Agricultural Products Supply Chain Risk Assessment Model Construction and Application in IOT Environment

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This paper constructs the operation model of agricultural products supply chain under an IoT (Internet of Things) environment, based on which the HHM (Hodrick-Prescott Filter) model is used to identify the risk. The ISM (Internal Supply Management) model was used to analyze risk factors. A risk index system was constructed, which was divided into three primary indexes and 18 secondary indexes. The backpropagation (BP) neural network approach was used to establish the risk assessment model. The sample data from 2017 to 2020 was employed as the test sample to test the network assessment model. There was a very small error in the risk level assessment and training results. The results showed that the risk level assessment model was highly operable and can have practical value for effective assessment of the risk level.

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INTRODUCTION

Facing the introduction of IoT technology, research on risk management should not be limited to the traditional model. Ideally, it should combine new development characteristics to improve the risk management under the IoT environment (Fontes and Freires 2018). From the theoretical level, on the one hand, academic research in this field should keep pace with the times and introduce new technologies, while the current food supply chain still lacks a scientific and reasonable index system and risk assessment research in the application of IoT technology (Verma *et al*. 2022). On the other hand, compared with other food supply chains, the influence factors of this field are more complex, the quantification of risk factors is more complicated, there is no more scientific method, and the index selection is more difficult. Therefore, this paper helps to enrich the theoretical results of this field risk research through the analysis and evaluation of risk (Mohammadi *et al.* 2021).

From the practical level, for enterprises, most agricultural products enterprises in the past are still relatively weak in the awareness of supply chain risks. They focus more on the creation of corporate profits and easily ignore the identification and control of this field of risks, thus causing economic losses. Thus, strengthening risk management can bring long-term benefits to enterprises (Liu 2022). In addition, the quality and safety of agricultural products can also bring adverse social effects, and strengthening risk management can also provide scientific and practical suggestions and measures for government departments (Reinhardt *et al.* 2001).

RELATED WORK

Starting from the 1990s, some scholars have asserted that the supply chain of agricultural products must satisfy six elements: large-scale production, continuous supply, member alliance, quality control, flexible production process, and technology information application (Uzogara 2000). In 2009, relevant experts explored the problems in food procurement and discussed how to manage and prevent risks; in 2020, many studies are showing that food is a necessity for human life, so the risk control of food is significant in the food supply chain (Des Roches *et al.* 2019).

Regarding the research on supply chain risk identification, scholars believe that cooperation, trust, and collaboration among companies can facilitate the establishment of an agricultural products supply chain. Some scholars believe that product quality risks exist in all aspects of agricultural products, from production to consumption, and these are rooted in the high-risk nature of agricultural products (Merriman *et al.* 2019). Some scholars have suggested using weight hierarchy analysis to assess, classify, and manage supply risks (César *et al.* 2018). Some scholars have combined AHP and FAHP to evaluate and classify the supply chain risks. Frequency domain analysis has been used to assess and control the supply chain risk and use the net present value of activity method to measure the cost of risk generation (Pascual *et al.* 2017). With the continuous development of theories, some scholars began to use the explanatory structure model to study the dependence of different levels of risks on each other in the agricultural supply chain. The power-change theory has been used to quantify the supply chain risks caused by internal and external environmental changes (Fortems-Cheiney *et al.* 2016). A method of quantifying supply chain risks based on a conceptual framework has been proposed, using graph theory to quantify information risks (Mulwa *et al.* 2016). Others have analyzed the factors affecting food safety from a supply chain perspective and concluded that the factors affecting food safety are: processing, logistics, source supply, and catering (Zhang *et al.* 2021).

IoT technology allows various links in the agricultural product supply chain (such as farms, warehouses, transportation, *etc.*) to obtain data in real time through sensors and devices, such as temperature, humidity, climate conditions, location, and other information. These data can be used to build risk assessment models and monitor risk points in the supply chain in real time, helping to promptly warn and manage risks.

The agricultural product supply chain in the Internet of Things environment involves multiple participants and links, generating a large amount of data. Using IoT technology, data from different sources can be integrated and combined with other external data (such as weather data, market data, *etc.*) to more comprehensively assess supply chain risks. Based on data collection and processing in the Internet of Things environment, the agricultural product supply chain risk assessment model can analyze and predict potential risk events in real time and provide decision support. This helps to respond and adjust immediately to risks in the supply chain, reducing the impact of risks and improving the resilience and flexibility of the supply chain. The agricultural product supply chain risk assessment model in the Internet of Things environment can achieve remote monitoring and management, and through remote equipment management and intelligent control, potential risk issues can be discovered and resolved in a timely manner. This remote monitoring and management capability helps increase efficiency, reduce costs, and reduce the risk of human error and operational errors.

