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Implementation and Guarantee Model Construction of Financial BPO Cost Control under Cloud Computing Platform

Jie Gao[a]

[a]*Finance Department, Zhaoqing College, Zhaoqing, Guangdong, 526061, China. 115064055292@163.com*

Abstract. This paper takes Enterprise T as the research object and evaluates the implementation effect of the three measures of tax cost, labor cost and operation cost proposed in the financial cost control link based on the cost control principle of financial BPO project. It further proposes the operational safeguard measures for financial BPO cost control, and establishes the cost early warning model under the financial BPO project by combining BP neural network, support vector machine and similar body synthesis algorithm. After the implementation of cost control strategies, the tax cost of Enterprise T is reduced to 372,800,000, the talent recruitment cost is stabilized at about 300,000~500,000,000, and the operation cost is reduced by 5.59% compared with the previous year. Using the cost early warning model to forecast and warn the costs of Enterprise T for the four quarters of 2024, the enterprise's four quarters of 2024 are generally in a more reasonable range of growth, only the third quarter's costs are low at 5.419%, in the white light area, but the warning is not serious, Enterprise T only needs to put forward targeted measures to solve the problem.

Keywords. Financial BPO; BP Neural Network; Support Vector Machine; Similar Body Synthesis; Cost Early Warning Models

1. Introduction

In recent years, along with the rapid development of the economy, all kinds of enterprises at home and abroad are facing the severe challenges of the global economic situation downturn. As some enterprises and even listed companies also have poor financial cost control ability, more and more enterprises have a certain degree of financial crisis or even on the verge of bankruptcy, the traditional financial management mode, obviously has been unable to meet the needs of the development of today's economic system [1-2]. Due to the scarcity of professional talents in finance and taxation, cumbersome and redundant enterprise organizational structure, and the lack of financial process management factors, these have become a stumbling block to the development of enterprises. If the company seeks better development, it must keep the smooth operation of the financial process system, therefore, the enterprise must try to use scientific cost control means of management [3-4]. Reasonable development of financial cost control plan is also increasingly being emphasized by corporate executives, through the reasonable financial BPO outsourcing to continuously reduce cost expenditures and thus enhance the enhancement of the core competitiveness of the product, reduce unnecessary cost expenditures, and save costs for the enterprise [5-6]. BPO outsourcing under the cloud computing platform not only saves time and cost, helps to improve the efficiency of the staff and the productivity of the enterprise, but also helps the enterprise to greatly open up new core revenue areas, in a better position to rationally allocate and utilize resources to expand other projects and core business.

Literature [7] presents a framework for business process outsourcing to the cloud that covers the outsourcing process lifecycle, detailing the phases associated with outsourcing decisions to minimize business process costs, duration and mitigate cloud risks. Literature [8] describes a comprehensive decision support that can help organizations to outsource their business processes by considering criteria of security, cost and performance to be able to make the decision correctly and quickly with reduced risk. Literature [9] designed and implemented a

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business process outsourcing cloud for insurance industry services to address the huge market demand in China, and gave the operation model and management model of the insurance industry service outsourcing cloud through cloud computing ecosystem to bring new changes in the insurance industry. Literature [10] studied the complex business process outsourcing cloud computing platforms for banking and insurance industries, focusing on their virtualization security, cloud data security, access control, and cloud auditing to satisfy specific security requirements. Literature [11] improves the market competitiveness of enterprises by improving cost management, using cloud computing technology in targeted business process outsourcing cost management to form a market-oriented cost control strategy, which fundamentally solves the problem of controlling the financial costs of enterprises. Literature [12] aims to explore the impact of outsourcing on firm performance, emphasizing the importance of implementing cost control policies within a company's organization as a way to achieve optimal results in terms of profitability and overall organizational success.

Based on the principle of financial BPO cost control, this paper proposes corresponding control strategies for three aspects of tax cost, labor cost and operation cost of T enterprise, and evaluates the implementation effect of the strategies. Combined with the actual characteristics and countermeasures of financial BPO cost control of Enterprise T, it puts forward the safeguard measures in three aspects, namely, formulating cost control standards, establishing business continuity management, and constructing cost early warning analysis model. Focusing on the cost alert model, it integrates BP neural network, support vector machine and AC algorithm to complete the construction of cost alert model. After two stages of cost warning alert and intensity analysis, the optimal length of the AC model is tested, and further cost warning prediction is carried out with the help of the AC model of this pattern length.

2. Financial BPO Cost Control Strategy and Implementation

2.1. BPO Cost Control

2.1.1. Meaning of BPO

Business Process Outsourcing (BPO), a subset of outsourcing, involves contracting specific business process operations and responsibilities to a third-party service provider. Initially, manufacturing companies in particular tend to choose to outsource their business processes, such as Coca-Cola, which has outsourced most of the business modules of its supply chain management to a BPO [13]. BPO is usually categorized into two types.

