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Computer-Aided Design AND APPLICATIONS

Application of Human-Computer Interactive Modern Financial Technology in Agricultural Supply Chain Finance Based on Artificial Intelligence Powered CAD

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Abstract. The integration and development of digital finance and the real economy, such as the widespread application of blockchain, will play an essential role in new technological innovation and industrial transformation. By leveraging AI-powered CAD, we analyze financial data and supply chain dynamics, providing real-time insights and visualizations that support strategic financial planning and risk management. The findings indicate that effective HCI design, combined with advanced CAD capabilities, significantly enhances user experience and satisfaction, leading to improved financial outcomes in agricultural supply chains. This paper combines big data technology to analyze the application of modern financial technology in agricultural supply chain finance, uses big data technology to mine rules and problems, and puts forward corresponding decision-making suggestions. Through experimental research, the method proposed in this paper can effectively dig out the application law of financial technology in agricultural supply chain finance. Furthermore, this paper effectively analyzes the role of financial technology in agricultural supply chain finance and puts forward reasonable suggestions.

Keywords: Big data; Artificial intelligence; Human-Computer Interaction in financial technology; supply chain finance
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1 INTRODUCTION

The agricultural supply chain is a network structure with application functions, and it is composed of multiple entities participating in agricultural production and operation, which mainly include agrarian product providers, production service providers, business sellers, consumers, etc. The basis for the widespread application of digital finance is the gradual improvement of hardware facilities and services. The endogenous driving force of the application is the needs of the participants in the connection of capital supply and demand, and the external thrust is the gradual release of policy dividends. The application foundation of digital finance in the agricultural supply chain is initially available [14].

The rapid development of my country's digital finance benefits from three essential factors: the shortage of traditional financial services, the relative tolerance of the regulatory environment, and the rapid development of information technology, brilliant phones, big data, and cloud computing. Economic integration and development, such as the widespread application of blockchain, will play an essential role in new technological innovation and industrial transformation. In the next period, digital finance will penetrate the agricultural field more deeply, and the farm supply chain will be the best carrier and implementation path, as well as a breakthrough and booster for the innovative development of the agricultural industry.

Establishing information infrastructure is the physical prerequisite and "hard foundation" for applying digital finance to the agricultural supply chain. Currently, e-commerce is developing rapidly, and online agricultural information activities are becoming more and more prosperous. They are integrated with offline agricultural production activities and proceed in an orderly manner. Combining modern information technologies such as cloud computing, big data, Internet of Things, and blockchain with modern agriculture has become the basis for large-scale agricultural enterprises, small and medium agricultural enterprises, farmers, and new agricultural business entities to participate in agricultural supply chain activities [11].

The convergence of fintech, agriculture, and e-commerce, aided by blockchain and big data analytics technologies, has disruptive potential. However, the successful adoption of these technologies depends significantly on efficient Human-Computer Interaction (HCI). By integrating HCI principles, the e-commerce platforms within this convergence can ensure user-friendly interfaces and seamless interactions, enhancing user engagement and satisfaction. Additionally, the integration of e-commerce allows for streamlined transactions and better market reach, while HCI enhances the usability and accessibility of these technologies. Effective e-commerce strategies combined with robust HCI can drive the adoption and success of these innovative solutions, making them more appealing and practical for end-users in both the fintech and agricultural sectors. Currently, most agricultural enterprises adopt endogenous financing models, and farming enterprises are mainly labor or technology-intensive enterprises, and their capital accumulation capacity cannot meet the demand [4]. From the perspective of external financing, agricultural enterprises financing through the capital market accounted for a minority, and bank credit is still the primary financing method for most agricultural enterprises [15]. The bank's tolerance for non-performing rates has remained the same due to the weak nature of agriculture. Compared with other industries, most agricultural enterprises have the characteristics of a long production cycle, high risk, limited collateral (pledged) items, and general financial credit status, which limit their ability to obtain bank credit funds. Large enterprises in the agricultural supply chain can replace rigid accounts receivable by issuing commercial bills. In contrast, small and medium-sized agricultural enterprises can obtain implicit commercial credit endorsements by holding the bills of core large enterprises. In addition to banks, financial institutions such as factoring companies and guarantee companies can all establish connections through credit management.

