Research on Data Management Capability Evaluation of Manufacturing Enterprises Based on Fermatean Fuzzy TOPSIS

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Abstract. In order to promote the effective improvement of data management ability of Chinese manufacturing enterprises. This paper refers to the data of the 2018 China Enterprise-Labor Matching survey and selects the relevant data of a total of 10 manufacturing enterprises distributed in Guangdong, Hubei, Jiangsu, Sichuan, Jilin and other five provinces as sample data. This paper constructs an evaluation index system of manufacturing enterprise data management ability from six dimensions, adopts Fermatean Fuzzy TOPSIS method to evaluate the data management ability of ten manufacturing enterprises, and analyzes the data management ability of the enterprises with the highest and lowest ranking. The results show that: There are some problems in the data management of manufacturing enterprises in China, such as lack of awareness of data management and weak data management ability in the diversity of enterprise data collection subjects.

Keywords: Data management ability, Fermatean Fuzzy Set, TOPSIS method, Relative entropy, Combination weighting method.

1 Introduction

With the rapid development of the global digital economy, data, as a new factor of production, has become a key driving force for the high-quality operation of national society. However, Chinese enterprises, especially manufacturing enterprises, still face problems such as insufficient data awareness in the process of Digital transformation, resulting in relatively slow progress of Digital transformation. Therefore, in-depth analysis of the data management capabilities of Chinese manufacturing enterprises will help promote the improvement of data management capabilities of Chinese manufacturing enterprises to further realize their Digital transformation. Currently, there is relatively little research on the evaluation of data management capabilities in manufacturing enterprises both domestically and internationally. Foreign research mainly focuses on the

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research on the role of big data management ability in improving enterprise decision-making ability [1] and the mediating role of data driven culture in the relationship between Big data analysis management ability and enterprise performance [2]. Domestic research mainly focuses on evaluating the management innovation ability, knowledge innovation ability, and information technology ability of manufacturing enterprises [3-4]. Some scholars have also conducted evaluation research on police data management ability or explored their maturity evaluation models [5]. In view of this, this paper selects ten representative manufacturing enterprises distributed in five provinces of China, as sample enterprises, and constructs an evaluation index system for data management capability of manufacturing enterprises from six dimensions, including the availability of data in the decision-making process and the degree of Data dependency in the decision-making process, Evaluate the data management capabilities of ten manufacturing enterprises using the Fermatean Fuzzy TOPSIS method. The innovation of this article lies in the improvement of the method for determining indicator weights, the adoption of Fermatean fuzzy set weighted geometric operators, and the combination of Fermatean fuzzy set and TOPSIS method, which can better solve multi-attribute decision-making problems with fuzziness. The specific structure of this article is as follows: Part 2 introduces the research methods used in this article; The third part is the selection of indicators, sample selection, TOPSIS method evaluation of enterprise data management capabilities, and analysis of data management capabilities of related enterprises; The fourth part is the conclusions.

2 Research Methods

2.1 Combination Weighting Method Based on Relative Entropy.

Analytic Hierarchy Process (AHP) [6] and Entropy Weight Method (EWM) [7] are the mainstream methods for determining indicator weights. The former is too subjective, while the latter cannot reflect the correlation between indicators.

Therefore, this article chooses a combination weighting method [8] that combines AHP and EWM to determine indicator weights. The specific steps are as follows:

First, any two weighting methods a and b are defined, and the weight vectors of m indicators are determined by a and b as v_a and v_b respectively, then the relative entropy between the two is expressed as $H(v_a, v_b) = \sum_{i=1}^{m} v_{ai} \log \frac{v_{ai}}{v_{bi}}$. Therefore, the weight vector determined by the combination weighting method can be calculated using equation (1):

$$\begin{cases} \min H(w) = \sum_{j=1}^{n} \sum_{i=1}^{m} w_i \log \frac{w_i}{v_{ji}} \\ s.t. \sum_{i=1}^{m} w_i = 1, w_i > 0, i = 1, 2, \ldots, m \\ w_i = \frac{\prod_{j=1}^{n} (v_{ji})^{\frac{1}{n}}}{\sum_{i=1}^{m} \prod_{j=1}^{n} (v_{ji})^{\frac{1}{n}}}, i = 1, 2, \ldots, m \end{cases} \tag{1}$$

