Research on Operational Risk Monitoring Method of Intelligent Financial System Based on Deep Learning and Improved RPA

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Abstract. The accuracy of traditional financial system operational risk monitoring is low. Therefore, this paper proposes a method of intelligent financial system operational risk monitoring based on deep learning and improved RPA. Set the financial monitoring index and obtain the warning threshold parameters; Using deep neural network method to mine key risk indicators and obtain reconstruction coefficients of data mining errors of financial system; By improving the RPA method to calculate the fit degree of financial risk, it matches the internal business process of the enterprise; The operational risk monitoring algorithm of financial system is designed to realize the operational risk monitoring of financial system. The experimental results show that the risk monitoring accuracy of the design method is 80.3%, and the overall test threshold of the model is 0.5 after the introduction of non-financial indicators, which shows that it can be applied in practice.

Keywords: Deep learning · Improve RPA · Intelligent financial system · Operational risk monitoring · Optimization algorithm

1 Introduction

As an important part of the national financial industry, banking is very important to promote national economic development. With the rapid development of China's economy, the speed of financial system reform is also faster and faster. As an important part of China's banking system, policy banks have played a strong role in promoting China's economic and financial system reform and maintaining economic stability and development. However, according to the research of relevant institutions in the United States, since the 1980s, several major international banks have suffered more than $200 billion in losses due to operational risks, which has brought huge losses to their own economy and banking operations [1, 2]. The huge losses caused by operational risk have attracted the attention of the Basel Committee on banking supervision, and also set off an upsurge of academic research on operational risk. In recent years, some domestic banking institutions, especially small and medium-sized financial institutions, have frequent major and important cases due to imperfect corporate governance, imperfect internal control

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system, or lack of effective supervision over the implementation of the system [3]. With the deepening of financial globalization, the rapid development of banking business and the continuous progress of information technology, the operational risks faced by the banking industry are more complex.

Due to institutional reasons, there is still a big gap between China's commercial banks and foreign commercial banks in terms of operational risk management. In particular, there are many deficiencies in China's financial institutions in terms of property right system, corporate structure and governance, which leads to the widespread existence of various operational risks in China's banking industry, especially small and medium-sized banks, and presents an increasingly serious trend and signs. Relevant systems and regulations have been issued for the management of operational risk of domestic commercial banks [4]. The prevention of operational risks has been standardized in 13 aspects, such as the construction of rules and regulations to prevent operational risks and the strengthening of audit construction. The establishment of operational risk early warning and monitoring system is the need for commercial banks to meet the needs of domestic supervision. The CBRC clearly requires commercial banks to establish an operational risk management system suitable for the nature, scale and complexity of the bank's business in accordance with the guidelines on operational risk management of commercial banks, so as to effectively manage the bank's operational risk.

Relevant scholars have studied this and made some progress. For example, reference [5] proposes a financial software operational risk prediction method based on nonlinear integration and deep learning. It obtains the types of financial software operational risk through big data mining, classifies operational risk attributes through AHP, trains operational risk data according to the deep learning method, solves financial software operational risk through nonlinear functions, and realizes financial software operational risk monitoring, This method can improve the monitoring time, but the monitoring accuracy is poor.

In view of the above problems, this paper proposes an operational risk monitoring method of smart finance system based on deep learning and improved RPA, which effectively improves the accuracy of operational risk monitoring.

2 Design of Operational Risk Monitoring Method of Intelligent Financial System Based on Deep Learning and Improved RPA

2.1 Calculation of Financial Monitoring Index

Financial risk monitoring index aims to reflect the financial risk status of enterprises. In order to achieve the goal of risk monitoring, this paper follows four basic principles in the setting of indicators: operability principle, comprehensiveness principle, continuity principle and comparability principle. The principle of operability emphasizes that the compilation of the index lies in application, the selected indicators must have reliable data sources and accurate quantitative methods, and the number of indicators should not be too large. The principle of comprehensiveness is that the financial risk of an enterprise is a multi-dimensional and multi-level complex system, which covers many aspects of profitability, development ability, solvency and operation ability. It is necessary to establish a comprehensive and systematic index system for evaluation [6]. The principle of continuity focuses on the essence of the evaluation content. The constructed index system should meet the dynamic monitoring function, so the selected indexes should be continuously available. Comparability principle through the differences of industry, scale, operation mode and other factors, different enterprise indicators are often not comparable in absolute numbers. Therefore, relative number indicators are used to weaken this influence, so as to ensure the same caliber of indicators of different enterprises horizontally and the same calculation method of different years vertically. The financial risk monitoring index in this paper consists of two parts: the individual financial risk monitoring index and the comprehensive financial risk monitoring index (R).