Offline transactions of traditional agricultural economic activities are relatively loose, and there are many obstacles, such as information asymmetry and opaque flow of production factors. However, the development of technologies such as big data, cloud computing, blockchain, artificial intelligence, and the Internet of Things converts the transaction information of agricultural enterprises into credit information, accurately matches the demands of the two ends of the capital supply and demand, and promptly follows up the changes in the supply and demand of production and consumption to guide production. Secondly, financial technology and supply chain development complement each other, forming a closer alliance between supply chain capital suppliers and demanders, product producers, and consumers. Through the integration of digital finance, the capital flow, information flow, and logistics of the individuals involved in the operation of the agricultural supply chain will form a closed loop of operation, which is convenient for taking advantage of the advantages of agricultural supply chain finance.

This article combines big data technology to analyze the application of modern financial technology in agricultural supply chain finance to improve the promotion of modern financial technology to agricultural supply chain finance.

2 RELATED WORK

The literature [9] gradually shifted the research focus on supply chain financial financing theory to integrating the three streams of information in the supply chain: logistics, information flow, and capital flow. Companies in the supply chain can use movable property such as accounts receivable, inventory, and equipment as collateral for financing. Through the analysis of such financing companies, it is found that the asymmetry of financing information can be solved by integrating various transaction objects and extending the transaction time, thereby solving the financing problem of small and medium-sized enterprises. Literature [22] defines supply chain finance according to the actual application level: the essence of supply chain finance is to regard the logistics companies, upstream suppliers, downstream distributors, supply chain management, and financial cross-fields in the supply chain as a whole operation, that is, this entire internal organization cooperates to help companies with financing difficulties in the chain to achieve a win-win situation. Partners share resources, capabilities, and information and can jointly diversify medium and long-term cooperation risks. Core companies dominate supply chain financial financing and enable companies on the chain to reduce financing costs and form a corporate financing ecosystem in the supply chain. Optimization combines cost analysis, scientific, financial management, and other new financial tools [6]. Literature [8] proves that companies in the supply chain can improve the financing capabilities of companies in the chain through the integration of logistics, information flow, and capital flow. In this regard, small and micro enterprises increasingly favor the supply chain financing model.

Literature [17] proposes that small and micro enterprises adopt the supply chain financial financing model not only because it can solve the problem of difficulty in obtaining financing in the bank but also because the financing cost of this model is relatively low. Literature [18] pointed out that some problems in the supply chain financing process can be solved using mathematical models. For example, in the credit rating of a lender, a regression model is used to determine which factors will affect the credit rating. Literature [3] pointed out that supply chain finance is based on the credit generated by the cooperation between upstream and downstream financing enterprises and core enterprises, and the core enterprises provide guarantee loans for upstream and downstream small and micro enterprises in banks to solve the financing of small and micro enterprises with weak upstream and downstream capabilities. Guarantee issues: core companies play a vital role in supply chain finance, which can help banks investigate and supervise financing companies' repayment capabilities.

Literature [19] discusses explicitly how the reverse factoring project, one of the supply chain financial services, can reduce the financing costs of financing companies. This project focuses on using the data on the Internet e-commerce platform to provide new opportunities for small and micro enterprises. Financing service projects. Literature [2] introduces the operating process of a financing model that combines supply chain finance and sales of goods orders. This model is a financing project supported by the buyer based on issuing purchase orders on the chain. The literature [7] indicates that in supply chain financing management, one pays attention to the operation of business processes and financial technology to prevent financial loopholes and losses. Literature [16] uses the fuzzy sequential regression model to evaluate the risks that supply chain financial financing may face. Finally, it proves that this model is an effective evaluation method through a case, which can reduce corporate risks. Literature [1] Given the overall development goals of small and micro enterprises, he positioned supply chain financial financing as a strategic planning goal for developing small and micro enterprises. This type of financing can achieve win-win cooperation between enterprises on the chain and increase the value of all parties. Literature [12] pointed out that blockchain technology has also begun to enter the supply chain financial financing project. However, it is still in the exploratory stage and is expected to accelerate the speed of capital operation in the supply chain.

Literature [13] pointed out that under the traditional financing platform, the characteristics of the financial system make SMEs unable to obtain financial support from banks, trust companies, and other financial institutions. This also inhibits the rational allocation of market resources. Small and micro enterprises are here. Under these circumstances, they are financially disadvantaged and need help to obtain the necessary funds for their development. Literature [5] established a SW model. The model analysis pointed out that small and micro enterprises have difficulty securing bank financing mainly because of their conditions. Their assets are all light, and there is no perfect financial system. The handling needs to be standardized. Even if small and micro enterprises are willing to lend at high interest rates, financial institutions are still reluctant to provide financing services. Literature [21] mentioned that because it is difficult for small and micro entities to obtain financial support from banks and other financial institutions, most enterprises will turn to private capital for financing. This is also the natural choice of the market. Private financing platforms are used to solve funding difficulties. Private capital plays a specific role in promoting corporate financing under the traditional financial system.

