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Credit evaluation and rating system for farmers' loans in the context of agricultural supply chain financing based on AHP-ELECTRE III

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Abstract: Farmers, often vulnerable within the agricultural supply chain, frequently encounter difficulties accessing and affording loans. This study introduces an innovative credit risk evaluation framework for farmers tailored to the agricultural supply chain. It includes three key aspects: farmers' credit characteristics, the operational status of the agricultural supply chain, and overall credit conditions. Initially, the analytic hierarchy process (AHP) was used to assign weight coefficients to indicators. Then, the Elimination et Choix Traduisant la Réalité III (ELECTRE III) model was employed to determine farmers' credit ratings. To demonstrate the impact of the agricultural supply chain on microfinance, the model's effectiveness was then tested with 398 microfinance survey responses from Fuping County (World Dairy Goat Industry Development Demonstration Zone), Shaanxi Province, China, and its accuracy was further verified using BP neural network analysis. The results demonstrated the model's proficiency in assessing farmers' credit levels within the agricultural supply chain, which can aid in the resolution of various credit assessment and rating challenges. Furthermore, this study offers valuable insights into the integration of multi-criteria decision-making and machine-learning methods.

Keywords: credit evaluation model; credit rating; credit risks; Back Propagation neural network; rural finance

Credit refers to the immediate payment of funds or the provision of collateral by both parties involved in an economic value exchange and plays a significant role in financial markets (Pattnaik et al. 2020). Microcredit has become an important alternative for poverty alleviation in developing countries as it guarantees access to financial resources for disadvantaged populations (Popa et al. 2022). As the primary beneficiaries of microcredit, farmers rely on an established effective credit rating system as the foundation and prerequisite for obtaining loans in the financial market (Yin et al. 2023). However, in China and many other developing countries, farmers are generally considered a vulnerable group within the supply chain and thus face difficulties obtaining loans and high borrowing costs. Furthermore, traditional farmers often encounter a situation of 'no collateral, no guarantee, and no credit history', leading to high loan risks. A lack of credit re-

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cords exacerbates the information asymmetry between farmers and formal financial institutions. Meanwhile, the risk of social exclusion and poverty is higher in rural regions than in urban regions, and financial institutions contribute relatively less capital to agricultural development, frequently resorting to passive measures when addressing farmers' financing needs (Chmelíková et al. 2021). This is because of the inability of financial institutions to genuinely distinguish between 'high-risk loans' and 'low-risk loans' (Kulshreshtha 1973). Consequently, farmers are excluded from accessing loans from formal financial institutions. Although informal financial institutions and private lending from traditional rural social groups can partially meet farmers' funding needs, they often impose high interest rates and lack standardisation. Rural residents also encounter various restrictions in accessing social security channels, thereby diminishing their capacity to withstand risks (Cheng et al. 2021). In this context, the emergence of agricultural supply chain financing is beneficial for alleviating the funding shortage problems farmers face.

Supply chain financing refers to transferring a core enterprise's sound credit to the upstream and downstream of the supply chain, thereby reducing the overall financial risks (Wang et al. 2013). Ultimately, this type of financing aims to improve the overall efficiency of the entire supply chain without compromising critical interests (Phillip 2010). Lewis (2007) noted that supply chain financing not only benefits all participants along the supply chain but also minimises financing costs and effectively controls credit risks. In different forms of supply chain models, agricultural supply chain financing is an effective means of addressing farmers' financial issues (Wang et al. 2013). Agricultural supply chain financing involves relevant financial service institutions and core enterprises performing a systematic analysis and evaluation of the development of an agricultural supply chain (Yin and Li 2022). Oberholster et al. (2015) found that agricultural value chain financing enhances agricultural production capacity, promotes agricultural development, and facilitates farmers' income growth. Due to factors such as geographical environment, level of economic development, lack of advanced technology, weak infrastructure, and low levels of organisation, the agricultural production models in most developing countries are primarily small-scale family farming (Aisaiti et al. 2019; Yi et al. 2021; Wang et al. 2022). This decentralised production model results in small production scales and low levels of standardisation, making it difficult to meet the demands for large-scale and standardised production in the supply chain, thus leading to a disconnect between farmers and the industry chain. Consequently, when farmers aim to expand their production scale, they often face a lack of financing channels and struggle to obtain sufficient funds for expansion and technological upgrades. Financial institutions, due to the lack of credit records and the high risks associated with farmers, tend to be cautious about offering agricultural loans. This makes it difficult for farmers to access financial support from the supply chain, hindering their development and creating a vicious cycle. Therefore, the first aim of this study is to broaden different financing models based on agricultural supply chains, thus widening farmers' financing channels and enhancing their financing capabilities. Furthermore, the second aim is to construct a scientific and standardised farmers' credit evaluation index system to effectively alleviate the information asymmetry between farmers and financial institutions, reduce farmers' loan default rates and financing costs, increase financial institutions' confidence in lending to farmers, and address the issues of 'difficult and expensive loans' for farmers.

Previous research indicates that credit evaluation methods or models can be categorised into subjective assessment methods or models, statistical analysis models, and machine learning methods. Subjective analysis methods include the analytic hierarchy process (AHP) (Roy and Shaw 2023), the Delphi method (Yu et al. 2020), and fuzzy mathematics (Jiao et al. 2007). However, subjective analysis methods are susceptible to the influence of experts' subjective factors when determining indicator weights. Statistical analysis models include logistic regression (Van Gestel et al. 2005) and logit regression (Zanin 2022). Examples of machine learning methods include the random forest algorithm (Wu and Wu 2016) and support vector machines (Van Gestel et al. 2005). Zhang and Gan (2019) empirically tested the prediction accuracy of artificial intelligence classification models such as support vector machines and Bayesian methods. They compared these with traditional econometric models, and their results demonstrated that the artificial intelligence classifiers significantly outperformed econometric models in terms of accuracy. Therefore, in recent years, many researchers have focused on improving machine learning algorithms. However, at the present stage of the study, the research on credit evaluation of farmers through machine learning methods is still limited.