Internet of Things technology can collect and monitor various data related to the agricultural product supply chain in real time and comprehensively, including meteorological data, soil data, crop growth data, as well as temperature and humidity data in storage and transportation, *etc*. Compared with traditional methods, the application of IoT technology makes data collection more accurate and efficient. The agricultural product supply chain in the Internet of Things environment involves multiple links and multiple participants. Each link generates a large amount of data, which comes from different sources. Through IoT technology, these data can be integrated to form a complete supply chain data system, and comprehensive analysis can be conducted based on this data system to better assess risks. Based on supply chain data in the Internet of Things environment, a real-time risk early warning system can be established. By monitoring and analyzing the data, potential supply chain risks, such as natural disasters, epidemics, quality problems, *etc*., can be discovered in a timely manner, so that corresponding measures can be taken, thereby reducing losses and impacts. The agricultural product supply chain risk assessment model in the Internet of Things environment can support the automation of decision-making. Through algorithms and machine learning technology, large amounts of data can be quickly processed and analyzed to generate decision-making recommendations. Such a model can help supply chain managers make better decisions and reduce the interference of human factors.

METHOD

Agricultural Products Supply Chain Operation Model

Based on the traditional operation model and the practical application of IoT, a model under the IoT environment consisting of growers, distributors, retail enterprises, and consumers is constructed (Sun and Zhu 2022). With the use and support of the IoT system, the operation of various links such as production, distribution, sales testing, and agricultural products traceability is ensured, and information sharing in each link is realized. The operation mode is shown in Fig 1.

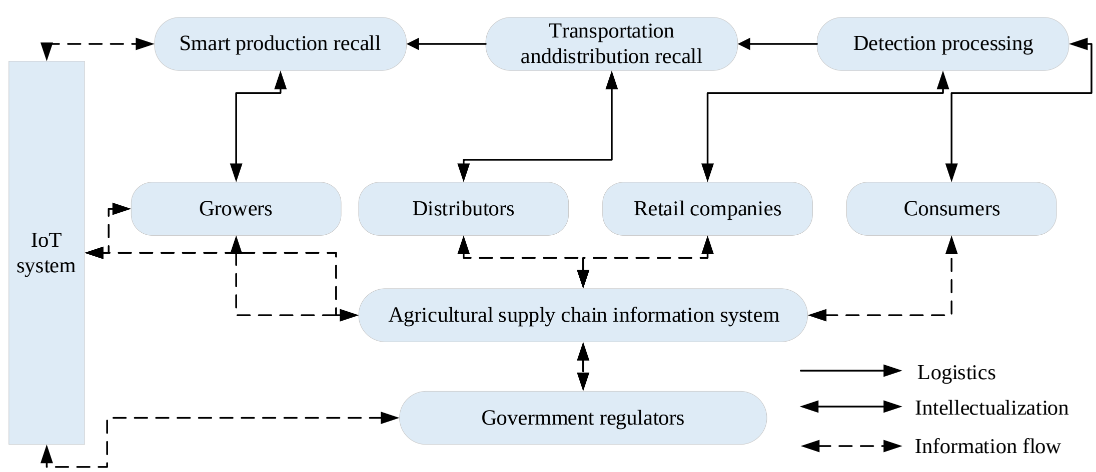

Fig. 1. Operation model in IOT environment

This paper divides its application of the agricultural supply chain into three aspects: the sensing layer, information layer, and perception layer. The agricultural supply chain IoT application system architecture is as shown in Fig. 2.

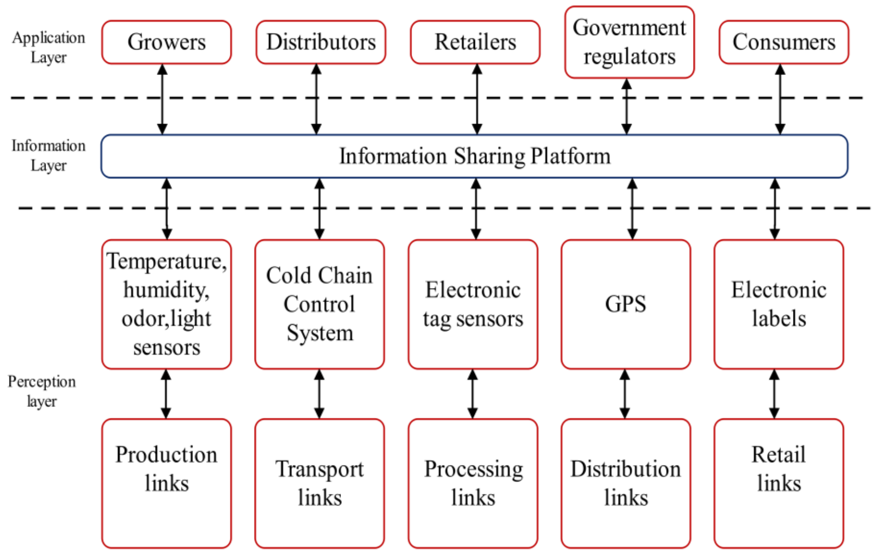

Fig. 2. Agricultural supply chain IoT application system architecture

HHM-ISM model in IoT environment

Agricultural products supply chain risk identification based on HHM

In the first step, different possible risk sources are selected, and risk scenarios are classified from several different perspectives based on the characteristics (Zihao *et al.* 2022).

The motivation for using artificial neural network modeling is that it can perform model construction and prediction by learning data characteristics, and it performs well on nonlinear and complex problems. In agricultural product supply chain risk assessment, due to the combination and interaction of various factors, risk assessment problems are nonlinear and highly complex, and it is difficult to solve these problems well with traditional modeling methods. The artificial neural network model is different from the traditional linear model in that it can simulate nonlinear relationships, making the model closer to the actual situation. During the training process, the artificial neural network model can adaptively adjust weights and thresholds to achieve better prediction results. The artificial neural network model can handle multi-dimensional and high-dimensional data, which is unmatched by other methods. Artificial neural network models can also maintain good predictive capabilities when there are missing or abnormal data in the data set. The artificial neural network model adopts an iterative optimization method, which can continuously optimize model performance during the continuous learning process.

