2023 2nd International Conference on Cloud Computing, Big Data Application and Software Engineering (CBASE) | 979-8-3503-3144-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/CBASE60015.2023.10439112

Construction and Analysis of Data Quality Scale for Manufacturing Multi-Value Chain Collaborative Data Space Based on Combinatorial Empowerment Model

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***Abstract*—In the management of data space, data quality is very important to realize the value of data. How to improve data quality and tap the potential value of data, this paper proposes a five-dimensional scale of data quality based on manufacturing multi-value chain collaborative data space, which includes five dimensions of data generation, data acquisition, pre-access processing, architecture construction and data access, which effectively makes up for the shortcomings of current literature. Meanwhile, the improved CRITIC model weighting method and the combined weighting model of principal component weighting method were established to calculate the data quality index and sub-index, and the data quality level and sub-index level of manufacturing enterprises in Beijing were evaluated. By developing and analyzing the scale of data quality, we provide practical experience for value mining of collaborative data space data of multi-value chain in manufacturing industry.**

Keywords-Manufacturing enterprises; Data Space; Data Quality Scale; Portfolio Empowerment Model

I. INTRODUCTION

The 20th Congress of the Communist Party of China reported that it insists on putting the focus of economic development on the real economy, advancing a new type of industrialization, and accelerating the construction of a strong manufacturing country, a strong quality country, a strong network country, and a digital China. With the development and maturity of network technologies such as big data and artificial intelligence, as well as the proliferation of data in manufacturing enterprises, how to extract useful information from the huge amount of data information to support the multi-value chain collaborative development of manufacturing enterprises? That is, how to allocate data resources by means of big data and artificial intelligence, so that manufacturing enterprises can coordinate the resources effectively, has become an important issue in manufacturing intelligent manufacturing research.

Data space is an important platform to efficiently solve the proliferation of data (large amount of structured and unstructured data) storage, addition, deletion and sharing, and is one of the effective means to make the management of data more flexible. Data quality is particularly important in extracting key data information from the data space or mining the value of the data to form effective decisions. Data quality is a multifaceted concept, and according to ISO 8000, data quality is usually defined as "the extent to which a set of inherent characteristics of the data satisfies the requirements". According to ISO 25012, data quality is "the extent to which the data meets the requirements defined by the product owner's organization". As you can see, data quality is defined by other attributes and has a critical role in strategic decision making for manufacturing companies.

Faced with the problem of data proliferation in manufacturing enterprises, data space becomes very important, but how to use the huge amount of data space data effectively, data quality is particularly critical. In other words, how to contour the multi-value chain synergy to improve the quality of data in manufacturing enterprises and help them make efficient decisions has become an urgent problem to be solved.

II. LITERATURE REVIEW

A. Status of research on manufacturing multi-value chain collaborative enterprise data space

Enterprise data space is a collection of whole-process data for a certain enterprise, which is more enterprise-specific and can effectively meet the individual production and operation management needs of enterprises. The data in the enterprise data space is not only conventional structured data, but also includes all structured and unstructured data in the whole life cycle of an enterprise, including multimodal text, tables, diagrams, audio, video and other files. When sharing data in the data space, the presence of unstructured data can affect the use and analysis of data.

Data space is a new paradigm of data management, which is different from the traditional data management concept, and it is a subject-oriented data management technique. The literature [1] proposes a protocol on efficient data retrieval from data spaces, which helps to retrieve and update data in heterogeneous data sources from multiple data sources and improve data quality and utilization efficiency.

Manufacturing multi-value chain collaborative data space is a new management theory and method with data modeling, rapid indexing, correlation representation, full chain search and integrated evolution as the key support methods. As shown in Figure 1, the main participants of multi-value chain collaborative data space in manufacturing industry are manufacturing enterprises, collaborative enterprise groups related to manufacturing enterprises, multi-value chain collaborative data space management third-party platforms and supervisory and management departments. including two main operation mechanisms of multi-value chain collaborative data space inside manufacturing enterprises and multi-value chain collaboration outside manufacturing enterprises [2].