The choice of evaluation indicators is also a focal point for many scholars. In authoritative rating agen-

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cies such as Standard and Poor's (2024) and Moody's (2016), clients' credit ratings are typically assessed based on several indicators, including asset turnover ratio, return on assets, debt ratio, and other relevant metrics. In contrast to international credit rating systems, the Chinese credit rating system tends to provide more consideration to clients' individual characteristics and information. The Postal Savings Bank of China (2009) established a credit rating indicator system for farmers from four perspectives, including family structure, willingness, and ability to repay debts, with 15 specific evaluation indicators, such as age, credit status, and average annual net household income per capita. Unlike the Postal Savings Bank of China, the Agricultural Bank of China (2008) considers health condition, in addition to factors such as age and family income, to evaluate farmers' credit risk levels. The specific categories of indicators used in international credit rating systems are not always fully disclosed to the public. Moreover, within the Chinese credit rating system, some indicators may not significantly affect clients' credit risk evaluation. Thus, scholars have researched other indicators to evaluate their influence on client credit risk. One classic principle is the 5C principle, which primarily evaluates individual credit based on character, capacity, capital, credit, and collateral (Knopf and Schoney 1993). Scholars have also researched indicators that influence farmers' credit from various other aspects. Key and McBride (2003) found that factors such as the age of the household head, educational level, and number of labourers can influence the credit rating of agricultural households in the US hog industry. Chmelíková and Redlichová (2020) studied the relationship between financial exclusion and over-indebtedness in peripheral Czech municipalities and found that banks prioritised factors such as applicants' age, citizenship, criminal history, education, entrepreneurial and job history, and free cash flow for repayments when issuing loans. Zhang et al. (2014) conducted a risk evaluation of agricultural products in the supply chain based on the Dempster-Shafer (d-s) theory, positing that agricultural supply chain financing could effectively address funding shortages and establish a risk evaluation indicator system for the agricultural supply chain financing from the perspectives of production, processing, marketing, and other aspects.

Professional financial institutions and scholars have different understandings of credit rating classifications. Standard and Poor's (2024) established 10 long-term credit rating grades, ranging from the highest to the lowest as follows: AAA, AA, A, BBB, BB, B, CCC, CC, C, and D. For short-term credit ratings, they used a set of six grades, in descending order: A-1, A-2, A-3, B, C, and D. According to the Agricultural Bank of China (2008), the credit scores obtained for loan customers are divided into four credit levels: excellent [85, 100], good [75, 85), fair [65, 75), and poor [0, 65). Yeh et al. (2012) employed the KMV credit rating prediction model, which utilises market information as a predictive variable to calculate the default distance of loan customers. Subsequently, based on these distances in different ranges, the authors classified loan customers as high, medium, or low risk.

A review of the abovementioned studies revealed limitations in the existing credit scoring systems and rating models. First, credit evaluation systems for specific groups, such as farmers, are underdeveloped and have rating indicators that lack descriptions related to the agricultural supply chain. Thus, using the existing credit evaluation systems for farmers may be inappropriate. Second, the current credit rating systems were constructed using relatively limited methods. Finally, some credit-rating classification systems based on credit scores are influenced by subjective judgment factors, thereby diminishing their feasibility.

To address these issues, this study examines the financing paths of farmers based on the agricultural industrial chain, establishes a credit rating index system for issuing loans to farmers, and uses the AHP to calculate the weight of each index. Based on this index, an Elimination et Choix Traduisant la Réalité III (ELECTRE III) algorithm is then used to construct a credit rating model for farmers. Empirical data are used to calculate the corresponding credit scores and rating classification levels. Unlike previous studies, this study innovatively integrates the AHP and ELECTRE III algorithms and incorporates a BP neural network to verify the accuracy of the evaluation results, thereby enhancing the persuasiveness and demonstrating the feasibility of the proposed credit evaluation system for farmers.

MATERIAL AND METHODS

Financing model

According to existing research and field surveys in Fuping County, Shaanxi Province, the main industrial chain financing models include the following: cooperative + farmer + financial institution; core enterprise + farmer + financial institution; core enterprise + cooperative + farmer + financial institution; and government + core enterprise + cooperative + farmer + financial institution.

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Figure 1 shows the operating mechanism of the core enterprise + financial institution + farmer model. The premise of this model is that farmers have stable purchasing and sales relationships with core enterprises. First, farmers sign purchase and sales contracts with core enterprises. Second, core enterprises with good credit can provide guaranteed services for farmers, and farmers can then use the purchase and sales contracts as collateral to apply for loans from banks. Third, banks provide direct or indirect financing to farmers through the prepayment of loans or offsetting sales on credit, thus completing the financing of the industrial chain.

Based on this model, farmers rely on an order contract relationship with core enterprises in the industrial chain, and financial institutions provide loans to farmers by examining the actual transactions between farmers and core enterprises and the credit status of core enterprises. Farmers do not need to provide collateral, as the order contracts between farmers and core enterprises are regarded as virtual collateral (Ma et al. 2011). If farmers default on loans, core enterprises can deduct part of their income to repay the loans. To a certain extent, this can alleviate the financial stress farmers face during production and operations. Simultaneously, this can simplify the bank approval process, mitigate credit losses caused by information asymmetry, and improve farmers' loan access.

Figure 2 shows the operating mechanism and characteristics of the core enterprise + cooperative + financial institution + farmers' model. The premise of this model is that farmers join agricultural cooperatives through land shares or voluntary participation, with the cooperative serving as the primary body. This forms vertically integrated cooperative relationships among agricultural raw material suppliers, producers, sellers, and

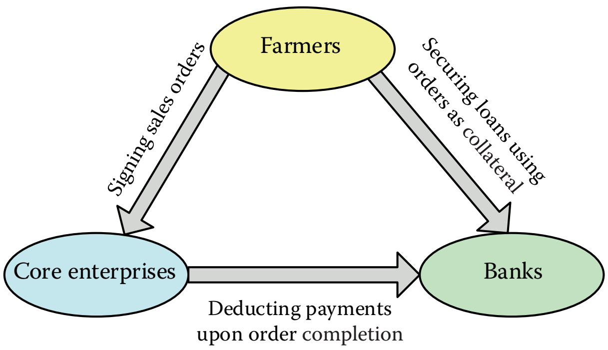

Figure 1. Core enterprises + financial institutions + farmers model

Source: Authors' own processing

logistics intermediaries, thereby meeting each entity's financial needs.