In the second step, each perspective delineated in the first step is further subdivided, and it is continuously iterated and repeatedly judged whether the current view can express the complete risk sources and prevent any error or omission. The HHM framework is finally determined, as shown in Fig. 3.

During this step, the identified perspectives are carefully analyzed to identify the key components or factors within each perspective that contribute to the overall risks in the agricultural supply chain. These components can include various aspects such as production, logistics, quality control, market demand, financial factors, and regulatory compliance.

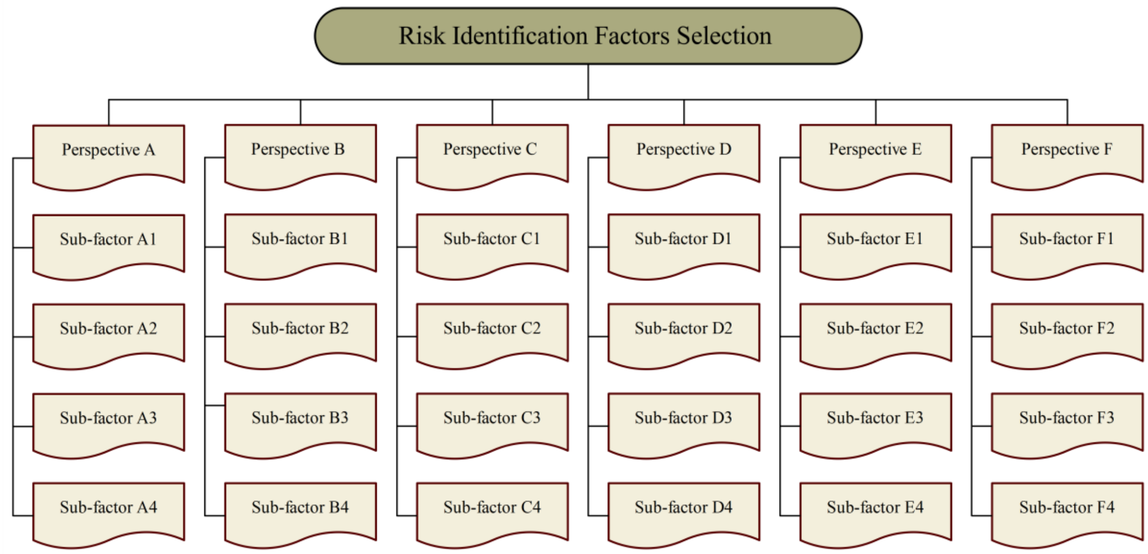

Fig. 3. HHM Framework

For each identified component, further subdivisions and categorizations are made to capture the specific elements or factors that may pose risks or influence the overall risk level. This can involve breaking down the components into sub-components or identifying specific risk factors associated with each component.

Throughout this process, it is crucial to continuously iterate and evaluate whether the current subdivisions and categorizations effectively express the complete range of risk sources. This iterative approach helps to ensure comprehensiveness and accuracy in identifying the risk factors. By continuously reviewing and judging the subdivisions, the goal is to prevent any potential errors or omissions in capturing the key risk sources. This evaluation process helps refine the risk assessment model and ensures that it provides a thorough understanding of the risks present in the agricultural supply chain in the IoT environment. In the third step, any two perspectives are selected and cross-tabulated for each of their subfactors, and the cross-tabulation between perspective C and perspective D is shown in Fig. 4.

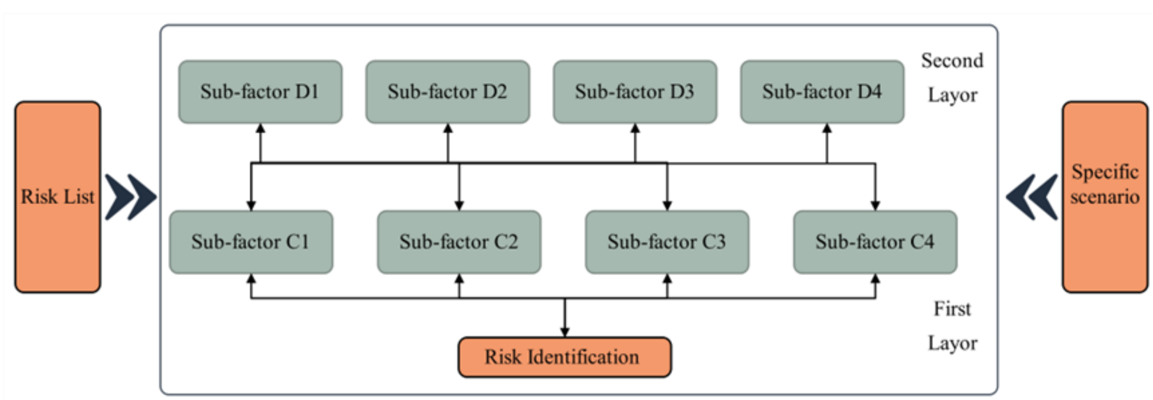

Fig. 4. Perspective C and D Risk Factor Identification HHM Sub-Framework

In the fourth step, all subfactors under perspective C and all subfactors under perspective D are analyzed two by two to obtain the influence of subfactors under perspective C by subfactors under perspective D, and the result is shown in Table 1.

