Research on Data Management Ability Evaluation of Manufacturing Enterprises Based on PROMETHEE Method of Hesitation and Fuzzy Language

Churan Lin[*1,2a], Mu Zhang[1,b]

(* marked as corresponding author):[a]1035024390@qq.com ; [b]rim_007@163.com

[1] School of Big Data Application and Economics, Guizhou University of Finance and Economics, Guiyang(550025), Guizhou, China
[2] Guizhou Institution for Technology Innovation & Entrepreneurship Investment, Guizhou University of Finance and Economics, Guiyang(550025), Guizhou, China

Abstract: In recent years, as the global economy has entered the era of big data, the importance of data management ability for Chinese enterprises in such fields as risk prediction, business model adjustment and value discovery has become increasingly prominent. Strengthening the capacity building of data management has become the key point for enterprises to promote digital transformation. Enterprises should deeply understand the inevitability of enterprise upgrading and transformation under the trend of digitalization, seize the data factor market to cultivate new opportunities, enhance the sense of responsible subject in managing and making good use of data resources, strengthen the construction of data management professionals. It has become an inevitable choice for enterprises to explore and develop the value of data, actively carry out digital transformation and use data to drive business development. However, how to improve the data management ability of the enterprise needs a more comprehensive evaluation and analysis of its data management ability. Therefore, this paper will evaluate the data management ability of manufacturing enterprises. Because people's judgment of things is often unable to give a simple and quantitative accurate judgment, but with certain ambiguity and hesitation, this paper will use PROMETHEE multi-attribute decision making method under hesitation fuzzy language information environment to evaluate and analyze ten selected manufacturing enterprise data management ability from six aspects, and put forward relevant suggestions. The results found that the top several enterprises perform better in frequency of using decision-making process data and frequency of using working process data. Therefore, as China's economy enters the era of big data, enterprises should make data management truly become an important link in the decision-making and working process of improving their data management ability, and more actively realize demand prediction and value creation for enterprises through data-driven decision-making.

Keywords: Hesitation Fuzzy Language; PROMETHEE Method; Multi-Attribute Decision Making; Manufacturing Enterprise; Data Management Ability

1. Introduction

Today, data is not only a national basic strategic resource and an important factor of production, but also a new engine to drive the economic development. With the vigorous

ICEMBDA 2023, October 27-29, Tianjin, People's Republic of China

DOI 10.4108/eai.27-10-2023.2341949

development of digital economy, the multiplier effect of data on production efficiency has become increasingly prominent. It has become an inevitable choice for enterprises to explore and develop the value of data, actively carry out digital transformation and use data to drive business development[1]. On this basis, in response to the new changes of the Chinese economy, the 2017-2019 Government Work Report continuously mentioned the important role of big data in China's economic development, and pointed out that China should implement big data development action. Under the guidance and support of national policies, the leading role of China's digital economy in economic and social innovation has been continuously enhanced, digital development has become a social consensus, the value of data elements has been continuously released, the market system of data elements has been continuously improved, and the process of digital transformation has been steadily accelerated[2].

At the same time, more and more theoretical analysis shows that with the increasingly extensive integration of big data technology and real economy, how enterprises use increasingly large and diversified data information resources is no longer just a problem of technological progress, but also poses new challenges to enterprise management practice innovation[3]. Li et al. (2021)[4] believes that under the background of the COVID-19 epidemic, emerging digital technologies has been recognized by the government. Therefore, traditional industries must grasp the direction of digital development and accelerate the pace of transformation. Chen et al. (2020)[5] believes that, faced with the improvement of digitization degree, enterprise management needs to strengthen the position of data collection, data sharing and data analysis to realize the value innovation driven by big data. And Zeng et al. (2020)[6] believes that under the condition of digital economy, enterprises will give birth to a new big data management decision-making paradigm. Therefore, studying the data management ability of enterprises from the perspective of micro enterprises has important theoretical value and practical significance[7]. Because people's judgment of things is often unable to give a simple and quantitative accurate judgment, but with certain ambiguity and hesitation, this paper will use PROMETHEE multi-attribute decision making method under hesitation fuzzy language information environment to evaluate and analyze manufacturing enterprise data management ability[8]. This paper refers to enterprise data management ability score index system constructed by Li et al. (2020)[9], evaluating the data management ability of manufacturing enterprises from six dimensions, which is a total of eleven indicators. The specific structure is as follows: Part 2 introduces the research methods; Part 3 is index selection, sample data and empirical analysis; Part 4 is conclusions and policy recommendations.

