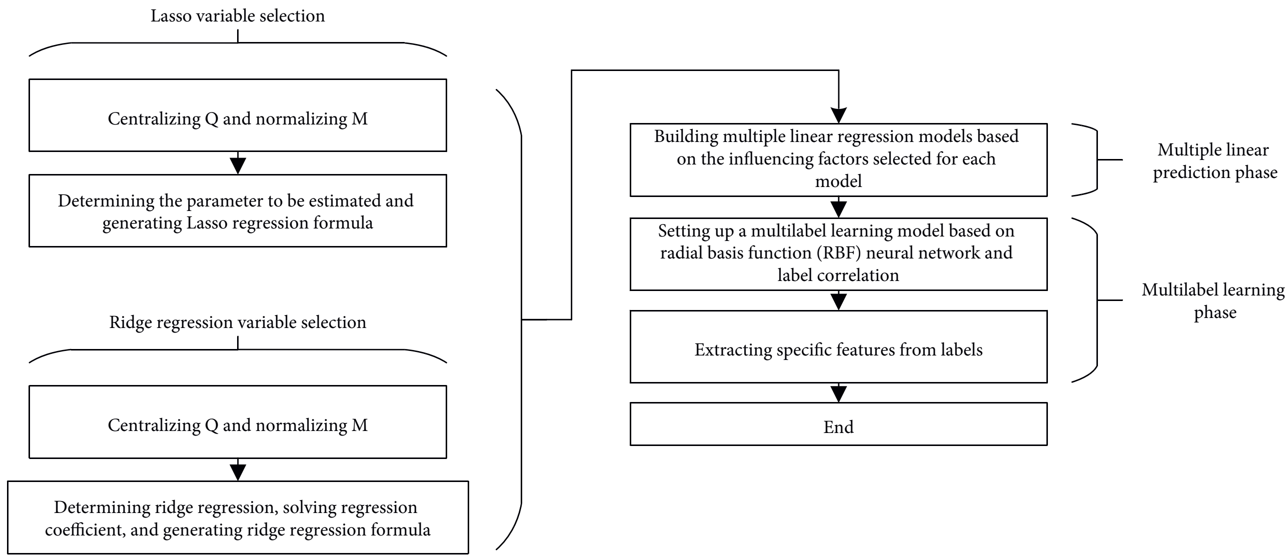

Figure 2: Flow of variable selection and linear regression.

$$Q = W\alpha + \sigma. \tag{11}$$

By least squares method, the regression coefficient α can be estimated as

$$\alpha = \left(W^T W\right)^{-1} W^T W. \tag{12}$$

The regression coefficient of ridge regression can be solved by

$$\alpha = \left(W^T W + lJ\right)^{-1} W^T Q. \tag{13}$$

Let $l \in [0,\ 1]$ be the ridge regression coefficient. The greater the value of l, the smaller the stability of the regression parameter to be affected by the multicollinearity between influencing factors, and the larger the variance of the predicted correlation. To mitigate the influence of variable dimensionality on predicted correlation, the teaching pressure factors of the model must be normalized before ridge regression. Let o_{ij} and e_{ij} be the values of original and normalized factors, respectively, and λ_j and ε_j be the arithmetic mean and standard deviation of variable j, respectively. Then, we have

$$e_{ij} = \frac{o_{ij} - \lambda_j}{\varepsilon_j}. \tag{14}$$

Figure 2 shows the flow of constructing linear variable regression models based on Lasso variable selection model and ridge regression variable selection model.

3. Multilabel Correlation Analysis

To automatically mine the correlations between teaching pressure factors and teachers' self-efficacy, this paper proposes a multilabel learning algorithm based on neural network and label correlation. The algorithm design mainly includes making reasonable use of the underlying correlation between teaching pressure factors, pruning additional features, exploring the correlation degree of the labels corresponding to the influencing factors, and reconstructing the feature set of factor attributes. Figure 3 shows the flow of the multilabel learning algorithm.