Table 1. Perspective C and Perspective D Risk Identification Matrix

Risk Factors		Perspective D			
		Sub-factor Da	Sub-factor Db	Sub-factorDc	Sub-factorDd
Perspective C	Sub-factor C1	CaDa	CaDb	CaDc	CaDd
	Sub-factor C2	CbDa	CbDb	CbDc	CbDd
	Sub-factor C3	CcDa	CcDb	CcDc	CcDd
	Sub-factor C4	CdDa	CdDb	CdDc	CdDd

In the fifth step, the above steps are repeated to obtain all risk factors. The accepted risk factors are filtered to exclude the factors with little relevance or duplication. The design process is shown in Fig. 5. The content of the HHM framework is shown in Fig. 6.

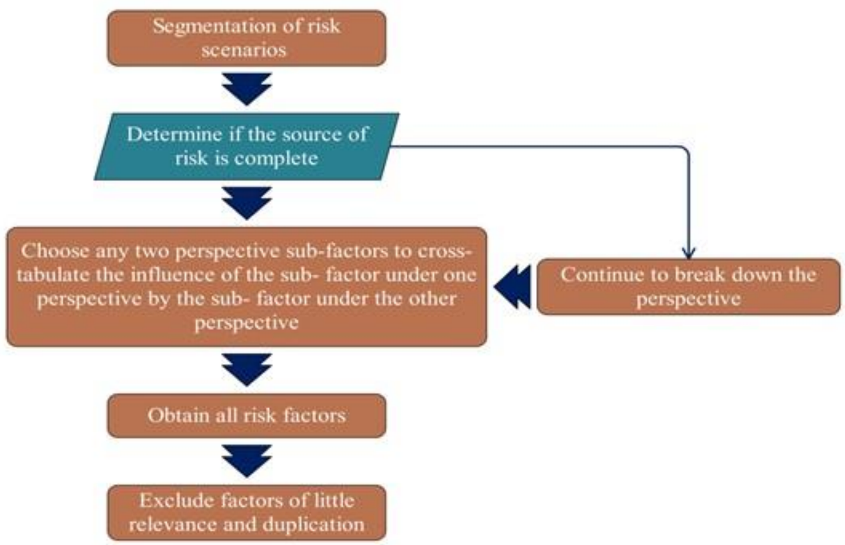

Fig. 5. The design process of the HHM framework

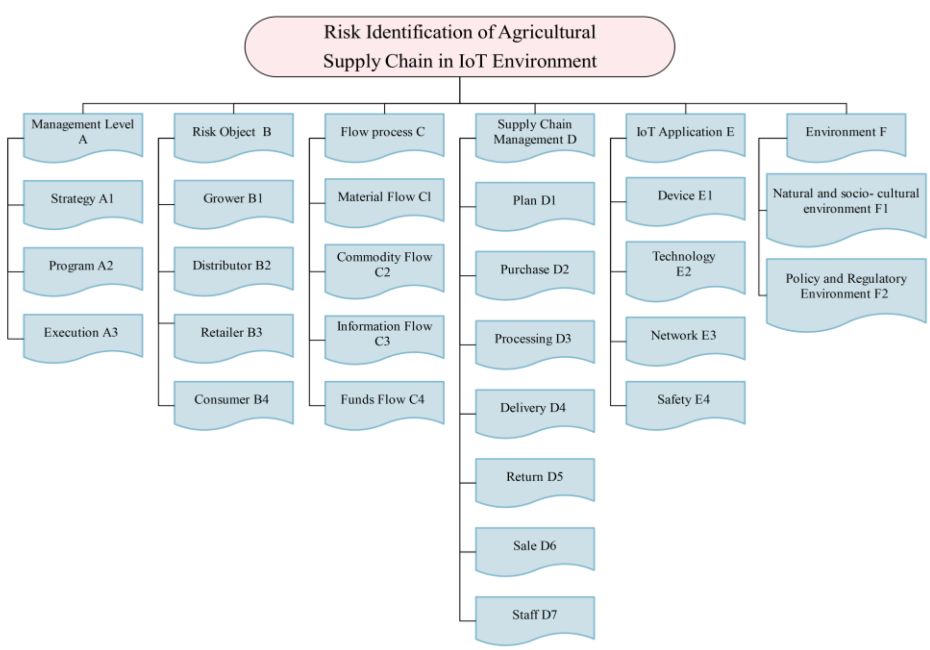

Fig. 6. HHM framework

In the following, the HHM model will be used to analyze the potential risk factors from two perspectives: management level and risk object, and the analysis process is shown in Table 2.

Table 2. Management Level - Risk Objects Risk Factor Identification Matrix

Risk Factors		Risk Objects			
		Grower	Distributor	Retailer	Consumer
Management Level	Strategy	Strategy	Strategy	Strategy Competition	—
	Program	Raw material input decision	Partner selection	Partner selection Demand fluctuation	—
	Execution	production safety materials Safety	Processing cost control Transportation	Transportation Product Damage	Cost control risk

The same method is used to identify risk factors for all subfactors in the HHM framework, and 235 risk factors can be theoretically derived. The risk index system used in this paper is shown in Fig. 7.

