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Strategies for Improving Labor Dispute Resolution Mechanisms under the Application of Artificial Intelligence

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ABSTRACT
The construction of harmonious labor relations is of great significance in improving the quality of public services and promoting social harmony and stability. The study uses multi-period DID algorithm to construct a mathematical model of artificial intelligence application and labor dispute resolution, and conducts research on the influence relationship between the two. Aiming at the lack of preventive mechanisms for labor dispute resolution at present, principal component analysis and artificial neural network are used to establish a labor relations early warning model. The results show that artificial intelligence application has a significant positive impact on labor dispute resolution at the 5% level, and there is regional heterogeneity.The prediction accuracy of PCA-ANN model on labor relations in the training set and test set is 81.25% and 85.71%, respectively, which presents a good effect of early warning of labor relations, and it can be used to improve the mechanism of labor dispute resolution. Finally, based on artificial intelligence technology, the online labor dispute resolution mechanism is proposed to prevent the escalation of labor disputes and improve the effectiveness of labor dispute resolution by focusing on prevention, secondary control and subsequent resolution.

Keywords: artificial intelligence, multi-period DID, principal component analysis, artificial neural network, early warning model, labor disputes

1. Introduction

Proper and fair handling of labor disputes, and effectively safeguard the labor relations between employers and employees is the legitimate rights and interests of the modern society, and promote the legalization and formalization of the employment of the whole society, is to build a harmonious socialist society in the new era is an important part of [1-3]. In recent years, with the rapid development of China's economy, labor disputes have been increasing year by year, and have always remained at a high level [4]. Due to the fact that China's labor dispute resolution mechanism focuses

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on solution rather than prevention, and the use of information technology is insufficient, resulting in labor dispute resolution cannot meet the needs of economic and social development [5]. How to build a convenient and efficient labor dispute resolution mechanism for the characteristics of labor disputes is an urgent problem to be solved at present [6]. Driven by the central policy, all levels of the two systems of courts and procuratorates have actively sought cooperation with the artificial intelligence technology sector in the market, and carried out a series of research and development and experimentation of intelligent judicial (procuratorial) platforms, which have achieved relatively rich results [7-9].

With the social changes and the development of the times, the concepts of "intelligent justice" and "intelligent court" have become the key words in China's judicial reform [10]. In line with the current development trend of intelligent justice and intelligent government, the quasi-judicial attributes of labor arbitration institutions will also be "intelligent labor arbitration court" construction as an important goal [11]. The main tasks of "Internet + mediation and arbitration" are four, the unification of the case handling system, strengthening personnel management, case data collection and statistical analysis and online mediation and arbitration platform construction. From the current practice of China's labor arbitration institutions at all levels around the world, the above four aspects of work are still in the initial stage, the construction progress of the intelligent labor arbitration court lags behind the progress of the construction of the intelligent court [12-14]. As labor arbitration and judicial trial have strong similarity in form and essence, the experience of smart court construction can provide more reference for the construction of smart labor arbitration court, on the other hand, considering the characteristics of labor arbitration, the construction of smart labor arbitration court will also face some unique challenges [15-16].

Ermakova, E. P, et al. discussed the practice of artificial intelligence technology in the judicial field, but the application is relatively shallow, and the in-depth application still needs to be further developed, and pointed out that it will have significant effects when used to assist judicial personnel in their work at this stage [17]. Zeleznikow, J et al. built an intelligent dispute resolution model with functions such as case management, consulting, communication, decision support, and drafting software [18]. Bakare, O. A has established a comprehensive human resources and legal risk management framework to resolve labor disputes in the oil management sector, which can effectively predict labor risks and resolve labor disputes in advance in accordance with laws and regulations, so as to help build a harmonious and sustainable working environment. [19]. Asri Wijayanti, C et al. elaborated on the insufficient application of AI technology in judicial practice, especially in labor disputes, and the urgent need for the state to adopt AI technology to improve the situation [20]. Popa-Roman, G et al. analyzed the impact of AI technology on the signing of collective labor contracts, collective labor contract disputes, and strikes in the judicial practice of labor disputes, and deepened the understanding of the role of AI technology in labor disputes [21].

The article focuses on labor dispute resolution under the application of artificial intelligence, puts forward research hypotheses and selects corresponding variables to construct a two-way fixed-effects multi-period DID model. After completing the validity test of the model, the baseline regression analysis and heterogeneity analysis of the model are conducted to test whether the assumptions made are valid. Subsequently, the labor relations evaluation indicators covering four dimensions: labor contract, labor disputes, working environment, and income security are selected, and the indicators are downscaled using principal component analysis, and combined with the optimized BP neural network, the labor relations early warning model is constructed, and the model is trained and tested to assess the labor relations early warning effect of the model. Finally, artificial intelligence technology is used to improve the labor dispute resolution mechanism and build a framework of labor dispute resolution mechanism consisting of three modules: online evaluation, online assistance and online adjudication, which integrates various ways of dispute resolution such as consultation, evaluation, negotiation, mediation, arbitration and trial, with a view to providing insights for the future development of labor dispute resolution mechanism.