Its operating mechanism includes the following: *i*) The agricultural cooperative uniformly purchases agricultural production materials from agricultural supply providers and then distributes them to farmers for farming and breeding purposes. *ii*) The agricultural cooperative signs order contracts with core enterprises. *iii*) The cooperative applies for bank loans based on the order contracts signed with core enterprises. *iv*) The bank uses those order contracts as collateral and provides loans to the cooperative through pre-loan assessment and post-loan supervision. *v*) When the order is completed, the bank deducts the loan amount from the core enterprise's sales proceeds. *vi*) In the agricultural industrial chain financing process, guarantee companies, trust companies, insurance companies, and other financial institutions can be introduced to provide guarantee and insurance services for cooperatives and agricultural supply providers, thereby establishing a risk protection mechanism and further improving agricultural industrial chain financing.

Figure 3 shows the operating mechanism of the government + core enterprise + cooperative + financial institution + farmers model. The government has two primary roles in this industrial chain financing model. Owing to the weak foundation of the agricultural industrial chain, incomplete industrial chains, and missing supply chains, the government's main role is to complete the industrial chain by introducing relevant leading enterprises and agricultural supply providers and providing technical guidance to farmers. Its operating mechanism is consistent with the core enterprise + cooperative + farmers + financial institution model.

The figures show that, in contrast to the singular borrowing model in which farmers interact with banks directly, the lending patterns derived from the agricultural supply chain model not only mitigate risks for all stakeholders but also alleviate adverse effects stemming from factors such as credit asymmetry. Therefore, to address the limitations of credit assessment research on farmer lending models in the context of the agricultural supply chain, it is crucial to explore novel credit assessment models, evaluation indicators, and credit rating classification systems from a new perspective.

Indicator selection and design

Farmers' credit risk refers to the likelihood that farmers will default on a loan due to uncertain factors. However, under the agricultural supply chain financing model, the sources of farmers' credit risk have transformed.

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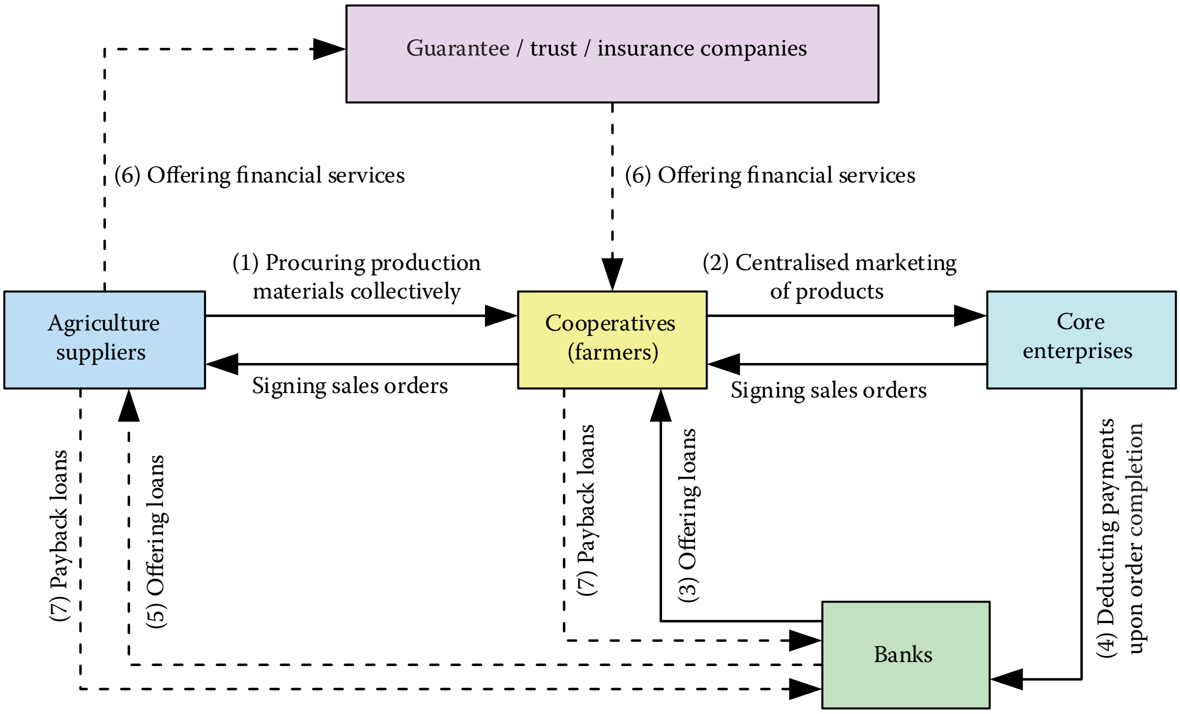

Figure 2. Core enterprises + cooperatives + financial institutions + farmers model

Source: Authors' own processing

In addition to farmers' credit characteristic risks, this model includes various factors, such as operational risks faced by the agricultural supply chain. This study summarises farmers' credit risk in relation to the following aspects: farmers' own credit characteristic risk, operational risk of the agricultural supply chain, and credit behaviour risk arising from borrowing and lending activities between farmers and financial institutions.

The crucial aspect of evaluating the credit risk of farmers is selecting the evaluation index system, which should be based on objective facts and the specific characteristics of the evaluation subject. However, there cannot be a one-size-fits-all index system, as it must be tailored according to the research circumstances (Wang 2022). In the agricultural supply chain financing model, multiple parties establish contractual relationships, and evaluating the creditworthiness of farmers involves a comprehensive evaluation with the participation of multiple stakeholders. Therefore, the credit evaluation of farmers in agricultural supply chain financing encompasses numerous indicators, necessitating the construction of a well-structured indicator system for comprehensive credit evaluation.

To ensure a more standardised and rational selection and design of indicators, this study incorporates the index system of the authoritative institution Standard and Poor's (2024) as its foundation. Additionally, it includes the farmer microcredit rating indicator system from the Agricultural Bank of China (2008), Industrial and Commercial Bank of China (2005), and Postal Savings Bank of China (2009). This study also draws on relevant research conducted by other scholars on credit evaluation indicators for farmers (Shi and Wang 2018; Zou and Li 2019). Finally, this study categorises the indicators influencing credit evaluations into four distinct logical levels, considering inherent farmer characteristics. The first is the goal level, which evaluates farmers' credit based on the agricultural supply chain financing model. The second is the primary criterion level, which encompasses the following three criteria elements: farmer credit features, agricultural supply chain operation status, and credit situation within the agricultural supply chain. The third is the secondary criterion level, which further subdivides the primary criterion level into 12 sub-criteria elements. The fourth is the alternative level. In this study, 32 indicator elements are selected as options to evaluate farmers' credit, the details of which are shown in Table 1.

