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Accounting and Financial Risk Management in the Funding Model for Government-Sponsored Affordable Housing Construction

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Abstract The construction of government-sponsored affordable housing projects requires a significant amount of capital, poses challenges in accounting and financial management, and entails high financial risks. This paper establishes a financial risk warning indicator system for affordable housing construction funding. Through the KW test, indicators that fail to pass the significance test are excluded. Factor analysis is then employed to streamline the indicators, identifying seven common factors: funding security, cost control, project management, operational efficiency, government compliance, market and external environment, and social impact. The extracted public factors are used as input variables for the BP neural network, forming a financial risk warning model for government-sponsored affordable housing construction based on the SSA-BP neural network. The financial risk prediction performance of the model was evaluated. The accuracy rate, recall rate, F1 score, and precision rate of the SSA-BP neural network model in this study were 93.2%, 96.1%, 92.8%, and 93.4%, respectively, all higher than those of the compared BP neural network model, logistic regression model, and KNN model, demonstrating excellent predictive performance.

Index Terms K-W test, factor analysis, BP neural network, Sparrow Search Algorithm, financial risk, affordable housing

I. Introduction

Affordable housing is a national initiative aimed at addressing the housing challenges faced by low- and middle-income individuals. It is a critical social welfare project that plays a significant role in maintaining social stability and effectively enhances public well-being and security [1]-[3]. Currently, the number of affordable housing construction projects in China is increasing, which brings economic benefits to construction companies while also posing financial risks due to the substantial capital requirements [4], [5].

Affordable housing construction is a public welfare housing project. Due to its non-profit nature, the project requires substantial funding from multiple sources, resulting in relatively complex accounting calculations. Regulatory authorities and fund providers also impose stricter requirements on accounting information disclosure [6]-[9]. This makes it challenging for construction companies to manage project funds, thereby increasing the likelihood of financial risks [10], [11]. Therefore, strengthening accounting and financial risk management in affordable housing construction is essential for the stable development of society [12], [13]. This requires companies to enhance financial risk management throughout the construction process [14]. First, it is necessary to strengthen price approval management, standardize price reporting and approval processes, ensure the standardization of price reporting, and reduce the occurrence of financial risks [15]-[17]. Second, it is necessary to strengthen management of the entire construction process of building projects [18]. This involves comprehensive management of project quality, construction safety, and construction schedules, collaborating with multiple parties to effectively mitigate risks [19], [20]. When signing contracts, it is essential to clearly define the responsibilities of all parties in the contract to reasonably allocate financial risks and reduce the financial risk exposure of construction companies [21]-[23]. Additionally, companies should strengthen management of construction project design to prevent arbitrary changes to project designs, which could increase the likelihood of financial risks for the company [24], [25].

Literature [26] highlights the positive development of housing security initiatives in China, but also identifies challenges such as oversupply, significant government fiscal pressures, and difficulties in securing construction funding. Based on this analysis, the paper proposes the involvement of social capital through mechanisms like REITs and PPPs in affordable housing construction, summarizes three construction models, and offers policy recommendations. Literature [27] emphasizes that high-rise building projects face numerous financial and economic risks, yet these risks receive little attention. By identifying risk factors and response measures, it demonstrates that “financial issues caused by estimation errors” are a significant factor contributing to financial and economic risks. Reference [28] introduces the current status of government-provided affordable housing and proposes ideas for cooperative housing, cooperative production, and supporting financing mechanisms aimed at supporting affordable housing. Reference [29] examined the risks associated with private sector participation in affordable housing and supporting infrastructure investment, as well as strategies to mitigate those risks. Based on a literature review, it concluded that market dynamics, construction material costs, and financial factors constitute risks to affordable housing. Reference [30] examined key aspects of strategic planning and investment analysis in the context of affordable housing. The study pointed out that both played an important role in promoting the implementation of affordable housing programs, effectively reducing risks and improving housing stability for populations affected by inadequate services.

This paper adopts a multi-faceted approach, considering aspects such as funding, debt repayment capacity, construction costs, project progress, and operational sustainability, to select 25 financial and non-financial indicators for the construction of a financial risk warning model for government-subsidized housing projects. The KW test method is proposed, where the P-value is calculated based on the value of the statistical quantity and the degrees of freedom, to determine whether there are significant differences between samples, thereby excluding financial risk warning indicators that fail the significance test. Factor analysis is employed to simplify the indicators, calculate factor loadings, and perform factor rotation to obtain the rotated component matrix, with the extracted common factors named accordingly. The obtained common factors are used as input variables for the BP neural network, with the structure of the input layer, hidden layer, and output layer determined, and the activation functions and mathematical expressions for the neurons defined. The Sparrow Search Algorithm (SSA) is used to simulate the sparrow's foraging process to find the optimal parameters in the mathematical expression of the BP neural network, thereby constructing a financial risk warning model for the funding of affordable housing construction based on the SSA-BP neural network. The SSA-BP neural network model is trained and tested with the unoptimized BP neural network as a comparison, and the financial risk prediction results of the two are compared. Four metrics—precision rate, recall rate, accuracy rate, and F1 score—were used, with the BP neural network model, Logistic regression model, and KNN model selected as comparison objects to validate the predictive performance of different evaluation models. Finally, specific countermeasures for controlling financial risks in affordable housing projects were proposed.

II. Financial Risk Warning Indicator System for Government-Supported Housing Construction Funds

Housing security is an important component of the national social security system and represents the most basic living security needs of the general public. Under the government's affordable housing construction funding model, funding sources are diverse, and the massive funding requirements have increased the complexity of accounting calculations and financial risks. This chapter will use the K-W test and factor analysis as theoretical foundations to establish a financial risk warning indicator system for government affordable housing construction funding.

II. A. Sample Selection and Data Sources

This paper takes Shanghai, China as the subject of study, and the data comes from the “China Statistical Yearbook,” “China Statistical Yearbook,” “China Land Resources Yearbook,” “Financial Institutions Annual Report,” “China Housing Provident Fund Annual Report,” etc. from 2017 to 2023.

II. B. Research Methods

This chapter establishes a financial risk warning indicator system for government-subsidized housing construction funds, employing research methods such as K-W tests and factor analysis.

II. B. 1) K-W test method

(1) Basic Principles of the K-W Test

The Kruskal-Wallis test (abbreviated as “K-W test”) is a nonparametric statistical method used to compare whether the median values of two or more independent samples are equal [31]. It is suitable for cases where the sample data does not follow a normal distribution or have equal variances, serving as a nonparametric alternative to analysis of variance (ANOVA). The following are the basic principles of the K-W test:

a) Rank Conversion

First, sort each sample data point, then assign each data point a corresponding rank (arranged from smallest to largest, with the smallest data point receiving the smallest rank).

