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Disclosure Model of Capital Accounting Information Based on Immune Particle Swarm Optimization Algorithm

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Abstract: *In order to analyze the tendency of capital accounting information disclosure, a capital accounting information disclosure model based on immune particle swarm optimization is proposed. From the level of corporate governance and financial status of enterprises to analyze and determine the factors that may affect the tendency of capital accounting information disclosure, the construction of enterprise capital accounting information disclosure impact index system; Based on this index, the model of capital accounting information disclosure is constructed, and the functional relationship between each factor variable and disclosure tendency is established. The immune system was used to optimize the particle swarm optimization algorithm, and the immune memory and self-regulation mechanism were used to maintain the particle concentration, ensure the diversity of the population, and avoid the disadvantage of particle swarm optimization algorithm easily falling into the local optimal solution. The immune particle swarm optimization algorithm was used to complete the parameter estimation of the capital accounting information disclosure model. The results show that the four factors of ownership structure, financial leverage, growth and audit opinion affect the disclosure tendency of capital accounting information of enterprises, and the accuracy of the research model for capital accounting information disclosure tendency analysis reaches 75%.*

Keywords: *Immune particle swarm optimization algorithm; Capital accounting information; Disclosure model; Index system*

1. Introduction

The relationship between the quality of capital accounting information disclosure and the efficiency of resource allocation affects the development of market economy [1]. Therefore, the capital market needs to coordinate this relationship and rationally combine the two to better serve the production, operation and management of enterprises [2]. In addition, the relationship between the quality of capital accounting information disclosure and the efficiency of resource allocation should be clarified [3] to help enterprises adapt to the development trend of market economy and improve their core competitiveness. Capital accounting information includes financial position, operating performance and cash flow [4]. It is in the form of financial statements, financial reports and notes. Before investment and borrowing, the primary consideration of investors or creditors is the financial status and operating results of the enterprise [5]. Make decisions based on relevance, reliability, comparability, and understandability. The timeliness of capital accounting information disclosure depends on the quality of capital accounting information. Therefore, it is necessary to optimize internal resource allocation from the perspective of capital accounting information disclosure quality. In order to maintain the normal operation of enterprises, in order to ensure the quality of capital accounting information disclosure, it is necessary to combine the development of enterprises, increase the number of capital accounting information disclosure, so as to ensure the rationality of internal decision-making of enterprises. At present, there are two major defects in the disclosure of enterprise capital accounting information, namely intentional distortion and unintentional distortion [6]. These two defects will damage the economic operation of enterprises. High quality capital accounting information disclosure can ensure the effective operation of the market.

Many scholars have conducted relevant studies, and earnings response coefficient and expected earnings growth represent the quality of earnings disclosure [7]. A new index is generated by combining loss aversion, income radicalization and income smoothness, which is used to investigate the time series of income opacity rankings of countries [8]. Tansey further improved the measurement method of information disclosure quality and constructed a composite index of information disclosure to measure the disclosure of enterprise risk information. Other relevant studies mainly focus on relative quantity, density, depth and future information abstracts [9]. Enterprise capital accounting information disclosure tendency is poor, so it is imperative to analyze the factors affecting the quality of capital accounting information disclosure. Through the analysis of the influencing factors, we can promote the construction of capital accounting information disclosure system of enterprises in China. Therefore, this paper studies the capital accounting information disclosure model based on immune particle swarm optimization. Particle swarm optimization (PSO) uses a random function to initialize the particle swarm and then uses a fitness evaluation system [10-11]. The convergence of the algorithm makes all particles in the particle swarm approach the optimal solution, which will lose the diversity of particles, which will slow down the convergence of the algorithm in the future operation. In order to solve the shortcomings of particle swarm optimization (PSO), immune algorithm (IA) was used to improve PSO. This algorithm not only keeps the characteristics of PSO algorithm simple and easy to use, but also overcomes the premature phenomenon in the process of searching the optimal solution.