During the training of the learning algorithm, a binary classifier is firstly trained for the label corresponding to each influencing factor, to obtain the predicted label $B_i'(1 \le i \le x)$ of each sample. Then, B_i' is combined with each sample feature to form the augmented feature sets of training samples and test samples (C_{TR}^{AF} and C_{TE}^{AF}). Based on C_{TR}^{AF}, the class $A_i(1 \le i \le y)$ is obtained through label training. Finally, label $B_i'(1 \le i \le x)$ is predicted for C_{TE}^{AF} based on A_i. The additional feature information of each label can be expressed as

$$R_j = B - \left\{b_j\right\}. \tag{15}$$

The additional feature information of each influencing factor is pruned to lower the probability of noise of the additional information, reduce the dimensionality of label information, and simplify the entire algorithm. Figure 4 shows the flow of pruning. Out of the 249 teachers selected for this research, 205 provided effective responses.

Firstly, the original training samples are divided into a training set C^{TR} and a verification set C^{VE} in a ratio of 8 : 2. Next, a binary classifier is trained on the training set C^{TR}, and the binary classifier corresponding to the label k_j of the j-th factor is denoted as A_j. Then, the label set of C^{VE} is verified. F1 is introduced to measure the hardness of the label:

$$F_1 = \frac{2 \cdot PR}{PR + RE}. \tag{16}$$

This paper adopts the following pruning formula to judge whether the label is prone to prediction failure:

$$b^d = \left\{k_j | F_1\left(A_j, C^{VE}\right) \ge \Psi, 1 \le j \le y\right\}. \tag{17}$$

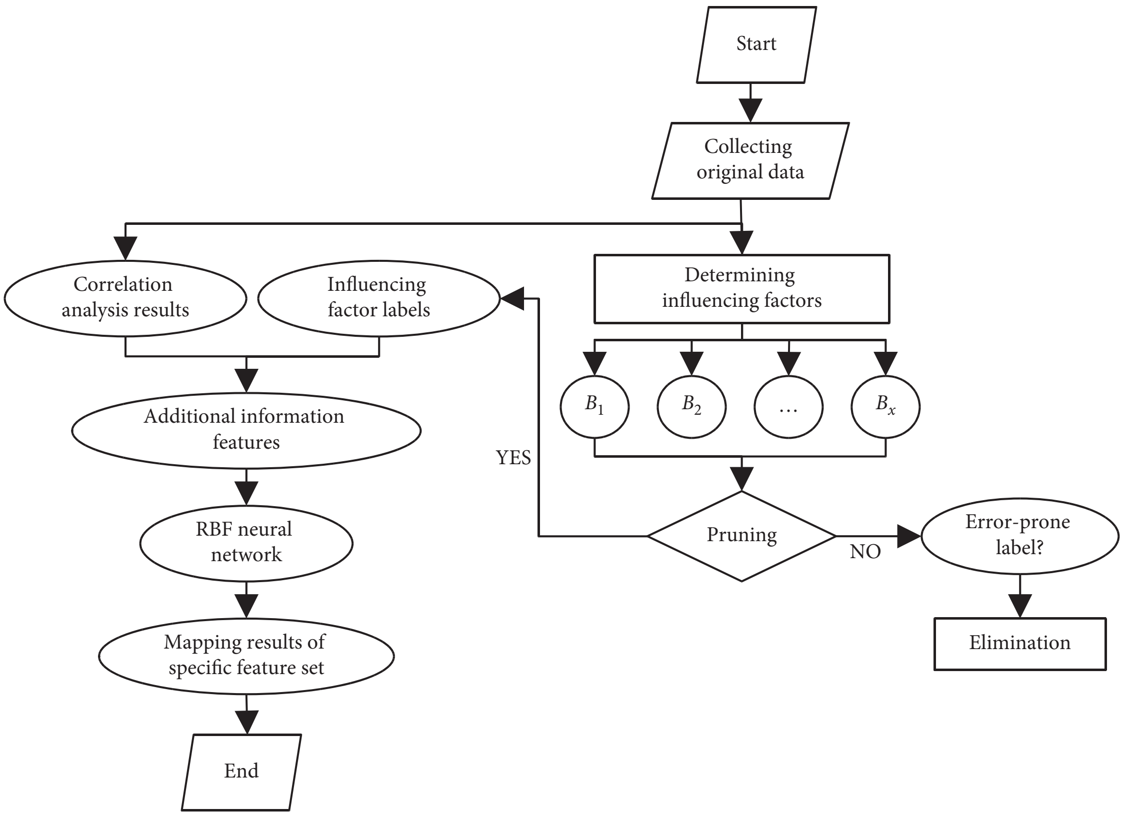

Figure 3: Flow of multilabel learning algorithm.