2.2 Fermatean Fuzzy TOPSIS Method

Fermatean Fuzzy TOPSIS [9] is one of the methods to solve multi-criteria decision-making problems. Compared with previous Fuzzy TOPSIS methods, the Fermatean fuzzy TOPSIS method expands the amount of fuzzy information and better reflects the fuzziness of decision plans. Specifically, in this article, there are many decision-making criteria, and decision-making involves more ambiguity. Therefore, this article chooses the Fermatean Fuzzy TOPSIS method to evaluate the data management capabilities of enterprises.

The concept of discrimination degree: Assuming that a decision model and algorithm evaluate a decision plan based on a decision coefficient α, the decision coefficient of the plan A_i is α_i, the decision coefficient of the plan A_j is α_j, and there is $\alpha_i > \alpha_j$. Then the differentiation degree of the decision model and algorithm for the plan A_i and the plan A_j can be expressed as equation (2):

$$\rho_{ij} = \frac{\alpha_i - \alpha_j}{\alpha_i} \times 100\% \tag{2}$$

Fuzzy set is a concept introduced by Professor Zadeh in 1965, referring to a class of objects with continuous membership levels. The Fermat fuzzy set refers to: if X is a domain, then $F = \left\{ \left\langle x, \mu F(x), \nu F(x) \right\rangle \middle| 0 \le \mu F^3(x) + \nu F^3(x) \le 1, x \in X \right\}$ is called a Fermatean fuzzy set on X， $\mu F(x), \nu F(x)$ represents the membership degree and non-membership degree of the element X in x belonging to F, respectively. Then $\pi_F(x) = \sqrt{1 - \mu_F{}^3(x) - \nu_F{}^3(x)}$.

represents the hesitancy degree of the fuzzy number $F = (\mu_F(x), \nu_F(x))$.

Specific process of applying Fermatean Fuzzy TOPSIS method.

Step 1. Generating Fermatean Fuzzy Decision Matrix.

Assuming there are M alternative solutions $S_i (i = 1, 2, \ldots, m)$, N decision criteria $C_j (j = 1, 2, \ldots, n)$, and the weights of each criterion are:

$w=(w_1,w_2,...,w_n)^T;0\le w_j\le 1;j=1,2,...,n;\sum_{j=1}^{n}w_j=1$. The fuzzy number of scheme i under criterion j is: $c_i\left(S_i\right)=\left(\mu_{ij},v_{ij}\right)$.

Considering the Pythagorean Fuzzy Weighted Geometry Operator (PFWG) [10] and the clear weight allocation of expert ratings in this paper, this paper proposes the Fermatean Fuzzy Geometry Operator (FFWG) to aggregate expert evaluations into a fuzzy decision matrix. This operator can more accurately reflect the contribution of data with larger weights to the overall average: let $\beta_i=(\mu_{ij},v_{ij})$ be a set of Fermatéan fuzzy numbers, with a weight vector of $\omega_i=\left(\omega_1,\omega_2,\cdots,\omega_n\right)^T,\sum_{i=1}^{n}\omega_i=1$. Then FFWG can be expressed as equation (3):

$$FFWG(\beta_1,\beta_2,\cdots,\beta_n)=\left(\prod_{i=1}^{n}u_i^{\omega_i},\sqrt[3]{1-\prod_{i=1}^{n}(1-v_i^3)^{\omega_i}}\right) \tag{3}$$

From this, the fuzzy decision matrix can be obtained as equation (4):

$$R=\left(c_j\left(S_i\right)\right)_{m\times n}=\begin{pmatrix}\left(\mu_{11},v_{11}\right) & \cdots & \left(\mu_{1n},v_{1n}\right)\\ \vdots & \ddots & \vdots\\ \left(\mu_{m1},v_{m1}\right) & \cdots & \left(\mu_{mn},v_{mn}\right)\end{pmatrix} \tag{4}$$

Step 2. Determine positive and negative ideal solutions, calculate the distance between alternative solutions and positive and negative ideal solutions.