2. Research methods

2.1. Entropy weight method

Entropy weight method is an objective empowerment method to determine the weight of indicators according to the information provided by the index[10]. This method does not require any assumption of the distribution pattern of the data, and it is relatively simple to calculate[11]. With n enterprises and m indexes(There are all benefit indexes in this paper) to form the original index data matrix. Then:

- Step 1: Calculating standardized values y_{ij} of the raw index data:

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

Where $\max(x_j)$ and $\min(x_j)$ indicate the maximum and minimum values of the j-th index, respectively.

- Step 2: Calculating the entropy value H_j of the j-th index:

$$H_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{2}$$

Where $p_{ij} = y_{ij} / \sum_{i=1}^{n} y_{ij}$; And introduction constant $k = (\ln n)^{-1}$ can ensure that it is satisfied $H_j = 1$ when p_{ij} of the j-th index is equal, this indicator cannot provide any information at this point. When $p_{ij} = 0$, let $p_{ij} \ln p_{ij} = 0$, so that $H_j \in [0,1]$.

- Step 3: Calculating the entropy weight w_j of the j-th index:

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{m}(1 - H_j)} = \frac{1 - H_j}{m - \sum_{j=1}^{m} H_j} \tag{3}$$

Where $w_j \in [0,1]$, and $\sum_{j=1}^{m} w_j = 1$.

2.2. PROMETHEE method of hesitation and fuzzy language

2.2.1. Relevant definition

- Definition 1:Let U be the set of language terms and G_H be the text free grammar, then the element of the text free grammar $G_H =(V_N, V_T, I, P)$ can be defined as follows: V_N = { subject word, compound word, unitary relationship, binary relationship, conjunction}; V_T = {"less", "more", "at least", "at most", "between", "and"," u_0 "," u_1 ",...," u_τ "}; $I \in V_N$; P= { I refers to the subject word or the compound word; the subject word refers to " u_0 "," u_1 ",...," u_τ "; the compound word refers to the unary relationship plus subject word, or binary relationship plus conjunction plus subject word; the unary relationship refers to"less" or "more"; the binary relationship refers to"between"; the conjunction refers to"and"}.
- Definition 2:Let E_{G_H} be a function that transforms the language expression $ll \in U_{ll}$ generated by the text free grammar G_H into the hesitant fuzzy language set H_U , U is the set of language terms adopted by the grammar G_H , U_{ll} is the set of all the expressions generated by the grammar G_H , then the language expression generated by the generation rules of the grammar G_H can be converted into a hesitant fuzzy language set through the conversion formula $E_{G_H} : U_{ll} \to H_U$, where:

  $E_{G_H}(U_g) = \{U_g \mid U_g \in U\}$;

E_{G_H} (no more than U_α)= $\{U_g \mid U_g \in U$ and $U_g \leq U_\alpha\}$;

E_{G_H} (less than U_α)= $U_g \mid U_g \in U$ and $U_g < U_\alpha\}$;

E_{G_H} (no less than U_α)= $\{U_g \mid U_g \in U$ and $U_g \geq U_\alpha\}$;

E_{G_H} (more than U_α)= $U_g \mid U_g \in U$ and $U_g > U_\alpha\}$;

E_{G_H} (between U_α and U_β)= $\{U_g \mid U_g \in U$ and $U_\alpha \leq U_g \leq U_\beta\}$.

- Definition 3:The positive ideal solution A^+ and negative ideal solution A^- of the hesitant fuzzy language are: $A^+ = \{ h_u^{1+}, h_u^{2+}, ..., h_u^{n+} \}$, $A^- = \{ h_u^{1-}, h_u^{2-}, ..., h_u^{n-} \}$, where:

$$h_u^{j+} = \begin{cases} i = {}^{\max}_{1,2,3,...,m}\ h_u^{ij+} = {}^{\max}_{\substack{i=1,2,3,...,m \\ l=1,...,\#h_u^{ij}}} \{u_{\delta_l^{ij}}\} & \text{for the benefit type attribute} \\ i = {}^{\min}_{1,2,3,...,m}\ h_u^{ij-} = {}^{\min}_{\substack{i=1,2,3,...,m \\ l=1,...,\#h_u^{ij}}} \{u_{\delta_l^{ij}}\} & \text{for the cost type attribute} \end{cases}$$