2. Impact of artificial intelligence applications on labor dispute resolution

The implementation of artificial intelligence policy promotes the development and application of artificial intelligence technology, leads the development of artificial intelligence industry, and changes the traditional production mode and labor form. Therefore, the thesis constructs a dummy variable of AI application policy release to study the role of AI application on labor dispute resolution by exploring the impact of AI application policy release on the harmony of labor relations.

2.1. Study design

2.1.1. Hypothesis development. In connection with the impact of AI applications on labor relations, the following hypotheses are proposed:

Hypothesis H1: Artificial intelligence application has a positive effect on labor dispute settlement.

Hypothesis H2: Artificial intelligence application has a promoting effect on the number of labor disputes settlement per labor.

Hypothesis H3: Artificial intelligence application has a promotional effect on the number of labor disputes settlement per output.

Due to the different economic foundation and artificial intelligence development level in different regions, the eastern and central regions have higher level of artificial intelligence development, while the western regions have weaker level of artificial intelligence technology due to geographic location, industrial foundation, etc., the following hypotheses are proposed:

Hypothesis H4: There is regional heterogeneity in the effect of artificial intelligence application on the frequency of labor dispute cases.

Hypothesis H5: The effect of AI application on the frequency of labor dispute cases is most significant in the eastern region.

2.1.2. Selection of variables. The explanatory variable is Labor Dispute Settlement (LDS), and in order to eliminate the influence of population and economic scale of provinces and cities in the panel data, the number of labor dispute cases per output (ILDN) and the number of labor disputes per labor (LLDN) are used to indicate the number of labor dispute settlement. The ratio of the number of labor dispute settlements accepted in a region in the year to the total GDP of the region in the year is used to represent the number of labor dispute cases per output, and the ratio of the number of labor dispute settlements accepted in the region in the year to the total number of employed people in the region in the year is used to represent the number of labor dispute cases per labor.

The core explanatory variable is Artificial Intelligence Application (AIU), which is represented by the implementation of AI application policies and embodied as a dummy variable in the measurement model. The year of policy issuance was obtained by searching through the regional government portals. In addition, the impact of economic system and structural transformation on labor relations is represented by urbanization and marketization, where marketization is the ratio of the number of people employed in non-state units in a region to the total number of people employed in urban areas in that region, and urbanization is the ratio of the number of people employed in urban areas in a region to the total number of people employed in that region. The impact of economic development on labor disputes is captured in terms of regional gross domestic product (GDP) and regional GDP per capita, as well as the regional GDP growth index. The regional urban unemployment registration rate and the education level of the labor force are used to capture the labor market situation.

The data used in this paper come from the 2018-2022 China Statistical Yearbook, China Labor Statistics Yearbook and statistical yearbooks of provinces and municipalities.

2.1.3. Model setup. In this paper, we establish a two-way fixed-effects multi-period DID model to construct a double difference statistic reflecting the effect of the policy by comparing the differences between the control group and the treatment group before and after the implementation of the policy on the application of AI, and to eliminate the influence of other unobservable factors on the explanatory variables to view the policy effect. Therefore, the following model is constructed:

$$Y_{it} = \alpha + \beta D_{it} + \gamma X_{it} + I_i + T_t + \varepsilon_{it} \tag{1}$$

In model (1), Yit is the explanatory variable that includes labor dispute resolution in i provinces at the moment of t, which is logarithmically valued in the model estimation. D_{it} is the core explanatory variable, which is 0 before the implementation of the policy in each province and 1 after the implementation, β is the coefficient of the core explanatory variable D_{it}, which portrays the impact of the implementation of the AI policy on the labor dispute resolution in each province, and a positive coefficient value of β indicates that the impact of the AI application policy on the labor dispute resolution is positive, with an obvious promotion effect. On the contrary, if the coefficient value of β is negative it indicates that the AI application policy has a negative impact on labor dispute resolution. X_{it} refers to the control variables constructed in this paper, and γ portrays the effect of control variables on labor dispute resolution. I_i is an individual fixed effect, T_t is a time fixed effect. ε_{it} is the error term.

2.2. Validity testing

2.2.1. Parallel trend test. The results of the parallel trend test of the model are shown in Figure 1, with the horizontal coordinate indicating the point of implementation of the AI application policy, "0" indicating the period when the policy was released, and the vertical coordinate indicating the corresponding regression coefficient for each period. From the results, the regression coefficients fluctuate around 0 before the point of implementation of the AI application policy, while the coefficients are significantly positive after the implementation of the policy. This indicates that the treatment and control groups have the same trend of change before the implementation of the AI application policy, and there is no significant difference, which satisfies the premise assumption of parallel trend. Therefore, the sample passed the parallel trend test for multi-period DID.

