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Research Article

Multiattribute Fuzzy Decision Evaluation Approach and Its Application in Enterprise Competitiveness Evaluation

Jing Li,[1] Yue Sun,[2] Lingling Gong ,[3] Nana Chai ,[4] and Yanfei Yin[1,5]

[1] *School of International Trade and Economics, University of International Business and Economics, Beijing 100029, China*
[2] *School of Labor and Human Resources, Renmin University of China, Beijing 100872, China*
[3] *Shanghai Golden Education, Financial Research and Study Center, ShangHai 200008, China*
[4] *College of Economics and Management, Northwest A & F University, Yangling 712100, China*
[5] *Research Institute of China Development Bank, School of Economics of Renmin University of China, Beijing 100872, China*

Correspondence should be addressed to Lingling Gong; michelle.gong@gaodun.cn and Nana Chai; cnn18435122665@163.com

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Multiattribute decision-making approach is one of the key complex system evaluation technologies which has attracted high attention of academic research studies. This paper establishes a novel multiattribute decision evaluation approach. First, we propose a high-dimensional data attribute reduction model based on partial correlation analysis and factor analysis methods. Second, based on the attribute weights calculated by multiple weighting methods, the corresponding multiple evaluation score vectors of the objects evaluated can be obtained. The final scoring vector can be determined by combining the quadratic combination weighting and the Spearman consistency test. Third, we use fuzzy C-means algorithm to grade evaluated objects. Finally, the established evaluation approach in this paper is verified by using the 107 observations in China. This approach also provides a decision-making example for attribute reduction of high-dimensional data, scoring of complex system evaluation, and clustering analysis when conducting evaluation in other fields.

1. Introduction

Multiattribute decision-making approach is ubiquitously used for project selection, e-learning website selection, pilot capability assessment, supplier selection, etc. Specifically, it can be used to measure passengers' satisfaction with high-speed rail, so as to further promote the development of high-speed rail industry [1, 2]. It can also be used for the selection of professional third-party reverse logistics providers and emergency response plan selection of civil aviation [3, 4]. However, the complexity and variability of the decision-making environment increase the difficulty of decision making [5]. For example, too many evaluation attributes make it impossible to effectively identify the objects of evaluation and the evaluation process is too time consuming. Multiattribute decision evaluation models emerge right at the time, which provide auxiliary reference or decision-making basis for decision makers. The rationality of the construction of multiattribute decision evaluation model is directly related to the decision-making effect [6]. Therefore, more and more literatures began to focus on the issue of multiattribute decision evaluation [7–9]. And they have applied these approaches to areas such as engineering, education, risk management, and so on [10–12].

High-dimensional data dimensionality reduction, comprehensive score calculation, and evaluation result clustering analysis are involved in the construction of multiattribute decision evaluation model. In the aspect of high-dimensional data dimensionality reduction, there are three main methods, i.e., rough set methods, statistical methods, and other methods such as particle swarm optimization (PSO), ant colony optimization, and so on [13, 14]. Li et al. proposed a two-phase biobjective attribute reduction approach which maximized the information content of attributes and minimized the number of attributes [15]. Four datasets were used for empirical analysis. The results showed that this method has advantages in attribute reduction of unbalanced samples, but it has the problem of insufficient classification accuracy and time consuming.

Attribute weight calculation is the key to multiattribute decision evaluation. Karahalios used AHP (analytic hierarchy process) to solve the attribute weights and used the TOPSIS method to obtain evaluation scores of ballast water treatment systems for ships [10]. Francesco et al. used the linear optimization model and iterative quadratic optimization model to calculate the most discriminating vector of weights based on the historical data [16]. Cui et al. calculated the attribute weights affecting mineral resources with the improved AHP and tested the robustness of the proposed weights [17]. Liu et al. used the grey DEMATEL (decision making trial and evaluation laboratory) method to compute the weight of each attribute and utilized the UL-MULTIMOORA (uncertain linguistic multiobjective optimization by ratio analysis plus full multiplicative form) method to evaluate four electric vehicles in Shanghai [18]. There are various methods to obtain attribute's weight, and different methods have different evaluation results. In practice, there is a problem of inconsistency in the result of evaluation ranks obtained by different weighting methods for the same evaluation object [19].

The clustering of evaluation results is also the key of multiattribute decision-making evaluation methods [20]. Cluster analysis methods include hard partitioned clustering and unsupervised learning methods [21]. However, the dividing effect of hard partitioning clustering methods depends on whether the dataset has well-defined boundaries, which cannot deal with the vagueness and uncertainty of data [22]. The unsupervised clustering method makes up for the defect of hard partition clustering, and the more mature algorithm is fuzzy C-means (FCM). Akman evaluated the development of green supply chain and green suppliers by clustering two times based on the data of automobile manufacturing companies by using FCM [23]. Hashem et al. used the FCM method to cluster 288 hospitals from 31 provinces in terms of GDP and population, forming six grades [24]. It shows that selection of clustering analysis algorithm has an important impact on the discrimination of the evaluation objects, classifying grades, and making correct decisions.