1. Back-office BPO outsourcing, including the outsourcing of business functions, such as financial accounting, procurement, human resources BPO outsourcing.

2. Front office BPO outsourcing, including customer service and other services such as sales or IT technical support outsourcing.

BPO can also be based on the location of the outsourcing service provider to distinguish between the following three categories.

1. Offshore BPO outsourcing, refers to the company signed outside the BPO outsourcing project.

2. Nearshore BPO outsourcing, refers to the company's neighboring (or nearby) countries to enter into a BPO contract outsourcing projects.

3. Onshore BPO outsourcing refers to the company's business BPO outsourcing to domestic contractors.

2.1.2. BPO Project Cost Control Principles

1. Cost minimization principle. The purpose of project cost control in the construction phase is to reduce the cost of project construction through technical, economic and other means, in order to achieve cost minimization and meet the requirements of the cost target. This stage seeks the possibility of cost reduction and reasonable cost minimization. First of all, an enterprise cannot blindly pursue cost minimization at the expense of the project's functionality and structural safety; according to the actual situation, a cost control program must be developed to meet the design and specification requirements. Secondly, the organization should build a management consciousness of cost reduction and explore ways to reduce cost.

2. Comprehensive cost control principle. Cost management is, within the scope of an enterprise, a whole-staff participation in the whole process of management, also known as “three full” management. The cost control system of the entire project has substantial content, including all departments, the responsibility of the leadership and the

team's responsibilities; cost control is everyone's responsibility, avoiding the emergence of a situation where no one takes ownership. Cost control requirements apply to the whole process across all stages of the construction project, with continuous advancement of the project, neither omission nor laxity, so that the construction project achieves effective cost control from beginning to end.

3. Dynamic control principle. Due to the special nature of the project, and the existence of variable factors during implementation, cost control should achieve dynamic management, preventing a situation in which the cost objectives set at the preliminary preparation stage cannot be achieved upon project completion — in particular where there is a large discrepancy that causes cost losses to the company. In the process of dynamic control, deviations should be identified in a timely manner, and all parties should actively organize effective control measures, thereby reducing the chances of cost increase.

4. Target management principle. In the early stage of project implementation, the project cost target should be decomposed, not only assigned to each department but also divided into the daily responsibilities of each manager, so that target responsibility is in place. In the process of effective control, phased evaluation of the target and corrective action form the target management technology, implementation, inspection and processing cycle, that is, the PDCA cycle method.

2.2. T Corporate Finance BPO Cost Control Strategies and Implementation

Today's BPO outsourcing business has entered a period of growth, accompanied by the expansion of the BPO industry among developing countries and the challenges of competitiveness, so the main part of the BPO financial cost control is that enterprises should start from the basic, low-risk business gradually outsourcing. T enterprise divides the main financial cost control links into three parts: tax costs, labor costs, and operating costs.

2.2.1. Tax cost control strategies

Reduce tax costs by outsourcing the finance BPO process and standardize the invoicing and payment process to avoid unprocessed business with excessively long billing periods. After outsourcing the finance BPO, the division of labor is divided according to the standard process and the staff's job responsibilities are refined.

For accounts payable accounting positions, a clear division of duties is conducive to improving the overall management of tax cost control in T enterprises [14]. To refine the division of labor is simply to arrange a group of financial staff to be responsible for the timely recording of invoices, while another group of financial staff is only responsible for payment processing, tax payment declarations and answering suppliers' inquiries. The finance BPO outsourcing tax cost control research solution strategy is mainly implemented through the payment of value-added tax, income tax and other taxes, accounting deadlines and supervision of BPO outsourcing cost control. Figure 1 shows the tax cost comparison of Enterprise T from 2019 to 2023 (unit: thousand yuan). Through the financial BPO cost control initiatives, standardization and clarification of the financial work responsibilities and division of labor, after the financial BPO outsourcing (May 2022), T enterprise's tax costs have been significantly reduced. For the year 2022, the tax cost of Company T was reduced to $372.8K from the annual high of $824K after the BPO outsourcing program. The implementation of the financial BPO outsourcing project used BPO financial outsourcing together with the implementation of tax cost control business process standardization and reform and centralization of financial work; through the combined use of these two approaches, tax costs were naturally significantly reduced.