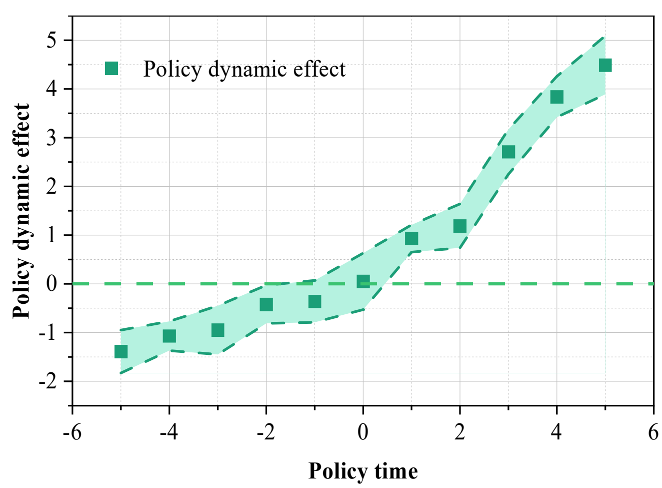


Fig. 1. Parallel trend test results of the model

2.2.2. Placebo test. The samples were grouped by province, and then a year was randomly selected from the year variable within each provincial group as the time of policy release in that province. Meanwhile, the above process was repeated 300 times to exclude the interference of other chance events on the estimation results, and the results of the placebo test are shown in Figure 2. The mean value of the regression coefficients is close to 0, and the vast majority of the P-values are greater than 0.1, the regression results are not significant, and the influence of random factors and other policies in the same period on the number of labor disputes closed is excluded.

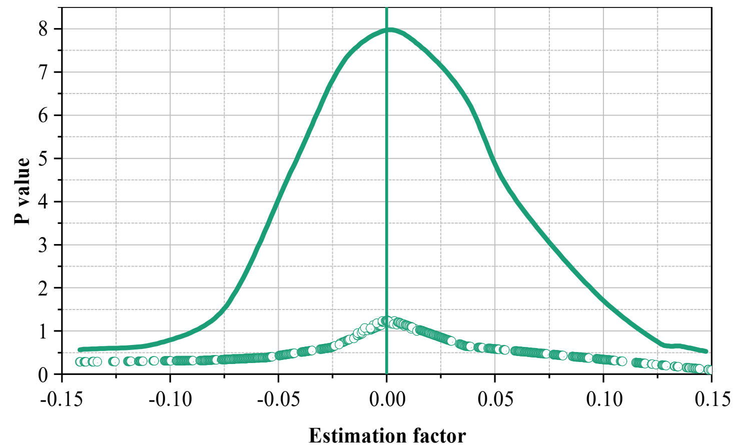


Fig. 2. Placebo test results

2.3. Analysis of regression results

Stata16 software is applied to regress the models on panel data with fixed effects respectively, and the baseline regression results of the models are shown in Table 1.Models (1) and (2) are regressions of labor disputes per laborer (LLDN) and labor disputes per producer (ILDN), respectively, with columns 1 and 3 controlling for both the region control variable, the region fixed effects, and the year fixed effects, and columns 2 columns and column 4 remove controls for region influences on this basis, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The regression coefficients of the policy dummy variables are all significantly positive ($p < 0.05$), indicating that the AI application policy significantly increases the number of labor disputes closed per laborer and the number of labor disputes closed per producer, and hypotheses H2 and H3 are tested. Since the number of labor disputes closed on average labor disputes and the number of labor disputes closed on average production indicate labor dispute resolution, the implementation of AI application has a facilitating effect on labor dispute resolution, and hypothesis H1 is verified.

Table 1. The benchmark regression results of the model

	(1)LLDN		(2)ILDN	
AIU	0.093***	0.241***	0.063**	0.084**
	0.036	0.024	0.067	0.033
Regional control variable	Yes	No	Yes	No
Regional fixation effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Clustering quantity	15	15	15	15
N	147	147	147	147
R2	0.762	0.411	0.526	0.471

2.4. Heterogeneity analysis

The sample provinces are divided into three groups: central, western and eastern, and a split-sample regression is conducted. The results of the heterogeneity test of the model are shown in Table 2. The effect of the AI application policy on the number of labor disputes closed per laborer (LLDN) is significantly positive in the west and east, and the significance level reaches 1% in the east, while the policy effect in the central region is positive but not significant. The effect of AI application policies on the number of labor disputes per worker (ILDN) is significantly positive in the eastern region, and the policy effect is positive but not significant in the eastern and western regions.

The results of the above heterogeneity analysis show that there is regional heterogeneity in the impact of AI application on labor dispute resolution, and that this facilitating effect is most significant in the eastern region, and hypotheses H4 and H5 are tested.

Table 2. The heterogeneity test results of the model

	(1)LLDN			(2)ILDN		
	East	Middle	West	East	Middle	West
AIU	0.299***	0.033	0.047*	0.226***	0.082	0.031
	0.066	0.009	0.025	0.019	0.024	0.065
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
N	68	68	68	68	68	68
R2	0.821	0.806	0.922	0.704	0.758	0.858

3. PCA-ANN-based early warning model for labor relations

The current labor dispute resolution mechanism has the problems of high cost, serious "information silo" phenomenon, lack of prevention mechanism, and low degree of intelligence. The previous analysis verified the promotion effect of artificial intelligence application on labor dispute resolution. Based on this, this chapter focuses on the problems of the current labor dispute resolution mechanism, using artificial intelligence technology, proposes a preventive method for labor dispute resolution, and establishes a labor relationship early warning model combining principal component analysis and neural network (ANN).