In summary, it is very important to select methods of dimensionality reduction of high-dimensional data, solution of comprehensive evaluation score, and clustering analysis for multiattribute decision making. The existing literatures make in-depth research on these three aspects. But there are still some problems that need to be improved. First, most of the existing literatures focus on one of the aforementioned issues. Few literatures conduct studies about multiattribute decision evaluation through systematic modeling from the perspective of complex system evaluation. Second, the existing literatures study on multiattribute decision evaluation mainly adopting the single weighting method to get the evaluation score. The rankings gained from different weighting ways of evaluation tend to result in inconsistent order relation. Third, in the field of engineering, a large number of literatures verify the evaluation effect of decision-making evaluation model by simulation [25–27]. Few literatures use actual data to prove the reasonability of the proposed method.

The contributions of this paper are as follows. First, from the perspective of complex system evaluation, a generalized multiattribute decision evaluation modeling method is proposed. This methodology combines the approaches of dimensionality reduction, solution of comprehensive evaluation score, and clustering analysis of evaluation results and improves the integrity of the evaluation model. Second, the paper uses three types of weighting methods and the Spearman consistency test to obtain the comprehensive evaluation score. It can make up the deficiency of inconsistent order relation resulted from different weighting methods. Third, the applicability of the proposed model is verified by the data of 107 financial enterprises in China from 2008 to 2014. Moreover, this method provides an example for effectively solving the problem of how to reduce the attributes of high-dimensional data, score solution of complex systems evaluation, and clustering analysis of evaluation results.

The remainder of the paper is organized as follows. Section 2 constructs the methodology. Section 3 is an empirical analysis. Section 4 is the conclusion.

2. Design and Methodology

In this section, the paper creates a multiattribute fuzzy decision evaluation approach. To begin with, we establish an attribute reduction model based on the partial correlation analysis (PCA) and factor analysis (FA) methods. Second, on basis of the attribute weights calculated by multiple weighting methods, the corresponding multiple evaluation score vectors Si of evaluated objects can be obtained. The final scoring vector $S = f(S_1, S_2, S_3, \ldots)$ can be determined by combining quadratic combination weighting and Spearman consistency test. Finally, we use FCM to grade evaluated objects according to their evaluation scores. The framework is shown in Figure 1.

2.1. Attribute Reduction Modeling. There are two steps to construct the attribute reduction model. First, the raw data of the attributes are preprocessed. After standardizing the attribute, the panel data are cross-sectioned on the basis of the matrix distance weighting. Second, the reduced attribute set is established by quantitative attribute selection method of PCA and FA.

2.1.1. Attribute Data Preprocessing. Due to the different units and dimensions of attributes, the raw data cannot be compared directly; they should be converted into values between the interval [0, 1] [13], called standardization. The attributes can be classified into three categories according to the definition of evaluation attributes: positive attributes, negative attributes, and moderate attributes. Besides, in order to avoid the randomness of the evaluation caused by single-year data, the multiyear panel data were introduced