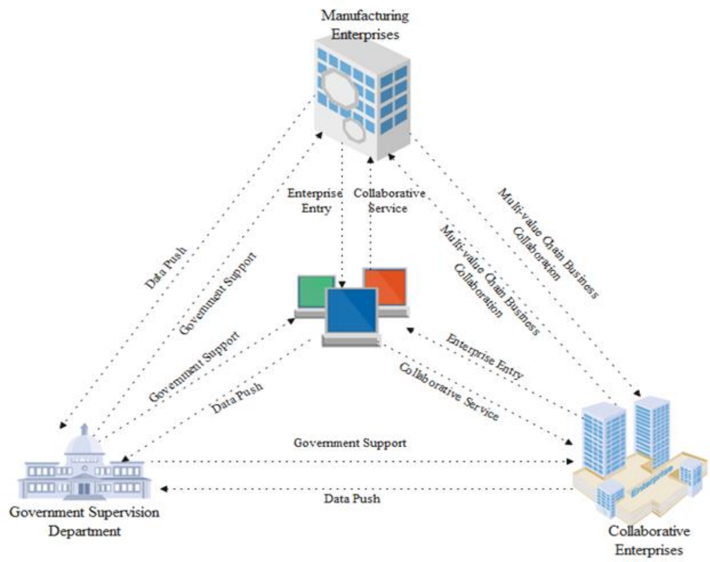

Fig. 1 Multi-value chain synergy operation mechanism diagram

The most important analysis of data quality in manufacturing multi-value chain enterprises is to establish the corresponding data quality evaluation scale by sorting out the factors related to the collaborative data space of manufacturing multi-value chain. At present, the data space of multi-value chain collaboration in manufacturing industry belongs to the knowledge frontier, and the evaluation system of data quality is not perfect to meet the development requirements of standardized intelligent manufacturing. Therefore, this paper constructs the evaluation scale of data quality of data space for the multi-value chain collaboration effect in manufacturing industry.

B. Status of research on data quality and related evaluation models

The concept of data quality is widely used in various industries. The literature [3] argues that the utility of electronic health records for research purposes will be hampered by data quality issues. the IT industry believes that some features and elements related to data quality should be considered from the initial stage of software development, setting specific features according to the perceived needs of different users [4].

The literature [5] argues that data is becoming a new fuel for economic wealth and the creation of novel and profitable business models, but there are still several key challenges to overcome for the data economy to truly flourish, among them, data quality can become an issue when data comes from heterogeneous sources or has different formats, standards and sizes. In this regard the NGSI-LD standard is used to harmonize and enrich heterogeneous data sources using linked data principles. The literature [6] points out that ensuring data quality is an important guarantee for extending product quality, as well as product renewal, during the product life cycle.

Data quality is assessed in four dimensions: first, the objectives of quality analysis, including quality assessment and quality improvement; second, quality control methods, including online, offline, and also hybrid; third, quality control techniques; and fourth, whether the quality control methods use any contextual information (inherent, systematic, organizational, or spatio-temporal context) [7].

Currently, the use of evaluation models can be quite extensive, and the commonly used ones include weighted TOPSIS[8], hierarchical analysis[9], coordination model[10], combined assignment model[11], and so on. Among them, the combined assignment model is objective and has a relatively small error. The literature [12] used the combined assignment model for flood risk evaluation and examined the evaluation level of flood risk during the operation of each station. The literature [13] used CRITIC method and ideal point method to construct a three-dimensional comprehensive evaluation model based on composite weights for scientific and technological achievements, which can better deal with the comprehensive problems of multiple indicators and factors, etc.

Therefore, based on the characteristics of data quality evaluation, this paper establishes a combined weighting model of CRITIC model assignment method and principal component analysis assignment method to develop and analyze the data quality scale of manufacturing multi-value chain collaborative data space, considering the influence of reducing subjective errors.