Firstly, the score function of the i-th alternative under criterion j can be expressed as equation (5):

$$SCORE_{ij}=\mu_{ij}^{3}-v_{ij}^{3} \tag{5}$$

From this, a score matrix can be generated as equation (6):

$$S=\begin{pmatrix}SCORE_{11} & \cdots & SCORE_{1n}\\ \vdots & \ddots & \vdots\\ SCORE_{n1} & \cdots & SCORE_{nn}\end{pmatrix} \tag{6}$$

Among them, a positive ideal solution (FFPIS) needs to satisfy the requirement of maximizing returns while minimizing costs, while a negative ideal solution (FFNIS) needs to satisfy the requirement of minimizing returns and maximizing costs. The optimal choice should be the closest to the positive ideal solution and the farthest away from the negative ideal solution. The formula for calculating the positive and negative ideal solutions and the distance between the alternative solution and the positive and negative ideal solutions are as equation (7), equation (8), equation (9), equation (10), equation (11) and equation (12):

$$S^{+}=\begin{cases}\max\left\langle score(C_j(S_i))\right\rangle \mid j=1,2,\dots,n, \\ \quad \textit{if } C_j \text{ is a benefit criterion} \\ \min\left\langle score(C_j(S_i))\right\rangle \mid j=1,2,\dots,n, \\ \quad \textit{if } C_j \text{ is a cost criterion}\end{cases}=\left\{(\mu_1^+,v_1^+),(\mu_2^+,v_2^+),\dots,(\mu_n^+,v_n^+)\right\} \tag{7}$$

$$\mathrm{D}(\mathrm{S}_i,\mathrm{S}^+)=\sum_{j=1}^{n}w_j d(C_j(S_i),C_j(S^+))=\frac{1}{2}\sum_{j=1}^{n}w_j\sqrt{\frac{1}{2}\left[(\alpha_{ij}^3-(\alpha_j^+)^3)^2+(\beta_{ij}^3-(\beta_j^+)^3)^2+(\pi_{ij}^3-(\pi_j^+)^3)^2\right]} \tag{8}$$

$$\mathrm{D}_{\min}(S_i,S^+)=\min_{1\le i\le m}\mathrm{D}(\mathrm{S}_i,\mathrm{S}^+) \tag{9}$$

$$S^{-}=\begin{cases}\min\left\langle score(C_j(S_i))\right\rangle \mid j=1,2,\dots,n, \\ \quad \textit{if } C_j \text{ is a benefit criterion} \\ \max\left\langle score(C_j(S_i))\right\rangle \mid j=1,2,\dots,n, \\ \quad \textit{if } C_j \text{ is a cost criterion}\end{cases}=\left\{(\mu_1^-,v_1^-),(\mu_2^-,v_2^-),\dots,(\mu_n^-,v_n^-)\right\} \tag{10}$$

$$\mathrm{D}(\mathrm{S}_i,\mathrm{S}^-)=\sum_{j=1}^{n}w_j d(C_j(S_i),C_j(S^-))=\frac{1}{2}\sum_{j=1}^{n}w_j\sqrt{\frac{1}{2}\left[(\alpha_{ij}^3-(\alpha_j^-)^3)^2+(\beta_{ij}^3-(\beta_j^-)^3)^2+(\pi_{ij}^3-(\pi_j^-)^3)^2\right]} \tag{11}$$

$$\mathrm{D}_{\max}(S_i,S^-)=\max_{1\le i\le m}\mathrm{D}(\mathrm{S}_i,\mathrm{S}^-) \tag{12}$$