3 BIG DATA RESPONSE MODEL

Logistic regression can be used to model the probability of an event. The standard nk of logistic regression is recorded as logit, which is $\log \frac{p_i}{1-p_i}$. Among them, p_i is the average of the binary dependent variable or the probability of an event occurring and $\frac{p_i}{1-p_i}$ is usually called the chance ratio. Therefore, $\log \frac{p_i}{1-p_i}$ can be expressed as a linear function of the independent variable, namely[20]:

$$\log \frac{p_i}{1-p_i} = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i \tag{1}$$

The probability p sub i. of the event's occurrence can be found through simple calculations.

$$p_i = \frac{\exp\ \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i}{1 + \exp\ \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i} = \frac{e^{Z_i}}{1 + e^{Z_i}} = \frac{1}{1 + e^{-Z_i}} \tag{2}$$

Among them,

$$Z_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i \tag{3}$$

Formula (2) is the logistic regression equation and has the following properties: When $Z_i \to \infty$, $p_i \to 1$; when $Z_i \to -\infty$, $p_i \to 0$; when $Z_i = 0$, $p_i = 0.5$. There is an inflection point in the logistic regression equation. Before the inflection point, as Z_i increases, p_i increases faster and faster. After the inflection point, as Z_i As it rises, the growth rate of p sub i. becomes slower and slower and gradually tends to 1.

In linear regression, the least square method is mainly used for parameter estimation. However, due to the nonlinear relationship between p_i and the regression coefficient in logistic regression, the least square method (OLS) cannot be used for estimation, and only maximum likelihood estimation can be used. The maximum likelihood estimation has the same properties as the least square estimation, which means that the maximum likelihood estimation of logistic regression has the properties of consistency, validity, and asymptotic normality[10].

The assumptions of logistic regression are very similar to those of linear regression. The logistic regression model also has some assumptions that differ from those of linear regression. In the context of e-commerce and Human-Computer Interaction (HCI), it is crucial to ensure these assumptions are met to develop accurate predictive models. There are many ways to test the goodness of fit in these models. For instance, in e-commerce applications, logistic regression can predict user behavior or purchase likelihood. At the same time, HCI principles can help design user interfaces that make these predictions actionable and understandable to users. Ensuring a good fit in logistic regression models enhances the effectiveness of e-commerce strategies and improves user experience through optimized HCI. For models with only nominal independent variables, Pearson's $chi-squared$ test can be used to compare the occurrence and non-occurrence frequencies of the predicted and observed events of the model to test whether the model is valid. T-squared statistics the following expression.

$$\chi^2 = \sum_{j=1}^{J} \frac{O_j - E_j}{E_j} \tag{4}$$

The log-likelihood function can also compare the observed and predicted values; L_s Does the set model estimate the maximum likelihood value? Corresponding to it is a benchmark model, which can accurately predict the observed value, denoted as L_f. By comparing L_s and L_f, The following formula can estimate the adequacy of the model represented by the data:

$$D = -2In\left(\frac{L_s}{L_f}\right) = -2\ \ InL_s - InL_f \tag{5}$$

When the independent variable contains continuous variables, the number of covariant types will be huge, resulting in Pearson's χ^2 and D values are not suitable for evaluating the goodness of fit. At this time, HL statistics need to be considered.HL statistic is an indicator similar to Pearson's χ^2 statistic and its formula is as follows:

$$HL = \sum_{g=1}^{G} \frac{y_g - n_g p_g}{n_g p_g\ \ 1 - p_g} \tag{6}$$

Among them, G represents the number of groups, n_g represents the number of cases in the g-th group, y_g represents the number of observations of events in the g-th group, p_g represents the predicted probability of the g-th group, and $n_g p_g$ is the expected number of events.