3.1. Research methodology

Using the primary data obtained from the research on labor-management relations of enterprises in a certain region, the research methods of principal component analysis and optimized BP neural network are used to conduct early warning research.

3.1.1. Principal component analysis. In the model study established in this paper, due to the high feature dimension of the input of the labor relations early warning indicator, the eigenmode function of each feature is included. When the feature dimension of the input data is too high, the model will face a heavy computational burden and may encounter problems such as dimensional explosion, which leads to the obstruction of the training process. Therefore, in order to improve the computational efficiency of the model, it is necessary to perform feature dimensionality reduction on the original input labor relations early warning indicator data, eliminating redundant information and retaining only a small number of principal components that carry the main information.

Principal Component Analysis (PCA) is a statistical method of data dimensionality reduction by using a few irrelevant principal component indicators to replace the original input indicators to minimize the loss of information, and PCA is introduced in this study to deal with the early warning indicator system of labor relations, and the basic principles and steps are:

Assuming the existence of n sample and the existence of m input indicators, the original inputs are normalized to form a matrix of:

$$X=\left(x_1,x_2,\ldots,x_m\right)=\begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \cdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{2}$$

The correlation coefficient matrix is first calculated for the normalized input matrix:

$$R=\begin{bmatrix} r_n & \cdots & r_{1m} \\ \vdots & \ddots & \cdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \tag{3}$$

where $r_{ij}(i,j=1,2,\ldots,m)$ is the correlation coefficient between x_i and x_j:

$$r_{ij}=\frac{\sum_{s=1}^{n}\left(x_{si}-\overline{x_t}\right)\left(x_{sj}-\overline{x_j}\right)}{\sqrt{\sum_{s=1}^{n}\left(x_{si}-\overline{x_i}\right)^2\sum_{s=1}^{n}\left(x_{sj}-\overline{x_j}\right)^2}} \tag{4}$$

Next, the eigenvalues $\lambda_i(i=1,2,\ldots,m)$ of matrix R_{nm} are calculated and ranked in order of magnitude, and the corresponding eigenvectors $e_i(i=1,2,\ldots,m)$ are computed, commonly by the Jacobi method.

Again, the principal component contribution and cumulative contribution are calculated separately:

$$\frac{\lambda_i}{\sum_{s-1}^{n}\lambda_s}(i=1,2,\ldots,p) \tag{5}$$

$$\frac{\sum_{s=1}^{j}\lambda_s}{\sum_{s-1}^{p}\lambda_s}(i=1,2,\ldots,p) \tag{6}$$

Finally, p principal components are extracted according to the requirements of feature root or cumulative contribution rate to complete the dimensionality reduction of the indicators. The analysis process of the output indicators is the same as that of the input indicators and will not be repeated.

Global principal component analysis is consistent with the principle of principal component analysis, with the advantage of incorporating time characteristics, transforming the time-series stereo data of each year to a unified global principal hyperplane, so that the principal components of each year have the same composition. The time-series stereo data table is generally:

$$D=\left\{X_t\in A_{n\times m},t=1,2,\ldots,T\right\} \tag{7}$$

where D is a sequence of n samples arranged in time t in a flat data table, all of which have exactly the same sample points and variable indicators. Performing principal component analysis on the entire time-series stereo data table D i.e., the global sample cluster points is global principal component analysis.

3.1.2. ANN algorithm. Artificial Neural Network (ANN), is a network model constructed with reference to the neuronal structure of the brain of living beings. Artificial neural networks can learn, analyze and process pre-inputs by dynamically adjusting the connection weights of each neuron node in the application. The error back propagation (BP) algorithm, through the forward propagation of the signal input and the learning of error back propagation, is a good solution to the problem of connection weights of the hidden layer introduced by the neural network, which makes the artificial neural network model results more accurate and reliable, and really has the ability to analyze the classification of nonlinear and complex targets.

1) BP Neural Network. BP neural network mainly includes the following three layers: input layer, hidden layer and output layer. In the process of network training and learning, the weight values between each neuron are constantly adjusted through the gradient descent method, and the input and output values are nonlinearly adjusted, so that the nonlinear relationship between the input function and the output value is finally simulated, and the neural network model is established.

The BP network structure consists of n input neuron, m hidden layer neurons, and l output layer neurons. The input is denoted as $X=\left(x_1,x_2,\ldots,x_n\right)^T$, the input of the middle layer is denoted as $H=\left(h_1,h_2,\cdots,h_m\right)^T$, and the output result of the output layer is denoted as $O=\left(o_1,o_2,\cdots,o_l\right)^T$. Given a training objective function of $D=\left(d_1,d_2,\cdots,d_t\right)^T$, the connection weights from the input layer to the hidden layer are denoted as 8 and the threshold is denoted as $V=v_{ij}=\left(v_1,v_2,\cdots,v_m\right)^T$, and the connection weights from the hidden layer to the output layer are denoted as $W=w_{ij}=\left(w_1,w_2,\cdots,w_l\right)^T$. The threshold value of the hidden layer is denoted as $\gamma=\left(\gamma_1,\gamma_2,\cdots,\gamma_m\right)^T$, and the inter-value of the output layer can be denoted as $\theta=\left(\theta_1,\theta_2,\cdots,\theta_l\right)^T$.