Step 3. Calculate the relative closeness between the alternative solution and the ideal point by equation (13):

$$RC(S_i)=\frac{D\left(S_i,S^-\right)}{D\left(S_i,S^-\right)+D\left(S_i,S^+\right)} \tag{13}$$

Step 4. Select the best solution based on the relative closeness index ranking by equation (14):

$$\zeta(S_i)=\frac{D\left(S_i,S^-\right)}{D_{\max}\left(S_i,S^-\right)}-\frac{D\left(S_i,S^+\right)}{D_{\min}\left(S_i,S^+\right)} \tag{14}$$

3 Empirical Analysis

3.1 Indicator Selection

Through a preliminary investigation and analysis of the data management situation of manufacturing enterprises in China, combined with the principles of scientific, operational, and universal evaluation model design, this article selects 11 sub indicators that can best measure the data management ability of manufacturing enterprises in China from six dimensions. The evaluation index system shown in Table 1 is constructed:

Table 1. Evaluation Indicators for Data Management Capability of Manufacturing Enterprises

Evaluation dimension	Subdivision indicators	Explanation of indicators
Decision process data availability (D1)	Decision process data availability (S1)	Can enterprises easily obtain relevant data in the decision-making process
Decision Process Data Dependency (D2)	Decision Process Data Dependency (S2)	The degree of dependence of enterprises on data for decision-making
Diversity of Enterprise Data Collection Entities (D3)	Diversity of enterprise data collection entities (S3)	Does the enterprise collect data from multiple channels
	Performance indicators from production technology/tools (S4)	The frequency of using data in the enterprise decision-making process reflected by production technology or tools
Frequency of Decision Process Data Usage (D4)	Formal/informal feedback from management (S5)	The frequency of using data in the decision-making process of the enterprise based on feedback from management personnel
	Formal/informal feedback from frontline workers (S6)	The frequency of data usage by frontline workers in the decision-making process of enterprises
	From external data of the enterprise (S7)	The frequency of data usage in the decision-making process reflected from external data of the enterprise
	From external data of the enterprise (S7)	The frequency of data usage by enterprises in the design of new products or services
Working process data usage frequency (D5)	Demand Forecast (S9)	The frequency of data usage by enterprises in demand forecasting
	Supply Chain Management (S10)	The frequency of data usage by enterprises in supply chain management
Using statistical methods to predict frequency (D6)	Using statistical methods to predict frequency (S11)	The frequency of enterprises using statistical methods to predict development situations, etc.

3.2 Sample Data

This article refers to the 2018 China Enterprise Labor Matching Survey data and selects relevant data from a total of 10 manufacturing enterprises from the general equipment manufacturing, automotive manufacturing, biopharmaceutical, and other manufacturing industries distributed in five provinces of China, including Guangdong, Hubei, Sichuan, Jiangsu, and Jilin, as sample data.

3.3 Fermatean Fuzzy TOPSIS method for Evaluating Enterprise Data Management Capabilities.

Step1. Determination of indicator weights. The weight of the indicators calculated using the aforementioned method is shown in Table 2:

Table 2. Indicator weight

weight	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
AHP	0.146	0.1698	0.1244	0.0594	0.0292	0.0681	0.0489	0.0989	0.0686	0.0876	0.0991
EWM	0.0365	0.0534	0.4375	0.0774	0.0571	0.0391	0.0416	0.0763	0.0710	0.0515	0.0587
Relative Entropy	0.1280	0.1507	0.1758	0.0623	0.0338	0.0633	0.0477	0.0952	0.0690	0.0817	0.0925

Step 2. Generating Fermatean Fuzzy Decision Matrix.