2. Basic Definitions

The construction of capital accounting information disclosure model includes three processes: (1) analyzing and determining the factors that may affect capital accounting information disclosure tendency; (2) establishing the functional relationship between factor variable and disclosure tendency; (3) parameter estimation based on immune particle swarm optimization algorithm.

2.1. Analysis on Factors Affecting the Quality of Capital Accounting Information Disclosure and Index Selection

2.1.1. Analysis of Factors Affecting the Quality of Capital Accounting Information Disclosure

From the perspective of corporate governance, the influence on the quality of capital accounting information disclosure is mainly reflected in ownership structure and board mechanism.

(1) Ownership structure. In order to reduce the problems of agency, the owners of the company need managerial ownership [12]. Generally, the managers are more motivated to disclose false information and manipulate the company performance and thus to maximize their own interests.

(2) Board mechanism. The board of directors is the core mechanism of corporate governance, which has a direct and very important influence on the quality of capital accounting information disclosure.

The financial situation has a direct impact on the quality of capital accounting information disclosure.It is embodied in the following aspects:

(1) Profitability. It can directly reflect the financial characteristics of a company.

(2) Company size. In order to reduce the financing cost and financing difficulty, large companies are more motivated to disclose high-quality capital accounting information.

(3) Asset-liability and financial leverage. The higher the financial leverage, the bigger the financial risk faced by enterprise, the greater the risk of being underestimated by the market. The managers choose to manipulate the information disclosed by capital accounting, and thus to alleviate the negative information transmitted to the market due to high debt ratio.

(4) Audit opinion. Auditor's opinion is an important index to evaluate the quality of capital accounting information disclosure. In the capital market, it is generally accepted that the statements audited by the four major accounting firms have higher credibility.

2.1.2. Index Selection

Based on the analysis for the factors that affect the quality of capital accounting information disclosure, the indexes influencing capital accounting information disclosure are selected to construct the index system. Constructing this system is to improve the comparability of capital accounting information disclosure qualities among different listed companies [13]. That is the horizontal comparability among companies. The comparability of financial accounting information disclosure quality of the same listed company in different years is called the vertical comparability within the company. The index system of influencing factors of capital accounting information disclosure quality is shown in Figure1.

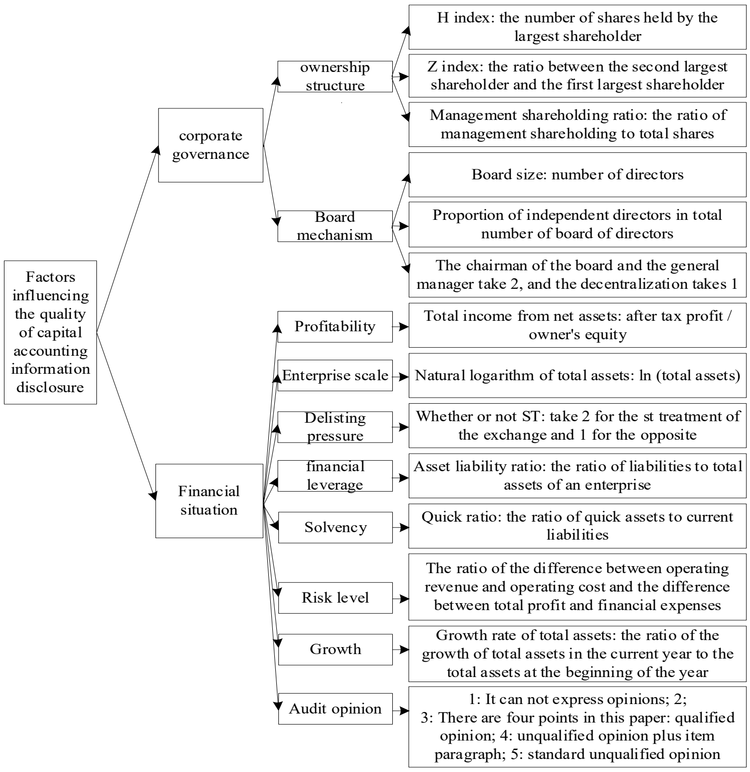

Figure 1: Index System of influencing factors of capital accounting information disclosure quality.