If there are data points with the same value, take the average of their ranks.

b) Calculation of Rank Sum

Sum the ranks of each sample to obtain the rank for each group.

The formula for calculating the KW statistic (H statistic) is:

$$H = \frac{12}{\mathrm{n}(n+1)} \sum_{i=1}^{K} \frac{R_i^2}{n_i} - 3(n+1) \tag{1}$$

Among them, n is the total sample size, k is the number of sample groups, R_i is the rank sum of the i-th group, and n_i is the sample size of the i-th group.

Calculate the p-value: The distribution of the KW statistic approximates the chi-square distribution, and the corresponding p-value can be calculated based on the value of the statistic and the degrees of freedom (k-1).

Based on the relationship between the p-value and the significance level, determine whether the null hypothesis (equal medians across groups) holds. The fundamental principle of the KW test lies in comparing whether there are significant differences in the rank sums across groups. If

the overall medians of the groups are equal, the rank sums of the groups should be similar, and the KW statistic will be close to zero; if the overall medians of the groups differ, the rank sums of the groups will show significant differences, the KW statistic will be large, and the corresponding P-value will be less than the significance level.

(2) Assumptions of the KW test

When conducting the KW test, we first establish the null hypothesis that the overall medians of the samples in each group are equal. Then, we perform hypothesis testing by calculating the KW statistic and the corresponding P-value to determine whether to reject the null hypothesis, thereby inferring whether there are significant differences between the samples.

It is important to note that the KW test assesses whether the overall medians of the samples are equal, so it does not require the data to meet the assumption of normal distribution. This makes the KW test more flexible in practical applications and suitable for various types of data distributions.

When conducting a KW test, it is also important to consider the independence of the samples and the sample size. Ensure that the samples come from independent populations and that each population has a sufficiently large sample size to guarantee the accuracy and reliability of the test results.

II. B. 2) Factor analysis method

(1) Factor Analysis Model

a) Model Assumptions:

Observed variables are influenced by latent factors, which cannot be directly observed.

There may be correlations between observed variables, and these correlations can be explained by latent factors.

Each observed variable has a factor loading with each latent factor.

b) Basic Expression:

The basic expression of the factor analysis model is a generalized form of the multiple linear regression model. Assuming there are p observed variables and q latent factors, the observed variables X can be expressed as a linear combination of the latent factors F and the factor loading matrix L plus an error term:

$$\grave{o} : X = LFT + \grave{o} \tag{2}$$

In this context, X is an n×p matrix of observed variables, F is an n×q matrix of factor scores, L is a p×q matrix of factor loadings, ϵ is an n×p matrix of error terms, and n is the sample size.

c) Model interpretation

The factor loadings L reflect the strength and direction of the relationship between the observed variables and the latent factors. If the absolute value of the factor loadings is large, it indicates a strong relationship between the observed variables and the corresponding latent factors.

The factor scores F are estimates of each individual's scores on the latent factors. They can help researchers understand individuals' performance and characteristics across different latent factors.

d) Model Fitting

Through factor analysis, latent factor structures can be estimated using the common variations among observed variables. The fit of the model can be assessed using various indicators (such as the magnitude of factor loadings, the proportion of variance explained, etc.) to determine the model's validity and interpretability.

The core of factor analysis models lies in reducing dimensionality and extracting latent structures to reveal the intrinsic relationships among multivariate data, providing important tools and theoretical foundations for data analysis and interpretation.

(2) Factor loadings

a) Factor loading formula: In factor analysis, for the i-th observed variable X_i and the j-th latent factor F_j, the factor loading λ_{ij} can be calculated using the following formula:

$$\lambda_{ij} = \frac{\text{cov}(X_i, F_j)}{\text{var}(F_j)} \tag{3}$$

Among them, $cov(X_i, F_j)$ represents the covariance between the observed variable X_i and the latent factor F_j, and $var(F_j)$ represents the variance of the latent factor F_j. If the absolute value of λ_{ij} is large, it indicates a strong relationship between the observed variable X_i and the latent factor F_j. The sign of λ_{ij} indicates the direction of the relationship between the variable X_i and the latent factor F_j: a positive sign indicates a positive correlation, and a negative sign indicates a negative correlation.

b) Principal component analysis method: Principal component analysis is a commonly used factor loading solution method. In principal component analysis, observed variables are typically centered and standardized, and then the factor loading matrix is calculated through eigenvalue decomposition (or singular value decomposition).

(3) Factor rotation

a) Rotation methods

Factor rotation can be divided into orthogonal rotation and oblique rotation. Orthogonal rotation preserves the orthogonality between factors, with common orthogonal rotation methods including transformed factor rotation and variance maximization rotation. Oblique rotation, on the other hand, allows for correlations between factors, with common oblique rotation methods including maximum likelihood rotation and minimum residual rotation.

b) Purpose of rotation

Simplify factor structure: Through rotation, the loadings in the factor loading matrix can be concentrated on certain factors, thereby simplifying the factor structure and reducing cross-loadings and confusion.

Improve interpretability: The rotated factor loadings are more intuitive and interpretable, aiding researchers in providing clearer explanations and understanding of the data.

Table 1: Financial indicators and non-financial indicators

Type of index	Serial number	Name of indicator
Fundraising	X1	The arrival rate of financial funds
	X2	Social financing gap rate
	X3	One-inch debt ratio
Debt solvency	X4	Asset-liability ratio
	X5	Flow ratio
	X6	Interest guarantee multiples
	X7	Equity coefficient
Construction cost	X8	Unilateral cost deviation
	X9	The proportion of engineering change cost
Project progress	X10	Completion rate of planned construction period
	X11	Delay rate of key nodes
Operational sustainability	X12	Rent collection rate
	X13	Operating cost coverage rate
	X14	Percentage of maintenance costs
	X15	Inventory turnover rate
Policy Compliance	X16	Policy subsidy realization rate
	X17	Land use procedures compliance
Market demand	X18	The vacancy rate of affordable housing
	X19	Waiting family satisfaction rate
External economic risks	X20	Inflation impact
	X21	Interest rate volatility risk
Social stability risk	X22	Household complaint rate
	X23	Negative Index of Public Opinion
	X24	Matching perfect rate

c) Rotation methods

When selecting a rotation method, consider the complexity of the factor structure, the correlations among factors, and the actual research requirements. Generally, if it is assumed that there is no correlation between factors, orthogonal rotation methods can be chosen; if it is believed that there may be correlations between factors, oblique rotation methods can be chosen.

d) Post-rotation evaluation

The rotated factor loading matrix should be evaluated, including checking the magnitude of the loadings, the distribution of the loadings, and the correlations between factors, to ensure that the rotated factor structure aligns with the actual situation and is interpretable.