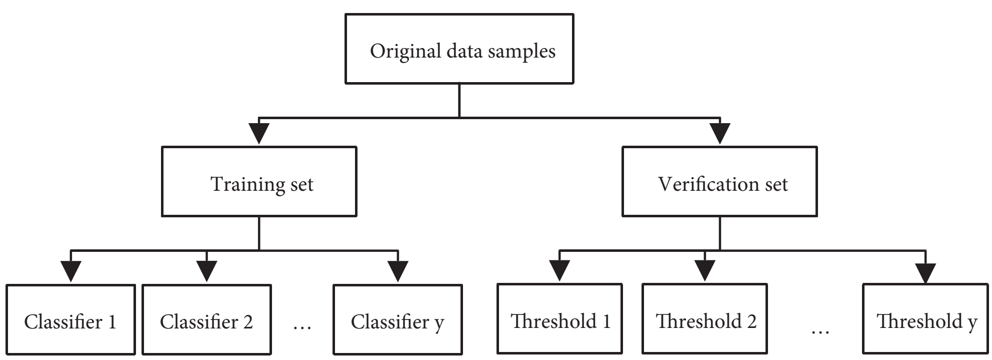

Figure 4: Flow of pruning.

Let Ψ be the preset threshold of F_1; $F(A_j,, C^{VE})$ be the F_1 of k_j; and Ψ_j be the threshold. If $\Psi_i > \Psi_j$, the label k_j of the j-th factor has a high confidence; if $\Psi_i < \Psi_j$, k_j is error-prone and should not be adopted as additional information.

Considering the inconsistency between the labels corresponding to different factors, this paper directly uses the predicted labels of these factors to train the label learning algorithm. The additional feature set of the influencing factors is constructed on RBF neural network.

As shown in Figure 5, the RBF neural network contains three layers: an input layer, a hidden layer, and an output layer. The hidden layer is activated by an RBF. Let o and ω be the center and expansion constant of the RBF, respectively. Then, the main forms of the RBF can be expressed as

$$\psi(a_t) = \exp\left(-\frac{1}{2\omega^2}g^2\right), \tag{18}$$

$$\psi(a_t) = \frac{1}{1 + \exp\left(g^2/\omega^2\right)}, \tag{19}$$

$$\psi(a_t) = \frac{1}{\sqrt{g^2 + \omega^2}}. \tag{20}$$

Formulas (18)–(20) are Gaussian function, inverse sigmoid function, and quasi-multi-quadratic function, respectively. Note that $g = ||a_t\text{-}o||$; the smaller the value of ω, the narrower the function, and the higher the selectivity.

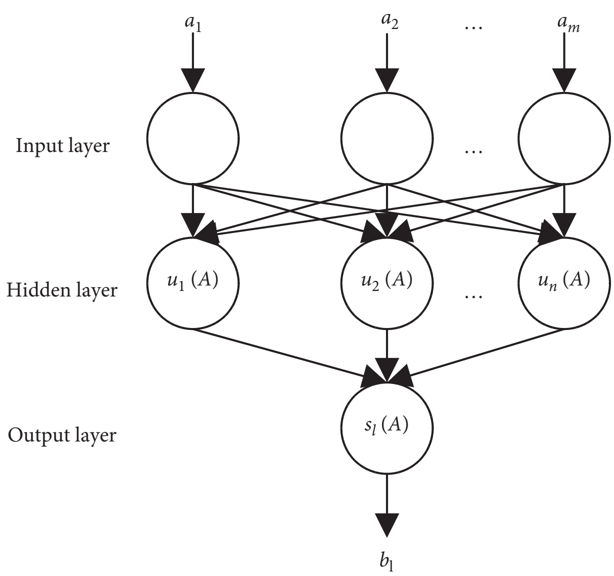

Figure 5: Structure of RBF neural network.