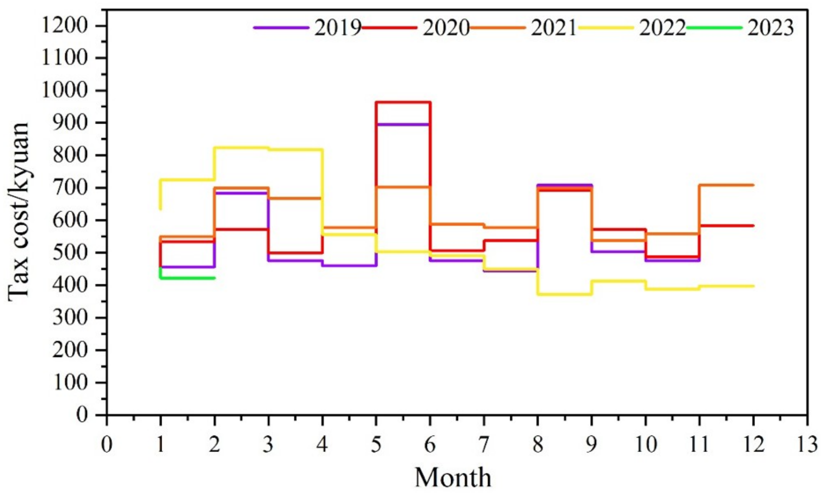

Figure 1. The tax cost comparison of 2019–2023 by T enterprise

2.2.2. Human cost control strategies

Studies have shown that the most effective way to reduce labour costs is to achieve the highest operational performance with the least number of personnel by simplifying the organizational structure, streamlining staffing, enhancing vocational training, streamlining and optimizing work processes and strengthening overtime control [15].

In order to better propose labor cost control strategies, Enterprise T turns to finance BPO outsourcing contractors; labor cost control can be carried out in the following areas: expanding the scope of responsibilities to control recruitment costs, streamlining expatriates to control placement costs, and controlling overtime activities to reduce the cost of overtime. Figure 2 shows the recruitment costs of Enterprise T for the years 2019–2023.

Compared with the recruitment cost data of previous years, the chart of data comparison shows that manpower cost consumption was high up to May 2022, reaching a peak of 3,500,095,000 in 2022; in addition to T enterprise recruiting a number of foreign workers, the general development of the economy also increased the cost of labor. The manpower cost control strategy adopted by T enterprise for headhunting recruitment cost reduction not only achieved the manpower cost control objectives set by T enterprise, but also provided the conditions for the efficient completion of business work. The cost control strategy to reduce headhunter recruitment costs within T enterprise's labor cost, in addition to achieving the labor cost control target, provided a prerequisite for the efficient completion of business work: after the drop in July, the recruitment cost was controlled at about 300~500 thousand.

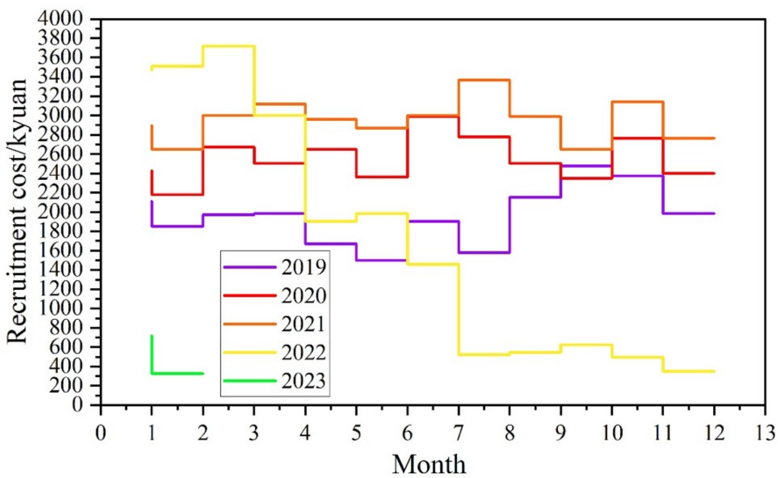

Figure 2. Recruitment cost of T Enterprise in 2019–2023

2.2.3. Operation cost control strategies

In the face of the two major problems plaguing the operation cost control and management of T enterprises — how to confirm the receivables deposit and travel reimbursement of operating cost control — these will be solved through financial BPO outsourcing [16]. With the help of financial BPO outsourcing, this opportunity fully rationalizes the company's financial work business processes, analyzes the links between the various departments of the business and, if necessary, undertakes business process reorganization, so that business processes are transmitted between each other in the fastest optimized form; it is also necessary to identify where the enterprise value chain lies, analyze the various elements that constitute the cost, and strengthen cost control through process optimization. According to the data in the previous chapter, it can be found that after the financial BPO outsourcing work, Company T can control operating costs smoothly.

Figure 3 shows the 2019–2023 operating costs of enterprise T. During the period of 2019–2022, operating costs accounted for a high proportion of the company's cost items, and the choice of the financial BPO outsourcing strategy correspondingly saved operating costs for enterprise T. Since travel costs are a large part of the cost management module of enterprise T, the financial BPO outsourcing strategy — with the advantages of its unique process-efficiency management — has enhanced the speed and accuracy of travel reimbursement processing, which is a cumbersome and heavy workload in enterprise T. After the formal delivery of the financial BPO outsourcing in May 2022, the operating cost of Enterprise T was reduced by at least 5.59% on average in comparison with 2021.