Data sources

The data for this study were collected over five years, from 2018 to 2022, in three townships and nine ad-

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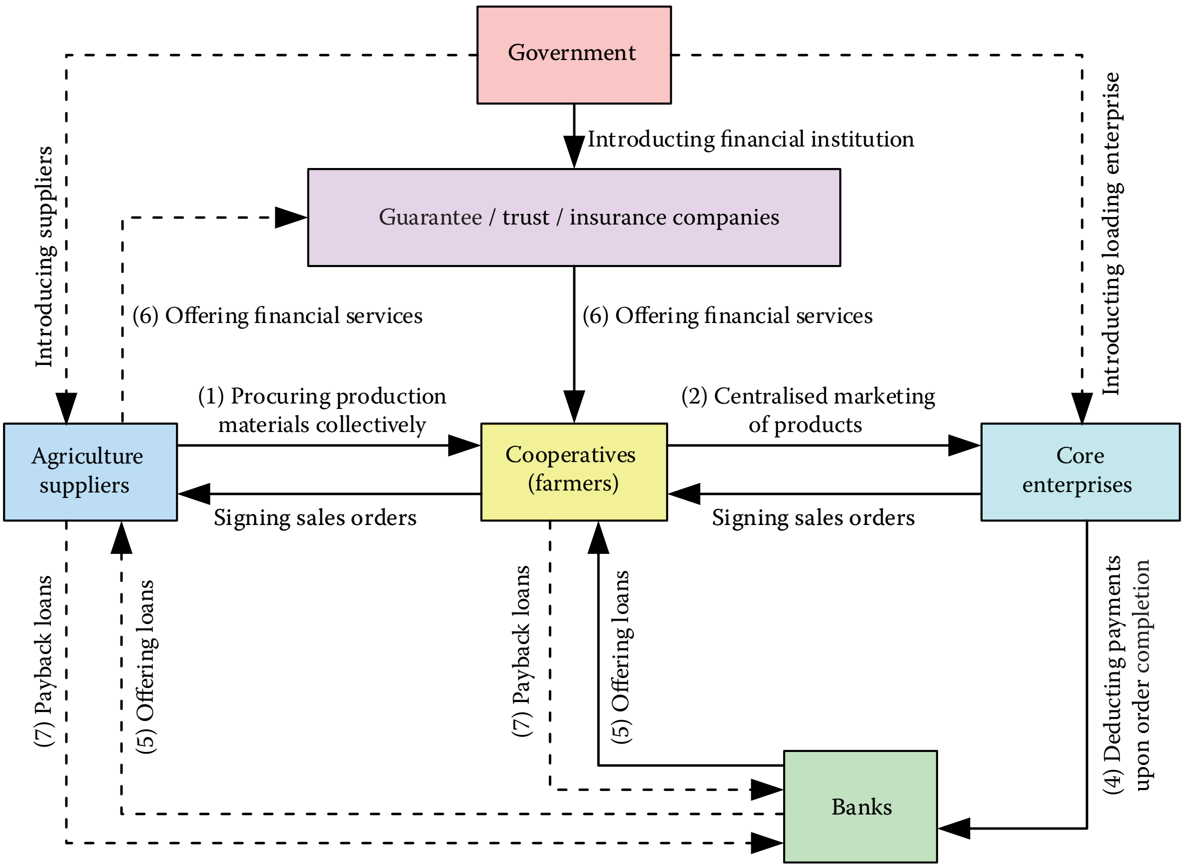

Figure 3. Government + core enterprises + cooperatives + financial institutions + farmers model

Source: Authors' own processing

ministrative villages located in Fuping County, Shaanxi Province, China. Fuping County is a national modern agricultural demonstration area and one of the top ten counties in China with characteristic agricultural practices. It boasts of a well-established persimmon and dairy goat industry and has been awarded the title of the 'World Dairy Goat Industry Development Demonstration Zone' by the International Goat Association and Organising Committee (Li and Zhi 2019). Therefore, the selection of Fuping County, which possesses well-developed agricultural supply chain infrastructure, illustrates the impact of the relevant agricultural supply chain on farmers' credit ratings.

In total, 750 households were selected as survey participants through random sampling. The survey was conducted through onsite interviews using structured questionnaires. The questionnaires covered a wide range of topics, including basic household information, farming activities, loan history, financing needs, participation in agricultural supply chains, and information related to agricultural supply chain financing. A total of 750 questionnaires were distributed, and 735 valid responses were received. After excluding outliers and missing data, based on the research objectives and practical survey circumstances, 398 households were retained as the analytical sample.

Methods

AHP method. After the credit rating system is determined, the next most important step is to determine the weight of each indicator using the AHP. The AHP is a method proposed by American operations researchers Saaty (1980) to address multi-objective decision-making problems. It breaks down complex problems into a hierarchy of objectives, criteria, and alternatives. Based on this hierarchy, mathematical methods are used to calculate the relative weights of the influencing factors at each level in relation to the overall goal, thereby solving multi-objective decision-making problems. For the application of the AHP method, the first step involves the hierarchical structuring of various indicators. Next, judgment

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Table 1. Design of farmers' credit evaluation index under agricultural supply chain financing model

Goal	Criteria	Sub-criteria	Alternatives
Farmer credit evaluation model based on agricultural supply chain (A)	farmer credit features (B1)	individual characteristics of farmers (C1)	ages (D1)
			dependency ratio (D2)
			education level (D3)
			social relationships (D4)
			credit history (D5)
		operational status of farmers (C2)	cultivated land area (D6)
			production technology level (D7)
			farming scale (D8)
		debt-paying capacity of farmers (C3)	total household assets (D9)
			annual household income (D10)
			annual household expenditure (D11)
			total household debt (D12)
		loan information (C4)	loan amount (D13)
			interest level (D14)
			repayment fund source (D15)
	agricultural supply chain operation status (B2)	supply chain stability (C5)	stability of farm-household and enterprise cooperation (D16)
			contract duration (D17)
			agricultural supply chain financing model (D18)
		environmental risks (C6)	natural disaster (D19)
			government support level (D20)
		market risks (C7)	stable sales channels (D21)
			payment period (D22)
		informatisation degree (C8)	Internet sales ratio (D23)
			level of maturity of social service platforms (D24)
		supply chain competitiveness (C9)	brand impact (D25)
			Is it possible to sell agricultural products at the market average price? (D26)
		enterprise reputation status (C10)	Is there any credit sales activity? (D27)
			Are related services available? (D28)
	credit situation within the agricultural supply chain (B3)	financial institution supervision status (C11)	pre-loan assessment (D29)
			frequency of post-loan tracking checks (D30)
		farmers' understanding of policies (C12)	understanding of the loan policies of financial institutions (D31)
			knowledge of agricultural supply chain financing status (D32)

Source: Authors' own processing

matrices are constructed for each level, and the corresponding eigenvalues and eigenvectors are computed. Finally, the weights of the alternatives in the solution layer are ranked against the goal layer, and the consistency is tested. This process is depicted in Figure 4.