The individual index of financial risk monitoring is a dynamic relative number compared with the “early warning critical value”, which measures that the actual financial index of an enterprise exceeds or fails to reach the “early warning critical value” (i.e. the safety margin or danger margin of a financial index). Its calculation formula is:

$$\mu_k = \frac{T_f - T_h}{|\delta_m|} \tag{1}$$

where, μ_k represents the individual index of financial risk monitoring; T_f actual index value of financial monitoring in the current period; T_h represents financial early warning index; δ_m represents the critical value of financial early warning. The calculation formula of the comprehensive index of financial risk monitoring is:

$$\mu_p = \frac{\delta_m - T_f}{T_h} \tag{2}$$

where, μ_p represents the comprehensive index of financial risk monitoring. If the financial monitoring index is the bigger the better index, the financial monitoring index is the smaller the better index or moderate index. Among them, the actual index value of financial monitoring in this period is various financial index data objectively existing in the financial report, and the critical value of financial early warning is the financial data obtained by stripping and calculating the financial data to judge whether there is an alarm. If the calculation result is positive, the result is the financial risk monitoring safety index; If the calculation result is negative, the monitoring and early warning indicators of financial risk can be obtained. Combined with the closed model in the dynamic monitoring factor, two heterogeneity measurement indicators with similarity can be obtained:

$$\mu_k = \frac{w_f \times \mu_f}{w_s \times \mu_s} + \left(w_f \times w_s\right) \tag{3}$$

where, μ_k represents the heterogeneity measurement index obtained after the combination of two similar monitoring data; w_f and μ_f represent the weight distribution and weight index of data respectively; w_s and μ_s represent the monitoring closure weight and closure index. There is an object feature with adjacent relationship in the merged area of the object, and the image structure of each area can be directly operated in the merging process [6]. The region adjacency graph needs to set the merging arc segment in the initial segmentation layer, and after obtaining the initial label, convert the energy at the cost of formula (4).

$$Q_f = \frac{\sum_{r=1}^{n} P_r}{\sum_{i=1}^{n} W_i + P_i} \tag{4}$$

where, Q_f represents the cost conversion energy of regional adjacent data; P_r represents the cost from the initial object to the final object; W_i represents the merging cost function of the divided region in the initial label; P_i represents the merging cost function of the divided region in the termination label. There are a large number of dynamic structures and feedback mechanisms in several existing risk monitoring systems, which determine the operation direction of the system as the final behavior. The system is influenced by internal and external forces and constraints, and develops and evolves according to a certain law. When delimiting the system boundary, we should try to make the boundary include all the quantities closely related to the modeling purpose, so as to ensure the overall integrity of the system, and pay attention to the closure of the system boundary. The operational risk monitoring system of medium-sized commercial banks is a huge complex system composed of multiple internal subsystems and external influence systems. Therefore, it is impossible to cover all the subsystems involved in the operational risk monitoring system of commercial banks and their related influencing factors and feedback paths in this paper. When establishing the system dynamics simulation model, this paper strives to not only complete the system modeling in a limited time, but also fully reflect the essence of the operational risk management of medium-sized commercial banks [7]. Therefore, this paper finally decided to complete two tasks: first, build the operational risk monitoring model of China's medium-sized commercial banks from a macro perspective, and draw the causal feedback diagram of its first-level sub model [8]. Second, select the most typical primary subsystem in the operational risk monitoring system as an example for model construction and simulation test, and get the most common problems of operational risk of medium-sized commercial banks by analyzing the current situation.