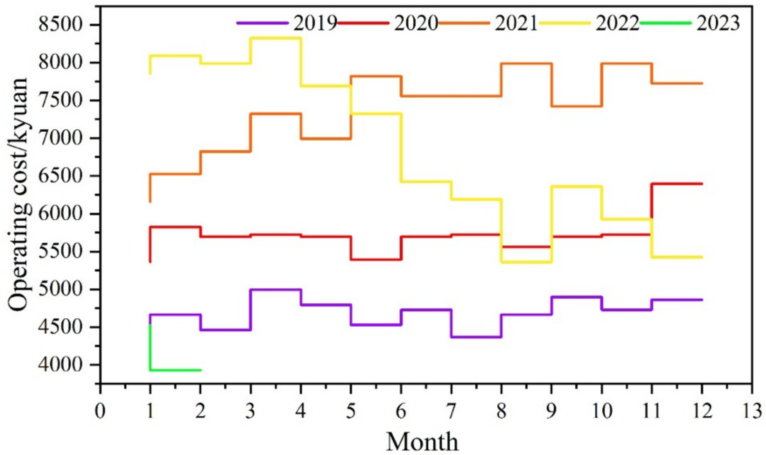

Figure 3. T enterprise 2019–2023 operating costs

3. T Corporate Finance BPO Cost Control Assurance Strategies

3.1. Financial BPO Cost Control Assurance Pathway

While BPO offshore or nearshore outsourcing has the advantages of good quality, high efficiency and low cost, there are also relative risks, such as data security protection issues, cost control analysis confusion, key personnel jumping ship and leaving, loss of business knowledge, knowledge transfer issues, ignoring corporate governance and regulations, and cross-border cultural differences, etc. In order to ensure the quality and efficiency of the financial BPO outsourcing of T enterprise, and to achieve the expected goals of the T enterprise group, it is essential to formulate relevant BPO cost control protection strategies. In the long run, in order to ensure that the choice of financial BPO outsourcing of T enterprises can be carried out smoothly and successfully, the formulation of corresponding cost control standards is the basis and prerequisite for the implementation of financial BPO outsourcing cost control, combined with the actual characteristics of the financial BPO cost control of T enterprises and the solution to the problem.

3.2. Cost Early Warning Model

3.2.1. BP Neural Networks

Neuron is the most basic component of a BP neural network and a nonlinear multi-input–output information processing unit. Figure 4 shows a typical neuron model.

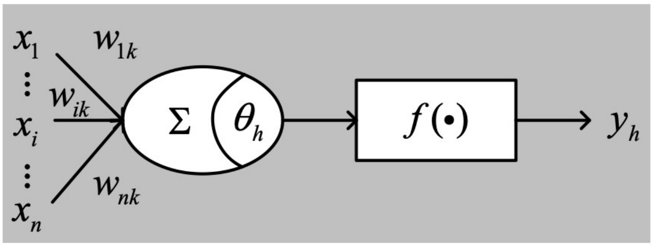

Figure 4. Neuron model

In Figure 4, $x = (x_1, x_2, \ldots, x_n)$ is the input information, wih is the weight corresponding to each input information, θk is the threshold value, f(·) is the transfer function, and yh is the output information. The relationship between inputs and outputs can be expressed as follows.

$$y_h = f\left(\Sigma^i w_{ik} x_i - \theta_h \right) \quad (1)$$

Generally, the S-type function is one of the more commonly used transfer functions, which can reflect the saturation properties of neurons. The expression of the S-type function is as follows.

$$f(x) = 1 / (1 + e^{-ax}) \quad (0 < f(x) < 1, a \text{ is constant}) \quad (2)$$

The thresholds of the neurons in each layer of the hidden and output layers are θh and γt respectively. The transfer function is f(·) and the error function is:

$$e(k) = (1/2) \Sigma_{t=1}^{q} \left(d_t(k) - yo_t(k) \right)^2 \quad (3)$$

The specific steps of the BP neural network algorithm are as follows.

Step 1. Initialization is done by assigning random initial values (0,1) to the connection weights and thresholds, and setting the computational accuracy value ε and the maximum number of learning times M.

Step 2. The k-th sample is chosen randomly, so that $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))$ is the input variable and $d(k) = (d_1(k), d_2(k), \ldots, d_q(k))$ is the corresponding expected output.