ELECTRE III method. After determining the weight of each indicator, the next step is to evaluate the farm-

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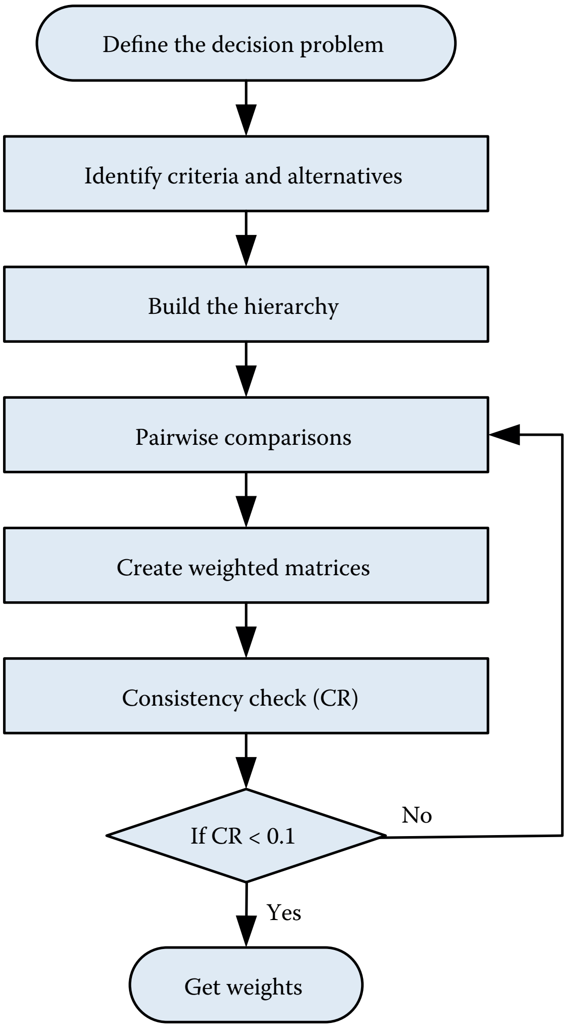

Figure 4. Flowchart of the analytic hierarchy process (AHP) method

Source: Authors' own processing

ers' credit levels. This study employs the ELECTRE III method to evaluate farmers' credit levels to avoid the limitations of traditional decision-making methods based on a simple weighted summation. The ELECTRE III is used for multi-criteria decision-making and can address complex decision problems involving multiple evaluation criteria and alternative solutions (Papadopoulos and Karagiannidis 2008; Angilella and Mazzù 2015). This model has been widely applied in various fields such as medicine, materials, energy, and the environment (Papadopoulos and Karagiannidis 2008; Angilella and Mazzù 2015). The fundamental concept of the ELECTRE III method is to compare alternative solutions and establish a preference order based on a set of evaluation indicators. Previous research (Angilella and Mazzù 2015) has confirmed that as a non-compensatory comprehensive evaluation method, this approach can overcome the limitations of traditional decision methods based on simple weighted summation, thus offering more objective and accurate outcomes.

Similar to other multi-attribute decision-making methods, ELECTRE III first requires the construction of a finite set B(b_1, …, b_m), which represents a collection of m farmers to be evaluated. X(x_1, …, x_n) represents the corresponding set of evaluation indicators x_j,n is the number of evaluation indicators, and W(w_1, …, w_n) denotes the set of weights assigned to evaluation criterion x_j. The weights used in this study were calculated using the AHP. Furthermore, a set A(a_{11}, …, a_{ij}, …, a_{mn}) was constructed to represent the attributes of individual farmer b_i on the evaluation indicator x_j; specifically, a_{ij} represents the attributes of individual b_i on evaluation criterion x_j.

The method then involves constructing three threshold sets and three indices as follows.

Strict preference threshold set P = (p_j|j = 1, …, n): This set defines the minimum performance difference required to establish a strict preference for one alternative over another on evaluation criterion x_j.

Indifference threshold set Q = (q_j|j = 1, …, n): This set defines the maximum acceptable performance difference between two alternatives on evaluation criterion x_j before indifference is declared.

Veto threshold set V = (v_j|j = 1, …, n): This set defines the minimum performance difference that, if exceeded, results in the rejection of one alternative in favour of another in the evaluation indicator x_j.

Concordance index **C**(i,k) represents the concordance index over farmers b_i and b_k with respect to the indicator x_j. This set defines farmer b_i as superior to farmer b_k considering all indicators; c_j(i, k) represents the concordance index over farmers b_i and b_k with respect to the indicator x_j, and w_j represents the weights assigned to the evaluation indicator x_j. The algorithm can be found as follows:

$$\mathbf{C}(i,k)=\frac{\sum_{j=1}^{n} w_j c_j(i,k)}{\sum_{j=1}^{n} w_j} \quad (1)$$

$$c_j(i,k)=\begin{cases}1 & \text{if } a_{kj}-a_{ij}\le q_j \\ \dfrac{p_j-(a_{kj}-a_{ij})}{p_j-q_j} & \text{if } q_j<a_{kj}-a_{ij}<p_j \\ 0 & \text{if } a_{kj}-a_{ij}\ge p_j\end{cases} \quad (2)$$

Discordance index **D** (i, k): This set defines whether the alternative or farmer b_i is not inferior to farmer b_k

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considering all indicators. $d_j(i, k)$ represents the discordance index over farmers b_i and b_k with respect to the indicator x_j and w_j represents the weights assigned to evaluation indicator x_j. The algorithm can be found as follows:

$$\mathbf{D}(i,k)=\frac{\sum_{j=1}^{n} w_j d_j(i,k)}{\sum_{j=1}^{n} w_j} \tag{3}$$

$$d_j(i,k)=\begin{cases}0 & \text{if } a_{kj}-a_{ij}\le p_j\\ \dfrac{(a_{kj}-a_{ij})-p_j}{\nu_j-p_j} & \text{if } p_j<a_{kj}-a_{ij}<\nu_j\\ 1 & \text{if } a_{kj}-a_{ij}\ge \nu_j\end{cases} \tag{4}$$

Angilella and Mazzù (2015) previously demonstrated that a limited discordance index can eliminate mutual substitutability among different evaluation objects under various indicators.