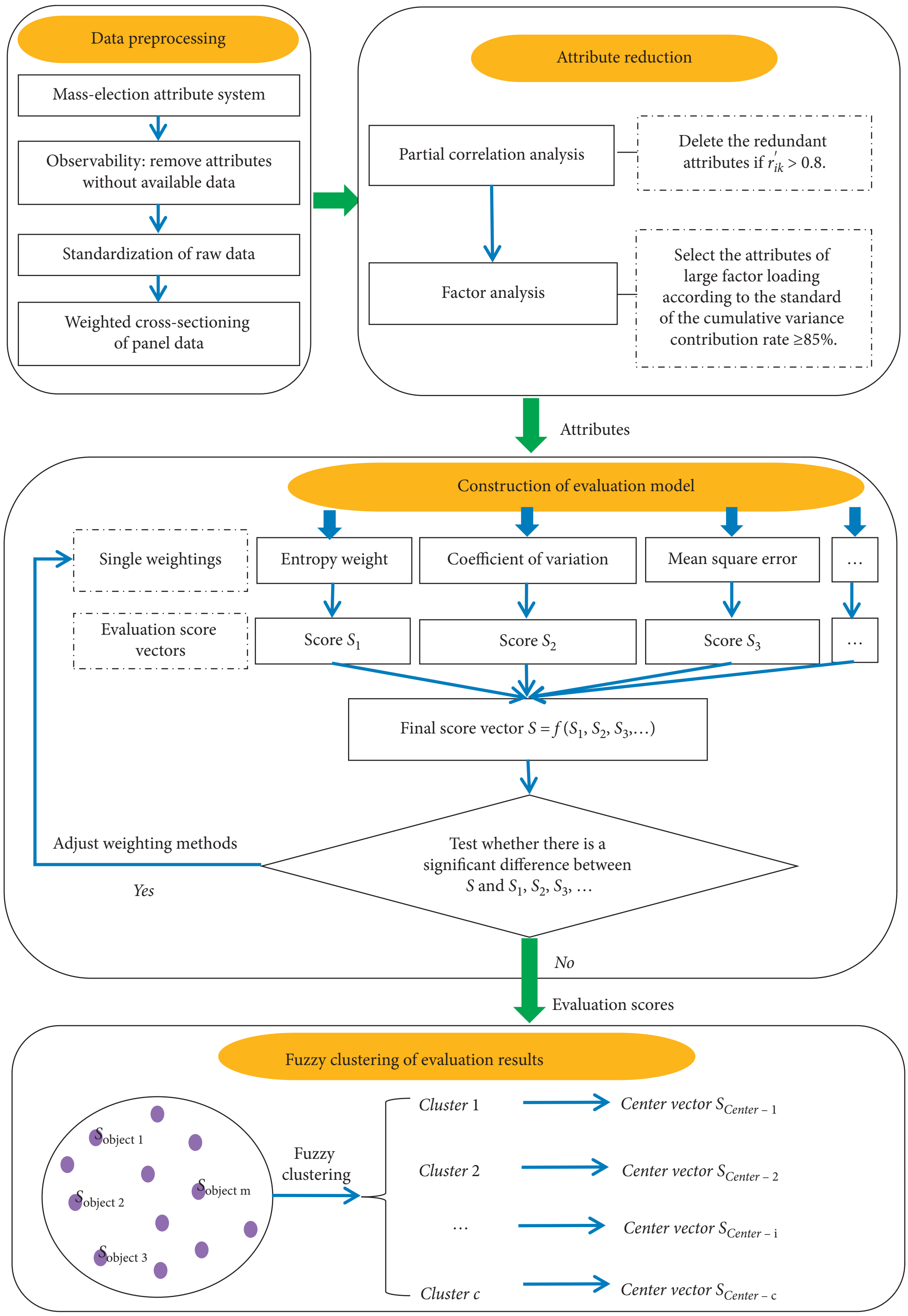

Figure 1: The multiattribute decision evaluation structure.

for modeling. It requires weighting the panel data and converting them into cross-sectional data.

Phase I: Standardization of Attribute Data. The standardization equations of positive, negative, and moderate attributes are represented by equations (1) to (3), respectively.

$$x_{ij} = \frac{v_{ij} - \min\limits_{1\le j\le n}\left(v_{ij}\right)}{\max\limits_{1\le j\le n}\left(v_{ij}\right) - \min\limits_{1\le j\le n}\left(v_{ij}\right)}, \tag{1}$$

$$x_{ij} = \frac{\max\limits_{1\le j\le n}\left(v_{ij}\right) - v_{ij}}{\max\limits_{1\le j\le n}\left(v_{ij}\right) - \min\limits_{1\le j\le n}\left(v_{ij}\right)}, \tag{2}$$

$$x_{ij} = \begin{cases} 1 - \dfrac{v_{i0} - v_{ij}}{\max\left(v_{i0} - v_{\min}, v_{\max} - v_{i0}\right)}, & v_{\min} < v_{ij} < v_{i0}, \\ 1, & v_{ij} = v_{i0}, \\ 1 - \dfrac{v_{ij} - v_{i0}}{\max\left(v_{i0} - v_{\min}, v_{\max} - v_{i0}\right)}, & v_{i0} < v_{ij} < v_{\max}, \end{cases} \tag{3}$$

where x_{ij} denotes the standardized score, v_{ij} denotes the attribute raw data, n denotes the number of evaluated objects, v_{i0} denotes the optimal value, $v_{\min}$ denotes the minimum value of the attribute raw data v_{ij}, and $v_{\max}$ denotes the maximum value of the attribute raw data v_{ij}.

Phase II: Panel Data Cross Section Processing.

Step 1: determine the optimal score matrix A^+ and the worst score matrix A^-.

Let a_{ij}^+ represent the attribute's optimal score in panel data, a_{ij}^- represent the attribute's worst score, x_{ij}^t stand for the standardized score in the t^{th} year, and T be the number of sections. The optimal score matrix A^+ consists of a_{ij}^+, while the worst score matrix A^- consists of a_{ij}^-, and the formulas are illustrated as follows [10]:

$$a_{ij}^+ = \begin{cases} \max\limits_{1\le t\le T}\left(x_{ij}^t\right), & i \text{ reprents the positive attribute}, \\ \min\limits_{1\le t\le T}\left(x_{ij}^t\right), & i \text{ reprents the negative attribute}, \end{cases} \tag{4}$$

$$a_{ij}^- = \begin{cases} \min\limits_{1\le t\le T}\left(x_{ij}^t\right), & i \text{ reprents the positive attribute}, \\ \max\limits_{1\le t\le T}\left(x_{ij}^t\right), & i \text{ reprents the negative attribute}. \end{cases} \tag{5}$$

Step 2: calculate the distance d_t^+ and d_t^-.

d_t^+ is the distance between the cross section score matrix A_t and A^+, while d_t^- denotes the distance between A_t and A^-, and the formulas are illustrated as follows:

$$d_t^+ = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}^t - a_{ij}^+\right)^2}, \tag{6}$$

$$d_t^- = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}^t - a_{ij}^-\right)^2}, \tag{7}$$

where m denotes the number of attributes.

Step 3: calculate the time weighting w_t of different years.