Step 3. The inputs and outputs of each neuron in the hidden and output layers are calculated for the k-th sample:

$$hi_h(k) = \Sigma_i w_{ih} x_i(k) - \theta_h \quad (h = 1, 2, \ldots, p) \quad (4)$$
$$ho_h(k) = f[hi_h(k)] \quad (h = 1, 2, \ldots, p) \quad (5)$$
$$yi_t(k) = \Sigma_h u_{ht} ho_h(k) - \gamma_t \quad (t = 1, 2, \ldots, q) \quad (6)$$
$$yo_t(k) = f(yi_t(k)) \quad (t = 1, 2, \ldots, q) \quad (7)$$

Step 4. Based on the actual output and the desired output, the partial derivatives of the error function for each neuron in the output layer are calculated as $\delta_t(k)$, i.e. the generalized error for each output neuron:

$$\delta_t(k) = [d_t(k) - yo_t(k)] \cdot yo_t(k) \cdot [1 - yo_t(k)] \quad (t = 1, 2, \ldots, q) \quad (8)$$

Step 5. The partial derivatives of the error function with respect to each hidden-layer neuron δh(k), i.e. the generalized error of each hidden-layer neuron, are calculated from $\delta_t(k)$, the connection weights of the hidden layer to the output layer, and the hidden-layer output calculated in Step 4:

$$\delta_h(k) = [\Sigma_t \delta_t(k) u_{ht}] \cdot ho_h(k) \cdot [1 - ho_h(k)] \quad (9)$$

Step 6. The connection weights uht and wih, and the thresholds γt and θh, are corrected according to Steps 4 and 5 respectively:

$$u_{ht}: u_{ht}^{N+1}(k) = u_{ht}^{N}(k) + \beta \delta_t(k) ho_h(k) \quad (10)$$
$$\gamma_t: \gamma_t^{N+1}(k) = \gamma_t^{N}(k) + \beta \delta_t(k) \quad (11)$$
$$w_{ih}: w_{ih}^{N+1}(k) = w_{ih}^{N}(k) + \eta \delta_h(k) x_i(k) \quad (12)$$
$$\theta_h: \theta_h^{N+1}(k) = \theta_h^{N}(k) + \eta \delta_h(k) \quad (13)$$

where N represents the number of iterations, β and η are correction coefficients, with $0 < \beta < 1$, $0 < \eta < 1$.

Step 7. The global error E is calculated, i.e.:

$$E = (1/2m)\ \Sigma_{k=1}\text{^}m\ \Sigma_{t=1}\text{^}q\ (\ d_t(k) - y_t(k)\ )^2 \quad (14)$$

Step 8. Determine whether the global error E is smaller than the established error ε. If E < ε, or the number of learning times exceeds M, end the training; otherwise, return to Step 3 and continue training.

3.2.2. Support vector machines

For the training sample set (xi, yi), i = 1, …, n, where the input variable xi ∈ R^n and the output value yi ∈ R, the basic idea of support vector machine regression is to find a nonlinear mapping Φ from the input space to the output space and, using this mapping, map the data X to a high-dimensional feature space F and regress it in the feature space with the following linear function:

$$f(x) = [w \cdot \varphi(x)] + b \quad (\Phi\!: R^m \rightarrow F;\ w \in F;\ b \text{ is the threshold}) \quad (15)$$

Let the insensitivity coefficient of the loss function be ε. Since the ε-insensitive loss function has better sparsity, the loss function is:

$$e = 0 \text{ if } |y - f(x)| \le \varepsilon;\ \ |y - f(x)| - \varepsilon \text{ if } |y - f(x)| > \varepsilon \quad (16)$$

If, after regression training, the difference between the constructed estimating function value f(x) and the decision value y is less than ε (any given positive number), then the loss is zero.

1. Linear support vector machine regression. This finds the method that minimizes the empirical risk, obtaining the optimal w and b. Assuming that the linear function can fit all training samples:

$$\min (1/2)\|w\|^2, \text{ s.t. } w\cdot xi + b - yi \le \varepsilon,\ \ yi - w\cdot xi - b \le \varepsilon \quad (i = 1,\dots,n) \quad (17)$$

Introducing slack variables ξi ≥ 0 and ξi* ≥ 0, with penalty factor C > 0 for samples exceeding the precision ε, Eq. (17) can be rewritten as:

$$\min (1/2)\|w\|^2 + C\Sigma_i(\xi_i+\xi_i^*), \text{ s.t. } w\cdot xi+b-yi\le\varepsilon+\xi_i,\ \ yi-w\cdot xi-b\le\varepsilon+\xi_i^* \quad (18)$$

Introducing Lagrange multipliers, the dual form of Eq. (18) is obtained from the saddle-point theorem as:

$$\max -(1/2)\Sigma_i\Sigma_j(a_i-a_i^*)(a_j-a_j^*)(x_i\cdot x_j) + \Sigma_i y_i(a_i-a_i^*) - \varepsilon\Sigma_i(a_i+a_i^*) \quad (19)$$

where ai, ai* are the Lagrange multiplier of sample point xi and the optimal solution of Eq. (18). The optimal weights w* and b* of the original problem are obtained as:

$$w^* = \Sigma_i\ (a_i-a_i^*)\ x_i \quad (20)$$

$$b^* = -(1/2)\ w^*\cdot(x_i+x) \quad (21)$$

Thus, based on w* and b*, the regression function is given by:

$$f(x) = \Sigma_i\ (a_i-a_i^*)(x_i\cdot x) + b^* \quad (22)$$

The input samples corresponding to a non-zero (ai−ai*) in Eq. (22) are the support vectors that the model is looking for.