II. C. Selection of financial risk warning indicators

This paper follows the principles of recognition, comprehensiveness, accessibility, importance, and completeness in selecting early warning indicators, and has selected 25 financial and non-financial indicators to construct a financial risk early warning model for government-subsidized housing construction funds. The specific financial and non-financial indicators are shown in Table 1. As can be seen, the 24 indicators are primarily categorized into nine types: funding procurement, debt repayment capacity, construction costs, project progress, operational sustainability, policy compliance, market demand, external economic risks, and social stability risks.

II. D. Simplified Financial Risk Warning Indicators

This section will combine the K-W test with factor analysis to simplify the financial risk warning indicators proposed above.

II. D. 1) KW Inspection

In this paper, a total of 24 financial and non-financial indicators were entered into SPSS for a KW test. A significance level of less than 0.05 was considered to have passed the significance test. The test results are shown in Table 2. As can be seen from the table, the significance values for the proportion of engineering change costs, inventory turnover rate, vacancy rate of affordable housing, and negative public opinion index are all greater than 0.05, failing to pass the significance test. The remaining 20 financial and non-financial indicators all passed the significance test.

Table 2: The results of KW nonparametric test

Variables	Name of indicator	Significance	Variables	Name of indicator	Significance
X1	The arrival rate of financial funds	0.004	X13	Operating cost coverage rate	0.009
X2	Social financing gap rate	0.001	X14	Percentage of maintenance costs	0.005
X3	Debt dependence rate	0.008	X15	Inventory turnover rate	0.202
X4	Asset-liability ratio	0.001	X16	Policy subsidy realization rate	0.008
X5	Flow ratio	0.003	X17	Land use procedures compliance	0.02
X6	Interest guarantee multiples	0.006	X18	The vacancy rate of affordable housing	0.317
X7	Equity coefficient	0.015	X19	Waiting family satisfaction rate	0.006
X8	Unilateral cost deviation	0.033	X20	Inflation impact	0.008
X9	The proportion of engineering change cost	0.335	X21	Interest rate volatility risk	0.004
X10	Completion rate of planned construction period	0.006	X22	Household complaint rate	0.017
X11	Delay rate of key nodes	0.002	X23	Negative Index of Public Opinion	0.399
X12	Rent collection rate	0.006	X24	Matching perfect rate	0.003

II. D. 2) Factor analysis

To avoid selecting too many indicators, which could lead to increased training burdens and longer training times for the BP neural network used in constructing a financial risk warning model for affordable housing construction funding, this section will use factor analysis to simplify the financial risk warning indicators.

(1) KMO and Bartlett's Test

Before conducting factor analysis, KMO and Bartlett's tests must be performed to verify whether the data is suitable for factor analysis. The KMO test examines the correlation between variables, while Bartlett's test assesses whether variables are independent. If the KMO value is less than 0.5, factor analysis is no longer suitable. For Bartlett's test, a value less than 0.01 indicates that the test is passed.

The data was entered into SPSS to perform the KMO and Bartlett tests, with the results shown in Table 3. The results indicate that the KMO value is 0.746, suitable for factor analysis; the Bartlett test statistic is 2488.815, with a significance level of 0.001, indicating high correlation and significance. In summary, the sample data is suitable for factor analysis.

(2) Extracting factors

The common factor variance represents the extent to which the original information contained in each variable can be extracted by the common factor, i.e., the extent to which the extracted common factor explains the original information contained in all variables. The general standard for selecting the number of common factors is: when the cumulative variance contribution rate reaches 75%, the factors accumulated to 75% can be selected as common factors. The total variance explanation is shown in Table 4. According to the analysis, the cumulative variance contribution rate of the first 6 factors is

74.32%, and the cumulative variance contribution rate of the first 7 factors is 79.38%, which is greater than 75%. Therefore, the first 7 factors (only common factors have data on extracted and rotated loadings) can be selected as common factors to represent the overall level.

Table 3: KMO and Bartlett tests

KMO and Bartlett tests		
KMO sampling appropriateness quantity		0.746
Bartlett sphericity test	Approximate chi-square	2388.815
	Degree of freedom	185
	Prominence	0.001

Table 4: Total variance explanation

Component	Initial eigenvalue			Extract the load sum of squares			Square sum of rotational loads		
	Total	Percentage variance	Cumulative (%)	Total	Percentage variance	Cumulative (%)	Total	Percentage variance	Cumulative (%)
1	5.388	0.2694	26.94%	5.388	0.2694	26.94%	4.301	0.21505	21.51%
2	3.836	0.1918	46.12%	3.836	0.1918	46.12%	3.162	0.1581	37.32%
3	1.713	0.08565	54.69%	1.713	0.08565	54.69%	2.546	0.1273	50.05%
4	1.402	0.0701	61.70%	1.402	0.0701	61.70%	1.978	0.0989	59.94%
5	1.388	0.0694	68.64%	1.388	0.0694	68.64%	1.341	0.06705	66.64%
6	1.137	0.05685	74.32%	1.137	0.05685	74.32%	1.314	0.0657	73.21%
7	1.011	0.05055	79.38%	1.011	0.05055	79.38%	1.233	0.06165	79.38%
8	0.851	0.04255	83.63%	-	-	-	-	-	-
9	0.806	0.0403	87.66%	-	-	-	-	-	-
10	0.583	0.02915	90.58%	-	-	-	-	-	-
11	0.443	0.02215	92.79%	-	-	-	-	-	-
12	0.385	0.01925	94.72%	-	-	-	-	-	-
13	0.328	0.0164	96.36%	-	-	-	-	-	-
14	0.217	0.01085	97.44%	-	-	-	-	-	-
15	0.19	0.0095	98.39%	-	-	-	-	-	-
16	0.114	0.0057	98.96%	-	-	-	-	-	-
17	0.105	0.00525	99.49%	-	-	-	-	-	-
18	0.051	0.00255	99.74%	-	-	-	-	-	-
19	0.048	0.0024	99.98%	-	-	-	-	-	-
20	0.004	0.0002	100.00%	-	-	-	-	-	-

The scatter plot is formed by sorting each factor's eigenvalue size and is used to display the importance of each factor. The horizontal axis is the factor number, and the vertical axis represents the corresponding eigenvalue size. The steeper the slope, the larger the corresponding eigenvalue, and the more obvious the effect. The scatter plot is shown in Figure 1. It can be seen that the first seven items have eigenvalues greater than 1 and relatively steep slopes (more obvious explanation of the original data), while the latter items have relatively gentle slopes. Therefore, by combining the above total variance explanation table and the scatter plot below, it can be concluded that selecting the first 7 items as common factors can provide a relatively complete explanation of the overall information.