Let c_t denote the relative closeness degree between A_t and A^+ and w_t denote the time weighting of the t^{th} year. Then,

$$c_t = \frac{d_t^-}{d_t^+ + d_t^-}, \tag{8}$$

$$w_t = \frac{c_t}{\sum_{t=1}^{T} c_t}, \tag{9}$$

where $\sum_{t=1}^{T} w_t = 1$.

Step 4: cross-sectioning of panel data.

Based on the time weighting vector $w = (w_1, w_2, \ldots, w_T)$, the cross-sectional data A can be obtained through $A = \sum_{t=1}^{T} w_t A_t$.

2.1.2. Construction of Attribute Reduction Model. In this section, the paper adopts the PCA to solve the partial correlation coefficient between the attributes, excluding the attributes reflecting information redundancy within the same criterion layer [28]. By using the FA [29], the attributes of large factor loading are selected, so as to construct the reduced attribute set.

Phase I: Attribute Reduction Based on PCA.

Step 1: calculate the correlation coefficient matrix R.

Let $\overline{x}_i$ and $\overline{x}_k$ denote the average value; then, R is given by

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mm} \end{bmatrix}, \tag{10}$$

where

$$r_{ik} = \frac{\sum_{j=1}^{n}\left(x_{ij} - \overline{x}_i\right)\left(x_{kj} - \overline{x}_k\right)}{\sqrt{\sum_{j=1}^{n}\left(x_{ij} - \overline{x}_i\right)^2}\sqrt{\sum_{j=1}^{n}\left(x_{kj} - \overline{x}_k\right)^2}}. \tag{11}$$

Step 2: determine the inverse matrix C.

$$\mathbf{C}=\mathbf{R}^{-1}=\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mm} \end{bmatrix}. \quad (12)$$

Step 3: calculate the partial correlation coefficient r'_{ik}.

$$r'_{ik}=\frac{-c_{ik}}{\sqrt{c_{ii}c_{kk}}}, \quad (13)$$

where c_{ii} and c_{kk} are elements on the diagonal of matrix c and c_{ik} is not the element on diagonal of the matrix.

Phase II: Attribute Selection Based on Factor Analysis. According to the standard of the cumulative variance contribution rate, which should be greater or equal to 85% [30], we can select attributes with large factor loading.

2.2. Quadratic Evaluation Modeling

2.2.1. Evaluation Model Based on Different Weighting Methods. In practice, the entropy weight, the coefficient of variation, and the mean square error have been widely used to calculate the weights of attributes in risk management, supplier selection, and green economy evaluation [19, 31, 32]. The paper adopts the three objective weighting methods. Entropy is a measure of uncertainty. The more information an attribute contains, the smaller the uncertainty would be and the smaller the entropy and the larger the weight are. The entropy value e_i can be given as follows:

$$f_{ij}=\frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \quad (14)$$

$$e_i=-\frac{1}{\ln n}\sum_{j=1}^{n} f_{ij}\ln f_{ij}. \quad (15)$$

Then, the entropy weight w'_i of the i^{th} attribute is given by

$$w'_i=\frac{1-e_i}{m-\sum_{i=1}^{m} e_i}. \quad (16)$$

The coefficient of variation is a value used to compare the data variability between different attributes. If the standardized score of an attribute has large data variability among different evaluated objects, it means that the attribute can distinguish the development status of different objects significantly. Thus, the attribute should be given a larger weight. We have

$$w''_i=\frac{\left(\sqrt{\sum_{j=1}^{n}\left(x_{ij}-\overline{x}_i\right)^2/n}\right)/\overline{x}_i}{\sum_{i=1}^{m}\left(\sqrt{\sum_{j=1}^{n}\left(x_{ij}-\overline{x}_i\right)^2/n}\right)/\overline{x}_i}. \quad (17)$$

The mean square error is a value to show the discrete degree of a certain attribute. If the standardized score of an attribute has a larger discrete degree in different evaluated objects, then the attribute has a greater impact on the evaluation results. It will be given greater weight. Then,

$$w'''_i=\frac{\sqrt{\sum_{j=1}^{n}\left(x_{ij}-\overline{x}_i\right)^2/n}}{\sum_{i=1}^{m}\sqrt{\sum_{j=1}^{n}\left(x_{ij}-\overline{x}_i\right)^2/n}}. \quad (18)$$

The three weightings w'_i, w''_i, and w'''_i are used to weight and add the cross-sectional data of each attribute. The corresponding score vectors S_1, S_2, and S_3 can be obtained by equations (19)–(21).

$$S_1=\left(s_j^1\right)_{1\times n}=\left(\sum_{i=1}^{m} w'_i x_{ij}\right)_{1\times n}, \quad j=1,2,\ldots,n, \quad (19)$$

$$S_2=\left(s_j^2\right)_{1\times n}=\left(\sum_{i=1}^{m} w''_i x_{ij}\right)_{1\times n}, \quad j=1,2,\ldots,n, \quad (20)$$

$$S_3=\left(s_j^3\right)_{1\times n}=\left(\sum_{i=1}^{m} w'''_i x_{ij}\right)_{1\times n}, \quad j=1,2,\ldots,n. \quad (21)$$