2. Nonlinear support vector machine regression. Nonlinear SVM regression maps the input sample xi to the high-dimensional feature space F through ψ: x → F, constructing the optimal hyperplane in feature space by performing the inner-product operation on xi. Generally, the inner product can be realized by a kernel function k(xi, x), and the dual form of Eq. (18) becomes:

$$\max -(1/2)\Sigma_i\Sigma_j(a_i-a_i^*)(a_j-a_j^*)k(x_i\cdot x_j) + \Sigma_i y_i(a_i-a_i^*) - \varepsilon\Sigma_i(a_i+a_i^*) \quad (23)$$

where ai, ai* is the Lagrange multiplier of sample point xi and the optimal solution of Eq. (22), from which:

$$w^*\cdot x = \Sigma_i\ (a_i-a_i^*)\ k(x_i, x) \quad (25)$$

$$b^* = -(1/2)\ \Sigma_i\ (a_i-a_i^*)\ [k(x_i,x_r) + k(x_i,x_s)] \quad (26)$$

where xr and xs are arbitrary vectors satisfying different constraints. Thus, the regression function is obtained as follows:

$$f(x) = \Sigma_i\ (a_i-a_i^*)\ k(x_i\cdot x) + b^* \quad (27)$$

3.2.3. Similar Body Synthesis (AC) Algorithm

Generally, the AC algorithm consists of the following steps.

Step 1: Generation of the pattern to be selected. Assuming that the study sample data has a real-valued m-dimensional sequence of N observations xi = {x1t, …, xmt} (t = 1, 2, …, N), i.e., each row of the matrix represents a sample data point and each column represents an indicator, a pattern Pk(i) is defined as a table containing k rows starting from row i, where k is called the pattern length (i = 1, 2, …, N−k+1):

$$P_k(i) = [x_{1i} \dots x_{mi}; \dots ; x_{1,i+k-1} \dots x_{m,i+k-1}] \quad (k \times m) \quad (28)$$

The selection of pattern length is generally a difficult problem; in practical applications, a suitable pattern-length interval k ∈ [kmin, kmax] is chosen according to the specific situation, considering all patterns.

Step 2: Transformation of the selected pattern. To transform the selected patterns to the same reference point as the reference pattern in order to make them comparable, a linear transformation is usually taken as the transformation between patterns:

$$T_i[P_k(i)] \text{ transformed via } \dot{x}_{l,j+j} = a_{i_0 l} + a_{i_1 l}\, x_{l,j+j} \quad (j=0,\dots,k-1;\ i=1,\dots,N-k+1;\ l=1,\dots,m) \quad (29)$$

Parameter ai_1i is the difference in state between the similar pattern and the reference pattern, and parameter ai_0i is the uncertainty. The data corresponding to the reference model is used as the target value, and the least-squares method is used to estimate, for each to-be-selected pattern, the unknown weights, and the sum of squared errors used to judge pattern similarity is calculated:

$$\text{(least squares estimation of } a_{i_0 l},\ a_{i_1 l} \text{ for each candidate pattern } P_k(i)) \quad (30)$$

Step 3: Selection of similar patterns. This step recognizes the similarity between pattern shapes (“pattern similarity”). To measure the similarity between the reference pattern PR and the transformed candidate pattern Pk(i), the distance between the i-th candidate pattern and the reference pattern is calculated:

$$d = 1/(k+1)\ \Sigma_{j=0}\text{^}(k-1)\ \Sigma_{r=1}\text{^}m\ (x_{r,i+j} - x_r,N-k+j+1)^2 \quad (31)$$

The similarity between the two patterns is then si = 1/di. The larger the distance value, the smaller the similarity of the patterns.