A confusion matrix is a table of frequency that divides observation cases into occurrences or non-occurrences of events, which can be used to test the accuracy of logistic regression model prediction. The method compares the predicted event probability with the set probability limit and divides the cases into predicted event occurrence or non-occurrence. When the expected probability of a case is greater than the probability limit, it is defined as occurring; otherwise, it is defined as the predicted event that does not happen. Usually, we use 0.5 as the probability limit, but it also depends on the actual situation. When all events are divided into occurrence or non-occurrence, an interactive table can be constructed to compare the predicted and actual conditions.

Decision tree is one of the commonly used methods of response models. The construction of its classifier does not require any domain knowledge or parameter settings. The results are displayed in the form of rules, which are intuitive and easy to understand. Therefore, this method is used in classification. Forecasting is viral. A decision tree is a structure similar to a flowchart, in which each internal node represents a test on an attribute, each branch represents an output of the test, and each leaf node stores a class Label. The top node of the tree is called the root node. If the χ^2 test is not significant, it means that the model fits well. Many decision tree algorithms exist, including ID3, C4.5, CART, etc. They all use a greedy (that is, non-retrospective) approach. The main difference is that the attribute selection metrics and splitting rules differ.

We assume that the data partition D is the training set of labeled class tuples. Moreover, we believe that the class label attribute has m different values, defining m different C_i $i = 1,2,\cdots m$, $C_{i,D}$ is the set of C_i tuples in D, and $|D|$ and $|C_{i,D}|$ respectively represents the number of $C_{i,D}$ Tuples in D.

ID3 algorithm: The ID3 algorithm is based on the information entropy theory and selects the attribute with the most significant information gain value in the current sample as the test attribute. This measurement method is based on Shannon's contribution to information theory. Shannon's information theory shows that the less uncertainty there is in an event, the more adequate the transmission of information is. Moreover, according to the information theory, the ID3 algorithm uses the uncertainty of the divided sample set to measure the division's quality. It uses the information gain value to measure it. Therefore, the ID3 algorithm selects the most significant information gain attribute at each non-leaf node as the test attribute. The information gain formula is as follows:

$$Info\ D\ = -\sum_{i=1}^{m} p_i \log p_i \tag{7}$$

Among them, p_i is the non-zero probability that any tuple in D belongs to C_i .

$Info\ D$ is the average amount of information required to identify the class label of the tuple in D. At this point, all our information is just the percentage of tuples of each class.

C4.5 algorithm: There is a problem with the information gain measurement; that is, the information gain measurement is biased towards tests with many outputs. The C4.5 algorithm uses a kind of information gain called gain rate to solve this problem. It uses the split information value to normalize the information gain. The divided information is defined as follows

$$SplitInfo_A\ D\ = -\sum_{j=1}^{v} \frac{|D_i|}{D} \times \log_2 \frac{|D_j|}{D} \tag{8}$$

This value represents the information generated by dividing the data set D into V partitions corresponding to the V outputs of the attribute A test. The formula for the gain rate is:

$$GrianRate\ A\ = \frac{Grian\ A}{SplitInfo_A\ D} \tag{9}$$

We choose the attribute with the most significant gain rate as the split attribute.

CART algorithm: The CART algorithm uses the Gini index to select the split rule, and the formula is as follows:

$$Gini\ D\ = 1 - \sum_{i=1}^{m} p_i^2 \tag{10}$$

The Gini index calculates the weighted sum of the impurity of each result division by considering the binary division of each attribute. For example, if the binary division of A divides D into D_1 and D_2, the Gini index of this division D is as follows:

$$Gini_A\ D\ = \frac{|D_1|}{D} Gini\ D_1\ + \frac{|D_2|}{D} Gini\ D_2 \tag{11}$$

Every possible binary division is considered for each attribute, and the attribute's subset that produces the smallest Gini index is selected as its split subset. When the decision tree is created, some branches are abnormal due to the noise and outliers in the data. Given the above situation, decision tree pruning can be used to deal with this problem.

The neural network has the following basic structure: the weighted sum of $n+1$ input independent variables $x_0, x_1, \cdots, x_n$ is μ, where $x_0 = 1, \omega = 0$; the above input passes through a nonlinear function φ; the output result y is generated;

$$y = \varphi\ \sum \omega_i x_i + \theta \tag{12}$$

Among them, ω_i is called the mutual correlation strength or weight, θ is similar to the constant term in the logistic regression equation. Its function is to convert the sum of weights into a reasonable range, and Y represents the final output result. The basic structure is shown in Figure 1.