2.2.2. Evaluation Model Based on Quadratic Combination Weighting. It is well known that the evaluation object score obtained through different weighting methods for the same evaluation object often faces the problem of inconsistent order relation of the evaluation rankings gained from different methods. To overcome this deficiency, it is necessary to optimize the evaluation result obtained by using the different weighting methods. Let $\overline{S}$ denote the mean score vector of different score vectors, and we have

$$\overline{S}=\frac{\left(S_1+S_2+S_3\right)}{3}. \quad (22)$$

The Spearman consistency test [33] is used to test whether there is a significant difference among $\overline{S}$, S_1, S_2, and S_3. (i) If there is no significant difference, then $\overline{S}$ is the final evaluation result. (ii) If there is a significant difference, then we can adjust the weighting methods until the score vector $\overline{S}$ can pass the Spearman consistency test.

2.3. Cluster Modeling of Evaluation Results.

FCM connects each evaluated object and all clustering together through a real value vector $U=(u_{ij})$, and the value u_{ij} is between 0 and 1. It is the membership degree of the j^{th} object to the i^{th} cluster. For a given object, if the value u_{ij} is close to 1, it means that the evaluated object has a strong relationship with a certain cluster. On the contrary, if the value is close to 0, then the object and the corresponding clustering relationship are weak. The m score vectors S_j $(j=1,2,\cdots,m)$ can be divided into c fuzzy groups by using FCM algorithm [34]. Let c_i denote the clustering center of the i^{th} group, $d(S_j, c_i)$ denote the Euclidean distance of c_i in the evaluated object S_j, and $n\in[1,\infty)$ be a weighted index. The clustering center c_i can be obtained by minimizing the nonsimilarity objective function $J(U,c_1,\ldots,c_c)$. We have

$$J(U, c_1, \ldots, c_c) = \sum_{i=1}^{c}\sum_{j=1}^{m}\left(u_{ij}\right)^n d^2\left(x_j, c_i\right). \tag{23}$$

The objective function $\overline{J}(U, c_1, c_2 \ldots, c_c, \lambda_1, \ldots \lambda_m)$ is established to obtain the necessary condition for minimizing equation (23):

$$\begin{aligned}\overline{J}&(U, c_1, c_2 \ldots, c_c, \lambda_1, \ldots \lambda_m)\\ &= J(U, c_1, c_2 \ldots, c_c) + \sum_{j=1}^{m}\lambda_j\left(\sum_{i=1}^{c} u_{ij} - 1\right)\\ &= \sum_{i=1}^{c}\sum_{j=1}^{m}\left(u_{ij}\right)^n d_{ij}^2 + \sum_{j=1}^{m}\lambda_j\left(\sum_{i=1}^{c} u_{ij} - 1\right).\end{aligned} \tag{24}$$

In equation (24), λ_j is the Lagrangian multiplier, and c_i and u_{ij} can be given by

$$c_i = \frac{\sum_{j=1}^{m}\left(u_{ij}\right)^n S_j}{\sum_{j=1}^{m}\left(u_{ij}\right)^n}, \tag{25}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(d_{ij}/d_{kj}\right)^{2/n-1}}. \tag{26}$$

Then, we can outline the FCM algorithm step by step, as shown in Algorithm 1.

3. Empirical Study

3.1. Source of Data. The multiattribute decision evaluation methods have been widely used in many fields, such as project selection, e-learning website selection, and pilot capability assessment. However, there are few reports on the application of multiattribute decision making in the competitiveness evaluation of financial enterprises. This is because the internal financial and nonfinancial data of financing enterprises are difficult to collect. Since those data are highly confidential, our research group spent around seven months collecting data through investigation and finally determined to use 107 RCCs in China for empirical study. For each RCC, we have collected 40 attributes, as shown in Table 1. All the data are collected from the statistical database of rural cooperative financial institutions from 2008 to 2014 and the China Statistical Yearbook. The raw data of RCCs' competitiveness are shown in Table 2.

3.2. Establishing the Reduced Attribute Set

3.2.1. Data Preprocessing of Evaluation Attributes. Substituting the raw data of evaluation attributes from Table 2 into equations (1)–(3), the corresponding standardized score can obtained as shown in Table 2. Substituting the standardized data into equations (4) and (5), the optimal score matrix A^+ and the worst score matrix A^- can be obtained. Substituting a_{ij}^+, a_{ij}^-, and a_{ij}^t into equations (6) and (7), we can calculate d_t^+, d_t^-, and c_t. Then, we can obtain the time weighting $w_t = (0.122, 0.139, 0.153, 0.160, 0.140, 0.148, 0.138)$. Finally, the cross-sectional data can be obtained, i.e., $A = \begin{pmatrix} 0.325 & \ldots & 0.112 \\ \ldots & \ldots & \ldots \\ 0.075 & \ldots & 0.082 \end{pmatrix}_{37\times 107}$.