2.2 Parameter Based Training Algorithm

To use the deep learning algorithm, it is necessary to first establish a CNN network, in which each level requires more than 32 layers of network functions. If the neuron between the explicit layer and the hidden layer is a feature detection device, it can be represented as the structure diagram shown in Fig. 1:

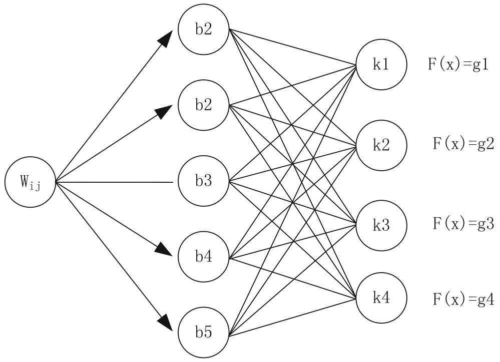

Fig. 1. Deep learning network model

As shown in Fig. 1, the energy function p is introduced, the hidden element state of $k_1 - k_4$ is taken as layer gn, and the explicit element state of $b_1 - b_5$ is taken as layer f(x). Different levels of weight values need to be connected between hidden elements and explicit elements. Then in the probability distribution function, there is the distribution law of energy function:

$$P(x) = \frac{\sum_{j=1}^{n} P\left(b_j, k_j\right)}{\sum_{i=1}^{n} g_n} \tag{5}$$

where, $P(x)$ represents the conditional probability distribution value between hidden layer and explicit layer; $P\left(b_j, k_j\right)$ represents the joint probability distribution function of the inner explicit layer and the hidden layer of the energy function, where b_j represents the explicit layer and k_j represents the hidden layer; g_n represents the probability distribution function of explicit and implicit elements. By deriving the two-dimensional random unit in the state variable into an activated function, the reconstruction coefficients of cycle times and errors can be obtained, and the training parameters of the financial system operational risk monitoring model can be obtained.

2.3 Financial Risk Fitness Measurement Based on Improved RPA

Guided by the target requirements, it is used to evaluate whether the characteristics of each business process are suitable for the use of RPA financial robot according to the following six aspects:

(1) Business volume. In the actual financial work, there are many businesses with large workload and easy to make mistakes. The application of RPA financial robot in these businesses to replace accountants can not only save human resources, but also improve the accuracy of work.
(2) Repeatability of work content. RPA technology is characterized by clear running scripts with rules. The more repetitive work in financial work means the higher

consistency of rules, the more suitable it is for the application of RPA financial robot.

(3) Degree of digitization. At present, RPA financial robot does not have the human thinking mode, but the embodiment of primary artificial intelligence. Therefore, the subsequent financial work can be carried out only by scanning documents through image technology and extracting useful digital information. Therefore, the process should be digital.

(4) Log in to the external information system. Because in the actual business processing process, it is troublesome to log in to multiple enterprise external information systems respectively, and it is necessary to manually download the relevant data information to be obtained, and then import it into the enterprise internal information system. This series of data transmission and interaction is troublesome, which is not conducive to the development of daily work. At this time, RPA financial robot can automatically log in to heterogeneous systems to complete the integration of underlying data. Therefore, businesses that need to log in to different information systems are more suitable for the application of RPA financial robot.

(5) Risk level and strategy formulation. Many work of financial management has a high degree of risk, and the whole process needs to be monitored or even completed manually. Similarly, some processes need to formulate the long-term development strategy of the enterprise. These two types of business processes that need to rely on the thinking and work experience of accountants are not suitable for the application of RPA financial robot.

(6) System upgrade. Because RPA financial robot belongs to a plug-in deployment and does not change the structure of the original system, it depends on the system operation. Once the system upgrade changes, the operation of RPA financial robot may be wrong and the operation script needs to be modified accordingly. Therefore, the process of preparing the system upgrade does not apply RPAS financial robot for the time being [9]. In different processes, RPA fitness model can be established, as shown in Fig. 2.

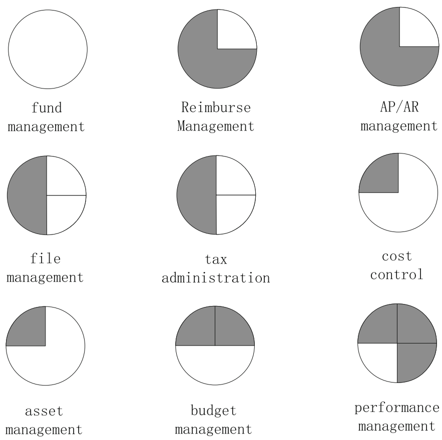

Fig. 2. Model for improving RPA fitness

As shown in Fig. 2, the RPA adaptability of each business process of the enterprise has a certain degree. The RPA adaptability of capital management business process is relatively high, followed by reimbursement management, collection management, payment management, file management, tax management and general ledger management, while the RPA adaptability of cost management, asset management, budget management, performance management and compliance management is relatively low. When determining the RPA suitability of business processes, enterprises should flexibly apply and analyze it in combination with the actual situation of their own business processes.