Since the hidden layer is similar to a "black box," in practice, it is difficult for modelers to understand how the neural network model is formed. Theoretically speaking, a neural network is a more sophisticated model, but its performance in database marketing could be better, and in many cases, the opposite situation occurs. Genetic algorithms have been developed quickly but will soon be a popular research direction. They are computer search methods for database marketing to find the best predictive models.

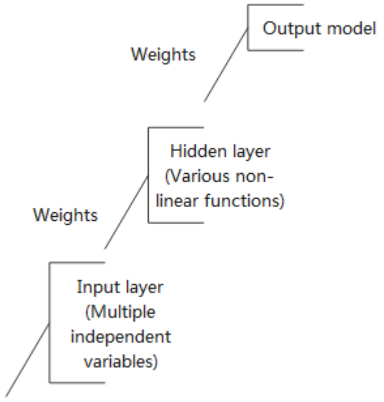

Figure 1: Neural network structure.

4 FINANCIAL RISK ANALYSIS MODEL OF AGRICULTURAL SUPPLY CHAIN

The system should be able to comprehensively cover ABC's agricultural product supply chain financial business customers' detailed information, agricultural product supply chain financial-related knowledge, business process information, etc., and provide necessary expansion support for developing the farm supply chain financial business. The system function module is shown in Figure 2.

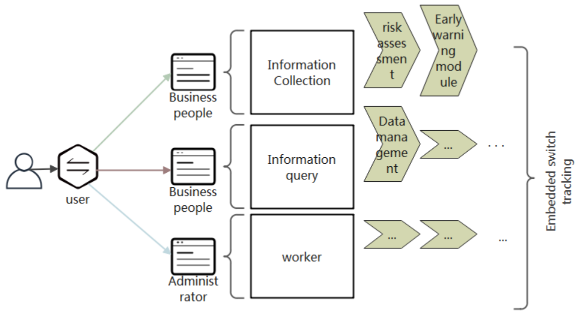

Figure 2: System function module.

Figure 3 shows the overall design of the financial risk assessment system for the entire agricultural product supply chain. It includes the input and storage process of supply chain-related data, risk calculation, rating results and early warning output, human-computer interaction, etc. This article mainly explains the system's structural logic and content composition by presenting the human-machine interface, inference engine, knowledge base, and dynamic database. The system business process is shown in Figure 4.

ODBC needs to be more efficient when helping external programs manipulate data. Microsoft provides an efficient data manipulation object, OLEDB, between ODBC and applications. The relationship is shown in Figure 5.

The "industrial chain + finance + agricultural small and micro entities" model effectively solves the problem of complex and expensive financing for agricultural small and micro entities. Its implementation is divided into two stages. The flow chart of the model is shown in Figure 6.

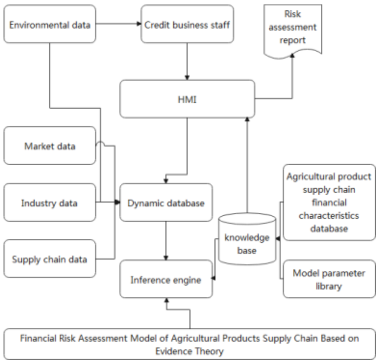

Figure 3: The structure diagram of the financial risk monitoring system of the agricultural product supply chain.

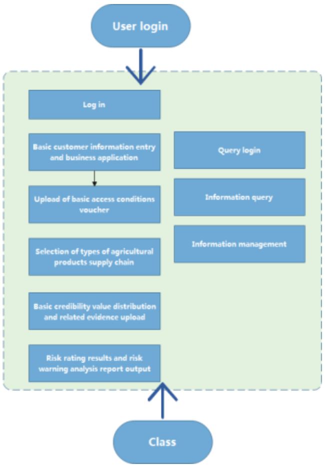

Figure 4: System business process.

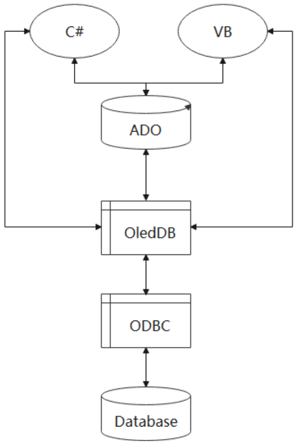

Figure 5: Database connection.