III. DATA QUALITY SCALE CONSTRUCTION

A. Scale construction

Data space data usually consists of multiple heterogeneous data, including both structured and unstructured data, making it difficult to evaluate the quality of data space data directly. In this regard, this paper summarizes the understanding of data quality from literature [14] based on the characteristics of data space data, and further extends and improves the content of data quality evaluation. In this paper, we believe that data quality should not only include three levels of data collection, data space construction and data use, but should be considered from the whole life cycle of data, i.e., including five stages of data generation, data acquisition, pre-access processing, architecture construction and data access, thus constructing a data quality evaluation scale, as shown in Table 1.

Table 1. Data quality evaluation scale

	Score Index	Indicators
Manufacturing Multi-Value Chain Data Space Data Quality Index	Data Generation	Legitimacy
		Identifiability
		Normality
		Objectivity
	Data Acquisition	Completeness
		Credibility
		Accuracy
		Consistency
		Timeliness
	Pre-access processing	Unbiased
		Validity
		Scientificity
		Timeliness
	Architecture Construction	Security
		Confidentiality
		Integrity
		Availability
		Uniformity
		Differences
	Data Access	Accessibility
		Relevance
		Error-free
		Traceability
		Comprehensibility

1) Data generation stage

a) Legitimacy

Legitimacy in the process of data generation means that the data should comply with relevant laws and regulations in the process of generation, and the data content and data definition should comply with the relevant standards, practices or regulations required by the competent authorities of the industry.

b) Identifiability

Identifiability means that the data can be recognized by an external party regardless of how or by what means it is generated, and that the data information can be encoded and decoded in its entirety.

c) Normality

Normality means that the data generated can meet certain standards, can be representative in one or more aspects, and can make normative statements about things.

d) Objectivity

Objectivity means that all the data generated is objectively real, its properties are not easily changed by external conditions, and every data is true and valid.

The data acquisition, architecture construction and data access breakdown metrics can be found in reference [14].

2) Pre-access processing

a) Unbiased

Unbiased means that there is no deviation between the expected value and the true value of data usage, and the unbiased nature of data is more useful to guide the stages of data collection, data space construction and usage. Under normal circumstances, there is a certain amount of bias in the data, and it becomes larger as the data lifecycle process evolves. Therefore, it is necessary to correct the bias by means of data feedback, so as to improve the data lifecycle process and maximize the value of data.

b) Validity

Validity refers to the proportion of the collected data that meets certain validity discriminatory criteria and meets the reception conditions, i.e., the data should be recorded and used in accordance with the agreed requirements to ensure that the completeness and consistency rules are satisfied. The validity index can be used to measure whether the data in the data space are valid or not, and can reflect the data quality in both the temporal and spatial dimensions.

c) Scientificity

Scientificity means that the data are scientifically clear in the stages of generation, collection, data space construction and use, and can withstand the test and screening of multiple ways or relevant theories, and also the data can truly reflect the characteristics of the data entity and maximize the value of the data.

d) Timeliness

Timeliness refers to the fact that the data called and extracted by the user should be current and up-to-date, without the problem of data lag and data obsolescence. The collected data should be provided to the destination within the time needed to meet the application or within the specified time. The timeliness index is used to measure whether the data quality of the data space meets certain requirements; if the data quality cannot be fed back in time, the conclusions drawn from the data analysis lose their reference significance.

B. Evaluation model

1) Improved CRITIC model empowerment method

Definition β_{ij} represents the raw data of the i th evaluated manufacturing enterprise in the j th indicator, and the raw data are standardized by using the extreme difference method of formula (1) to eliminate the difference in magnitude between indicators. The formula is as follows:

$$\varphi_{ij}=\frac{\beta_{ij}^{+}-\min(\beta_{i}^{+})}{\max(\beta_{i}^{+})-\min(\beta_{i}^{+})},\ j=1,2,3,\cdots,n \quad (1)$$

The coefficient of variability γ_j corresponding to each indicator is calculated to characterize the variability of the indicator. The formula is as follows.

$$\gamma_j=\frac{\partial_j}{\bar{\phi}_j},\ j=1,2,\cdots,n \quad (2)$$

$$\partial_j=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(\varphi_{ij}-\phi_j)^2},\ j=1,2,\cdots,n \quad (3)$$

$$\bar{\phi}_j=\frac{1}{m}\sum_{i=1}^{m}\varphi_{ij},\ j=1,2,\cdots,n \quad (4)$$