2.4 Design the Operational Risk Monitoring Algorithm of Financial System

For the financial risk monitoring of enterprises, we should not only estimate the point of the risk prediction value of the financial risk, but also estimate the range of the risk prediction value, and determine that this range includes the credibility of the financial risk, that is, interval estimation of the financial risk prediction of enterprises.

The first step for banks to carry out comprehensive financial risk control and monitoring is to clearly define financial risks. In the work, the definition of financial risk is mainly based on the relevant systems and methods of financial risk control formulated by the head office. However, these systems and methods are formulated based on the level of the head office. The definition of financial risk is very broad. There are many financial risk indicators in the reference library and there is no clear risk threshold. In many financial systems, there is no detailed financial risk, no reference database of financial risk indicators in line with their own conditions, and no differentiated quantitative indicators and thresholds are formulated according to policy business and non policy business, resulting in the lack of a clear grasp of financial risk by the personnel of the centralized Department of risk control. Moreover, most financial departments do not correctly understand their own nature and policy risks, which will directly lead to the difficulty of enterprises to bear the debts caused by poor management [10]. Therefore, the operational risk monitoring algorithm of financial system is designed, as shown in Fig. 3.

As shown in Fig. 3, after receiving the business data, the master program starts the rule engine interface. The rule engine obtains the business transaction code by analyzing the business data. Its function is to accurately obtain the parent rule information of this business from the shared memory. The engine starts to analyze and filter the parent rule, get n sub rule keywords, and then provide the basis for finding the sub rule configuration information of shared memory. Start to analyze and process sub rules one by one, convert the data according to its rules to obtain the result string, and then obtain the operation result through the result calculation function. Then, the parent rule result string composed of N sub rule operation results is returned to the parent rule result operation function for final result calculation. Finally, judge whether the risk conditions are met according to the final results, and then register the risk alarm data.

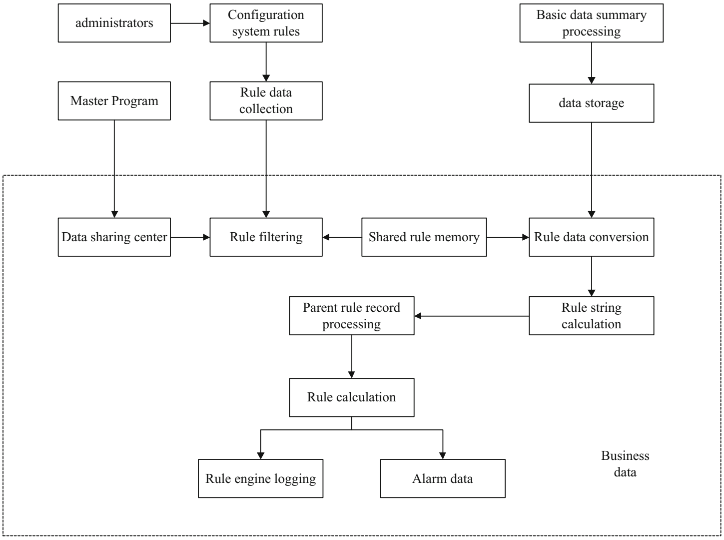

Fig. 3. Rule data flow chart

3 Case Analysis

3.1 Model Adaptability Test

So far, excellent scholars at home and abroad have shown through a large number of empirical analysis that the logstic model has the advantages of high discrimination ability, wide application range, simple results and easy operation in the credit risk monitoring of commercial banks. Although the amount of data processing and calculation required by the model is large and the program is complex, we can still overcome this problem with the help of statistical software and make the analysis results more accurate. And the model has been applied in dealing with the credit risk of China's commercial banks for many years, which is rooted in China's financial industry. As a nonlinear probability regression model, we can set up different classification basis through default samples and non default samples, and analyze the default probability of enterprises on the basis of linear regression equation.

$$P_m = \frac{1}{1 + \exp(-(a_i + b_i x))} \tag{6}$$

where, P_m represents the default probability of the enterprise based on the linear regression equation; a_i and b_i are parameters of independent variable function; x represents the independent variable in the function. Suppose the probability of financial crisis of an enterprise, that is, the probability of credit risk of commercial banks is P(x), then the probability of non occurrence is 1 − P(x). we can get the possibility of enterprise default by calculating the ratio relationship between the two probabilities, and we can estimate the size of credit risk faced by commercial banks.

$$\ln \frac{P_k(x)}{1 - P_k(x)} = a_i + \sum_{i=1}^{n} b_i x \tag{7}$$

where, $P_k(x)$ represents the credit risk faced by commercial banks. In the process of adaptability test, make full use of the relevant theoretical properties of linear regression model, comprehensively estimate the parameters through the maximum likelihood method, explain the relationship between the variables of the selected index parameters, and predict the risk probability of commercial banks.