As can be seen from Figure 1,after considering the environment of China's securities market, we construct two one-level measurement indicators: corporate governance indicators and financial status indicators. It can be subdivided into 10 two-level measurement indicators: ownership structure index, board mechanism index, profitability index, enterprise scale index, delisting pressure index, financial leverage index, solvency index and risk level index, growth index and audit opinion index. There are 14 three-level measurement indexes: H index with negative influence, Z index with positive influence, management shareholding ratio with negative influence, board size with positive influence, proportion of the independent board of directors with positive influence, separation of ownership and control index with negative influence, return of net assets index with positive impact, enterprise scale index with positive impact, ST index with negative impact, asset liability ratio index with negative impact, quick ratio index with positive impact, operating leverage index with negative impact, total asset growth rate index with positive impact and auditor opinion index with positive impact. The impact index system of capital accounting information disclosure is constructed.

2.2. Construction of Capital Accounting Information Disclosure Model

y^* denotes the tendency of capital accounting information disclosure. y denotes the result of capital accounting information disclosure. Then, the model of capital accounting information disclosure can be constructed.

$$y = \begin{cases} 0, y^* < 0 \\ 1, y^* > 0 \end{cases} \tag{1}$$

Where y is the observable value. All the values of capital accounting information disclosure are 1, and the opposite value is 0. y^* is called latent variable. Its expression is:

$$y^* = F\left(\vec{x} \cdot \vec{\beta} + u\right) \tag{2}$$

The value of y^* cannot be observed directly. $\vec{x} = (x_1, x_2, \cdots, x_n)$ represents the vector composed of various factors influencing the disclosure of capital accounting information. $\vec{\beta} = \left(\beta_1, \beta_2, \cdots, \beta_n\right)^T$

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represents the undetermined parameter vector. $\vec{x}\cdot\vec{\beta}$ represents the inner product of two vectors. u represents the fitting constant term. Let F be the cumulative probability density function of standard normal distribution. That is:

$$F(y)=\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{y^2}{2}\right) \tag{3}$$

According to the model, the expected value of y^* is the probability of $y=1$ [14]. And then:

$$E\left(y\cdot\left|\vec{x},\vec{\beta}\right.\right)=1\times p\left(y=1\left|\vec{x},\vec{\beta}\right.\right)+0\times P\left(y=0\left|\vec{x},\vec{\beta}\right.\right) \tag{4}$$

And the probability of $y=1$ is the probability of y^*. Thus:

$$\begin{aligned}p\left(y=1\left|\vec{x},\vec{\beta}\right.\right)&=P\left(y^*>0\right)\\&=P\left(\left(F\vec{x},\vec{\beta}+u\right)>0\right)\end{aligned} \tag{5}$$

According to Formula (3), the following results can be obtained.

$$F^{-1}\left(P\right)=\vec{x}\cdot\vec{\beta}+u \tag{6}$$

Where P is the probability of disclosing capital accounting information.

The parameters in Formula (6) can be estimated by the known data information. In addition, the significance of factors can be tested.

The probability of capital accounting information disclosure is determined by the factors that affect capital accounting information disclosure tendency. This model can analyze the marginal effect of each factor on capital accounting information disclosure tendency, and provide strong support for changing the attitude of enterprises to capital information disclosure [15]. Meanwhile, the model can also get the marginal influence of various factors on the probability of capital accounting information disclosure. In this way, if the values of a group of factor variables x are given, we can predict and evaluate the selection of capital accounting information disclosure policy.