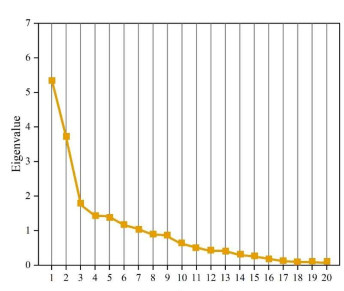


Figure 1: Stone map

After identifying the seven common factors, rotation processing is required to clarify the relationships between the data. The rotation is performed using the variance maximization method to obtain the rotated component matrix. The rotated component matrix is shown in Table 5.

(1) Common factor F1 can be explained by the fiscal funding availability rate, social financing gap rate, debt dependency ratio, asset-liability ratio, and current ratio, and is named the funding security factor.

(2) Common factor F2 can be explained by single-party cost deviation and maintenance cost ratio, primarily reflecting the risk of cost overruns in construction and operations associated with the government's funding model for affordable housing construction. Therefore, common factor F2 can be named the "cost control factor."

(3) Common factor F3 can be explained by the completion rate of the planned construction schedule and the delay rate of critical milestones, primarily reflecting issues of schedule and quality control in government-sponsored affordable housing construction projects. Therefore, common factor F3 can be named the engineering management factor.

(4) Common factor F4 can be explained by rent collection rate and operational cost coverage rate, primarily reflecting potential sustainability issues in the operational capacity of government-funded affordable housing construction projects under the current funding model. Therefore, common factor F4 can be named the Operational Efficiency Factor.

(5) Common factor F5 can be explained by policy subsidy fulfillment rate, land use procedure compliance, and supporting facility completion rate, primarily reflecting the risks posed to the government's affordable housing construction funding model by policy changes and implementation deviations. Therefore, common factor F5 can be named the government and compliance factor.

(6) Common factor F6 can be explained by the impact of inflation and interest rate volatility risks, primarily indicating the economic fluctuations and mismatches in demand encountered during the government's affordable housing construction funding process. Therefore, common factor F6 can be named the market and external environment factor.

(7) Common factor F7 can be explained by the satisfaction rate of waiting households and the complaint rate of residents, primarily reflecting the close relationship between government affordable housing construction and social stability and public satisfaction. Therefore, common factor F7 can be named the "Social Impact Factor."

Table 5: Rotated component matrix

Name of indicator	1	2	3	4	5	6	7
The arrival rate of financial funds	0.937	-	-	-	-	-	-
Social financing gap rate	0.92	-	-	-	-	-	-
One-inch debt ratio	0.843	-	-	-	-	-	-
Asset-liability ratio	0.838	-	-	-	-	-	-
Flow ratio	0.718	-	-	-	-	-	-
Interest guarantee multiples	-	-	-	-	-	-	-
Equity coefficient	-	-	-	-	-	-	-
Unilateral cost deviation	-	0.95	-	-	-	-	-
Completion rate of planned construction period	-	-	0.969	-	-	-	-
Delay rate of key nodes	-	-	0.969	-	-	-	-
Rent collection rate	-	-	-	0.835	-	-	-
Operating cost coverage rate	-	-	-	0.799	-	-	-
Percentage of maintenance costs	-	0.927	-	-	-	-	-
Policy subsidy realization rate	-	-	-	-	0.322	-	-
Land use procedures compliance	-	-	-	-	-0.385	-	-
Waiting family satisfaction rate	-	-	-	-	-	-	0.445
Inflation impact	-	-	-	-	-	0.866	-
Interest rate volatility risk	-	-	-	-	-	0.38	-
Household complaint rate	-	-	-	-	-	-	0.814
Matching perfect rate	-	-	-	-	0.909	-	-

Based on the above analysis, out of the initial 24 indicators selected from both financial and non-financial metrics, four non-significant indicators—engineering change cost ratio, inventory turnover rate, vacant rate of affordable housing, and negative public opinion index—were removed after applying the KW non-parametric test; The remaining 20 indicators were subjected to factor analysis and reduced, resulting in the extraction of seven common factors: financial security, cost control, engineering management, operational efficiency, government and compliance, market and external environment, and social impact. These seven common factors comprehensively reflect the accounting challenges and financial risks faced by the government's affordable housing construction funding model and serve as input variables for training the BP neural network.

III. Financial Risk Warning Model for Raising Funds for Affordable Housing Construction

In the previous chapter, this paper established a financial risk warning indicator system for government-subsidized housing construction funds and simplified the financial risk warning indicators through factor analysis, extracting seven public factors as input variables for the BP neural network. This chapter will propose a method for optimizing the BP neural network based on the Sparrow Search Algorithm (SSA) and construct a financial risk warning model for government-subsidized housing construction funds based on the SSA-BP neural network.

III. A. Model structure design based on BP neural networks

When using a BP neural network, specific model parameters must be set to determine the topological structure of the prediction network, allowing data to be transmitted forward through the neural layers [32]. For a BP neural network, the following model structures must be determined:

(1) The number of structures in the input layer, hidden layer, and output layer

The hidden layer of a neural network can include multiple layers, but in practice, it is most commonly set to a single hidden layer. Therefore, we select a BP neural network with one hidden layer. Assuming that each task time prediction model has m data attributes, the number of input nodes is m, and the input column vector $x=[x_1,x_2,...x_m]^T$, and the number of output nodes y is 1. According to the empirical formula, the number of hidden layer nodes n is:

$$n=\sqrt{m+1}+a \tag{4}$$

In the formula, a is an empirical parameter, generally taken as an integer between 1 and 10. The specific number of hidden layer nodes can be selected during model training by choosing the number of nodes with the smallest training error as the optimal number of hidden layer nodes. The training error is calculated using the mean square error function $(MSE_{Training})$ of the training set, with the calculation formula as follows:

$$MSE_{Training}=\sum_{1}^{z_{Training}}\frac{(y^{'}-y)^2}{z_{Training}} \tag{5}$$

In the equation, $y^{'}$ represents the predicted value of the network output; y represents the corresponding actual value; $Z_{Training}$ represents the number of training samples.

The prediction neural network model is shown in Figure 2.