$$h_u^{j-} = \begin{cases} i = {}^{\max}_{1,2,3,...,m}\ h_u^{ij+} = {}^{\max}_{\substack{i=1,2,3,...,m \\ l=1,...,\#h_u^{ij}}} \{u_{\delta_l^{ij}}\} & \text{for the cost type attribute} \\ i = {}^{\min}_{1,2,3,...,m}\ h_u^{ij-} = {}^{\min}_{\substack{i=1,2,3,...,m \\ l=1,...,\#h_u^{ij}}} \{u_{\delta_l^{ij}}\} & \text{for the benefit type attribute} \end{cases} \qquad j=1,2,...,n$$

2.2.2. Hesitation fuzzy language PROMETHEE multi-attribute decision method based on improved preference function

Hesitation fuzzy language allows decision makers to make qualitative description of objective things in situations such as incomplete information and multiple different hesitant information languages, meeting the needs of realistic decision-making process[12]. The algorithm steps are presented below:

- Step 1: Determine a scheme set $A = \{a_1, a_2, ..., a_n\}$ consisting of n schemes and an attribute set $C = \{c_1, c_2, ..., c_m\}$ consisting of m attributes. The set of weights of each attribute is $W = (w_1, w_2, ..., w_m)^T$, where $0 \leq w_j \leq 1$ and $\sum_{j=1}^{m} w_j = 1$.

- Step 2: Use language expression to give qualitative evaluation of the performance of each scheme a_i under each attribute c_j . Generate the language expression ll according to the text free grammar G_H given in Definition 1.

- Step 3: According to the conversion function E_{G_H} given in Definition 2, convert the language expression ll into hesitant fuzzy language set H_U .

- Step 4: Let the number of hesitating fuzzy language $h_u^{ij} = \{u_{\delta l}^{ij} \mid l = 1, ..., \# h_u^{ij}\}$ $(i = 1, 2, \dots, m; j = 1, 2, \dots, n)$ represent the degree of satisfaction of scheme a_i on attribute c_j . For each hesitating fuzzy language set, define

$\sigma_u^{ij} = \sum_{l=1}^{\#h_u^{ij}} \delta_l^{ij}$ as the sum of all hesitating fuzzy languages in the set. The deviation of any pair of schemes a_i and a_k on attribute c_j is $\mathrm{d}_j(a_i, a_k) = \sigma_u^{ij} - \sigma_u^{kj} (i, k = 1,2,...,n)$.

- Step 5: Calculate its deviation $d_j = (A_j^+, A_j^-)$.
- Step 6: Using the linear preference criterion function in the preference function, the strict preference threshold takes $\mathrm{v} = \theta \mathrm{d}_j(A_j^+, A_j^-), 0 < \theta < 1$: when the difference between $f(a_i)$ and $f(a_k)$ is 0 indicates that scheme a_i is not different from scheme a_k; when the difference between $f(a_i)$ and $f(a_k)$ is greater than $\theta \mathrm{d}_j(A_j^+, A_j^-)$ indicates that scheme a_i is strictly better than scheme a_k. Therefore, the modified linear criterion preference function is as follows:

$$P_j(a_i, a_k) = \begin{cases} 0, & d_j(a_i, a_k) \le 0 \\ \dfrac{d_j(a_i, a_k)}{\theta d_j(A_j^+, A_j^-)}, & 0 < d_j(a_i, a_k) \le \theta d_j(A_j^+, A_j^-) \\ 1, & d_j(a_i, a_k) > \theta d_j(A_j^+, A_j^-) \end{cases} \tag{4}$$

Under the benefit attribute c_j , the degree to which scheme a_i is superior to scheme a_k is expressed by the modified linear criterion preference function.

- Step 7: Determine the priority index $\pi(a_i, a_k)$. The priority index represents the degree to which scheme a_i is superior to scheme a_k. The closer it is to 1, the better scheme a_i is.

$$\pi(a_i, a_k) = \sum_{r=1}^{m} w_j p_j(a_i, a_k) \tag{5}$$

Where $j = 1,2,...,m; i, k = 1,2,...,n$.