2.3. Parameter Estimation of Model

Particle swarm optimization (PSO) is a stochastic optimization method based on swarm, without crossover operator and mutation operator. In fact, the swarm follows the optimal particle in the solution space to search [16]. The algorithm simulates the predation behavior of birds. Each bird is named as a particle without mass and volume, and many particles coexist and cooperate to search. According to its own and group experience, each particle "flies" to a better position in the problem space. The best position passed by the particle itself in the flight process is called the individual optimal value V_p , and the best position experienced by the whole population is called the global optimal value V_g . Each particle updates its state by Formula (7) and Formula (8):

$$s_{n+1}=c_0s_n+c_1\left(V_p-x_n\right)+c_2\left(V_g-x_n\right) \tag{7}$$

$$x_{n+1}=x_n+s_{n+1} \tag{8}$$

In formulas, s_n denotes the velocity vector of particle. x_n represents the position of current particle. V_p represents the position of the best solution found by the particle. V_g represents the position of optimal solution found by the whole population. c_0 , c_1 and c_2 represent the cognitive coefficients of the population. Generally, c_0 is a stochastic number between $(0,1)$. c_1 and c_2 are stochastic numbers between $(0,2)$.

In the process of updating particle swarm, the particle swarm optimization algorithm does not compare the fitness before and after the update, so it is unable to guarantee that the particles always move to the better region, and invalid search will occur. In addition, particle swarm optimization "flies" to the

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optimal solution according to all particles and their own search experience. In the process of evolution, the diversity of particle swarm will decrease, and the poor diversity will lead to premature convergence, affecting the global search ability. The immune information processing mechanism of immune system is introduced into particle swarm optimization algorithm. Meanwhile, the immune memory and self-regulation mechanism are used to maintain the concentration of particle, thus ensuring the diversity of population and avoiding the shortcomings of particle swarm optimization algorithm falling into local optimal solution. Therefore, the parameter estimation of capital accounting information disclosure model adopts the immune particle swarm optimization algorithm.

The implementation process of immune particle swarm optimization algorithm is shown in Figure 2.

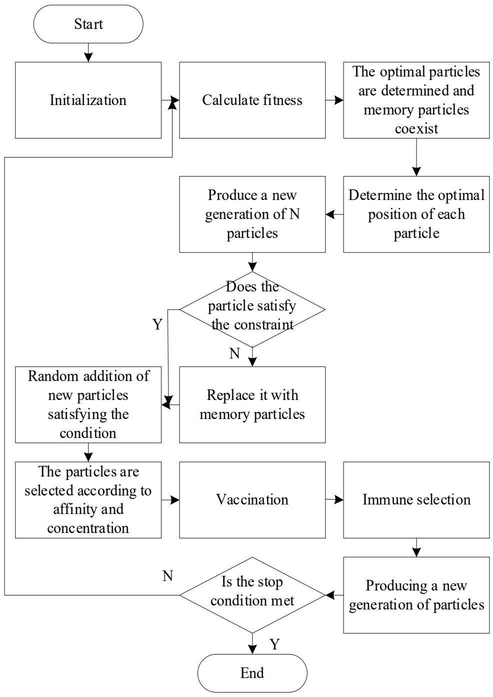

Figure 2:Implementation flow of immune particle swarm optimization algorithm.

The immune particle swarm optimization algorithm is divided into three parts [17]: (1) standard particle swarm optimization algorithm (2) realization of immune memory and immune regulation (3) vaccination and immune selection.

In order to estimate the parameters of capital accounting information disclosure model, we can set the parameter search space of model as T dimension and use N particles to search it with. The position of each particle is a T-dimensional vector, and the vector in each dimension represents the weight of a model. That is $x_i = (x_{i1}, x_{i2}, \cdots, x_{iT})$. x_{iT} is the coordinate of particle i in T-dimensional space. The calculation process is shown as follows:

(1) Within the allowable range of storage capacity in each period, N groups of expected income change sequences are generated randomly. They are $\left(V_1^1, V_2^1, \cdots, V_T^1\right), \cdots \left(V_1^N, V_2^N, \cdots, V_T^N\right)$. N particles (T is the calculation period, i.e. various states of particle) are randomly initialized to test whether the status of each particle meets the impact index of capital accounting information disclosure. If not, the particle swarm should be reinitialized.