3.2.2. Establishing the Attribute Set of RCCs' Competitiveness Evaluation. According to reference [28], the partial correlation threshold value r_0 can be set to 0.8. Substituting the data of matrix A into equations (10) to (13), the partial correlation coefficient r_{ik}' can be calculated. We eliminated five attributes by using PCA. The deleted attributes are marked as "Deleted by the PCA" in column 6 of Table 1.

According to the standard of the cumulative variance contribution rate, which should be greater or equal to 85%, this paper selected 20 attributes with large factor loading. They are marked with "Retained" in Table 1. In addition, the deleted attributes by using FA are marked as "Deleted by FA."

3.3. Evaluating RCCs' Competitiveness. Substituting the data of matrix A into equations (14) to (22), the evaluation score vectors of different weighting methods and their mean value score vector are obtained, which are shown in Table 3. By using the Spearman consistency test method, we found that the mean score vector and the evaluation score vectors of different weighting methods are significantly correlated at 0.01 level. Thus, it passes the test. It shows that the mean score vector is the final evaluation score. From the empirical results in Table 3, it can be found that order relation of S_1, S_2, and S_3 is different from the order relation $\overline{S}$ obtained by the method proposed in this paper. S_1, S_2, and S_3 are solved separately by the entropy weight, the coefficient of variation, and the mean square error. It directly proves the relative effectiveness of the method proposed in this paper compared with a single weighting method.

3.4. Cluster Analysis of Evaluation Result

3.4.1. Cluster Analysis of RCCs' Competitiveness Level. In order to analyze the overall competitiveness level of RCCs, 107 RCCs were divided into five categories according to the criterion of "very low," "low," "medium," "high," and "very high competitiveness." The paper sets the clustering number $c = 5$, the maximum iteration number $T = 1000$, the fuzzy number $\omega = 2$, and the threshold $\varepsilon = 0.00001$ [34]. Then, the clustering results and changing trend of the objective function of 107 RCCs can be found in Figures 2 and 3 and Table 4.

3.4.2. Cluster Analysis of RCCs' Regional Competitiveness. To describe the competitiveness of RCCs in different districts, we divided 107 RCCs according to their districts. They belonged to 10 different districts, namely, Yulin, Yanan, Baoji, Xianyang, Shangluo, Tongchuan, Ankang, Weinan, Hanzhong, and Xi'an. At the same time, 10 districts were grouped into three categories according to "high," "medium," and "low." The cluster results are shown in Figures 4 and 5 and Table 5. Table 5 shows that the

The FCM algorithm:
Input: dataset: the mean score vector $\overline{S}$;
Method:
(1) Set parameters: clustering number c, the maximum iteration T, the threshold ε, the fuzzy number ω; for the iteration counter $t = 0$
(2) **if** $|U^{(t)} - U^{(t-1)}| \geq \varepsilon$, **then**
(3) $t = t + 1$
(4) According to equation (24), a membership degree $U^{(t)}$ is formed;
(5) According to equation (23), a new cluster center $c_{c(t)}$ is formed;
(6) **else**
(7) Attach $c_1, c_2, \ldots, c_c$
(8) **end if**
(9) **end for**
Output $c_1, c_2, \ldots, c_c$

Algorithm 1: FCM algorithm execution process.

Table 1: Evaluation attributes of RCCs' competitiveness.

No.	First criterion layer	Second criterion layer	Attribute	Attribute type	Reduction result
1			$X_{11,1}$: asset-liability ratio	Negative	Retained
...		X_{11}: solvency	...	...	...
16			$X_{11,16}$: deposit and loan ratio	Negative	Deleted by FA
17			$X_{12,1}$: the ratio of operating costs to operating income	Negative	Retained
...	X_1: the internal financial factors of RCCs	X_{12}: profitability	...	...	...
24			$X_{12,8}$: cost to income ratio	Negative	Deleted by FA
25			$X_{13,1}$: provision coverage	Moderate, (100%)	Retained
...		X_{13}: operating capacity	...	...	...
29			$X_{13,5}$: net profit growth rate	Positive	Deleted by FA
30			$X_{2,1}$: the credit concentration ratio of the largest single group client	Negative	Retained
31	X_2: the internal nonfinancial factors of rural credit cooperatives		$X_{2,2}$: sensitivity of interest rate risk	Positive	
32			$X_{2,3}$: credit concentration	Negative	Deleted by FA
33			$X_{3,1}$: per capita net income of rural residents	Positive	Retained
...	X_3: the macroeconomic conditions of RCCs		...	...	...
40			$X_{3,8}$: RMB deposits in the financial institutions	Positive	Deleted by FA

Table 2: Raw data and standardized data of evaluation attributes for RCCs' competitiveness.