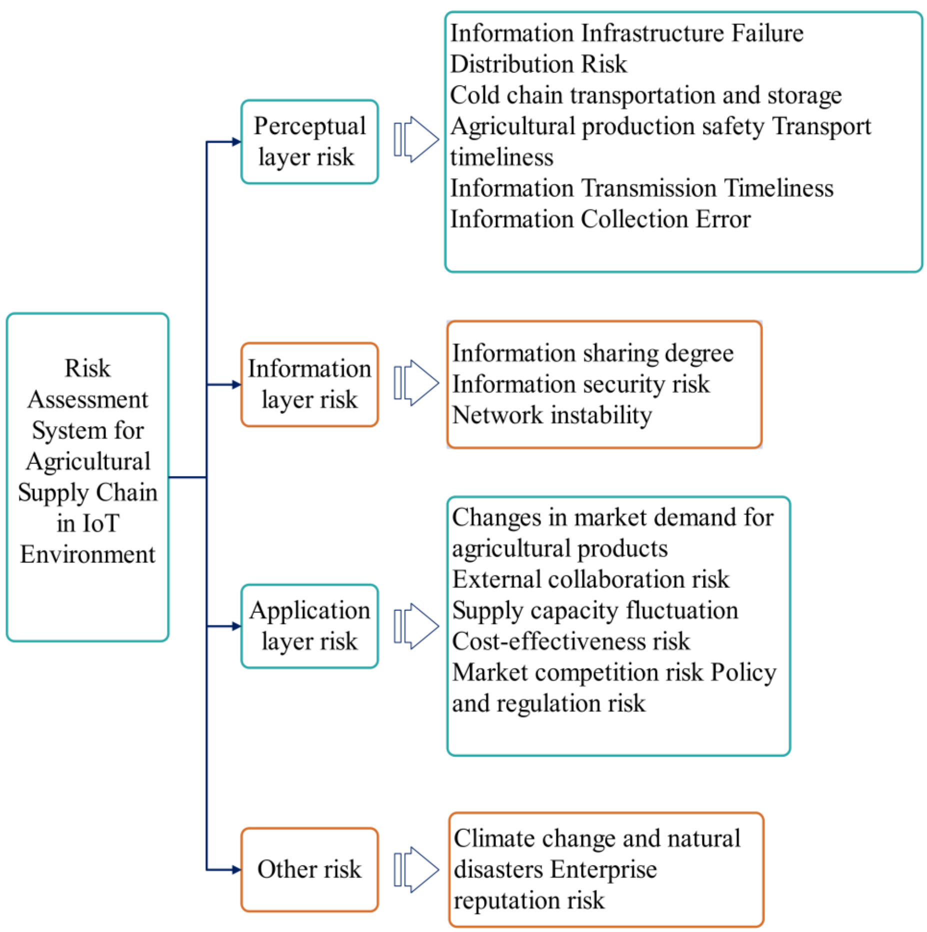

Fig. 7. Risk assessment index system in IoT environment

Agricultural products supply chain risk factor analysis based on ISM

In the first step, the correlation matrix of adjacent factors is constructed. The influencing factors $\mathrm{T}_1, \mathrm{T}_2, \cdots \mathrm{T}_\mathrm{o}$ of the system are determined, and the association matrix S is built. The judgment conditions of the relationship between factors are as follows:

$$\begin{cases} 1 \text{ There is an influence between factors} \\ 0 \text{ There is no influence between factors} \end{cases}$$

The second step is to construct the power operation of mClose $(S+I)$ for some integer o until Equation 1 holds (Zihao *et al.* 2022).

$$CapN = (S+I)^{o+1} = (S+I)^{o} \neq (S+I)^{2} \neq (S+I), \mathrm{o} = 1,2,3,\cdots \tag{1}$$

From this, the reachable set and the antecedent set can be determined and expressed by Eqs. 2 and 3:

$$S(T_i) = \{T_i \in O \mid n_{ij} = 1\} \tag{2}$$

$$B(T_i) = \{T_j \in O \mid n_{ij} = 1\} \tag{3}$$

The third step is to construct the hierarchical identification model (Fan *et al.* 2022).

$$S(T_i) \cap B(T_i) = S(T_i) \tag{4}$$

In the fourth step, a multi-level structure recurrence diagram is produced.

Through the above HHM-based risk identification of agricultural products supply chain in IoT environment, 234 risk factors can be theoretically derived, 38 risk factors are extracted after filtering the data, and these are further constructed by 18 risk factors according to the principle of index system selection. According to the interrelationship of the 18 risk factors, the key factor is assumed in the correlation matrix, and finally, the correlation matrix S.

$$S = \begin{bmatrix}
1 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \\
1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\
1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\
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0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\
1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1
\end{bmatrix}$$

The association matrix R is calculated according to Equation 1, and the reachable matrix N is obtained as:

$$N = \begin{bmatrix} 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Hierarchical processing of N with Eq. 4 is used to obtain the risk factor interaction relationship and get the hierarchical relationship of risk factors of agricultural products supply chain under IoT environment. The results are shown in Table 3. The final multi-level recursive structural model is shown in Fig 8.