- Step 8: According to the priority index, calculate the outflow $\phi^+(a_i)$ and the inflow $\phi^-(a_i)$ for each scheme:

$$\phi^+(a_i) = \sum_{r=1}^{m} \pi(a_i, a_k) = \sum_{i=1}^{n} \sum_{r=1}^{m} w_j p_j(a_i, a_k) \tag{6}$$

$$\phi^-(a_i) = \sum_{r=1}^{m} \pi(a_k, a_i) = \sum_{i=1}^{n} \sum_{r=1}^{m} w_j p_j(a_k, a_i) \tag{7}$$

Where $j = 1,2,...,m; i, k = 1,2,...,n$. $\phi^+(a_i)$ indicates the degree of a_i exceeding other schemes; $\phi^-(a_i)$ indicates the possibility of other schemes exceeding scheme a_i.

- Step 9: Calculate the net flow of the scheme a_i .

$$\phi(a_i) = \phi^+(a_i) - \phi^-(a_i) \tag{8}$$

The larger $\phi(a_i)$ is, the better the scheme a_i is. If $\phi(a_i) > \phi(a_k)$, scheme a_i is better than scheme a_k. Similarly, the full ordering of the scheme is obtained.

3. Empirical analysis

3.1. Index selection

Considering the scientific, operational and universal factors of data, combined with the preliminary investigation and analysis of data management in manufacturing enterprises in China, this paper constructs a score index system of enterprise data management ability of 11 indicators in six dimensions, including frequency of using decision-making process data, frequency of using working process data, and prediction using statistical methods, so as to evaluate and study the data management ability of manufacturing enterprises.The detailed indicators are shown in Table 1:

Table 1. Indicators and data related to enterprise data management ability.

Indicator type		Index interpretation
Availability of decision-making process data		Whether the company can easily obtain the relevant data in the decision-making process
Dependence degree of decision-making process data		Dependence of enterprises in making decisions based on data
Diversity of enterprise data collection subjects		Whether the enterprise collects data from multiple channels
Frequency of using decision-making process data	Performance indicators from production technology/tools	The frequency of data used in the enterprise decision-making process as reflected by production technologies or tools
	Formal/informal feedback from management	The frequency of data used by enterprises in the decision-making process according to the feedback from management personnel
	Formal/informal feedback from front-line workers	The frequency of data used by enterprises in the decision-making process according to the feedback from front-line workers
	External data from enterprises	The frequency of data used in the enterprise decision-making process as reflected by the external date from enterprises
Frequency of using working process data	Design of new products and services	The frequency of data used by enterprises in designing new products or services
	Demand forecast	The frequency of data used by enterprises in demand forecasting
	Supply chain management	The frequency of data used by enterprises in supply chain management
Prediction using statistical methods		The frequency with which enterprises use statistical methods to forecast their development

3.2. Sample data selection

The data used in this paper are from CEES data jointly conducted by scientific research institutions. In 2018, CEES reference to management organization practice survey questionnaire design ideas of the United States in 2015, for the first time collected the data of Chinese manufacturing enterprises about 11 indicators, and the relevant measures of data management ability of 1942 effective samples were obtained. Ten of the manufacturing enterprises are randomly selected as samples for evaluation and research.

3.3. Empirical analysis

First of all, we need to evaluate the data management ability of the selected ten manufacturing enterprises. The evaluation indicators include above 11 indicators.

Therefore, the ten manufacturing enterprises are $A = (A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10})$. Evaluation index has 11 main attributes, namely "decision-making process data availability"(c_1), "decision-making data dependence"(c_2), and then the remaining indicators are c_3 to c_{11} in turn.