This article invites three experts to rate the performance of 10 selected enterprises under the manufacturing enterprise data management capability evaluation index system based on 2018 CEES data. Expert 1 and Expert 3 respectively serve in the big data management departments of automobile manufacturing companies and textile enterprises. Expert 2 is a member of the DAMA China Council, committed to research and practice in data architecture. Considering factors such as the industry reputation of the three experts, their ratings have been assigned weights of (0.3, 0.4, 0.3). Due to space limitations, the specific rating results of the three experts are not displayed. The summary results of the three experts' ratings are calculated using equation (3) to obtain the following Fermat fuzzy decision matrix as shown in Table 3:

Table 3. Fermatean Fuzzy Decision Matrix

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
A	(0.13,0.9)	(0.54,0.54)	(0.23,0.8)	(0.3,0.85)	(0.53,0.5)	(0.16,0.87)	(0.1,0.9)	(0.27,0.84)	(0.24,0.8)	(0.2,0.84)	(0.27,0.85)
B	(0.53,0.5)	(0.53,0.5)	(0.23,0.8)	(0.9,0.1)	(0.86,0.15)	(0.87,0.16)	(0.9,0.1)	(0.86,0.15)	(0.74,0.25)	(0.9,0.22)	(0.8,0.18)
C	(0.86,0.15)	(0.77,0.32)	(0.3,0.8)	(0.86,0.15)	(0.86,0.15)	(0.77,0.32)	(0.87,0.16)	(0.87,0.15)	(0.86,0.15)	(0.87,0.1)	(0.86,0.17)
D	(0.53,0.57)	(0.73,0.2)	(0.74,0.28)	(0.24,0.8)	(0.23,0.8)	(0.24,0.8)	(0.24,0.8)	(0.86,0.15)	(0.86,0.15)	(0.86,0.15)	(0.24,0.8)
E	(0.54,0.54)	(0.54,0.54)	(0.15,0.84)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.77,0.32)	(0.13,0.9)
F	(0.54,0.54)	(0.54,0.54)	(0.15,0.84)	(0.54,0.54)	(0.54,0.54)	(0.77,0.32)	(0.27,0.8)	(0.54,0.54)	(0.27,0.8)	(0.54,0.54)	(0.54,0.54)
G	(0.77,0.32)	(0.77,0.32)	(0.15,0.84)	(0.27,0.8)	(0.27,0.8)	(0.27,0.8)	(0.54,0.54)	(0.27,0.8)	(0.27,0.8)	(0.27,0.8)	(0.27,0.8)
H	(0.27,0.8)	(0.27,0.8)	(0.15,0.84)	(0.77,0.32)	(0.77,0.32)	(0.54,0.54)	(0.54,0.54)	(0.27,0.8)	(0.77,0.32)	(0.77,0.32)	(0.27,0.8)
I	(0.27,0.8)	(0.27,0.8)	(0.15,0.84)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.27,0.8)
J	(0.77,0.32)	(0.77,0.32)	(0.15,0.84)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)	(0.87,0.15)

Step 3. Determine positive and negative ideal solutions.

By calculating equation (5), the score matrix can be obtained as table 4:

Table 4. Fermatean Fuzzy Score Matrix

Score	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
A	-0.727	0.000	-0.500	-0.587	0.024	-0.654	-0.728	-0.573	-0.498	-0.585	-0.594
B	0.024	0.024	-0.500	0.728	0.633	0.654	0.728	0.633	0.390	0.718	0.506
C	0.633	0.424	-0.485	0.633	0.633	0.424	0.654	0.655	0.633	0.658	0.631
D	-0.036	0.381	0.383	-0.498	-0.500	-0.498	-0.498	0.633	0.633	0.633	-0.498
E	0.000	0.000	-0.589	0.655	0.655	0.655	0.655	0.655	0.655	0.424	-0.727
F	0.000	0.000	-0.589	0.000	0.000	0.424	-0.492	0.000	-0.492	0.000	0.000
G	0.424	0.424	-0.589	-0.492	-0.492	-0.492	0.000	-0.492	-0.492	-0.492	-0.492
H	-0.492	-0.492	-0.589	0.424	0.424	0.000	0.000	-0.492	0.424	0.424	-0.492
I	-0.492	-0.492	-0.589	0.655	0.655	0.655	0.655	0.655	0.655	0.655	-0.492
J	0.424	0.424	-0.589	0.655	0.655	0.655	0.655	0.655	0.655	0.655	0.655