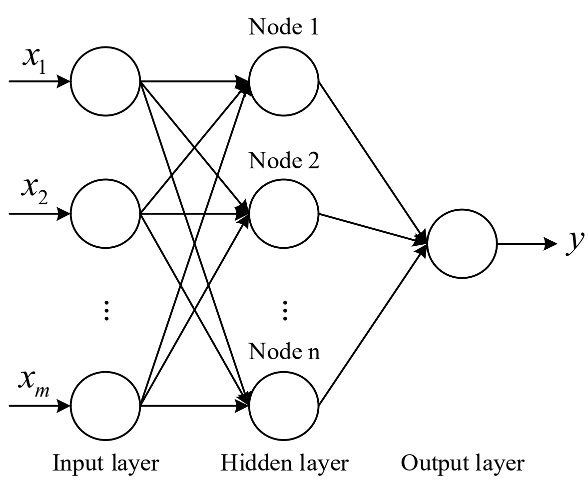


Figure 2: Prediction neural network model

(2) Neuron activation functions

In order for the hidden layer network to effectively fit nonlinear functions, the hidden layer activation function $f(x)_1$ must use the logsig function, which is a logarithmic S-shaped function with a value range of [0, 1]. The output activation function

$f(x)_2$ uses the purelin function, which allows the neural network's output results to be unrestricted. The mathematical expressions for each activation function are:

$$f(x)_1 = \frac{1}{1+e^{-x}} \tag{6}$$

$$f(x)_2 = x \tag{7}$$

(3) Mathematical expression of BP neural network

Combining the above, we can write the expression of a three-layer BP neural network, whose general matrix form is:

$$y = f(W^{(o)} f(W^{(h)} x + b^{(h)}) + b^{(o)}) = W^{(o)} f(W^{(h)} x + b^{(h)}) + b^{(o)} \tag{8}$$

In the equation, the superscripts (o) and (h) denote the output layer and hidden layer, respectively; w_{ji} is the weight matrix, where the first subscript j of w_{ji} represents the index of the neurons in the lower layer, the second subscript i is the index of the neurons in the previous layer; x and b are vectors representing the input and threshold, respectively, where $b^{(h)} = [b_1^{(h)}, b_2^{(h)}, \ldots b_n^{(h)}]^T$ and $b^{(o)} = b_1^{(o)}$. Then, equation (8) can be rewritten as equation (9):

$$y = [W_1^{(o)} \ldots W_n^{(o)}] \times f\left(\begin{bmatrix} W_{11}^{(h)} & \ldots & W_{1m}^{(h)} \\ \ldots & \ldots & \ldots \\ W_{n1}^{(h)} & \ldots & W_{nm}^{(h)} \end{bmatrix} \begin{bmatrix} x_1 \\ \ldots \\ x_m \end{bmatrix} + \begin{bmatrix} b_1^{(h)} \\ \ldots \\ b_n^{(h)} \end{bmatrix} \right)_1 + b^{(o)} \tag{9}$$

III. B. Model optimization analysis based on the sparrow search algorithm

The Sparrow Search Algorithm (SSA) has the ability to handle large-scale, nonlinear, and discontinuous problems because it no longer strictly relies on gradient information [33]. The SSA algorithm simulates the foraging process of sparrows to find the optimal parameters in the mathematical expression of the BP neural network, i.e., the optimal weights W_{ji} and the optimal threshold b.

Assuming that there are s sparrows searching for optimal parameters in the search space, the positions of each sparrow can be represented by the following matrix in the mathematical model:

$$A = \begin{bmatrix} a_{1,1} & \ldots & a_{1,d} \\ \ldots & \ldots & \ldots \\ a_{s,1} & \ldots & a_{s,d} \end{bmatrix} \tag{10}$$

In the formula, d represents the variable dimension of the optimization problem. For example, $a_{1,1}$ represents the first dimension component of the position of the first sparrow. The adequacy of the reserve energy at the sparrow's position represents the value of the sparrow's fitness function. The fitness function is selected as the average mean square error of the training set and the test set, and the calculation formula is as follows:

$$f = \frac{MSE_{Training} + MSE_{Test}}{2} \tag{11}$$

In the equation, $MSE_{Training}$ represents the mean squared error value of the training set, and MSE_{Test} represents the mean squared error value of the test set, where the calculation formula for MSE_{Test} is based on formula (5). The smaller the fitness function value, the more accurate the training, and the better the model's predictive accuracy. The fitness value of s sparrows is expressed as follows:

$$F_A = \begin{bmatrix} f([a_{1,1} & \ldots & a_{1,d}]) \\ f([a_{2,1} & \ldots & a_{2,d}]) \\ & \ldots & \\ f([a_{m,1} & \ldots & a_{m,d}]) \end{bmatrix} \tag{12}$$

In the equation, F_A represents the fitness value of the sparrow population. For example, $f([a_{1,1}...a_{1,d}])$ denotes the fitness value of the first sparrow. Sparrows with higher F_A values can prioritize food acquisition during the search process. The position of the discoverer at each update iteration can be described as:

$$A_{i,j}^{t+1}\begin{cases} A_{i,j}^{t}\cdot\exp\left(\dfrac{-i}{\alpha\cdot\eta}\right) & R_a < ST \\ A_{i,j}^{t}+Q_a\cdot l & R_a \geq ST \end{cases} \tag{13}$$

In the equation, t is the number of iterations, $i=1,2,....m, j=1,2,....d$, $A_{i,j}^{t}$ denotes the j th component of the i th sparrow at the t th iteration; $\alpha(\alpha\in(0,1])$ and Q_α are random numbers, but the former follows a uniform distribution, and the latter follows a normal distribution; η is a constant representing the maximum number of iterations for detector updates; $R_\alpha(R_\alpha\in[0,1])$ represents the warning value, $ST(ST\in[0.5,1])$ represents the safety value, with $ST=0.8$; l is a $1\times d$ row vector, and all vector elements are 1.

As stated in the rules, when the discoverer finds a location rich in food resources, the joiners tend to move toward the discoverer's location or its surrounding area. This movement behavior can be described by the position update formula:

$$A_{i,j}^{t+1}\begin{cases} Q_\alpha\cdot\exp\left(\dfrac{A_{worst}^{t}-A_{i,j}^{t}}{2}\right) & i>\dfrac{s}{2} \\ A_{worst}^{t+1}+|A_{i,j}^{t}-A_{worst}^{t+1}|\cdot B^{+}\cdot l & otherwise \end{cases} \tag{14}$$

In the equation, A_{worst}^{t} represents the worst discoverer position of F_A in the current global search, A_{best}^{t+1} represents the best position currently being searched by the discoverer; $B^{+}=B^{\tau}(BB^{T})^{-1}$, where B is a $1\times d$ row vector, and the vector elements are randomly assigned values of 1 or -1; $i>\frac{s}{2}$ indicates that the F_A of the i th joiner is relatively low, failing to successfully obtain food, and is in a state of hunger. This individual needs to fly to other areas to explore in order to increase F_A.