- Step 1: The 11 attributes are assigned according to the entropy weight method, and the final set of weights is $w = (0.0752, 0.0724, 0.1821, 0.0916, 0.0921, 0.0705, 0.0985, 0.0810, 0.0624, 0.0885, 0.0857)^T$.
- Step 2: The linguistic term set U of the above 11 attributes can be expressed as U = $\{u_0 = \text{worst},\ u_1 = \text{worse},\ u_2 = \text{bad},\ u_3 = \text{medium},\ u_4 = \text{good},\ u_5 = \text{better},\ u_6 = \text{perfect}\}$.
- Step 3: In order to get a reasonable and comprehensive evaluation result, we set up a decision-making group, which includes the experts in evaluating the data management ability of enterprises, and each expert will evaluate the data management ability of each enterprise. They may have different opinions on the performance of the data management capabilities of different enterprises. For example, one expert might consider one of the corporate decision process data availability performance as "perfect" and another person as "better". If they fail to persuade each other to agree, then the result of this performance evaluation is $\{u_5, u_6\}$. If all decision makers agree that the company's demand forecast is "better", then the assessment result is $\{u_5\}$. After the discussion of them, the qualitative evaluation information of 10 banks' performance under 11 attributes is given by using language expressions for the above problems.
- Step 4: According to the conversion function E_{GH}, the expert's language expression ll is transformed into the hesitation fuzzy language number, and then the hesitation fuzzy language evaluation matrix H_U is constructed. As shown in Table 2:

Table 2. Hesitation fuzzy language evaluation matrix

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}
a_1	$\{u_0\}$	$\{u_0\}$	$\{u_0, u_1\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_4, u_5\}$
a_2	$\{u_0\}$	$\{u_0\}$	$\{u_0, u_1\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$	$\{u_0\}$
a_3	$\{u_4, u_5\}$	$\{u_4, u_5\}$	$\{u_0, u_1\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$
a_4	$\{u_4, u_5\}$	$\{u_4, u_5\}$	$\{u_3\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$

a_5	$\{u_4, u_5\}$	$\{u_4, u_5\}$	$\{u_0, u_1\}$	$\{u_6\}$	$\{u_3\}$	$\{u_6\}$	$\{u_6\}$	$\{u_3\}$	$\{u_4, u_5\}$	$\{u_4, u_5\}$	$\{u_1, u_2\}$
a_6	$\{u_6\}$	$\{u_4, u_5\}$	$\{u_4\}$	$\{u_3\}$	$\{u_3\}$	$\{u_3\}$	$\{u_3\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_0\}$
a_7	$\{u_1, u_2\}$	$\{u_0\}$	$\{u_0, u_1\}$	$\{u_6\}$	$\{u_6\}$	$\{u_6\}$	$\{u_6\}$	$\{u_3\}$	$\{u_4, u_5\}$	$\{u_4, u_5\}$	$\{u_4, u_5\}$
a_8	$\{u_3\}$	$\{u_3\}$	$\{u_1, u_2\}$	$\{u_4, u_5\}$	$\{u_6\}$	$\{u_4, u_5\}$	$\{u_0\}$	$\{u_4, u_5\}$	$\{u_3\}$	$\{u_4, u_5\}$	$\{u_3\}$
a_9	$\{u_3\}$	$\{u_3\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$
a_{10}	$\{u_0\}$	$\{u_1, u_2\}$	$\{u_0, u_1\}$	$\{u_0\}$	$\{u_0\}$	$\{u_1, u_2\}$	$\{u_1, u_2\}$	$\{u_0\}$	$\{u_1, u_2\}$	$\{u_0\}$	$\{u_0\}$

- Step 5: Determine the A^+ and A^- of the hesitant fuzzy language , where $A^+=\{U_6, U_5, U_3, U_6, U_6, U_6, U_6, U_5, U_5, U_5, U_5\}$, $A^-=\{U_0, U_0, U_0, U_0, U_0, U_0, U_0, U_0, U_0, U_0, U_0\}$. These 11 attributes are all benefit attributes, therefore, calculate the difference $d_j = (A_j^+, A_j^-)$ between the A^+ and A^- to further determine the preference function. The degree to which scheme a_i (i=1,2,3,4,5,6,7,8,9,10) outperforms the other scheme a_k (k=1,2,3,4,5,6,7,8,9,10) under the benefit attribute is calculated by the improved linear criterion preference function. (Based on the need for the facts of the decision and the investor's preference for the degree of strict superiority, let θ =0.6) .
- Step 6: The priority index is calculated according to Formula (5).
- Step 7: The outflow $\phi^+(a_i)$ and inflow $\phi^-(a_i)$ are calculated according to Formula (6) and Formula (7).
- Step 8: The net flow of scheme a_i is calculated from Formula (8). The results are shown in Table 3.