Credibility index $\mathbf{S}(i, k)$: This set defines farmer b_i is at least as good as alternative b_k, based on the pairwise comparisons of all farmers, and constitutes a credibility matrix $\mathbf{S}$. The algorithm is as follows:

$$\mathbf{S}(i,k)=\begin{cases}\mathbf{C}(i,k) & \text{if } F(i,k)=\phi\\ \mathbf{C}(i,k)\prod_{j\in F(i,k)}\dfrac{1-d_j(i,k)}{1-\mathbf{C}(i,k)} & \text{if } d_j(i,k)>\mathbf{C}(i,k)\end{cases} \tag{5}$$

where: $F(i, k)$ – set of indicators that satisfy $d_j(i, k) > \mathbf{C}(i, k)$; if all $d_j(i, k) < \mathbf{C}(i, k)$, $F(i, k)$ is an empty set.

With the ELECTRE III method, farmers' credit scores were ranked using credibility matrix $\mathbf{S}$. Consistency credibility pertains to the level of harmony or dependability in the credibility values allocated to various pairs of alternatives or farmers within the decision-making process. Let Φ^+ denote the degree to which farmer a is superior to all other farmers, which can be expressed as follows:

$$\Phi^+(b_i)=\sum_{i\in B}\mathbf{S}(i,k) \tag{6}$$

Non-consistency credibility indicates the level of difference in credibility values among various alternatives within the decision-making process. Let Φ^- denote the degree to which farmer a is inferior to all other farmers, which can be expressed as follows:

$$\Phi^-(b_i)=\sum_{i\in B}\mathbf{S}(i,k) \tag{7}$$

Net credibility is the difference between consistency credibility and non-consistency credibility, reflecting the impact of the mutual substitution effect between the evaluation indicators of an individual and those of others on the evaluation results. Let Φ denote net credibility, which can be expressed as

$$\Phi(b_i)=\Phi^+(b_i)+\Phi^-(b_i) \tag{8}$$

By incorporating the credibility index, the credit evaluation model for farmers constructed using the ELECTRE III method can effectively avoid the influence of mutual substitution between the evaluation indicators, ensuring the authenticity and reliability of the credit evaluation results.

Data standardisation and normalisation method. Given the disparate measurement scales across various indicators, they had to be standardised and normalised. The min-max normalisation technique was used for this purpose. Specifically, when dealing with positively and negatively oriented indicators, the standardisation formula was as follows:

$$a_{ij}=\frac{x_{ij}-\min_{1\le i\le m} x_{ij}}{\max_{1\le i\le m} x_{ij}-\min_{1\le i\le m} x_{ij}} \tag{9}$$

$$a_{ij}=\frac{\max_{1\le i\le m} x_{ij}-x_{ij}}{\max_{1\le i\le m} x_{ij}-\min_{1\le i\le m} x_{ij}} \tag{10}$$

where: a_{ij} – standardised score of the j^{th} indicator for the i^{th} farmer; x_{ij} – raw data of the j^{th} indicator for the i^{th} farmer.

According to Shi and Chi (2014), when a borrowing farmer's age falls within the interval [31, 45], it signifies that their creditworthiness is favourable. Therefore, when dealing with interval-based indicators, let h_1 and h_2 represent the left and right boundaries of the optimal range for each indicator, respectively. The standardisation formula was then applied as follows:

$$a_{ij}=\begin{cases}1-\dfrac{h_1-x_{ij}}{\max(q_1-\min_{1\le i\le m} x_{ij},\max_{1\le i\le m} x_{ij}-q_2)}, x_{ij}<h_1\\ 1-\dfrac{x_{ij}-h_2}{\max(q_1-\min_{1\le i\le m} x_{ij},\max_{1\le i\le m} x_{ij}-q_2)}, x_{ij}>h_2\\ 1,\quad \text{others}\end{cases} \tag{11}$$

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BP neural network method. Finally, the effectiveness of the AHP-ELECTRE III credit rating model was verified using the BP neural network method. A BP neural network is a type of artificial neural network widely used in machine learning and pattern recognition tasks. Neural networks, based on a nonlinear mapping structure inspired by the human brain, have proven to be universal and highly flexible approximators for generating any type of data. It is a powerful model that can be employed for predictions in situations in which the underlying data generation processes are unknown (Kohzadi et al. 1995). It is a feedforward neural network, which means that information flows in one direction: from input to output layers. The network structure is intricate and offers superior discriminative power, allowing meaningful features to be extracted from vast datasets. This makes it well-suited for pattern recognition and classification tasks. Evidence indicates that neural network methods can perform certain multi-target prediction tasks, yielding more accurate predictions compared to traditional methods such as econometric modelling or Autoregressive Integrated Moving Average (ARIMA) (Kohzadi et al. 1995). Therefore, this study used the BP neural network method to validate the farmer credit evaluation model and analysed its predictive accuracy using MATLAB.

The number of neurons in the input layer must be determined based on the features of the samples, with the input layer having as many nodes as the number of indicators affecting farmer credit. Therefore, in this study, 32 indicators from the solution layer that affect farmer credit were designated as the input layer of the BP neural network method, setting the input layer size to 32. The credit evaluation of farmers in this study constituted a multiclass classification problem in which the output layer represents the farmer's credit rating. Therefore, the output layer was set to one to output the farmer's credit rating, which is a real number, rounded to the nearest whole number corresponding to one of the ratings from 1 to 5 in Table 2. Owing to the limited sample size, this study can only validate the results using the same sample set; however, doing so may lead to overly optimistic accuracy in the estimation and prediction outcomes. To address this issue, this study adopted the approach of Nayak and Turvey (1997) and randomly divided the samples into two groups: the training set was randomly defined as 70% (278 samples) of the raw sample size, and the test set as 30% (120 samples). This ensured that the situations in the samples were independently and identically distributed as those used in the model estimation.