No.	Criterion layer	Attributes	Raw data														
			2008							. . .	2014						
			Yan'an district			. . .	Hanzhong district			. . .	Yan'an district			. . .	Hanzhong district		
			RCC 01	. . .	RCC 13	. . .	RCC 97	. . .	RCC 107	. . .	RCC 01	. . .	RCC 13	. . .	RCC 97	. . .	RCC 107
1	X_{11}	$X_{11,1}$	0.830	. . .	0.791	. . .	0.969	. . .	0.956	. . .	0.934	. . .	0.883	. . .	0.903	. . .	0.959
. . .	...	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
37	X_3	$X_{3,8}$	545.75	. . .	545.75	. . .	534.07	. . .	534.07	. . .	1231.77	. . .	1231.77	. . .	1390.67	. . .	1390.67
—	Standardized data																
38	X_{11}	$X_{11,1}$	0.177	. . .	0.218	. . .	0.032	. . .	0.045	. . .	0.467	. . .	0.837	. . .	0.692	. . .	0.281
. . .	...	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
74	X_3	$X_{3,8}$	0.088	. . .	0.088	. . .	0.086	. . .	0.086	. . .	0.073	. . .	0.073	. . .	0.083	. . .	0.083

competitiveness of RCCs in different regions is unbalanced. Yulin district is the strongest, while RCCs in Xi'an district are the weakest.

3.4.3. Key Attribute Mining of the RCCs' Competitiveness. First, we extract the key criterion layer of influencing RCCs' competitiveness. The ranking results of weights in

Table 3: Evaluation scores of RCCs' competitiveness.

No.	The district of RCCs location	Different weighting scores			Combination evaluation scores
		S_1	S_2	S_3	$\bar{S}$
1	Ansai district	0.180	0.227	0.366	0.258
...	...	...	...	...	...
107	Lüeyang district	0.066	0.099	0.174	0.113

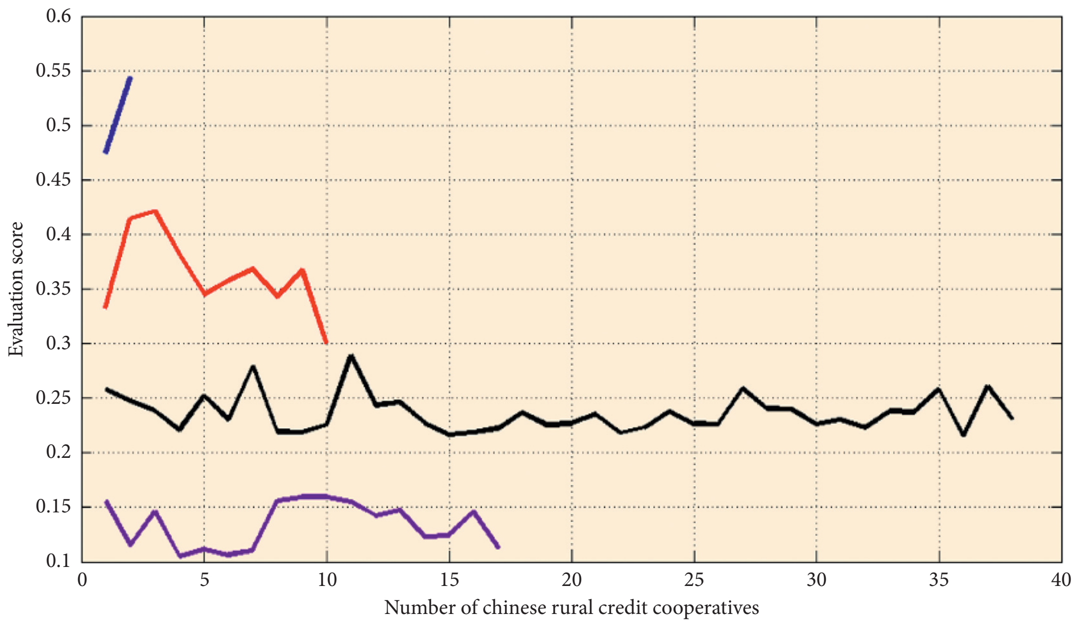

Figure 2: Clustering results of 107 RCCs (five categories).