Training a multilabel learning model requires a lot of distinguishable information. To acquire more distinguishable information, the feature set containing the label attribute of each factor needs to be reconstructed, and the essential attributes of each label should be extracted from the original data on the corresponding teaching pressure factor. Fully considering the binary features of factor labels, this paper denotes the sample instances belonging to label b_l as H_w and those not belonging to that label as X_l. Then, H_l can be defined as

$$H_l = \{a_i | (a_i, B_i) \in C, b_l \in B_i\}. \tag{21}$$

X_l can be defined as

$$X_l = \{a_i | (a_i, B_i) \in C, b_l \notin B_i\}. \tag{22}$$

Next, k-means clustering is adopted to capture the attributes of H_l and X_l. H_l is divided into f'_l nonintersecting clusters with the cluster heads of $\{h_1^l, h_2^l, \ldots, h_f^l\}$, while X_l is divided into f''_l nonintersecting clusters with the cluster heads of $\{x_1^l, x_2^l, \ldots, h_{f'}^l\}$. Among the multilabel learning samples of teaching pressure factors, $|X_l| << |H_l|$ normally holds. This leads to the imbalance between positive and negative labels among the learning samples. To solve the problem, it is assumed that the number of positive labels equals that of negative labels:

$$f_l = f'_l = f''_l. \tag{23}$$

Let $\eta \in [0, 1]$ be the ratio parameter controlling the number of clusters. Then, the number of clusters of H_l and X_l can be configured by

$$f_l = \left[\eta \cdot \min\left(|H_l|, |X_l|\right)\right]. \tag{24}$$

The augmented feature sets C_{TR}^{AF} and C_{TE}^{AF} are imported to the neural network. The number of nodes on the hidden layer is set to $2f_l$. The original vector of the basis function for label y_k is denoted as $D_l = \{h_1^l, h_2^l, \ldots, h_{f+}^l, x_1^l, x_2^l, \ldots, h_{f'}^l\}$, i.e., the center of radial basis. Let $DIS(A\text{-}D_l)$ be the Euclidean distance from the eigenvector to the original vector. By taking Gaussian function as the activation function, the activation function of the hidden layer can be expressed as

$$u(A) = \exp\left(-\frac{\mathrm{DIS}(A - D_l)^2}{2\Phi_j^2}\right). \tag{25}$$

The formula of the expansion parameter $\Phi_j (k \le k \le y)$ can be rewritten as

$$\Phi = \left(\frac{2 \cdot \sum_{i=1}^{y-1} \sum_{j=i+1}^{y} DIS\left(D_i, D_j\right)}{y(y-1)}\right). \tag{26}$$

Formula (26) shows that Φ_j is the mean distance between the original vectors of two basis functions. Thus, the mapping from the additional feature set of the original influencing factors to the feature set of labels can be determined, once the center and the expansion parameter of the radial basis are confirmed. Let RV_l^i be the true value of the i-th sample A_i on label b_k. Then, the mapping from a specific feature set to the output layer can be given by

$$s_l(A) = \sum_{l=1}^{f_l} v_l u_l(A), \tag{27}$$

where $V = [v_1, v_2, \ldots, v_{fl}]$ is the weight matrix calculated by the minimum quadratic sum of squares:

$$GQ = \frac{1}{2} \sum_{i=1}^{f} \sum_{l=1}^{f_l} \left(s_l(A_i) - RV_l^i\right)^2. \tag{28}$$

If $RV_l^i = 1$, A_i belongs to label b_l; if $RV_l^i = 0$, A_i does not belong to label b_l.

4. Experiments and Result Analysis

To facilitate subsequent modeling and data description, this paper defines nine independent variables for teaching pressure: overload pressure W_1, working duration pressure W_2, further education pressure W_3, title evaluation pressure W_4, pressure of changing teaching method W_5, pressure of conflict between personal life and work W_6, interpersonal interaction pressure W_7, pressure from personal quality defects W_8, and student management pressure W_9.

The nine teaching pressure factors were organized into a comparative series, and the quantified values B of teachers' self-efficacy were grouped into a reference series. By the averaging method, the sample data on the teaching pressure and self-efficacy in a fixed period were nondimensionalized, to facilitate comparison and eliminate the influence of dimensionality. Table 1 shows the difference series between reference and comparative series. Further, the correlation coefficient and correlation degree between the two series were computed. The maximum and minimum absolute differences of the matrix were 0.513 and 0.003, respectively. Table 2 ranks the correlation degrees.

Table 1: Difference series between reference and comparative series.