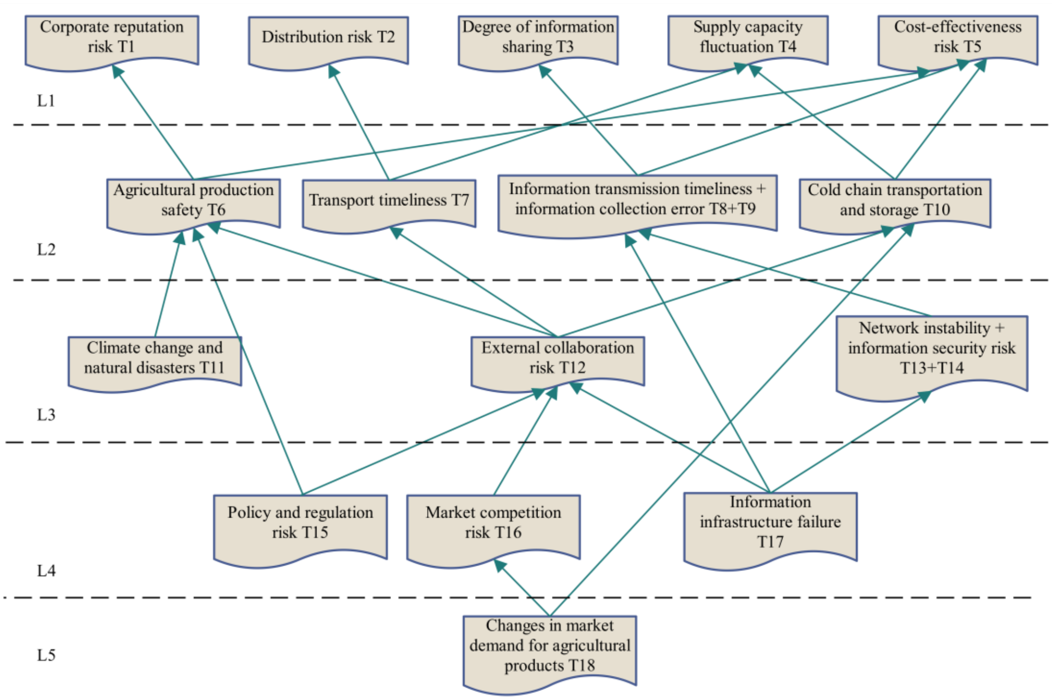

Fig. 8. Multi-level recursive structural model of agricultural supply chain factors in IoT

Table 3. Hierarchical Relationship of Agricultural Products Supply Chain Risk Factors

Level	Key Factors
L1	3 9 14 15 19
L2	4 5 6 7 8
L3	10 11 12 18
L4	2 16 17
L5	12

RESULTS

Agricultural Products Supply Chain Risk Assessment Based on BP Neural Network

Regarding the input layer, this paper uses the fuzzy integration principle and programming operations to obtain the specific risk operation data in the final index (Suardin *et al.* 2007). These initial indicators are preprocessed using principal component analysis, and then the error is reduced using the Kaiser normalized maximum variance method. As can be seen from Table 4, the 18 indicators converged after 7 iterations of rotation, and three principal factors were extracted using principal component analysis, with a cumulative variance contribution of 85.82%.

Table 4. Rotated Factor Component Matrix

	1	2	3
B1	0.922	0.221	-0.081
B2	0.688	0.584	0.128
B3	0.927	0.115	0.003
B4	0.887	0.223	0.122
B5	0.323	0.182	0.003
B6	0.743	0.455	0.179
B7	0.771	0.564	0.224
B8	0.632	0.345	0.222
B9	0.123	0.564	0.322
B10	0.177	0.555	0.132
B11	0.763	0.621	0.344
B12	0.332	0.465	0.771
B13	0.234	0.332	0.632
B14	0.555	0.323	0.123
B15	0.234	0.151	0.332
B16	0.345	-0.112	0.234
B17	-0.889	-0.232	0.555
B18	0.231	0.122	0.234

Positive and negative values respectively indicate the degree of impact of different factors in the agricultural supply chain on the end-to-end risk of the supply chain. Specifically, a positive value indicates that this factor is likely to have a positive impact on the risk, while a negative value indicates that it is likely to have a negative impact on the risk. In Table 4, the influence coefficient of factors is 0.922, which is a positive value. This means that improved levels of traceability and quality control may help reduce risks in agricultural supply chains. Similarly, the influence coefficient of factors is -0.081, which is negative, indicating that environmental issues may increase supply chain risks.