3.2 Data Sample Collection and Inspection

This paper selects 20 listed enterprises from the credit analysis system of commercial banks in the research example, including 11 enterprises with non-performing loan ratio higher than 8% (risk probability is 1) and 9 low-risk enterprises (risk probability is 0). Combined with the database information, this paper takes the annual data of these companies as the modeling sample, and the data of the previous year as the prediction and detection model to judge the correctness of credit risk. The monitoring indicators are shown in Table 1.

Table 1. Selection of financial indicators

Type	Purpose and principle of selection	Specific indicators
Corporate profitability	Corporate profitability is one of the most important indicators of a company and the best embodiment of the company's development potential. Accumulating profits to increase the value of the company's assets is a way to reflect the healthy financial situation and operating effect of listed companies	Return on net assets
		Profit rate of total assets
		Cost profit margin
		Net profit margin on sales
Solvency of the company	The company's solvency is an indicator reflecting the healthy state of enterprise capital flow. Being able to repay the loan in time and effectively shows that the company is in good operation. At the same time, it will also strengthen the company's credit system to facilitate fund-raising during industrial expansion	Current ratio of net assets
		Cash flow ratio
		Interest cover
		Property right ratio

(*continued*)

Table 1. (*continued*)

Type	Purpose and principle of selection	Specific indicators
Asset management capability of the company	Corporate asset management is one of the most important aspects of corporate development. Reasonable and effective management can make the company have long-term development ability. Reasonable management of assets can effectively improve the speed of asset flow and utilization	Turnover rate of accounts receivable
		Total asset turnover
		Inventory turnover
		Turnover rate of current assets
Operation and development capacity of the company	The operation and development ability of a company represents the development prospect of a company. The change of this index can predict the development direction and trend of the company, which is conducive to a more comprehensive understanding of the state of the company	Growth rate of operating revenue
		Net profit growth rate
		Growth rate of total assets

As shown in Table 1, through financial indicators and non-financial indicators as variables, all testing processes are through spss18 Created by 0. The stock code and risk status information of 20 listed enterprises and the scores of non-financial index scale statistics are shown in Table 2.

Table 2. Company risk and non-financial index scale

Code	Abbreviation	Risk status	Score situation
602563	X1	1	545
604156	X2	0	663
603258	X3	1	425
604652	X4	1	822
603654	X5	1	336
602142	X6	0	234
609634	X7	1	512

(*continued*)

Table 2. (*continued*)

Code	Abbreviation	Risk status	Score situation
604512	X8	0	163
607458	X9	1	242
606325	X10	0	112
602312	X11	1	263
603245	X12	0	321
606328	X13	1	541
606632	X14	1	444
601425	X15	1	263
602362	X16	0	135
601141	X17	0	226
602352	X18	1	332
601252	X19	0	622
603274	X20	0	214

The data test includes two steps, first through the K-S sample data test, and then the mean test. Both processes include significance test. K-S sample data test method was first used in foreign commercial banks to test the probability of data in a certain range, that is, normality test. During this test, if the sample data obeys the distribution within the specified range of the test, the smaller the statistical quantity s is, it belongs to the normal distribution. Otherwise, the larger the s value is, the larger the s value is, it indicates that the data index does not obey the distribution within the specified range and belongs to the non normal distribution. The test results are shown in Table 3.