Then the output of the j st neuron of the hidden layer at this point can be expressed as:

$$h_j=f\left(\sum_{i=1}^{n}v_{ji}x_j\right),j=1,2,\cdots,m \tag{8}$$

Further the output of the k st neuron output layer can be expressed as:

$$o_k=f\left(\sum_{i=1}^{n}w_{kj}h_j\right),k=1,2,\cdots,l \tag{9}$$

Then the mean square error of the neural network is:

$$E=\frac{1}{2}\sum_{k=1}^{l}\left(d_k-o_k\right)^2 \tag{10}$$

It is obtained by substituting Eq. (8) and Eq. (9) into Eq. (10) and then organizing:

$$E=\frac{1}{2}\sum_{k=1}^{l}\left(d_k-f\left(\sum_{j=1}^{m}w_{kj}f\left(\sum_{i=1}^{n}v_{ji}x_i\right)\right)\right)^2 \tag{11}$$

There is a total of $(n+l+1)m+l$ parameter to be determined in this neural network, and using an iterative learning algorithm, the parameter needs to be re-updated and estimated in each round of iterations. The updated estimate for any parameter v in the network is given by:

$$v\leftarrow v+\Delta v \tag{12}$$

Assuming that the Sigmoid function is used as the activation function in the above network model structure, the Sigmoid function properties can be utilized to calculate the update parameters:

$$f'(x)=f(x)(1-f(x)) \tag{13}$$

The BP algorithm continuously tunes the parameters by gradient descent. Assuming a given learning rate of η, then $\Delta w_{kj}=-\eta\frac{\partial E}{\partial w_{kj}}$, $j=1,\cdots,m$, $k=1,\cdots,l$, substituting the intermediate function of the hidden layer can be obtained:

$$net_k = \sum_{j=1}^{m} w_{kj} h_j$$
$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial w_{kj}} \tag{14}$$

Let $-\frac{\partial E}{\partial net_k} = g_k^o$, then the above equation can be organized as:

$$\Delta w_{kj} = \eta g_k^o h_j \tag{15}$$

Further one can organize g_k^o as:

$$g_k^o = (d_k - o_k) o_k (1 - o_k) \tag{16}$$

Eventually an updated formula for w_{kj} can be obtained:

$$\Delta w_{kj} = \eta g_k^o h_j = \eta (d_k - o_k) o_k (1 - o_k) h_j \tag{17}$$

The same can be sought:

$$\Delta \theta_j = -\eta g_k^o \tag{18}$$

$$\Delta v_{ji} = \eta e_i x_i \tag{19}$$

$$\Delta y_h = -\eta e_i \tag{20}$$

Where: e_i is $\left(\sum_{k=1}^{t} \eta (d_k - o_k) o_k (1 - o_k) w_{jk} \right) h_i (1 - h_i)$.

Although BP neural networks are widely used in various current research fields, they also suffer from the following main shortcomings: slow convergence, easy to fall into local minima, and no specific choice or formula for network design and the setting of the number of neurons.

2) Optimization of BP neural network. According to the shortcomings of the BP neural network in the previous section, the L-M (Levenberg-Marquardt) algorithm can effectively reduce the iteration time and solve the problem of slow convergence of the network and the problem of falling into the local minima. The L-M algorithm is essentially an improvement of the Gause-Newton method, which utilizes constraints on optimization to solve the problem of the optimality of the problem. The L-M algorithm is essentially an improvement of the Gause-Newton method, which uses the optimality condition of the constrained optimization problem to solve the problem that the estimated value is far away from the optimal value at the beginning of the iteration stage, and combines these two methods to realize the optimization of BP neural network algorithm.

The iterative formula for the LM algorithm is:

$$u_{k+1} = u_k - \left(J_k^T J_\mathrm{k} + \lambda I \right)^{-1} J_k^T e_k \tag{21}$$

Where: u_k - k nd iteration, weights and sums between layers, λ - network learning rate, I - unit matrix, e_k - - error between the output and the standard value, J_k - Jacobi matrix. The Jacobi matrix is shown below:

$$J_k = \begin{bmatrix} \frac{\partial e_1(u_k)}{\partial u_1} & \cdots & \frac{\partial e_1(u_k)}{\partial u_N} \\ \vdots & & \vdots \\ \frac{\partial e_M(u_k)}{\partial u_1} & \cdots & \frac{\partial e_M(u_k)}{\partial u_N} \end{bmatrix} \tag{22}$$

3.2. Sample determination

In this paper, a total of 30 enterprises in a certain region were selected as research objects, and questionnaires were issued to the employees of these 30 enterprises using random sampling to obtain the various factors affecting labor relations and the employees' evaluation of the current labor relations situation of the enterprises in the form of questionnaires, respectively.