Table 2. Results of farmers' credit ratings

Sample number	Credit score [Φ (b_i)]	Rank	Sample proportion (%)	Sample size	Credit classification
b_{380}	386.112	1			
…	…	…	10	40	1 (A)
b_{274}	171.466	40			
b_{52}	169.570	41			
…	…	…	20	79	2 (B)
b_{320}	14.810	119			
b_{183}	13.807	120			
…	…	…	40	159	3 (C)
b_{109}	–57.138	278			
	-57.648	279			
…	…	…	20	80	4 (D)
b_{256}	–106.860	358			
b_{354}	–107.229	359			
…	…	…	10	40	5 (E)
b_8	–378.167	398			

Source: Authors' own processing

RESULTS AND DISCUSSION

Data standardisation and normalisation results. Using formulas (9–11) to normalise the raw data, the detailed descriptive statistics of individual characteristics for the sampled farmers were derived, as presented in Table S1 in the Electronic Supplementary Material (ESM).

Determination of the indicator weights. Based on the AHP, 10 valid questionnaires confirmed through consistency tests were used to collect scores from 12 experts who had extensive experience in credit evaluation, rural finance, and credit risk assessment and are familiar with the AHP. Using the Yaahp software, judgment matrices and weights were obtained based on the constructed farmer credit evaluation model. Using the scores from the 10 experts, judgment matrices for each indicator level were derived separately, which, in turn, allowed us to determine the weights corresponding to the higher-level indicators. The results are presented in the third column of Table S1 in the ESM.

As shown in Table S1 in the ESM, among the first-level criteria, farmers' credit characteristics had the greatest impact on farmers' credit, with a weight of 0.497. Next was the operation status of the agricultural industrial chain, whereas the financing situation of the agricultural industrial chain had the smallest impact on farmers' credit, with a weight of 0.217.

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According to the weight distribution of the second-level criteria, those with higher weights were the farmers' loan situation, debt repayment ability, understanding of financing policies, and operating conditions and the supervision of financial institutions, with weights of 0.193, 0.144, 0.128, 0.095, and 0.089, respectively. These secondary criteria were important indicators that can be used to measure farmers' creditworthiness.

The weight distribution at the scheme level indicated that sources of repayment funds, understanding of agricultural industrial chain financing, loan amount, annual household income, post-loan tracking inspection frequency, and understanding of financial institution loan policies had the largest weight coefficients: 0.078, 0.077, 0.066, 0.057, 0.057, and 0.051. These indicators had a relatively high importance in influencing farmers' credit.

Determination of the threshold credit rating value. The ELECTRE method used a combination of thresholds to determine the consistency and non-consistency indices. In existing research, most threshold combinations are primarily determined through decision-makers' preferences (Galo et al. 2018) or expert assessments (Shi and Wang 2018), introducing subjectivity into the threshold-setting process. The standard deviation reflected the dispersion of the dataset. To mitigate the influence of subjective preferences on threshold selection, this study used multiple simulation and training iterations to verify that the results are stable and reliable when the indicator for the preference threshold is the standard deviation of data, the indifference threshold is set at 0.3 times the standard deviation, and the veto threshold is 0.8. Table S2 in the ESM presents the set of thresholds for each indicator.

Determination of net credibility credit score. The ELECTRE III method was implemented using formulas (1–8) and MATLAB. Normalised data from farmers, along with indicator weights and corresponding thresholds, were input into the program. The outputs, including consistency credibility, nonconsistency credibility, and net credibility, are presented in Table 3.

Credit rating classification. According to Shi et al. (2015), given that the number of borrowers among farmers closely approximates a normal distribution, farmers' credit scores are categorised into five levels, ranging from A to E, based on a high-to-low ranking. The specific allocation of farmers to each credit level was determined based on the sample proportions outlined in Table 4. The net credibility scores of the 398 farmers were sorted in descending order, as shown in Table 3. By allocating 10% of the total to A-rated farmer credit scores, 40 farmers were identified as fitting the A credit rating classification. The credit score range for A-rated farmers was [171.466, 386.112], with similar evaluations applied to farmers in other credit rating classifications, as presented in Table 2. The survey results indicate that the data in Tables 2 and 4 are generally consistent with the actual situation in the region. Farmers rated C to E were considered credit-constrained, whereas those rated A and B were not.

Table 3. Farmers' credibility credit scores

Sample number	Consistency credibility [$\Phi^+ (b_i)$]	Non-consistency credibility $\Phi^- (b_i)$]	Net credibility [$\Phi (b_i)$]
b_1	19.198	32.896	–13.698
b_2	226.740	23.842	202.898
b_3	36.312	88.253	–51.941
b_4	27.920	48.879	–20.959
b_5	225.767	22.843	202.924
...	...	...	...
b_{394}	327.881	15.967	311.915
b_{395}	4.837	205.561	–200.724
b_{396}	131.666	19.181	112.486
b_{397}	8.517	18.748	–10.231
b_{398}	4.827	209.098	–204.271

Source: Authors' own processing

Results of the rationality analysis of the credit rating model based on the BP neural network. The predicted error histogram diagram is illustrated in Figure 5. The red histogram represents the non-consistency predicted results, and 16 instances of non-matching outcomes were found within 30% of the test dataset. Therefore, the final model shows a predictive accuracy of 86.67%, indicating that the discriminative capacity of the model constructed in this study is favourable.

The results of this study demonstrate the high accuracy of the credit rating model developed for farmer loans. This model not only considered individual

Table 4. Credit rating standards for farmers

Credit rating	Sample proportion (%)	Cumulative proportion (%)	Credit standing
A	10	10	excellent
B	20	30	good
C	40	70	fair
D	20	90	poor
E	10	100	bad