In the sparrow population, scouts with danger awareness capabilities are randomly selected during the foraging process to issue alarm signals. The position update formula for scouts is:

$$A_{i,j}^{t+1}\begin{cases} A_{best}^{t}+\gamma\cdot|A_{i,j}^{t}-A_{best}^{t+1}| & F_i>F_{best} \\ \dfrac{A_{i,j}^{t}+|A_{i,j}^{t}-A_{worst}^{t+1}|}{F_i-F_{worst}+\mu} & F_i=F_{best} \end{cases} \tag{15}$$

In the equation, A_{best}^{t} represents the best position in the current search; γ is used to control the step size for finding the optimal solution and follows a standard normal distribution; β is a random number in the range $[0, 1]$, indicating the direction of the sparrow's movement; F_i represents the fitness value of the sparrow in the current iteration, where F_{best} and F_{worst} are the global best and global worst fitness values, respectively; μ is an extremely small constant used to prevent the denominator of the calculation formula from becoming zero.

III. C. Building a financial risk prediction model

The data regression prediction method based on the SSA-BP neural network combines the global search capability of the Sparrow Search Algorithm with the nonlinear modeling capability of the BP neural network, thereby enhancing the accuracy of data regression prediction tasks. Model training is conducted separately, and prior to model training, data processing is performed on the input layer of the model, specifically data normalization, which linearly transforms the input data into the range $[0, 1]$ to ensure that the input values fall within the domain of the hidden layer activation function $f(x)_1$. The formula for data normalization is:

$$\overline{x}_i=\frac{x_i-x_{\min}}{x_{\max}-x_{\min}} \tag{16}$$

In the equation, $\bar{x}_i$ represents the normalized input value; x_i represents the original input value; $x_{\max}$ and $x_{\min}$ represent the maximum and minimum input values, respectively. The prediction accuracy R is used to evaluate the prediction performance, with the average absolute error $\bar{A}_e$ and the average relative error $\bar{R}_e$ reflecting the closeness of the predicted data to the actual data. The calculation formulas are as follows:

$$R = 1 - MAPE = \frac{1}{z_{Test}} \sum_{1}^{z_{Test}\left|\frac{y-y'}{y}\right| \times 100\%} \tag{17}$$

$$\bar{A}_e = \frac{1}{z_{Test}} \sum_{z_{Test}} |Predictedvalue - Actualvalue| \tag{18}$$

$$\bar{R}_e = \frac{1}{z_{Test}} \sum_{z_{Test}} \frac{|Predictedvalue - Actualvalue|}{Actualvalue} \tag{19}$$

In the equation, y' represents the predicted value; y represents the corresponding actual value; z_{Test} represents the number of samples in the test set.

It is important to note that the inputs and outputs of the BP network are normalized, so the model's output prediction values must be denormalized to match the scale of the true values y. The formula for denormalizing the output data is:

$$y' = y_{norm}(y_{\max} - y_{\min}) + y_{\min} \tag{20}$$

In the equation, y_{norm} represents the predicted value before normalization; $y_{\min}$ represents the minimum true output value of the sample data; $y_{\max}$ represents the maximum true output value of the sample data.

In summary, the algorithmic process of the financial risk warning model for government-subsidized housing construction funding is shown in Figure 3. First, the sample data is normalized, and the weights W and thresholds b in the mathematical expression of the BP network are initialized based on the predefined network topology structure. Then, the SSA algorithm is used to train the prediction model until the termination criteria of the search algorithm are met. Finally, the obtained parameters are used as optimal parameters in the neural network for prediction.

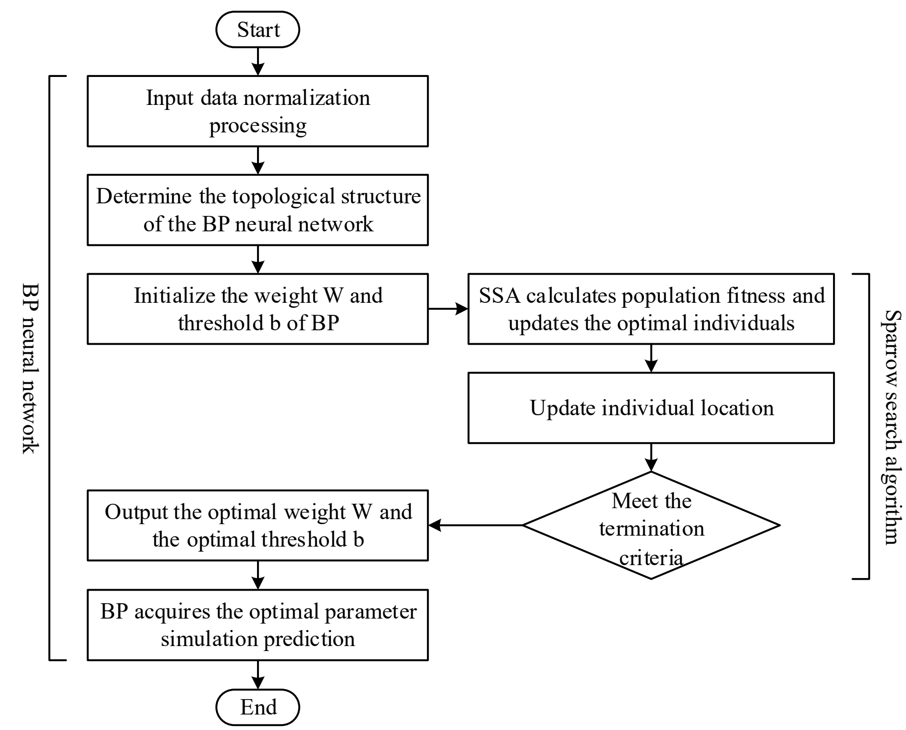


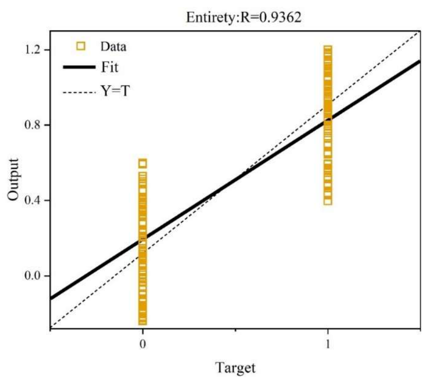
Figure 3: Algorithm flow of the marshalling station operation time prediction model

IV. Empirical Study on Financial Risk Warning Model for Fund Raising in Affordable Housing Construction

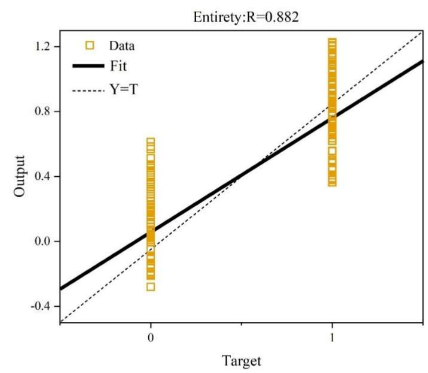
This chapter will use the SMOTE oversampling method to balance the sample data and then feed it into the SSA-BP neural network model for training, and then test the predictive performance of the SSA-BP neural network model.