In this paper, the sample labor relations risk level is divided into two categories, the classification standard is: calculate the average value of the enterprise sample index data, if the average value <2, it is defined as a high-risk enterprise of labor relations performance. If the average value >2, it is defined as a good labor relations performance enterprise. In the end, a total of 8 out of 30 enterprises were judged to have high-risk labor relations, and the warning type was defined as 1, while 22 enterprises had good performance, and the warning type was defined as 0.

3.3. Construction of the indicator system

From four aspects, namely, labor contracts, labor disputes, working environment, and income security, a labor relations early warning evaluation index system is established, and 12 secondary indicators are screened and refined.

Labor contracts: signing of collective contracts X1 and performance of collective contracts X2.

Labor disputes: occurrence of labor disputes X3 and mediation of labor disputes X4.

Working environment: layoffs X5 and working environment satisfaction X6.

Income Security: Minimum Wage Ratio X7, Pension Insurance Payment X8, Medical Insurance Payment X9, Work Injury Insurance Payment X10, Maternity Insurance Payment X11 and Unemployment Insurance Payment X12.

3.4. Principal component analysis

Using principal component analysis to reduce the dimensionality of labor relations influencing factors, simplify the spatial dimensions of the expression of input information, reduce the complexity of the neural network constituting the system, improve fault tolerance and anti-interference ability, and determine the input layer of the neural network. Secondly, the comprehensive score of labor relations is constructed, and the risk level of labor relations is reclassified based on the original labor relations classification standard into 2 (heavy alarm), 1 (light alarm) and 0 (no alarm) to determine the output layer of the neural network. Finally, the neural network is used to establish a risk warning model for labor relations.

Through principal component analysis, the cumulative variance contribution rate of each indicator variable is 84.52%, which can be divided into 3 principal components, and the results of the rotated component matrix are shown in Table 3. Principal component 1 is mainly affected by pension insurance payment X8, medical insurance payment X9, work injury insurance payment X10, maternity insurance payment X11, unemployment insurance payment X12, and the component coefficients are above 0.78, so the first common factor is named as “income security factor”. Principal component 2 is mainly influenced by satisfaction with working environment X6 (0.819) and minimum wage X7 (0.785), so it is named “working environment factor”. Principal component 3 is mainly affected by collective contract signing X1, collective contract fulfillment X2, labor disputes X3 and labor disputes mediation X4, with component coefficients greater than 0.68, so it is named "labor contract-dispute factor".

Table 3. The result of the rotating composition matrix

	Principal component		
	1	2	3
X1	0.157	0.426	0.831
X2	0.219	0.302	0.749
X3	0.467	0.083	0.688
X4	0.201	0.312	0.836
X5	0.513	0.319	0.375
X6	0.443	0.819	0.211
X7	0.306	0.785	0.078
X8	0.837	0.423	0.270
X9	0.791	0.253	0.425
X10	0.873	0.192	0.504
X11	0.782	0.351	0.334
X12	0.842	0.113	0.142

From this, the contribution rate of the three principal component factors is obtained, which is used as weights to determine the comprehensive score value of labor relations and classify the labor relations of the 30 sample enterprises. The comprehensive score value and classification of labor relations are shown in Figure 3. Define the comprehensive score less than 6.0 as heavy alarm (2), the comprehensive score between 6.0-6.5 as light alarm (1), and the comprehensive score greater than 6.5 as no alarm (0). It can be determined that 7 of the 30 enterprises have labor relations that exhibit heavy alarm, 10 have labor relations that exhibit light alarm, and 13 have labor relations that exhibit no alarm.