Step 4: Extension of similar patterns is combined to obtain predictions. Assuming F similar patterns of pattern length k have been selected, A_1, A_2, …, A_F, with reference pattern PR, and corresponding variables to be predicted Y_1, Y_2, …, Y_F and YR (k-dimensional column vectors), the linear GMDH model is used and denoted as follows:

$$Y_r = \Sigma_j{\in}J\ g_j\ Y_j \quad (32)$$

where J is a subset of {1, 2, …, F}, and gj is the weight coefficient of the corresponding model; if gi = 0, model Yj does not appear in the combination. When k×m is very small, the weights {gi} are taken as equal weights with Σgj = 1, i.e.:

$$y\_\{N+1\} = \Sigma_{j=1}\text{^}F\ g_j\, y\_\{j+k+i-1\} \quad (i = 1, 2, \dots, \tau) \quad (33)$$

In this case, the prediction range is τ, and the extensions of the variable to be predicted in the reference model and the similar model, yN+1 and yj+k+i−1 respectively, are combined to obtain the final prediction from the F similar models.

3.2.4. Cost Early Warning Modeling

Figure 5 shows the cost early warning model, mainly through the first stage of the BP–SVM model to analyze the alertness and intensity of the cost alert of enterprise T, and then combined with the second stage of the AC algorithm to predict the future cost alert of enterprise T. According to the results of the two-stage early-warning research and the current situation of enterprise T, corresponding measures to solve the problem are proposed.

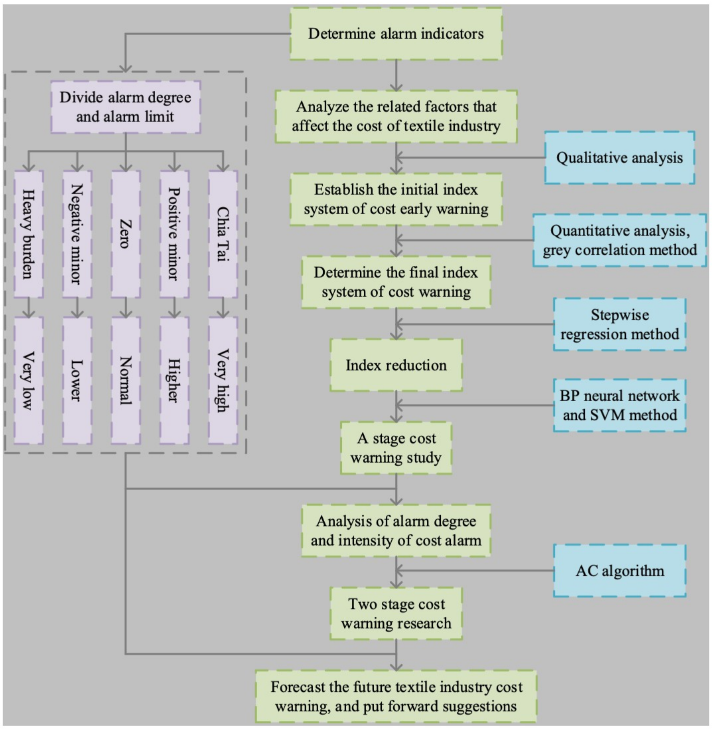

Figure 5. Idea diagram of constructing the cost early warning model

3.3. Early warning effect of the financial BPO cost control model

3.3.1. Data pre-processing

Considering the availability and continuity of the sample data, this paper preliminarily analyzes the degree of correlation between main business income, main business cost, main business tax and surcharge, rent, current asset turnover times, labor wages, national income, consumption level of urban residents, management expenses, inventory turnover rate, and the two alarm indicators — cost growth rate and cost amount — across the 20 quarters from 2019 to 2023. Five indicators — main business income, main business cost, rent, labor wages and inventory turnover rate — were selected as the input variables of the BP-SVM-AC early warning model, and the cost growth rate was used as the output variable. The sample data of the 20 quarters from 2019 to 2023 were used as the training sample set of the model, and the sample data of the 4 quarters of 2024 were used as the test sample set, allowing the first-stage and second-stage cost early warning models of the enterprise to be developed.

1. Analysis of the alertness and intensity of first-phase cost alarms. Based on the distribution of cost and expense growth rate in the sample data of the enterprise for the 20 quarters from 2019 to 2023, and the principles of minority, majority and half, together with the application of certain statistical tools, the alert level for the enterprise's cost and expense growth rate is classified into five risk warning levels — white, blue, green, yellow and red — corresponding to very low, low, normal, high and very high alert. The white light indicates a very low alert, the blue light a low alert, the green light a normal alert, the yellow light a high alert, and the red light a very high alert. Table 1 shows the scope of this categorization.