IV. A. Training and testing of the SSA-BP neural network model

The training and fitting results of the SSA-BP neural network model and the BP neural network model are shown in Figure 4. Figures (a) and (b) correspond to the SSA-BP neural network model and the BP neural network model, respectively. The dashed lines in the figure represent the true value - output = target, while the solid lines represent the best-fit linear regression lines between the output and the target. The R value indicates the relationship between the output and the target. If R is closer to 1, it indicates a stronger linear relationship between the output and the target, while if R is closer to 0, it indicates a weaker linear relationship between the output and the target. As shown in the figure, the R value of the SSA-BP neural network model training set is 0.936, indicating that the SSA-BP neural network training model has a good fit. The R value of the BP neural network model training set is 0.882, indicating that the BP neural network model has a poorer fit than the SSA-BP neural network.



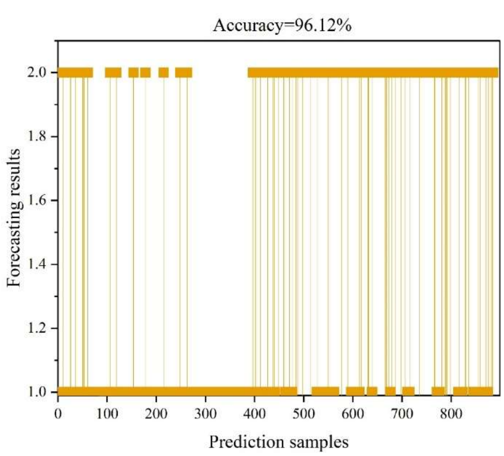
(a)SSA-BP



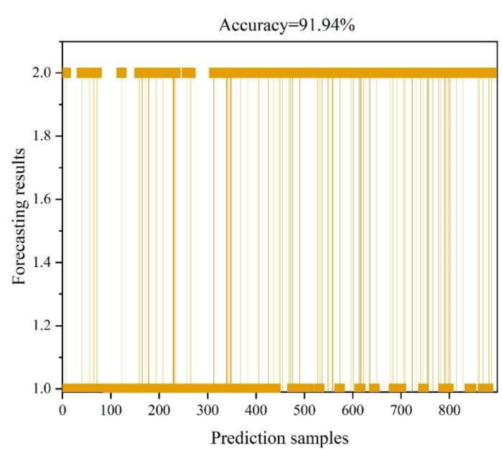
(b)BP

Figure 4: Model training fitting situation

The training set data was input into the SSA-BP neural network and BP neural network models to obtain the training set prediction results and accuracy rates, as shown in Figure 5. Figures (a) and (b) correspond to the SSA-BP neural network model and the BP neural network model, respectively. The prediction accuracy of the SSA-BP neural network training is 96.12%, and the prediction accuracy of the BP neural network training is 91.94%. Both models demonstrate good training performance and can be used for predicting the test set.



(a)SSA-BP



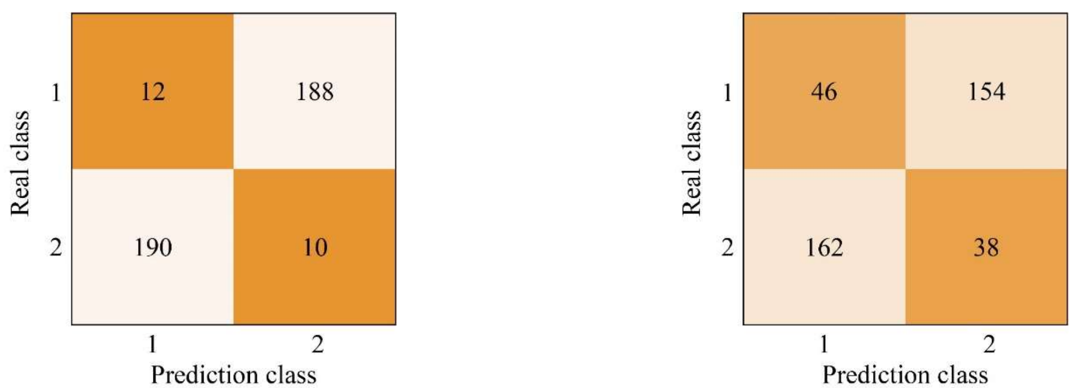
(b)BP

Figure 5: Comparison of prediction results of training set

IV. B. Analysis of SSA-BP neural network model results

This paper aims to study the accounting and financial risk warning of government affordable housing construction fund raising models. Compared with affordable housing construction projects that are in a healthy state, projects that are in a warning state or will be warned are more meaningful to study. This paper marks financial warning projects as Positive (i.e., “positive examples”) and uses the number ‘2’ to represent them; financially healthy enterprises are marked as Negative (i.e., “negative examples”) and use the number “1” to represent them. The four possible outcomes are: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP indicates that the model correctly predicts positive examples as positive, TN indicates that the model correctly predicts negative examples as negative, FP indicates that the model incorrectly predicts negative examples as positive, and FN indicates that the model incorrectly predicts positive examples as negative.

The confusion matrices for the SSA-BP neural network and BP neural network models on the test set are shown in Figure 6, with Figures (a) and (b) corresponding to the SSA-BP neural network model and BP neural network model, respectively. As shown in the figure, the SSA-BP neural network correctly predicted 188 warning enterprises and 190 healthy enterprises, incorrectly classified 12 warning enterprises as healthy enterprises, and incorrectly classified 10 healthy enterprises as warning enterprises, with an overall prediction accuracy rate of 94.5%. The overall prediction accuracy rate of the BP neural network was 79%, which is 15.5% lower than that of the SSA-BP neural network model. From this comparison of the prediction results between the SSA-BP neural network and the BP neural network, it can be seen that the SSA-BP neural network performs better than the BP neural network in the application of financial early warning for the funding of affordable housing construction.