Year	2008	2009	2010	2011	2012	2013	2014
W_1	0.1358	0.0265	0.1254	0.0956	0.2561	0.0524	0.0365
W_2	−0.3254	−0.3325	−0.4251	−0.3126	−0.3265	−0.3142	−0.3326
W_3	0.1325	0.1246	0.0352	0.1264	0.1052	0.0562	0.0751
W_4	−0.185	−0.172	−0.212	−0.118	−0.105	−0.106	−0.145
W_5	−0.3625	−0.4526	−0.2514	−0.3625	−0.3514	−0.2875	−0.2956
W_6	−0.362	−0.195	−0.254	−0.324	−0.156	−0.236	−0.152
W_7	−0.3625	−0.1542	−0.5214	−0.3261	−0.2517	−0.3625	−0.4582
W_8	−0.3625	−0.3624	−0.1652	−0.2547	−0.3185	−0.2674	−0.2854
W_9	0.2145	0.3614	0.1247	0.2851	0.0147	0.1504	0.0536
Year	2015	2016	2017	2018	2019	2020	2021
W_1	0.0395	0.1625	0.1524	0.1326	0.1254	0.1145	0.1025
W_2	−0.2315	−0.1958	−0.1625	−0.0325	0.0254	0.2685	0.3965
W_3	0.0856	0.0625	0.1132	0.1052	0.2514	0.3251	0.1025
W_4	−0.131	−0.102	−0.045	−0.006	0.028	0.165	0.153
W_5	−0.2415	−0.1958	−0.1925	−0.1746	0.1634	0.2135	0.0195
W_6	−0.241	−0.362	−0.251	−0.162	0.125	0.256	0.482
W_7	−0.1362	−0.2574	−0.3615	−0.1625	0.1254	0.2856	0.3471
W_8	−0.3846	−0.1824	−0.2851	0.1358	0.3541	0.1254	0.2614
W_9	0.0471	0.0851	0.1246	0.0258	0.0214	0.0254	0.0362

Table 2: Correlation degree ranking.

Factor	W_1	W_2	W_3	W_4	W_5
Correlation degree	0.7528	0.5712	0.8124	0.7846	0.8328
Ranking	5	8	2	3	1
Factor	W_6	W_7	W_8	W_9	
Correlation degree	0.7656	0.6943	0.5482	0.6814	
Ranking	4	6	9	7	

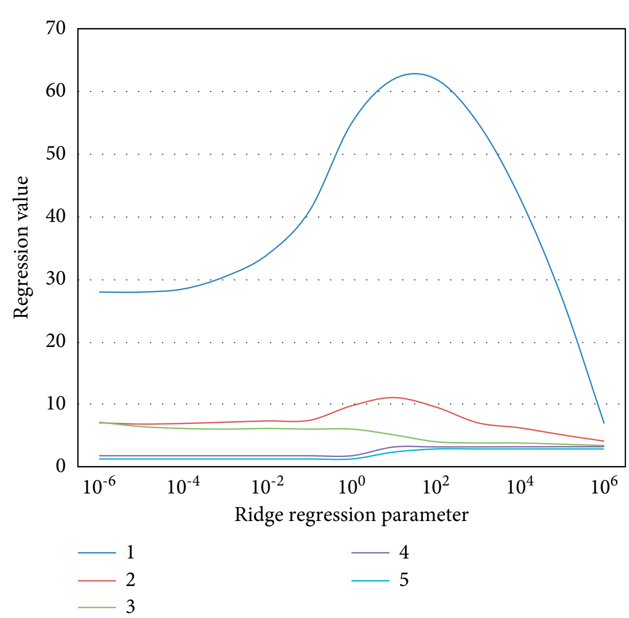

Figure 6: Ridge traces of main influencing factors.

When the correlation degree is greater than 0.8, the teaching pressure factor is very highly correlated with self-efficacy; when the correlation degree is between 0.8 and 0.75, the two have a relatively high degree of correlation; when the correlation degree is between 0.75 and 0.7, the two have a general degree of correlation; when the correlation degree is between 0.7 and 0.65, the two are barely correlated; when the correlation degree is smaller than 0.65, the two are weakly correlated. As shown in Table 2, W_5, W_3, W_4, W_6, and W_1 are main influencing factors, while W_2, W_7, W_8, and W_9 are barely correlated factors.

The ridge variable selection model was constructed by ridge trace method and cross validation. Figure 6 presents the ridge traces of main influencing factors. From top to bottom, the five curves represent the regression curves of W_5, W_3, W_4, W_6, and W_1 generated with different values of the ridge regression parameter. As the parameter increased continuously from zero, the regression linearity of W_5 increased temporarily and then declined continuously, while the regression curves of W_3, W_4, W_6, and W_1 remained stable. The standard regression coefficient only oscillated very slightly.