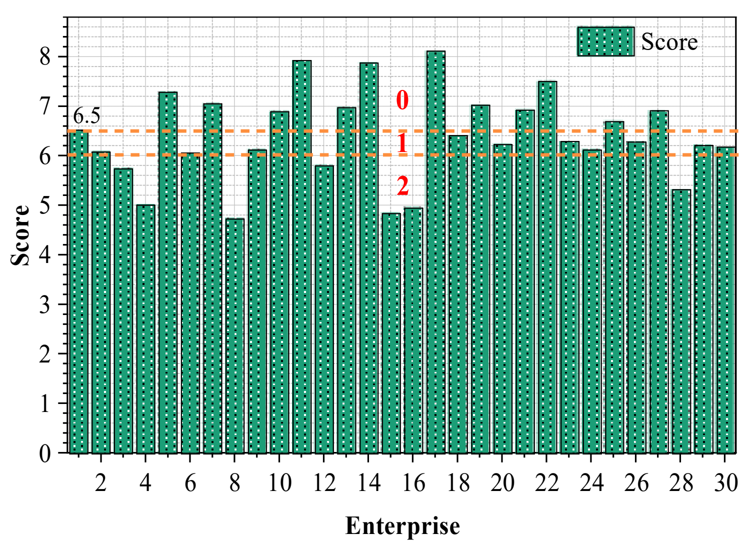
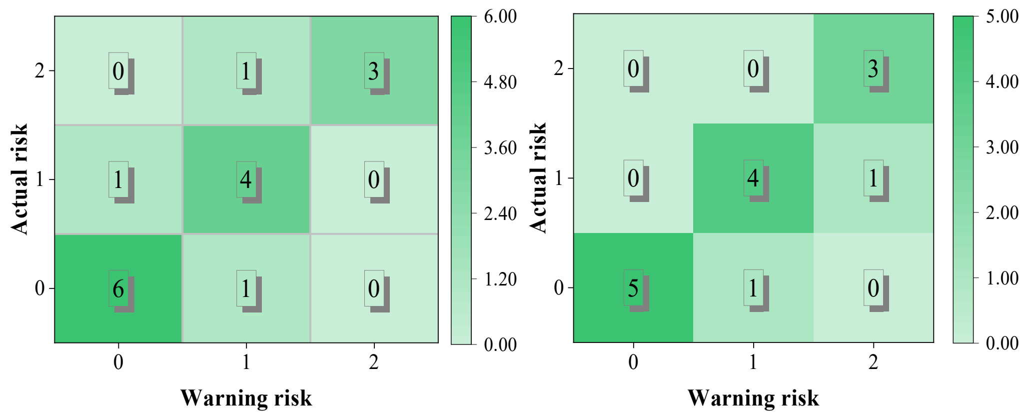


Fig. 3. The comprehensive score and classification of labor relations

3.5. Analysis of forecast results

In this paper, a three-layer optimized BP neural network is used, and the number of nodes (number of neurons) in the input layer is determined by the number of principal components determined by principal component analysis, i.e., the income security factor, the working environment factor, and the labor contract-dispute factor, and the number of nodes (number of neurons) in the output layer is determined by the comprehensive score value of labor relations, and the output layer is designated as three nodes, i.e., the output labor relations The performance is heavy alarm (2), light alarm (1) and no alarm (0).

Matlab programming is used to conduct iterative trials, set the parameters, and test in the training set and test set, the sample set test accuracy results are shown in Fig. 4, (a) and (b) are the results of labor relations prediction in the training set and test set, respectively. The results show that in the training sample, the actual outputs of 3 enterprises are invalid, and the correct rate reaches 81.25%. In the test sample, the actual output results of 2 firms failed with a correct rate of 85.71%. The accuracy of both training and test samples is high, so the construction of labor relations early warning model using principal component-neural network in this paper is effective.



(a)Training set (b)Testing set

Fig. 4. Results of the sample set test accuracy

4. Strategies for improving the mechanism for resolving labor disputes

According to the concept of modern dispute resolution mechanism, if the center of gravity of labor dispute resolution is changed from settlement to prevention, and artificial intelligence is applied to the traditional mechanism, giving full play to the advantages of "Internet+", and combining with the proposed early warning model of labor relations, a new type of online resolution mechanism is constructed, which integrates all kinds of resources for labor dispute resolution, and integrates various functions such as consultation, evaluation, conciliation, mediation, arbitration, trial, etc., and connects all the data related to labor dispute resolution. The "integrated" platform integrates all kinds of labor dispute resolution resources, combines various functions such as consultation, assessment, assistance, mediation, arbitration, trial, etc., and connects all the data related to labor dispute resolution, which will achieve twice the result with half the effort, and effectively solve the problems existing in the current labor dispute resolution mechanism.

4.1. Overall architecture

Based on the application of artificial intelligence technology, the overall architecture of the online labor dispute resolution mechanism is shown in Figure 5, including three levels of dispute prevention, dispute control, and dispute resolution.

The first level is online assessment, whose function is to answer parties' inquiries and help them assess their problems to avoid getting into legal difficulties. It also uses the Labor Relations Early Warning Model to predict the harmony of labor relations and prevent labor disputes. The second level is online assistance. Its function is to help parties negotiate or conciliate, provide them with advice, and control the transformation of disputes into cases. This function is realized in two ways, one is for the assistants to provide positive guidance to the parties through a question-and-answer style, and the other is to help the parties resolve their differences through an automatic negotiation system. The third level is online adjudication. Its function is for the arbitration department or the court to make an award on the case, in whole or in part, based on the electronic documents submitted online, and this mechanism belongs to the adversarial system of online claims and defenses. The award is binding and enforceable. By triaging the first two tiers, as few disputes as possible enter this tier.