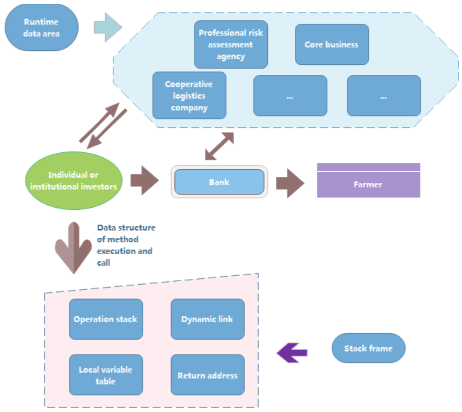

Figure 6: The "Industrial chain + Finance + Agricultural small and micro entities" model flow chart.

Figure 7 shows the flow chart of the operation process of the financing method of "industrial chain + finance + agricultural small and micro entities."

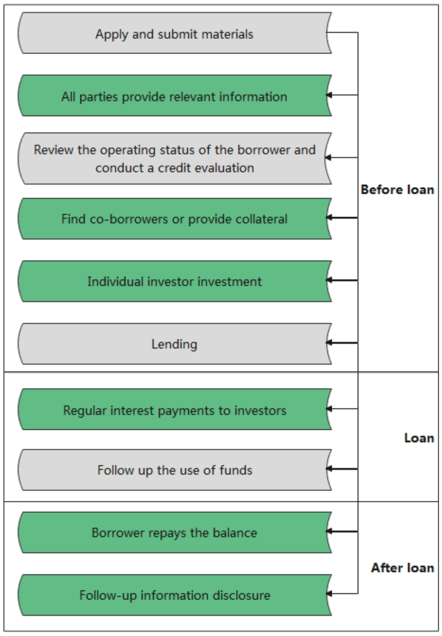

Figure 7: Flow chart of the "Industrial chain + Finance + Agricultural small and micro entities" operation mode.

5 RESEARCH ON THE APPLICATION OF MODERN FINANCIAL TECHNOLOGY IN AGRICULTURAL SUPPLY CHAIN FINANCE BASED ON BIG DATA

This article combines big data technology to analyze the application of modern financial technology in agricultural supply chain finance. It uses big data technology to mine rules and problems and, on this basis, proposes corresponding decision-making suggestions. Therefore, this paper collects relevant data through the Internet and then analyzes the data mining effect of agricultural supply chain finance. The results are shown in Table 1 and Figure 8.

NO	*Agricultural Finance Data Mining*	*NO*	*Agricultural Finance Data Mining*	*NO*	*Agricultural Finance Data Mining*
1	*87.40*	*24*	*87.10*	*47*	*84.21*
2	*85.55*	*25*	*86.34*	*48*	*83.18*
3	*82.47*	*26*	*88.52*	*49*	*81.55*
4	*79.76*	*27*	*86.88*	*50*	*91.74*
5	*90.09*	*28*	*80.74*	*51*	*81.10*
6	*78.94*	*29*	*86.68*	*52*	*84.27*
7	*90.54*	*30*	*89.86*	*53*	*83.96*
8	*90.93*	*31*	*90.54*	*54*	*87.85*
9	*84.60*	*32*	*82.68*	*55*	*84.98*
10	*83.93*	*33*	*87.22*	*56*	*88.81*
11	*79.60*	*34*	*88.66*	*57*	*91.41*
12	*80.97*	*35*	*82.59*	*58*	*88.47*
13	*87.21*	*36*	*83.80*	*59*	*88.16*
14	*83.13*	*37*	*89.39*	*60*	*80.41*
15	*83.88*	*38*	*88.65*	*61*	*79.54*
16	*79.53*	*39*	*88.02*	*62*	*86.47*
17	*86.46*	*40*	*83.82*	*63*	*90.10*
18	*78.40*	*41*	*88.46*	*64*	*89.23*
19	*78.16*	*42*	*78.31*	*65*	*83.85*
20	*79.25*	*43*	*90.77*	*66*	*78.63*
21	*89.55*	*44*	*78.78*	*67*	*78.14*
22	*87.57*	*45*	*89.38*	*68*	*90.17*
23	*88.91*	*46*	*82.05*	*69*	*90.51*

Table 1: Statistical table of the data mining effect of agricultural supply chain finance.