(a)SSA-BP (b)BP

Figure 6: Confusion matrix

IV. C. Model Comparison and Evaluation

To evaluate the predictive performance of the financial risk warning model for affordable housing construction funding based on the SSA-BP neural network constructed in this paper, this section will use four metrics—precision, recall, accuracy, and F1 score—to assess the model's predictive performance. The BP neural network model, Logistic regression model, and KNN model will be selected for comparison and validation. The comparison of precision, recall, F1 score, and accuracy rates for each model is detailed in Table 6. As shown, the SSA-BP neural network model achieves a precision rate of 93.2%, which is 4.8%, 4.7%, and 7.6% higher than the KNN model, BP neural network model, and Logistic regression model, respectively. In terms of recall rate, all models achieved recall rates above 90%, but the SSA-BP neural network model achieved a recall rate of 96.1%, the highest among the four models. This indicates that when predicting actual government affordable housing construction projects, the SSA-BP neural network model has a higher probability of successful prediction. The F1 score comprehensively reflects both precision and recall, thereby better reflecting the predictive performance of the warning system for enterprises. The SSA-BP neural network model achieved the highest F1 score of 92.8%, surpassing the KNN model, BP neural network model, and Logistic regression model by 2.6%, 2.5%, and 5.3%, respectively. Accuracy reflects the probability of successfully predicting the outcomes of all healthy affordable housing construction projects and warning affordable housing construction projects, representing the overall accuracy of the model. The SSA-BP neural network model achieved the highest accuracy of 93.4%, indicating that, overall, the SSA-BP neural network model has the best predictive performance.

Table 6: Comparison of evaluation indexes of each model

Model	Precision rate	Recall rate	F1 score	Accuracy rate
SSA-BPNN	0.932	0.961	0.928	0.934
BPNN	0.885	0.942	0.903	0.901
Logistic	0.856	0.904	0.875	0.887
KNN	0.884	0.928	0.902	0.893

In summary, when using the model to conduct financial risk warning for government affordable housing construction projects, the effectiveness of the warning application is as follows: SSA-BP neural network model > BP neural network model > KNN model > Logistic regression model. The financial risk warning model for affordable housing construction funding based on the SSA-BP neural network model constructed in this paper demonstrates excellent predictive performance, enabling effective financial risk prediction during the accounting and funding processes of government affordable housing construction projects.

V. Financial Risk Countermeasures for Government-Sponsored Affordable Housing Construction Projects

This paper constructs a financial risk warning model for the funding of affordable housing construction projects to predict financial risks during the accounting and funding processes of government-sponsored affordable housing projects. Given the various financial risks associated with affordable housing projects, affordable housing construction entities must implement the following financial risk control measures.

(1) Strengthen cash flow management and improve the efficiency of operational fund utilization

To reduce the probability of financial risks and accelerate project construction, construction investment companies must strengthen cash flow management for affordable housing projects and enhance the efficiency of operational fund utilization: first, they must ensure daily cash flow safety management; second, they must establish a cash flow early warning system and strengthen supervision.

(2) Conduct tax planning to reduce corporate costs and expenses

Tax planning is a model through which enterprises utilize reasonable financial means and tax incentives to reduce corporate costs and expenses. Affordable housing construction companies should fully leverage existing tax incentives for tax planning: first, select raw material suppliers reasonably; second, adopt a labor dispatch model through labor companies to reduce corporate tax risks.

(3) Enhance the professional competence of financial personnel and strengthen their risk management awareness.

To mitigate project financial risks, companies must strengthen training and education for financial personnel, enhance their professional competence, and reinforce their risk management awareness: First, affordable housing investment and construction companies should promptly conduct training and education for staff in accordance with the latest financial work requirements to improve their professional capabilities. Second, enhance the risk control awareness of financial personnel. Financial personnel are the primary agents of financial risk management. Practice has proven that only by enhancing the risk management awareness of financial personnel can financial risks be avoided. Therefore, affordable housing projects must cultivate the risk awareness of financial personnel and foster a strong culture of financial risk management within the company.

VI. Conclusion

To achieve financial risk warning and management for government-sponsored affordable housing projects, a financial risk warning indicator system for government-sponsored affordable housing construction funds has been established. The K-W test and factor analysis methods were used to simplify the indicators. In the K-W test, the significance values of indicators such as the proportion of engineering change costs, inventory turnover rate, vacancy rate of affordable housing, and negative public opinion index were all greater than 0.05, indicating they passed the significance test and were therefore excluded. The KMO value obtained through the KMO and Bartlett tests was 0.746, with a significance level of 0.001, indicating high correlation and significance, thereby confirming that the sample data in this study is suitable for factor analysis. The cumulative variance contribution rate of the first seven factors is 79.38%, which is greater than 75%. Therefore, the first seven factors are selected as common factors to represent the overall level. Using the variance maximization method, the rotated component matrix is obtained. Based on their explanations, the factors F1 to F7 are named financial security, cost control, engineering management, operational efficiency, government and compliance, market and external environment, and social impact, respectively.

The extracted factors were used as input variables for the BP neural network. The Sparrow Search Algorithm was employed to optimize the optimal parameters of the BP neural network, thereby constructing a government-backed affordable housing construction financial risk warning model based on the SSA-BP neural network. The SSA-BP neural network model and the

BP neural network model were trained and tested. The R-values of the training sets for the two models were 0.936 and 0.882, respectively, with prediction accuracies of 96.12% and 91.94%, respectively. The BP neural network model's fitting performance and prediction accuracy were significantly inferior to those of the SSA-BP neural network model. Further comparison of the financial risk prediction results between the SSA-BP neural network model and the BP neural network model showed that the overall prediction accuracy of the SSA-BP neural network model was 94.5%, which was 15.5% higher than that of the BP neural network model, indicating better prediction performance. Additionally, the BP neural network model, Logistic regression model, and KNN model were selected as comparison models, and the prediction performance of the models was evaluated using four metrics: precision rate, recall rate, accuracy rate, and F1 score. The SSA-BP neural network model achieved precision, recall, F1 score, and accuracy rates of 93.2%, 96.1%, 92.8%, and 93.4%, respectively, all of which were the highest among all models, demonstrating the most outstanding financial risk warning performance.

Finally, in response to the various financial risk issues faced by government-sponsored affordable housing construction projects, corresponding financial risk mitigation strategies are proposed from three aspects: cash flow management, tax planning, and financial personnel training.

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