Determine the positive and negative ideal solutions as:

$$S^{+}=\begin{Bmatrix}(0.86,0.15)(0.77,0.32)(0.74,0.28)(0.9,0.1)(0.87,0.15)(0.87,0.15)\\(0.9,0.1)(0.87,0.15)(0.87,0.15)(0.9,0.2)(0.87,0.15)\end{Bmatrix}$$

$$S^{-}=\begin{Bmatrix}(0.13,0.9)(0.27,0.8)(0.15,0.84)(0.3,0.85)(0.23,0.8)(0.24,0.8)\\(0.1,0.8)(0.27,0.84)(0.24,0.8)(0.2,0.84)(0.13,0.9)\end{Bmatrix}$$

Step 4. Calculation and ranking of relative closeness.

Using the above data and calculating the relative closeness according to equation (13) and equation (14) for sorting, the results shown in Table 5 can be obtained:

Table 5. Relative Proximity Index and Ranking

Enter-prise	Distance from FFPIS	Distance from FFNIS	Relative closeness index $\zeta(S_i)$	Ranking
A	0.6881	0.1887	0.0412	10
B	0.3096	0.5851	0.1250	3
C	0.2150	0.7128	0.1469	1
D	0.4123	0.5476	0.1091	4
E	0.4130	0.5275	0.1072	5
F	0.4630	0.3732	0.0853	8
G	0.5343	0.4629	0.0887	7
H	0.5977	0.3127	0.0657	9
I	0.5452	0.4776	0.0893	6
J	0.2439	0.6972	0.1416	2

Based on the above empirical results, it is shown that under the evaluation index system of data management ability in manufacturing enterprises, Company C performs best, while Company A perform worst. The relative closeness obtained by using Fermatean fuzzy weighted geometric operator to aggregate expert fuzzy evaluation will be compared with that obtained by using simple Fermatean fuzzy weighted operator to aggregate expert fuzzy evaluation. The results are shown in the Table 6:

Table 6. Comparison of Differentiation Degrees of Aggregation Operators

Aggregation operator	Mean discrimination degree（%）
Fermatean Fuzzy weighted geometric operator	33.32
Fermatean Fuzzy weighted operator	33.04

It is shown that the Fermatean fuzzy weighted geometric operator better integrates the fuzzy evaluation of experts.

3.4 Analysis of Data Management Capabilities of Relevant Enterprises

Based on the data management ability scores of the two companies, it is shown that Company C performs significantly better than other companies in terms of decision data availability, diversity of enterprise data collection entities, and frequency of decision process data usage, while Company A generally performs poorly in terms of decision process data availability and dependence on decision process data, Especially, the degree of dependence on data in the decision-making process and the diversity feedback scores from management on the data collection entities of the enterprise are at extremely low levels.

4 Conclusions

Firstly, manufacturing enterprises generally have weak data management capabilities in terms of the diversity of enterprise data collection entities. Based on the above results, we can draw the conclusion that the data management ability of manufacturing enterprises in the diversity of enterprise data collection entities is generally weak.

Secondly, manufacturing enterprises generally lack awareness of data management. Some manufacturing enterprises have more traditional management models and have significant deficiencies in the application of big data and data management. Some enterprises, even though they realize the importance of data management, still have insufficient funds and personnel Due to non-standard management processes and other reasons, further improvements in enterprise data management cannot be achieved.

In addition, this article also uses the Fermat fuzzy weighted geometric operator to aggregate the expert's scores into the expert decision matrix. Compared to the ordinary Fermat fuzzy weighted operator, the Fermat fuzzy weighted geometric operator can better integrate the fuzzy evaluation of experts.

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