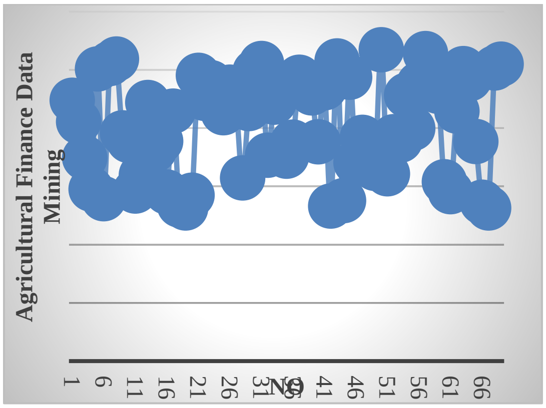

Figure 8: Statistical diagram of the data mining effect of agricultural supply chain finance.

The above research shows that the method proposed in this paper can effectively identify the application law of financial technology in agricultural supply chain finance. Moreover, on this basis, corresponding decision-making suggestions can be evaluated. The results obtained are shown in Table 2 and Figure 9.

NO	*Agricultural Finance Decision*	*NO*	*Agricultural Finance Decision*	*NO*	*Agricultural Finance Decision*
1	*78.32*	*24*	*86.71*	*47*	*82.13*
2	*75.99*	*25*	*74.25*	*48*	*79.49*
3	*89.68*	*26*	*83.90*	*49*	*84.37*
4	*87.19*	*27*	*89.37*	*50*	*83.43*
5	*74.25*	*28*	*80.71*	*51*	*78.63*
6	*89.15*	*29*	*89.40*	*52*	*89.61*
7	*79.49*	*30*	*80.85*	*53*	*88.63*
8	*89.27*	*31*	*85.75*	*54*	*79.89*
9	*75.33*	*32*	*85.09*	*55*	*77.04*
10	*80.65*	*33*	*82.45*	*56*	*90.25*
11	*87.25*	*34*	*77.67*	*57*	*90.89*
12	*85.97*	*35*	*89.80*	*58*	*77.64*
13	*85.69*	*36*	*90.73*	*59*	*78.52*
14	*83.75*	*37*	*82.19*	*60*	*90.51*
15	*83.16*	*38*	*83.88*	*61*	*76.08*
16	*85.16*	*39*	*88.65*	*62*	*80.31*
17	*76.45*	*40*	*76.46*	*63*	*80.07*
18	*86.39*	*41*	*81.04*	*64*	*90.95*
19	*74.86*	*42*	*76.69*	*65*	*76.98*
20	*82.27*	*43*	*84.19*	*66*	*90.57*
21	*83.61*	*44*	*89.34*	*67*	*90.47*
22	*85.29*	*45*	*79.16*	*68*	*77.88*
23	*79.45*	*46*	*88.08*	*69*	*87.70*

Table 2: Statistical table of the effect of decision-making suggestions.

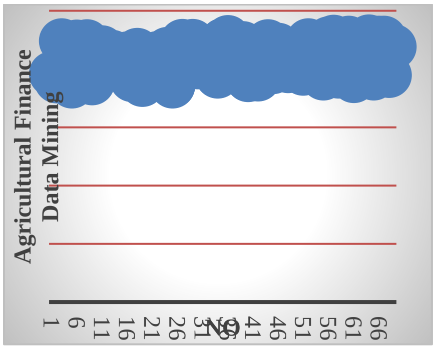

Figure 9: Statistical diagram of the effect of decision-making suggestions.

Based on the above statistical analysis, the method proposed in this paper can effectively analyze financial technology in agricultural supply chain finance and make reasonable suggestions.

6 CONCLUSIONS

The deep integration of digital technology and the agricultural industry has reshaped the business model of the farm supply chain. It has also brought tremendous changes to the financial sector and promoted the rapid development of digital finance. The development of digital finance has also made agricultural supply chain finance participants more diversified. The changes to the traditional agricultural supply chain are the closer connection of participants, digital credit into commercial credit, more obvious standardized features, traceable information, financial resource trajectory, and effective reduction of financing costs. Based on the application prospects of digital finance in the supply chain field, this paper combines big data technology to analyze the application of modern financial technology in agricultural supply chain finance. It uses big data technology to mine rules and problems and put forward corresponding decision-making suggestions on this basis. Through experimental research, the method proposed in this paper can effectively explore the application of financial technology in agricultural supply chain finance, analyze its practical implications, and offer reasonable suggestions. Integrating e-commerce and Human-Computer Interaction (HCI) principles further enhances this analysis by addressing digital marketplaces' impact and ensuring user-friendly, accessible technological solutions.

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