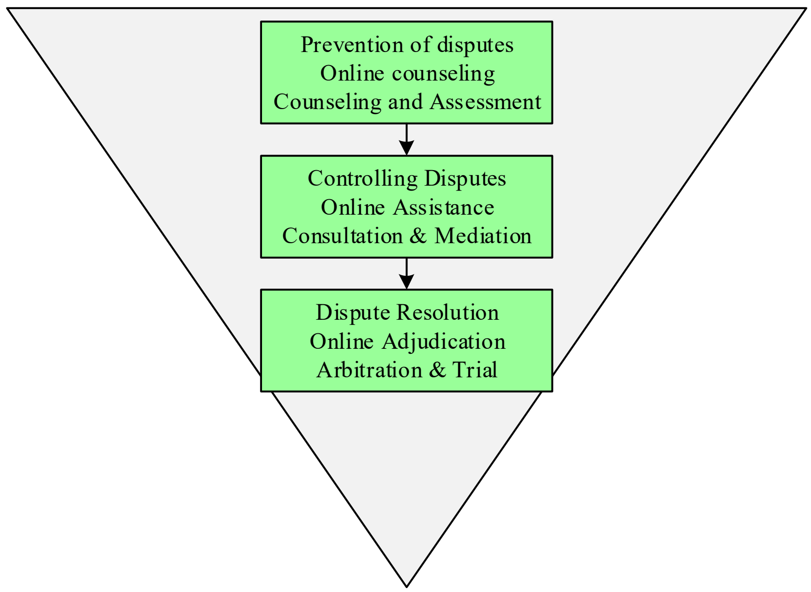


Fig. 5. The overall structure of the work dispute online resolution mechanism

4.2. Functional modules

4.2.1. Online assessment module. The online assessment module can provide the parties with business consulting, help the parties conduct self-assessment of labor dispute issues, promptly eliminate impractical requests, and provide open, transparent, and uniform adjudication standards, thus allowing the parties to have predictability in adjudicating disputes, and reducing the disconnect between the parties due to cognitive errors. The labor relations early warning model can also be used to observe the degree of harmony in labor relations and prevent disputes from arising.

4.2.2. Online assistance module. The online facilitation module allows parties to clarify points of contention, minimize disagreements, work together, reach agreement and control disputes. In the module, the artificial intelligence and the facilitator are guided by rules, through which the parties alternately submit statements and responses on their arguments until a single argument is produced, which is affirmed by one party and denied by the other, called a "point of contention".

The function of identifying and resolving "points of contention" in the Online Assistance for Labor Disputes module will be supported in two ways. The first is through an automated labor dispute negotiation platform, which helps parties resolve their differences through a dialogue process. The second way is to integrate personnel from grass-roots labor service stations, trade unions, people's mediation committees and other institutions with mediation functions to provide services to both parties online, actively guiding them to narrow down the points of contention and reach agreement on some or all of them.

4.2.3. Online adjudication module. If the parties are unable to agree on a “point of dispute”, an adjudicator is required to adjudicate the “point of dispute”, which leads to the online adjudication module. The module consists of the following contents:

1) Labor arbitration module. The two parties to the arbitration will express and respond to each other's opinions either synchronously or asynchronously through the online system, and the adjudicator will confirm the undisputed part of the dispute between the two parties. For the disputed part of both parties, the arbitration award is made.

2) One-click case filing module. The online labor dispute resolution mechanism is designed with the function of “one-click filing”. If the party concerned is not satisfied with the arbitration award and chooses to file a case with one click, all the data in the arbitration will be imported into the litigation system, so there is no need to fill in the information of the party concerned, the content of the pleadings such as the litigation request, and there is no need to go to the court specifically to file a case on the spot. Online technology will share the data of arbitration and litigation, realizing the effective connection between arbitration and litigation.

3) Pre-trial preparation module. The module to change the traditional mode by the judge or clerk to organize the exchange of evidence, by the parties through the online procedure, the arbitration award on their own to express their views on the facts identified, has been imported evidence does not need to repeat the submission.

4) Adjudication module. On the basis of the award, the judge clarifies the “points of contention”, identifies and determines the facts of the specific case, and makes a judgment on the disputed issues.

5. Conclusion

In order to build a harmonious labor relationship under the application of artificial intelligence, it is necessary to clarify the impact of the application of artificial intelligence on the settlement of labor disputes, and this paper constructs a model using the multi-period DID algorithm, and carries out testing and regression analysis. Then combined with the principal component analysis and the improved error back propagation algorithm, the early warning model of labor relations is proposed. And then explore the improvement strategy of labor dispute resolution mechanism.

1) The application of AI has a significant positive promotion effect on the number of labor disputes settled per laborer and the number of labor disputes settled per output ($p < 0.05$), so the application of AI has a certain positive impact on the settlement of labor disputes, and there is regional heterogeneity in this impact effect, with the most significant impact effect in the eastern region.

2) Using the model for early warning prediction of labor relations, the prediction accuracy on the training set and test set is 81.25% and 85.71%, respectively. The labor relations early warning model established in this paper combining principal component analysis and neural network has a high accuracy of early warning ability on labor relations, and provides an effective analysis method for the improvement of the prevention mechanism of labor disputes.

3) Proposing a labor dispute resolution mechanism consisting of three functional modules, namely, online assessment, online assistance and online adjudication, which, by increasing the investment in the dispute prevention and control process, enables disputes to be continuously filtered, greatly reduces the number of cases that enter the arbitration department and the courts, and lowers the cost of dispute resolution. At the same time, the use of online technology has greatly accelerated the efficiency of labor dispute handling and improved the effectiveness of labor dispute resolution.

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