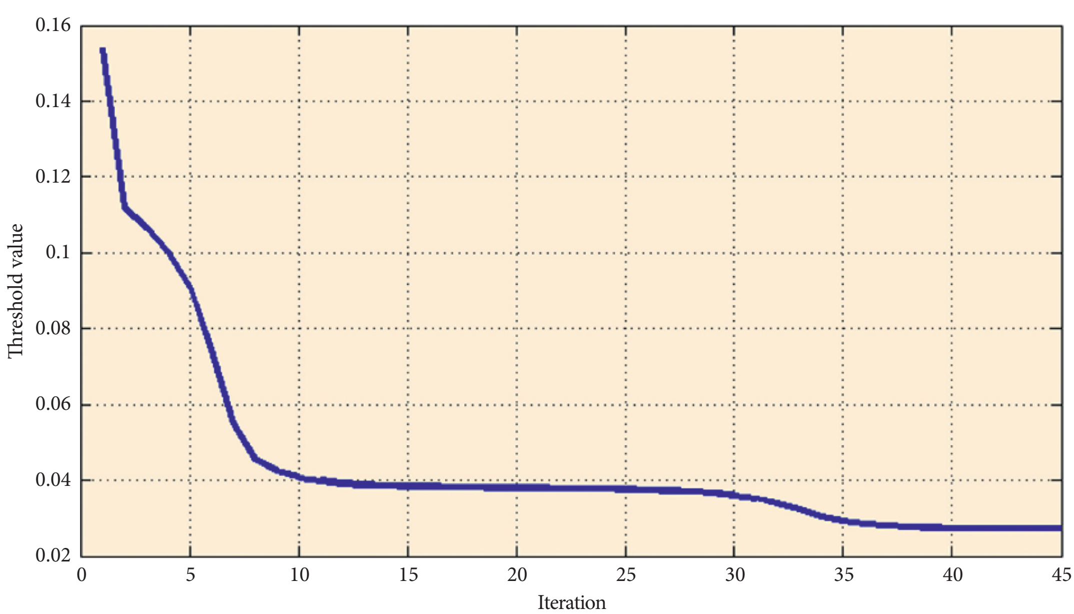

Figure 3: Changing trend of objective function of 107 RCCs' competitiveness.

descending order are w (X11) = 0.451 > w (X12) = 0.258 > w (X3) = 0.120 > w (X2) = 0.101 > w (X13) = 0.070. It indicates that in the evaluation of competitiveness for RCCs, solvency is at the core position. Second, we select the advantageous and disadvantageous factors by utilizing the inferior constraint evaluation method [35]. By comparing and analyzing

Table 4: Cluster result of 107 RCCs.

No.	Cluster center	Number of RCCs	Rank
Cluster 1	0.497	2	Very high competitiveness
Cluster 2	0.360	10	High competitiveness
Cluster 3	0.235	38	Medium competitiveness
Cluster 4	0.192	40	Low competitiveness
Cluster 5	0.130	17	Very low competitiveness

Figure 4: Clustering results of RCCs' district competitiveness (three categories).

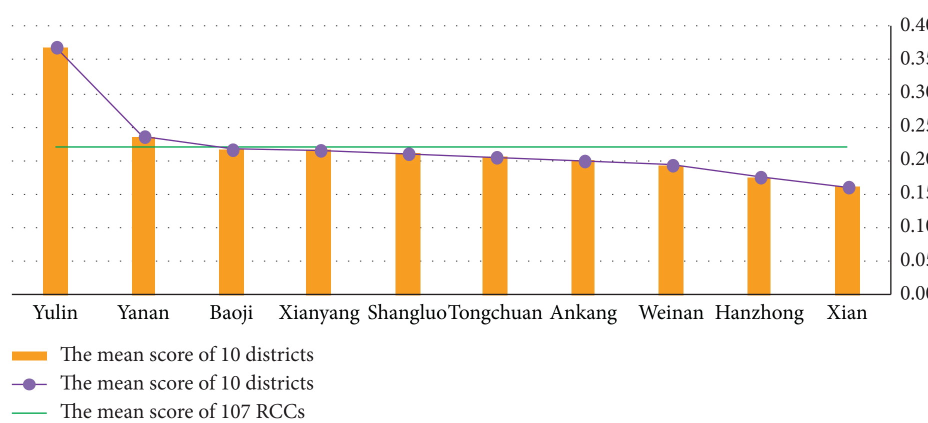

Figure 5: Comparison of competitiveness level of RCCs in different districts.

Table 5: RCC cluster result based on regional competitiveness.

No.	District	The mean score of RCCs' district competitiveness	Cluster center	Rank
1	Yulin	0.369	0.369	High competitiveness
2	Yanan	0.236	0.213	Medium competitiveness
...	...	...		
8	Weinan	0.194		
9	Hanzhong	0.176	0.173	Low competitiveness
10	Xi'an	0.161		

the calculated results, we found that different RCCs vary in their advantageous and disadvantageous factors to influence the competitiveness. For instance, after excluding the attribute "X11, 4: loan-loss provision ratio", the ranking of the Dingbian RCC (in Yulin) dropped from "medium competitiveness" to "very low competitiveness." It means that "X11, 4: loan-loss provision ratio" is the advantageous factor for Dingbian RCC.

4. Conclusion

In order to solve the problems of attribute reduction of high-dimensional data, score solution of complex system evaluation, and clustering analysis of evaluation results in decision making, a new multiattribute decision evaluation model is constructed from the perspective of complex system evaluation. Firstly, this paper combines partial correlation and factor analysis methods to eliminate the attributes reflecting information redundancy and extract the key attributes with large information content. Then, we can construct the reduced attribute set. Second, on basis of the attribute weights calculated by multiple weighting methods, the corresponding multiple evaluation score vectors of evaluated objects can be obtained. The final scoring vector can be determined by combining the quadratic combination weighting and the Spearman consistency test. It avoids the phenomenon of inconsistent order of evaluation results caused by using single weighting method. Third, this paper uses the FCM algorithm of unsupervised algorithms for the evaluation result clustering analysis. Finally, the methodology is detailed using actual rural credit cooperative data in China. By using the data of 107 RCCs in China, the empirical results show that the decision evaluation model can solve the problem of inconsistency of ordering relationship. The model can be applied in other fields.

Data Availability

All the data are highly confidential. These data were collected from the statistical database of rural cooperative financial institutions from 2008 to 2014 and the China Statistical Yearbook.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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