Table 3. Computing result

	Outflow	Inflow	Net flow	Ranking
a_1	0.6426	4.4350	-3.7924	8
a_2	0	4.8633	-4.8633	10
a_3	1.5698	2.4213	-0.8515	7
a_4	2.9659	1.9559	1.0100	5
a_5	4.6261	1.0061	3.6201	1
a_6	4.0913	1.6672	2.4241	4
a_7	4.8817	1.4038	3.4779	2
a_8	4.7100	1.3618	3.3482	3
a_9	1.9365	2.4588	-0.5223	6
a_{10}	0.0857	4.2037	-4.1180	9

The full ranking of the available scheme is $a_5 > a_7 > a_8 > a_6 > a_4 > a_9 > a_3 > a_1 > a_{10} > a_2$. It can be seen that among the ten enterprises, enterprise a_5 has the best data management ability, and a_2 has the worst data management ability.

The enterprise with the best data management ability is a state-owned enterprise engaged in the manufacturing of electronic devices and equipment. In the process of enterprise development and digital transformation, state-owned enterprises can get more and more national policy and financial support. And since its establishment, the enterprise has actively responded to the initiative of digital transformation of manufacturing industry, made full use of more adequate resource and policy support of state-owned enterprises, vigorously developed digital technology, and applied big data to enterprise production, thus improving production efficiency and data utilization rate. Therefore, enterprises a_5 have good performance in the four aspects of data availability in decision-making process, data dependence in decision-making process, frequency of data use in decision-making process and frequency of data use in working process.

The enterprise with the worst data management ability is a private enterprise engaged in garment manufacturing with a small scale. In the process of improving the data management ability, it obtains less policy support, and it is difficult to obtain sufficient capital and talent investment. And private enterprises may pay less attention to government policies and have lower sensitivity in their daily business activities, so it is weak in the acquisition and application of data resources. It can also be seen from the score of data management ability that enterprise a_2 is at a backward level in all aspects of data management.

And among the ten selected sample enterprises, even the enterprise which performs best under the index of diversity of enterprise data collection subjects is only in the middle level. It can be seen that manufacturing enterprises are generally weak in the diversity of enterprise data collection subjects. This shows that at the present stage, there are still some shortcomings in data management of Chinese manufacturing enterprises, such as the lack of data circulation mechanism among enterprises and the low utilization rate of data, and its potential value needs to be further explored.

4. Conclusion and suggestion

This paper uses PROMETHEE method based on hesitancy fuzzy language to measure the data management ability of 10 manufacturing enterprises, and finally comes to the conclusion that the data management ability of enterprises a_5 is the best and the data management ability of enterprises a_2 is the worst. As can be seen from the above, the top several enterprises have good performance in frequency of data use in decision-making process and working process. At the same time, the diversity of data collection subjects of the ten enterprises is insufficient. In view of this conclusion, this paper puts forward the following three suggestions:

First, as China's economy enters the era of big data, enterprises not only need to develop the fields of Internet and ICT, but also need to improve their data management ability and aiming at the changing business environment of the digital economy, to make data management truly become an important link in the decision-making and working process of enterprises[13]. And as the "leader" of China's economic rise, state-owned enterprises want to achieve sustainable, healthy and stable development, they must take into account the background of big data era, find a development path in line with the actual situation, constantly improve their data management ability, and maximize the economic and social benefits[14].

Second, under the economic background of digital transformation, the management practice and innovation of Chinese enterprises will undergo important changes[15]. In the new economic environment, management practice should no longer be limited to tapping the potential of the efficiency of enterprise production and operation organization process, but should more actively realize demand prediction and value creation for enterprises themselves through the effective application of multi-source heterogeneous data and data-driven decision-making.

Finally, in the process of improving the data management ability of manufacturing enterprises, the government should increase policy support to help enterprises in digital transformation. Enterprises should also actively respond to the call of the government, increase capital and talent investment, develop big data technology, and improve the ability of data resource acquisition and application.