Risk level	**1**	**2**	**3**	**4**	**5**
Signal light	White light	Blue light	Green light	Yellow light	Red light
Comprehensive warning limit degree (%)	$(-\infty,6.88]$	$(6.88,9.85]$	$(9.85,19.25]$	$(19.25,23.55]$	$(23.55,+\infty]$

Table 1. Warning limit of cost growth rate

2. Analysis of the alertness and intensity of two-stage cost alarms. The warning indicators of main business revenue (X1), main business cost (X2), rent (X5), labor wage (X8), inventory turnover ratio (X12), and cost growth rate (Y1) and cost amount (Y2) are used as input and output variables, respectively, of the BP-SVM-AC early warning

model, based on the sample data of the 20 quarters from 2019–2023. Since the input variables of the AC model involve some macroeconomic variables, and the cyclicality of China's economic fluctuation is roughly around 5 years, the pattern length of the AC model was set as k ∈ [2,5], producing predicted values for Q4 of 2023. Table 2 shows the predicted values of each variable in Q4 of 2023 (after indexation). It can be seen that when the pattern length of the AC model is 5, the cost and expense growth rate is smallest at 113.211%, while the predicted values of the other indicators are 128.364, 119.365, 118.265, 108.699 and 108.265.

k	Y1	X1	X2	X5	X8	X12
2	116.214	112.324	115.514	116.215	109.254	121.265
3	116.524	123.487	114.325	117.896	117.295	119.254
4	117.625	125.365	127.584	115.265	114.598	114.565
5	113.211	128.364	119.365	118.265	108.699	108.265

Table 2. Predicted values for variables (after indexation) — 2023.Q4

3.3.2. Predicted versus actual values

Table 3 shows the predicted and actual values of each variable in 2023.Q4 (after indexation). From Table 3, it is not difficult to find that when the model length is 4, the prediction error of each variable in the AC model is smallest, and the prediction effect is best: the predicted value of the total cost in 2023.Q4 is 15,638,800 yuan. Therefore, the AC model with this pattern length can be used for the cost warning of the enterprise in the coming year (i.e., 4 quarters).

	Y2	X1	X2	X5	X8	X12
2024.Q4 Actual value (10k yuan)	1578.56	4875.36	1074.56	184.36	56.21	3.45
Predicted value (k=2)	1795.26	4123.55	1123.58	185.66	64.25	3.25
Predicted value (k=3)	1647.26	4678.52	1174.69	172.55	58.48	3.87
Predicted value (k=4)	1563.88	4915.15	1065.26	167.45	55.36	3.55
Predicted value (k=5)	1452.36	4875.56	1045.96	185.74	43.15	5.45
Relative error (%) k=2	14.59	6.24	6.26	1.633	10.96	3.17
Relative error (%) k=3	8.26	4.26	11.26	6.26	2.34	4.55
Relative error (%) k=4	2.36	2.79	0.98	0.24	2.07	2.86
Relative error (%) k=5	3.21	0.48	1.58	9.264	24.96	48.56

Table 3. Predicted and actual values for each variable (after indexation) — 2023.Q4

3.3.3. Cost vigilance forecast

Table 4 shows the cost alert prediction for the four quarters of 2024. Through this prediction, the enterprise's cost and expense growth rate for the four quarters of 2024 falls within a more reasonable growth range; only the third quarter's cost and expense growth rate is low, at 5.419%, in the white-light area, but the alert is not particularly serious. The actual situation of the third quarter can then be used to observe the impact of cost-related factors and put forward targeted solutions. However, in terms of the overall forecast trend, in 2024 the enterprise's costs and expenses for the four quarters are generally in a state of growth.

Quarter	Total cost – predicted value after normalization	Cost expense growth rate (%)	Alarm degree
2025.Q1	1678.2654	7.314%	Blue light area
2025.Q2	1876.5659	11.816%	Green light area
2025.Q3	1978.2654	5.419%	White light area
2025.Q4	2146.7966	8.519%	Blue light area

Table 4. Cost warning forecast for quarters 1–4 of 2024

4. Conclusion

According to the principle of financial BPO cost control implementation, this paper proposes the financial BPO cost control strategy for the test enterprise T from three aspects — tax cost, human cost and operation cost — and analyzes its implementation effect. It proposes the realization path of financial BPO cost control guarantee, integrates the BP neural network, support vector machine and AC algorithm, constructs the financial BPO cost warning model, and predicts the cost vigilance of enterprise T.

1. After the implementation of the cost control strategy, the financial BPO tax cost of T enterprise in 2022 dropped from the highest value of 824,000 yuan to 372,800 yuan. After 2 months of implementation, the recruitment cost of talents was controlled at about 30~500,000 yuan. The operating cost was reduced by about 5.59% compared with the year before implementation.

2. When the step length of the AC model is 4, the prediction error of each variable is smallest and the prediction effect is best; at this length, the predicted value for the 4th quarter of 2023 is 15,638,800 yuan, and the cost warning of the next year can be carried out with the help of the model of this length. The cost alert prediction for T enterprise's 1st–4th quarters of 2024 shows that only the 3rd quarter's cost and expense growth rate is low, at 5.419%, in the white-light area, but the alert is not serious; T enterprise can combine the actual situation of the 3rd quarter and put forward targeted measures to solve the problem.

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