Regarding the output layer, the number of risk levels is represented by node sections, which are generally divided based on the evaluation results corresponding to the expected output values in the training sample data (Yadav *et al.* 2017). The research process used SPSS18.0 software to pre-process the training samples. The weight values of the three common factors were set as the proportion of their variance contribution to the total variance contribution, and the combined score of each training factor was obtained after the weighting calculation. Among them, the scores of each common element are as follows:

$Fp_1=(0.601\times B_1+0.867\times B_3+0.758\times B_4+0.823\times B_5+0.753\times B_6+0.812\times B_7+0.625\times B_9+ ... +0.863\times B_{18})/(0.601+0.867+... +0.863)$

$Fp_2=(0.885\times B_2+0.632\times B_6+0.72\times B_8+0.626\times B_9+... +0.789\times B_{25})/(0.885+0.632+... +0.789)$

$Fp3=(0.789\times B_{22})/0.789$

The weight of the total variance contribution of the main factor is

$F=(45.008\times Fp_1+36.996\times Fp_2+9.721\times Fp_3)/86.232$

The final composite factor scores were obtained as shown in Table 5

Table 5. Combined Factor Scores of Training Factors

	1	2	3	Composite Factor Score
2011	-1.322	-0.456	0.543	-1.002
2012	-0.767	-0.872	0.278	-0.802
2013	0.101	0.112	0.003	-0.332
2014	-0.232	0.343	0.122	-0.243
2015	-0.812	0.222	0.003	-0.072
2016	0.882	0.161	0.155	0.002
2017	0.233	0.987	0.567	0.234
2018	0.684	0.199	1.010	0.775
2019	1.129	0.212	1.222	1.034
2020	0.234	0.978	1.230	0.455

The distribution of risk assessment levels are shown in Table 6

Table 6. Risk Level

Risk Level	Risk Degree	Combined Factor Value Range	Assessment Output	Display Signal
1	Significant Risk	(-∞,-1)	[1000]	Red
2	Major Risk	(-1,0)	[0100]	Orange
3	General Risk	(0,1)	[0010]	Yellow
4	Low risk	(1∞)	[0001]	Blue

Regarding determining the implied layer, the software MATLAB 2020a was used in this work to take the values and cobble together the trials in turn (Li and Sun 2022). This paper established a 12×13×3l model. The BP structure hidden layer node number training effect is shown in Fig. 9.