Table 3. K-S test

Indicator name	S value	Significance P value
X1	1.142	0.007
X2	1.635	0.008
X3	2.415	0.000
X4	1.336	0.006
X5	2.254	0.000
X6	1.156	0.004
X7	2.324	0.000

(*continued*)

Table 3. (*continued*)

Indicator name	S value	Significance P value
X8	1.526	0.006
X9	3.333	0.000
X10	1.748	0.008
X11	1.569	0.005
X12	2.254	0.000
X13	2.145	0.000
X14	2.263	0.000
X15	1.321	0.006
X16	1.123	0.005
X17	2.425	0.000
X18	2.415	0.000
X19	1.635	0.004
X20	1.415	0.006

As shown in Table 3, the larger the statistic s, the lower the significance p value. When the s value is greater than 2.0, the p value is 0.000, indicating that the selected sample data does not conform to the normal distribution. Based on the above research results, it can be found that the indicators of 20 listed enterprises generally do not obey the normal distribution. Through the comparative analysis of literature in recent years, this result is effective. The purpose of mean test on sample data is to distinguish the index distribution of high-risk enterprises and low-risk enterprises. If the sample data follows the normal distribution, the mean test can be carried out through the t-test method commonly used in the parameter test method; If the sample data does not obey the positive distribution, the mean value of the index can be tested by nonparametric test method to obtain higher test accuracy. However, considering that these indicators may have multicollinearity in the test process, the amount of calculation will be increased in the process of model construction, resulting in reduced accuracy and complexity of the model, so on this basis, the indicators are further screened by principal component analysis to ensure that there is no influence of multicollinearity and build the model accurately. At this time, the comprehensive model of credit risk monitoring of commercial banks can be expressed as:

$$P_d = \frac{P_k(x)}{\sum_{i=1}^{n} F_x} \tag{8}$$

where, P_d represents the identification accuracy of risk monitoring; F_x represents the performance proportion of enterprise asset management. Through the above model, the prediction and judgment of data indicators are established, and the corresponding monitoring and judgment results are obtained.

3.3 Risk Monitoring Capability Test

The establishment of the model does not only depend on the application of the sample data, but also the accuracy of the model is the best embodiment of the prediction ability of the model. The accuracy can ensure the correctness of the application in the process of credit risk monitoring. The sample data of 43 listed enterprises in 2016 is taken as the verification sample. The nonlinear integrated deep learning method, artificial intelligence method and the method in this paper are used to improve the accuracy of financial system operational risk monitoring. The results are shown in Table 4.

Table 4. Operational risk monitoring accuracy of financial system

Sample data volume/GB	Operational risk monitoring accuracy of financial system/%		
	Methods in this paper	Artificial intelligence method	Nonlinear integrated deep learning method
100	99.6	82.5	69.2
200	98.5	80.2	72.8
300	99.0	76.9	75.3
400	92.9	78.3	78.1
500	96.3	79.3	82.6
600	95.1	80.0	85.0

From the analysis of Table 4, when the financial sample data is 100\,GB, the accuracy of the financial system operational risk monitoring of the method in this paper is 99.6%, the accuracy of the artificial intelligence method is 82.5%, and the accuracy of the non-linear integrated deep learning method is 69.2%; When the amount of financial sample data is 500\,GB, the accuracy of financial system operational risk monitoring of the method in this paper is 96.3%, the accuracy of financial system operational risk monitoring of the artificial intelligence method is 79.3%, and the accuracy of financial system operational risk monitoring of the nonlinear integrated deep learning method is 82.6%; The risk monitoring accuracy of this method is always high, which indicates that the operational risk monitoring effect of this method is good.

4 Concluding Remarks

Aiming at the risks existing in the operation of smart financial system, taking 20 private enterprises as analysis samples, this paper establishes an operation risk monitoring method of smart financial system based on deep learning and improved RPA. The system adopts a non coupling technology to obtain and analyze the transaction data in the operation of accounting business without affecting the normal operation of various monitored business systems. It is a risk management system for the risk supervisors of grass-roots legal entities of associated press and the personnel of business management department of provincial associated press. It will not affect and embed into any system, nor will it affect the change of computer room, network and other infrastructure supporting the operation of the system and its operation security. Based on the RPA system process monitoring log, user information, financial work scene and other relevant data, the system studies the user portrait construction technology of the financial system to find the system problem users in time. In the integration of financial system operational risk loss event database and RPA system process monitoring log, the system operational risk discovery model based on in-depth learning is studied to realize the accurate identification of loss events. It can also form user portraits based on user static data information, build event maps based on dynamic RPA process operation data, establish a risk prevention and control model based on event transmission chain analysis, and support multiple intelligent risk prevention and control analysis scenarios such as illegal clue analysis and risk transmission analysis.

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