Data is not only a national basic strategic resource and an important factor of production, but also a new engine to drive the economic development[16]. It has become an inevitable choice for enterprises to explore and develop the value of data, actively carry out digital transformation and use data to drive business development. And strengthening the capacity building of data management is the key point for enterprises to promote digital transformation. Enterprises should deeply understand the inevitability of enterprise upgrading and transformation under the trend of digitalization, seize the data factor market to cultivate new opportunities, enhance the sense of responsible subject in managing and making good use of data resources, strengthen the construction of data management professionals, truly give full play to the empowering role of data in enterprise production and operation, continuously improve the level of data management, and improve the endogenous motivation and ability of digital transformation[17].

Acknowledgements: This research was funded by the Regional Project of National Natural Science Foundation of China, grant number 71861003.

References

[1] Liang Jingang, Yang Hui. (2023) Research on the Evaluation and Optimization of Data Management Ability in the Construction of Smart Medical Insurance. Chinese Journal of Health Information Management **20 (01)**: 36-40.

[2] Wang Jianhu, Zhou Ming, Liu Tongfeng. (2022) Research and Practice of Data Management Ability in Big Data Center. Metallurgical Automation **46 (S1)**: 251-255.

[3] Wan Fang, Zhou Xiping. (2021) Maturity Assessment of China's Police Data Management Capability Based on DCMM. Journal of Yunnan Police Officers College **(01)**: 90-96.

[4] Li Tang, Li Qing, and Chen Chuxia. (2020) The Effect of Data Management Ability on Enterprise Productivity — Comes from the New Findings of the Chinese Enterprise-Labor Force Matching Survey. Industrial Economy of China **(06)**: 174-192.

[5] Chen Jian, Huang Shuo, and Liu Yunhui. (2020) From Energizing to Enabling — Enterprise Operations Management in the Digital Environment. Manage the World **(2)**: 117-128.

[6] Chen Guoqing, Zeng Dajun, Wei Qiang, Zhang Mingyue, Guo Xunhua. (2020) Decision Paradigm Change and Enabling Innovation in the Big Data Environment. Manage the World **(2)**: 95-105.

[7] Yang Jinkun, Han Chunhua, Wei Guanghao, Wan Fangfang. (2020) Research on the Maturity of Marine Data Management. Ocean information **35 (04)**: 1-8.

[8] You Jie, Wang Huiwen. (2023) A Multi-attribute Decision Approach Based on Interval Hesitation Fuzzy Preference Relationship. Journal of Hainan Normal University (Natural Science Edition) **36 (01)**: 17-23.
[9] Qiu Wanhua. (2002) Management Decision and Applied Entropy, in Machinery Press (eds),Beijing.
[10] Wang Lei, Zhou Yanan, Zhang Yu. (2017) Evaluation of Development Level and Obstacle of Low-carbon Cities Based on Entropy Right -TOPSIS Method — Takes Tianjin as Example. Science and Technology Management Research **37 (17)**: 239-245.
[11] Liao Huchang, Yang Zhu, Xu Zishui, Gu Xin. (2019) Application of PROMETHEE Method in the Brand Evaluation of Sichuan Wine. Control and Decision-Making **34 (12)**: 2727-2736.
[12] Wu Shuangsheng, Lin Jie, Yang Yushu, Huang Donghong. (2023) Hesitation Fuzzy Language Distance Measure and Its Application in Multi-Attribute Decisions. Operations Research and Management **32 (02)**: 61-67.
[13] Liang Kunhua. (2023) The Impact of Digital Transformation on the Operation of Manufacturing Enterprises. Modern Corporate Culture **(02)**: 58-60.
[14] Liu Xin, Liu Lu. (2023) Research on the Quality Management of Manufacturing Enterprises under the Background of Digital Transformation. Electronic Product Reliability and Environment Test **41(01)**: 75-78.
[15] Ma Wen, Zhang Xinyang, Zhao Xiaoping. (2019) Research on the Maturity Evaluation Model of Data Management Capability of Power Grid Enterprises. Software **40 (04)**: 108-111.
[16] Shamim Saqib, Yang Yumei, Zia Najam UI, Shah Mahmood Hussain. (2021) Big Data Management Capabilities in the Hospitality Sector: Service Innovation and Customer Generated Online Quality Ratings. Computers in Human Behavior.
[17] Zotoo Isidore Komla, Lu Zhangping, Liu Guifeng. (2020) Big Data Management Capabilities and Librarians' Innovative Performance: The Role of Value Perception Using the Theory of knowledge-based Dynamic Capability. The Journal of Academic Librarianship **47(2)**.