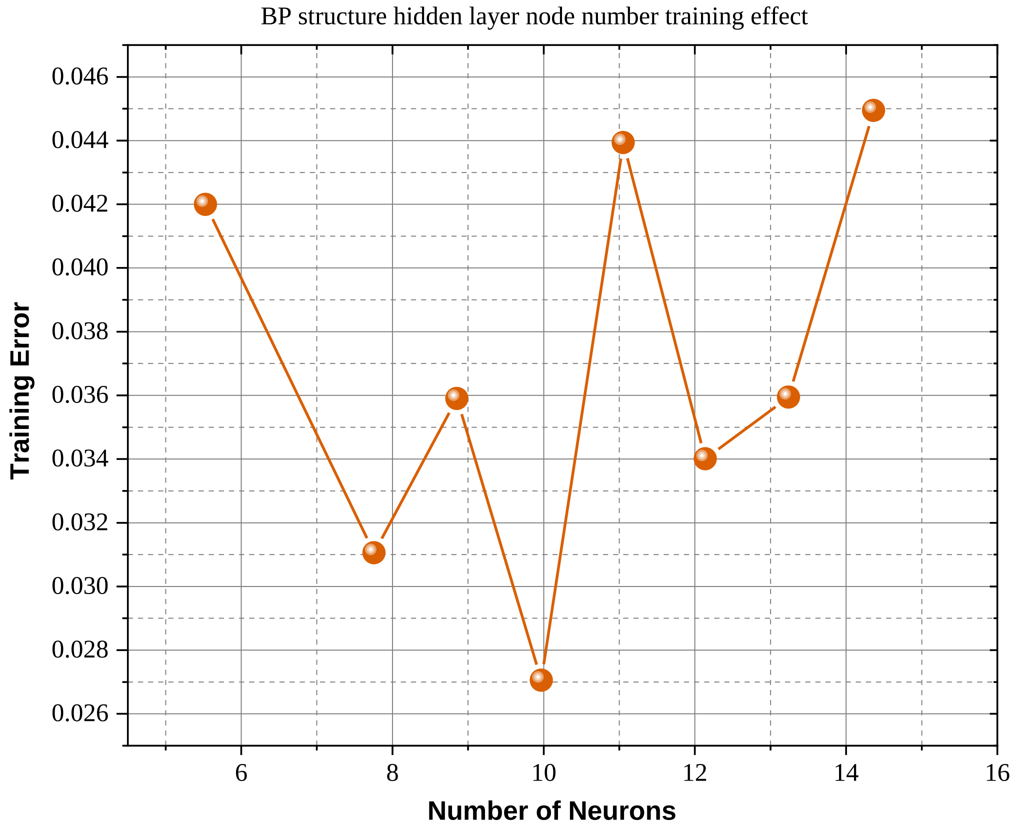

Fig. 9. BP structure hidden layer node number training effect

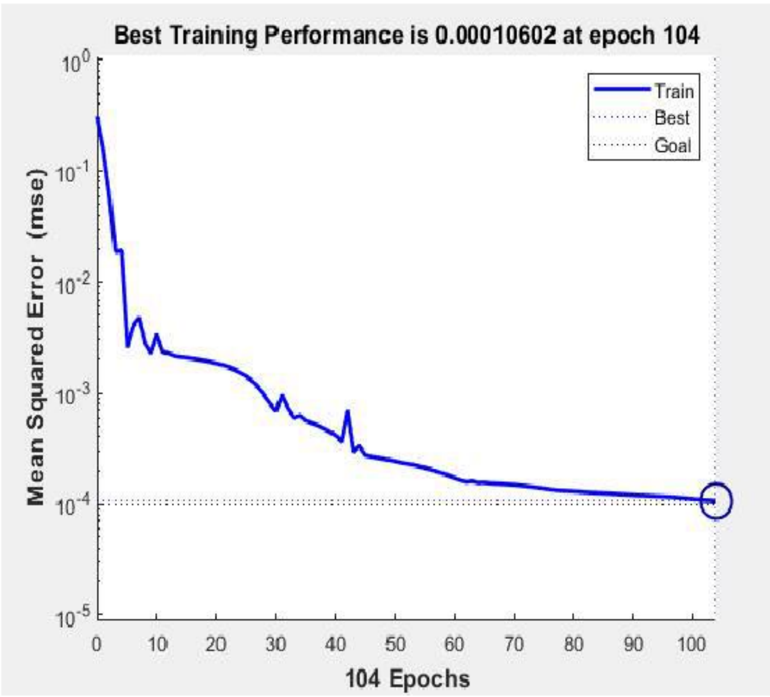

Fig. 10. Network training error variation curve

Model Training and Testing

This paper used the data from 2012 to 2016 as the training samples. The actual data are determined as the number of nodes in the input layer of the model. Data import function was used to establish the evaluation network, and the "Newff()" network running program was used to conduct BP neural network training. As shown in Fig. 10, when the model is trained to 106, the performance of the whole risk level assessment model reaches the best state, and the training effect was optimal.

As shown in Fig. 11, the actual output value and the expected target value were positively distributed, the sample fit was good, and the accuracy of the training sample was 98.382%. The training sample set fit well and can reach the expected target.

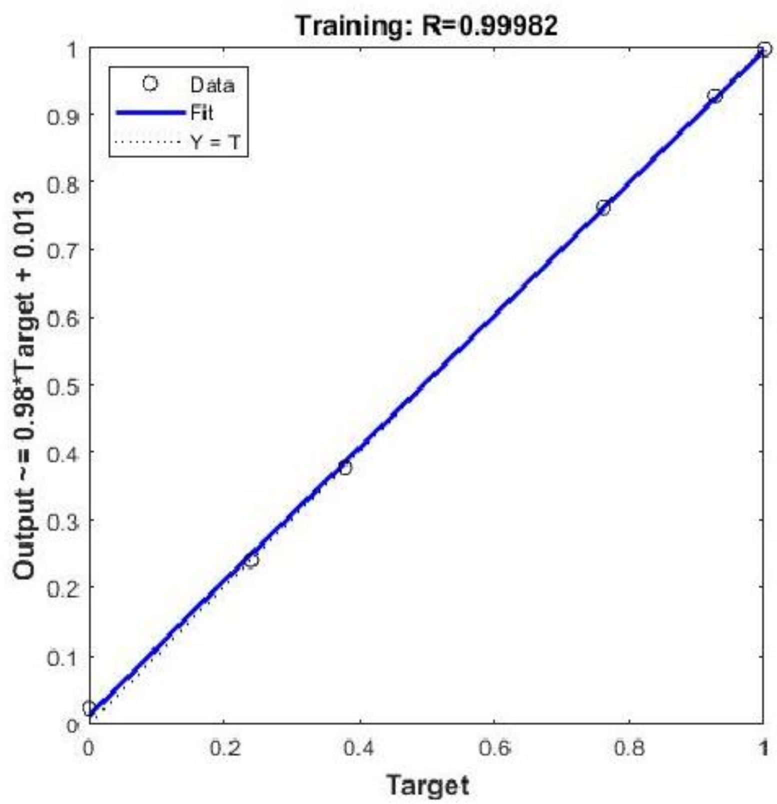

Fig. 11. Predicted data vs. actual data results

In this paper, the sample data from 2017 to 2020 was selected as the test sample, thus testing the network evaluation model, and the results are detailed in Table 7.

Table 7. Network Test Output Results

Year	Expected Output	Actual Output	Risk level	Display signal	Output identification
2017	0.434	0.323347898	2	Yellow	[0010]
2018	0.632	0.702127032	2	Yellow	[0010]
2019	0.765	0.734320098	2	Yellow	[0010]
2020	1.021	1.023883981	1	Blue	[0001]

It can be concluded that the model training error was very small, thus meeting the requirement of small gap between the desired output value and the actual output value and indicating that a better model is established.

CONCLUSION

This work involved construction of an operation model of agricultural products supply chain under IoT environment. Based on this approach, the HHM model was used to identify the risk under an IoT environment. The ISM model was used to analyze risk factors, and the risk index system was constructed, which was divided into three primary indexes and 18 secondary indexes. The back-propagation (BP) neural network was used to establish a risk assessment model. Sample data from 2017 to 2020 was used as the test sample to test the network assessment model. There was a very small error in the risk level assessment and training results, and a good model was established. The risk level assessment model was found to be highly operable and have practical value that can effectively assess the risk level. A shortcoming of this work is that the prediction results are random because the weight thresholds are generated randomly. To deal with this, there is a need to continue to optimize the structural parameters in the future, such as selecting the minimum number of implied layer neurons corresponding to the mean squared difference value MSE by using a circular statement algorithm.

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