Source: Authors' own processing

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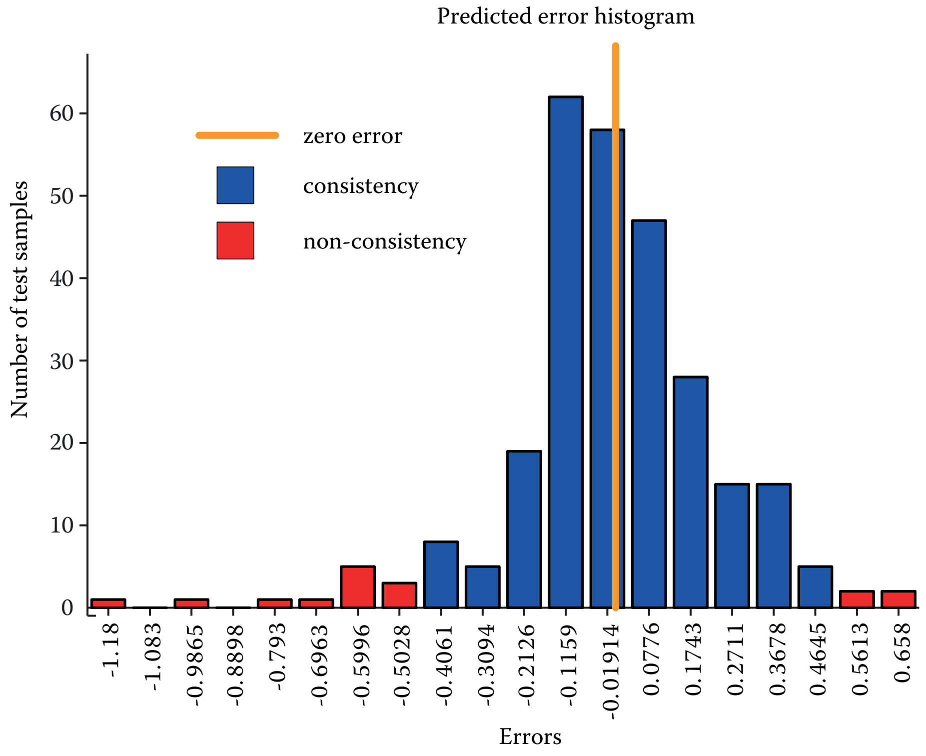

Figure 5. Predicted error histogram by BP (Back Propagation) neural network

Source: Authors' own processing

farmer characteristics but also comprehensively incorporated fundamental aspects of the agricultural supply chain, effectively reflecting specific credit rating features associated with farmer loans. Its broad applicability extends to developing countries, where it can be used to thoroughly assess credit risks in the context of loans for farmers.

This study established a financing mechanism for farmers based on the agricultural industrial chain credit system and accordingly constructed a credit evaluation index system for farmers. The study then employed a combination of the AHP and ELECTRE III methods to construct a credit rating model for farmers' loans, and conducted an empirical analysis. Finally, a BP neural network was used to predict farmers' credit levels, with a consistency rate of 86.67% compared with the previous rating model.

Since the 1970s, when American operations researcher Saaty first proposed the AHP method, it has been widely applied in fields such as business and management (Srinivasan and Bolster 1990; Chen and Chiou 1999). During the 1990s, the AHP method gradually expanded to other areas of application such as education, healthcare, and environmental protection (Liberatore and Nydick 1997; Singpurwalla et al. 1999; Kurttila et al. 2000). Scholars have since improved the AHP method, e.g. by combining it with fuzzy mathematics in the fuzzy analytic hierarchy process (FAHP) to address uncertainties in subjective judgments inherent in traditional AHP. Additionally, AHP has been integrated with other multi-criteria decision-making methods, such as TOPSIS and DEA, forming more complex decision support systems (Che et al. 2010; Roy and Shaw 2023). In recent years, with the advancement of computing technologies, scholars have combined AHP with big data analysis and artificial intelligence, enhancing its applicability in modern complex decision-making environments (Ren et al. 2019; Jiang 2021). This study, in particular, combined the AHP method with ELECTRE III, and neural networks were employed to validate the results. The ELECTRE III method is a classic non-compensatory multi-attribute decision support method. Unlike with the AHP, low scores in some evaluation criteria cannot be compensated for by high scores in other criteria, thus overcoming the limitations of traditional decision-making methods based on simple weighted summation. This results in a more comprehensive and rigorous evaluation process. Vezmelai et al. (2015) used the ELECTRE III method for the credit ratings of 20 companies. Chavira et al. (2017) and Shi and Wang (2018) used the same method for credit ratings for farmers' loans. These results indicate the effectiveness of the proposed method. Neural net-

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works have strong learning and generalisation capabilities. A trained neural network can perform well on new data and handle many complex problems and tasks. However, these networks are highly dependent on data, and the prediction accuracy can significantly decrease or even fail when using a small data sample.

CONCLUSION

Based on microdata from 398 rural households in Fuping County, Shaanxi Province, this study used an integrated approach combining the AHP and ELECTRE III. By leveraging this methodology within the context of agricultural supply chain financing, a comprehensive framework was established for evaluating rural farmers' creditworthiness. This framework includes credit evaluation indicators, a credit rating model, and credit score classification. In addition, the BP neural network method was applied to assess the model's performance in predicting rural farmers' credit ratings. The findings are summarised below.

This study innovatively integrated analysis of the operational mechanisms and characteristics of the agricultural supply chain financing model into a rural farmer credit rating model. It established a credit evaluation and rating indicator system grounded in the agricultural industry supply chain. Furthermore, reliability was ensured by creating a four-tier indicator system encompassing 32 influencing factors.

Utilising the constructed indicator system, the AHP was used to determine the weighted values of each indicator's impact on the decision objective (i.e. rural farmers' creditworthiness). This study's findings show that scheme-level indicators such as the source of repayment funds, understanding of agricultural supply chain financing, loan amount, annual family income, frequency of post-loan monitoring, and knowledge of financial institution loan policies had coefficients with relatively higher weights, indicating a more substantial impact on rural farmer creditworthiness.

By introducing the non-consistency index $D(i, k)$ and thresholds within the ELECTRE III method, this study effectively mitigated the impact of the interplay between rural farmer indicators on evaluation outcomes and the limitations of individual subjective judgments. This ensured the accuracy of the findings. Simultaneously, utilising the characteristics of a normal distribution for credit rating classification ensured the rationality of the sample distribution.

Furthermore, the innovative integration of the rural farmer credit evaluation model with the BP neural network method enhanced the empirical validation accuracy of the rural farmer credit evaluation results. The ultimate accuracy of 86.67% underscored the substantial practical value and predictive precision of the farmer credit risk evaluation model based on the AHP–ELECTRE III method within the context of agricultural supply chain financing.

Overall, the credit rating system for farmers constructed in this study considered individual factors and examined the influence of agricultural supply chain financing factors. Moreover, the 32 evaluation indicators not only reflected the impact of internal factors, such as farmer income and debt, on rating outcomes but also included external factors, such as environmental risks and policies. This comprehensive approach is suitable for practical applications by financial institutions for rating farmers seeking loans. This research demonstrated extensive practical applicability that is not limited to specific regions or study samples.

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