The correlation degree between teaching pressure factors and teachers' self-efficacy was predicted by the constructed model, with the data samples of 2014–2017 being the training set and those of 2018–2021 being the testing set. Tables 3 and 4 present the correlation analysis results based on multiple linear regression and RBF neural network, respectively. The two tables display the error, relative error, and MRE between the training set results and the test set results.

Table 3: Correlation analysis results based on multiple linear regression.

Year	2014	2015	2016	2017
True value	5887.2	6025.2	5986.1	5968.4
Predicted value	5748.5824	5864.2548	5896.2547	5869.3251
Error	−28.2	−235.1	−96.2	−149.2
Relative error (%)	0.5	3.6	1.7	2.3
MRE (%)		2.2		
MAE		125		
RMSE		148		

Note. MRE: mean relative error, MAE: mean absolute error, RMSE: root mean square error.

Table 4: Correlation analysis results based on RBF neural network.

Year	2018	2019	2020	2021
True value	6652	6694	—	—
Predicted value	6724	6958	7223	7452
Error	74	253	—	—
Relative error (%)	1.2	4.2	—	—
MRE (%)	2.56		—	—

Table 5: Simulation results of different models.

Algorithm number	*A*	*B*	*C*	*D*	*E*
1	0.201	0.345	0.452	0.162	0.674
2	0.202	0225	0.452	0.172	0.758
3	0.203	0.225	0.554	0.254	0.721
4	0.208	0.255	0.462	0.185	0.754
5	0.198	0.275	0.465	0.185	0.752
6	0.185	0.265	0.462	0.178	0.756
7	0.195	0.254	0.462	0.162	0.758

Table 6: Runtime before and after pruning.

Dataset number	1	2	3	4	5
After	10.7524	6.5241	5.2682	0.3527	96.2548
Before	31.0214	13.2547	12.5846	1.0245	231.5648
Ratio	2.95861	2.04562	2.32641	3.01542	2.52162

To verify its effectiveness, our model was compared with six other multilabel learning algorithms through simulation, namely, binary relevance, classifier chains, calibrated label ranking, random k-labelsets, machine learning–k-nearest neighbors (ML-KNN), and machine learning–decision tree (ML-DT). The performance was evaluated by five metrics: A: ratio of difference; B: error ratio of top-ranking label; C: mean distance between predicted label set and actual label set; D: error ratio of the ranking of error-prone labels; E: correct ratio of the ranking of high confidence labels. The simulation results of different models are displayed in Table 5. It can be seen that our model performed better than the 6 contrastive algorithms on all five metrics. Hence, the algorithm performance can be improved by fully utilizing the label correlations corresponding to the influencing factors.

Table 6 compares the runtime before and after pruning. Before the operation, the algorithm was highly complex. After the operation, the runtime was greatly shortened and was linearly correlated with the scale of the labels corresponding to the influencing factors. Because of the rising prediction accuracy of correlation degree, the proposed algorithm has an ideal overhead of time complexity.

5. Conclusions

This paper mainly analyzes and evaluates the relationship between teaching pressure and self-efficacy of college teachers based on artificial neural network. Firstly, the author created a GRA model for the teaching pressure and self-efficacy of college teachers and detailed the analysis procedure. Next, the possible multicollinearity of the GRA model was tested in two steps: computing the Pearson correlation coefficient and calculating the VIF. Then, a linear regression model was established based on Lasso variable selection model and ridge regression variable selection model and used to eliminate the multicollinearity between various teaching pressure factors in the GRA model. Finally, a multilabel learning algorithm was developed based on neural network and label correlation to automatically mine the correlations between the various teaching pressure factors and teachers' self-efficacy.

Through experiments, the difference series between reference and comparative series, as well as correlation degree ranking, were obtained. The results show that overload pressure W_1, further education pressure W_3, title evaluation pressure W_4, pressure of changing teaching method W_5, and pressure of conflict between personal life and work W_6 are the main influencing factors, while working duration pressure W_2, interpersonal interaction pressure W_7, pressure from personal quality defects W_8, and student management pressure W_9 are barely correlated factors. After that, the ridge traces were plotted for the main influencing factors. The correlation analysis results were obtained based on multiple linear regression and RBF neural network. Moreover, the error, relative error, and MRE between the training set results and the test set results were displayed, and the runtime before and after pruning was summarized. The experimental results fully demonstrate the effectiveness of our model.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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