(2) The fitness of each particle in particle swarm is calculated. The capital accounting information disclosure model solves the problem of the largest tendency of capital accounting information disclosure [18], so the fitness function of particle can be obtained by changing of capital accounting information disclosure model

$$f(x) = \frac{C}{V} \tag{9}$$

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In the formula, C is a constant. In order to intuitively reflect the fitness of particle when $f(x) \le 1$, C can be adjusted according to specific conditions;

(3) A new generation of N particles is formed. According to the fitness of particle, we can find the best position V_p searched by each particle so far, the best position V_g of particle swarm in this iteration and the best position V_G searched by particle swarm so far. After updating each particle, we can see that:

$$V_t^i(k+1) = wV_t^i(k) + c_1 r_1\left(V_p^i(k) - V_t^i(k)\right) + c_2 r_2\left(V_g^i(k) - V_t^i(k)\right) \tag{10}$$

$$V_t^i(k+1) = V_t^i(k) + V_t^i(k+1) \tag{11}$$

Where, k denotes the number of iterations. w denotes the inertia weight. r denotes a random function. The value range is 0-1.

(4) Immune memory and immune regulation.

① N particles are monitored. If the position of the particle is an infeasible solution, we can replace it with memory particle (V_g can be regarded as the memory cell).

② If the position of the particle is a feasible solution, on the basis of N new particles, N_1 new particles meeting the requirements are randomly generated. The particle concentration is calculated by the fitness of particle.

$$D(x_i) = \frac{1}{\sum_{i=1}^{N+N_1}\left|f(x_i) - f(x_j)\right|} i = 1,2,\cdots(N+N_1) \tag{12}$$

The selection probability determined by the concentration is shown as follows:

$$P(x_i) = \frac{\frac{1}{D(x_i)}}{\sum_{i=1}^{N+N_1}\frac{1}{D(x_i)}} \tag{13}$$

According to the probability value, $N+N_1$ particles are sorted. The first N particles with large values are selected as the next generation of evolution to generate a new generation of particles.

(5) The realization of vaccination and immune selection. V_G generated by each iteration can be considered as the solution closest to the optimal solution, and a component can be used as a vaccine to inoculate and select the particle.

① Immune selection. It is necessary to check whether the inoculated particles meet the conditions. If not, we should give up it. If yes, we can calculate the fitness. If the fitness is less than that before inoculation, we should give up it, otherwise the probability is calculated [19]. In the probability calculation, the influencing factors of enterprise capital accounting information are discretized into m intervals. In this population, the sign corresponding to the influencing factors of enterprise capital accounting information in component $V_{i,j}$ is the probability of $k_1 (0 \le 1 \le m)$.

$$P_1(V_{i,j}) = \frac{1}{N}\sum_{i=1}^{N} a_1 \tag{14}$$

Where, $a_1 = \begin{cases} 1 & g(V_{i,j}) = k_1 \\ 0 & \text{other} \end{cases}$。

In the early stage of evolution, most of the components in particle were generated randomly, so it was difficult to form a stable component. As the particles began to fly to the "two extreme values ", the concentration of marker symbol k_1 corresponding to the component $V_{i,j}$ in the particle swarm will be

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increased. When the concentration reaches a setting threshold, the component with the marker symbol k_1 can be extracted as a "vaccine". However, there may be several particles marked with the symbol k_1 in the position of component $V_{i,j}$, and the values of the allelic component $V_{i,j}$ are not equal. Therefore, the component $V_{i,j}$ corresponding to the particle with the largest fitness can be used as the value of storage capacity of the "vaccine".

② Vaccination. A particle is randomly selected from N new particles, and the value of position of allelic component $V_{i,j}$ in the extracted particle is replaced with the corresponding value $V_{i,j}$ of "vaccine". Thus, an inoculation is completed.

③ Generate a new generation of particles.After the vaccination and immune selection have been executed for q times (i.e., q vaccinations), a new generation of N particles are generated, and then the next iteration is carried out.

(6) Judge whether the stop condition is met. The stopping condition is usually determined by the maximum number of iterations and the required prediction accuracy. If the conditions have been met, the optimization is completed. If the conditions are not met, we can switch over to step (2).

3. Results

In order to verify the application performance of the capital accounting information disclosure model based on immune particle swarm optimization algorithm, the annual report data of companies in a province of China in 2018 was collected as the research sample. The data was from CSMAR database. After excluding listed companies in financial industry, companies with data missing and companies with abnormal data, 14 three-level indexes of listed companies in 2018, such as annual H index, Z index, management stock ownership ratio, board size, proportion of independent directors, separation of ownership and control, return on net assets, natural logarithm of total assets, ST or not, asset liability ratio, quick ratio, degree of operating leverage, total assets growth rate and auditor opinion, were collected. There are 232 observation data without considering cash dividend and stock return rate in every month. All of them constitute the original variables of the designed model.

Firstly, the parameter vector $\vec{\beta}$ in Formula (6) is estimated, and the significant influence of variable is judged by the model. Meanwhile, the variables that are not significant enough when the significance level is 5% are eliminated. The remaining variables after elimination are estimated again, and the goodness-of-fit test and prediction test are carried out. Finally, the conclusions can be drawn.

Ten bi-level measures are estimated and tested. The estimated results are shown in Table 1.

Table 1: Estimation results of all variables.

Variable	Coefficient	Standard error	Z-statistic	Test
Ownership structure	0.627416	0.342469	1.839046	0.0672
Board mechanism	0.182227	0.264649	0.692153	0.4906
Profit ability	-0.02334	0.044536	-0.535108	0.5938
Enterprise scale	6.39E-07	0.003846	0.000959	0.9999
Delisting pressure	0.119694	0.198065	0.607656	0.5453
Financial leverage	0.004346	0.002843	1.550919	0.1223
Solvency	0.059412	0.063129	0.957302	0.3401
Risk level	0.54611	0.445876	1.226699	0.2215
Growth	0.005286	0.003596	1.485858	0.1387
Audit opinions	0.005793	0.004383	1.299747	0.1948

Table 1 shows that the influence of board mechanism, profitability, enterprise size, delisting pressure, solvency and risk level on capital accounting information disclosure tendency is not significant, and some are extremely insignificant. Therefore, these factors can be eliminated in further estimation. The remaining four variables such as ownership structure, financial leverage, growth and design opinions are. The results are shown in Table 2.

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Table 2: Estimation results of the remaining four factor variables.

Variable	Coefficient	Standard error	Z-statistic	Test
Ownership structure	0.697767	0.321227	2.17371	0.0309
Financial leverage	0.005469	0.002279	2.142908	0.0145
Growth	0.006441	0.003463	1.889431	0.0601
Audit opinions	0.006886	0.004389	1.58476	0.1144

For 95% of the confidence level, Table 2 shows that only shareholding structure and financial leverage have significant impact on the disclosure tendency of capital accounting information, but the growth opportunity and audit opinion have a relatively significant impact.

In order to further verify the effectiveness of the designed model, we also conducted a Wald test on the assumption that the coefficients of factor variables such as board mechanism, profitability, enterprise size, delisting pressure, debt servicing ability and risk level are O at the same time. The test results are shown in Table 3.

Table 3: Wald test results.

Null hypothesis	C(3)=0;C(4)=0;C(5)=0;C(6)=0;C(8)=0;C(9)=0		
F-statistic	1.018302	Probability	0.415144
Chi square	6.104259	Probability	0.411846

The results in Table 3 show that the assumption that the coefficients of board mechanism, profitability, enterprise size, delisting pressure, debt servicing ability and risk level are all zero at the same time, so it is reasonable to delete these factor variables from the model.

Therefore, it can be confirmed that the result estimated by Formula (6) is:

$$F^{-1}(P) = 0.697 + 0.005 + 0.006 + 0.006 - 0.576 \tag{15}$$

In the formula, 576 is a fitting constant.

Thus, the equation that determines the probability of accounting information disclosure of enterprise capital is obtained.

$$\hat{y}^* = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{0.697+0.005+0.006+0.006-0.576} \exp\left(\frac{-t^2}{2}\right) dt \tag{16}$$

The fitting quality of model is an important aspect. For this model, it is not appropriate to use R^2 to evaluate the goodness of fit. Therefore, Hosmer-Lemeshow statistics is used to test the goodness of fit of the model. According to the prediction probability of model, the goodness of fit of H-L statistics test model is to divide all observation units into ten equal parts and then calculate according to the measured values and theoretical values of different values of each group of factor variables. The statistics is $Q_p = \sum_{k=1}^{s} \sum_{j=1}^{n} \frac{\left(A_{k_j} - T_{h_j}\right)^2}{T_{h_j}}$, where s represents the number of factor variables. h is the index of factor variables, and its value is from 1 to s. $j = 1, 2, \cdots, n$ indicates different values of dependent variable. n is the number of groups. A represents the actual value. T represents the analog value, and $Q_p \cdot x^2(n-2)$. The significance probability is 0.0562, which is greater than 0.05. Therefore, the goodness of fit is good.

Finally, we test the prediction ability of model. The results are shown in Table 4.

Table 4 :Test results.

	Model in this work		
	Drp=0	Drp=1	Total
P(Dep=1)<=Fitting constant	125	42	167
P(Dep=1)>Fitting constant	16	49	65
Total	141	91	232
Correct quantity	125	49	174
Accuracy/%	88.65	53.85	75.0
Error rate /%	11.35	46.15	25.0

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According to Table 4, the correctness of the results obtained by the designed model includes two cases

(1)Dep=0 and P(Dep=1)<= prediction results of fitting constants;

(2)Dep =1 and P(Dep=1)>prediction results of fitting constants.

There are 125 prediction results with Dep = 0 and P (Dep = 1) <= fitting constants and prediction results with Dep = 1 and P (Dep = 1) > fitting constants. The sum of the two is divided by the total number of samples (232), and the total accuracy is 75%. It can be seen that the prediction results of this model are satisfactory.

Finally, we can see the ownership structure, financial leverage, growth and audit opinion significantly affect the disclosure tendency of enterprise capital accounting information.

4. Discussions

The analysis results of this paper show that the two indicators representing enterprise strength, enterprise size and profitability, can not significantly affect the tendency of capital accounting information disclosure of enterprises, which shows that enterprise strength does not necessarily translate into enthusiasm for enterprise development. On the other hand, as representative enterprises in China, listed companies generally have strong comprehensive strength, and these two indicators have been implied in the characteristics of the sample as a whole, so the corresponding variables cannot have a large enough impact. Whether this conclusion is valid or not needs to be further tested in combination with the data of more non-listed companies. Another conclusion worth paying attention to is that the ownership structure of enterprises has the most significant impact on the tendency of capital accounting information disclosure, which undoubtedly provides the most important direction for promoting the construction of capital accounting information disclosure system in China. The third conclusion is that the indicators representing the growth potential of enterprises have a significant impact on the tendency of capital accounting information disclosure, which indicates that high-growth enterprises pay more attention to corporate transparency and effectively alleviate the information asymmetry between investors and enterprises in the market. The fourth conclusion is that the Chinese government does promote the implementation of enterprise development through the direct influence of state-owned shares on listed companies. However, it is an inevitable policy to reduce the holding of state-owned shares, which requires the government to strengthen the supervision and management of enterprises' capital work, so that investors' expected return on investment is reduced, so the financing cost of enterprises is correspondingly reduced, and as a result, enterprises have a better return on shares. It can be seen that the disclosure of high-quality enterprise capital accounting information can truly state the real situation, operating condition, financial risk and cash flow of the enterprise to the market and investors, which reduces the predicted risk of investors when making investment decisions, and then investors reduce the required rate of return.

5. Conclusions

(1) The capital accounting information disclosure of enterprises is the basis for the healthy and orderly operation and development of the securities market.

(2) The four factors of ownership structure, financial leverage, growth and audit opinion significantly affect the disclosure tendency of enterprise capital accounting information.

(3) The capital accounting information disclosure model based on immune particle swarm optimization algorithm is studied. The empirical results show that the application performance of this model is satisfactory.

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