The correlation coefficient matrix C_{ij} of the standardized index matrix is calculated, which leads to equation (5) to portray the conflicting nature among the indicators, and finally the weight w_j is calculated. The formula is as follows.

$$\lambda_{ij}=\sum_{i=1}^{m}(1-|c_{ij}|),\ j=1,2,\cdots,n \quad (5)$$

$$f_j=\frac{\gamma_j\lambda_{ij}}{\sum_{j=i}^{n}\gamma_j\lambda_{ij}},\ i=1,2,\cdots,m \quad (6)$$

In the above equation, denotes the total number of evaluated manufacturing enterprises, n denotes the total number of evaluation indicators, ∂_j denotes the standard deviation of each evaluation indicator, and $\bar{\phi}_j$ denotes the average value of each evaluation indicator.

2) Principal component analysis weighting method

First, dimensionless processing of the raw data for positive and negative indicators; Second, find the covariance matrix $R_{n\times n}$ of each indicator, as well as its characteristic roots θ_j and the corresponding unit eigenvectors b_j ; Third, the cumulative variance contribution of the first k principal components is calculated , and when the cumulative variance contribution of the first k principal components $\alpha_{(k)}\geq 80\%$, it means that the first k principal components contain most of the information of all the original data, and the first k principal components can be used to replace all the original data, i.e., k is determined as the number of extracted principal components. All components of the first k unit feature vectors are taken as absolute values to obtain vector $b_j=(b_{1j},b_{2j},\cdots,b_{nj})^{\mathrm{T}},(j=1,2,\cdots,k)$. The percentage of the variance of the extracted principal components to the cumulative variance of the extracted k principal components is used as the weight, and the vector $c_j=(c_{1j},c_{2j},\cdots,c_{nj})^{\mathrm{T}}(j=1,2,\cdots,k)$ is weighted and summed to obtain vector $v=(h_1,h_2,\cdots,h_n)^{\mathrm{T}}$. Then all components of vector v are normalized to obtain the weights of each evaluation index.

$$y_{ij}=\frac{\beta_{ij}-\min\limits_{1\leq i\leq m}(\beta_{ij})}{\max\limits_{1\leq i\leq m}(\beta_{ij})-\min\limits_{1\leq i\leq m}(\beta_{ij})} \quad (7)$$

$$y_{ij}=\frac{\max\limits_{1\leq i\leq m}(\beta_{ij})-\beta_{ij}}{\max\limits_{1\leq i\leq m}(\beta_{ij})-\min\limits_{1\leq i\leq m}(\beta_{ij})} \quad (8)$$

$$\alpha_{(k)}=\frac{\sum_{j=1}^{k}\theta_j}{\sum_{j=1}^{n}\theta_j},\quad k=1,2,\cdots,n \quad (9)$$

$$g_j=\frac{h_j}{\sum_{j=1}^{n}h_j},\quad j=1,2,\cdots,n \quad (10)$$

3) Exponential synthesis method

The combined weight ω_j of each evaluation index derived from the combined weight model based on the improved CRITIC model weighting method and the principal component analysis weighting method.

$$\omega_j=\frac{f_j+g_j}{2},\quad j=1,2,\cdots,n \quad (11)$$

Based on the combined weights ω_j of each evaluation index, the data y_{ij} after dimensionless processing is linearly weighted to obtain the data quality index of each manufacturing enterprise:

$$I_i=\sum_{j=1}^{n}\omega_i y_{ij},\quad i=1,2,\cdots,m \quad (12)$$

The value of I_i ranges from 0 to 1, and the closer to 1 indicates a higher level of data quality for manufacturing enterprises.

IV. EXAMPLE ANALYSIS

In this paper, by researching and collecting data from eight manufacturing enterprises in Beijing in the process of purchasing, logistics, production, outbound and sales, and combining the experience of experts in related fields, we simulated the index data of the data whole life cycle process of eight manufacturing enterprises in Beijing, and determined the combination weights of the indexes through the combination weight model of the improved CRITIC model assignment method and the principal component analysis assignment method, and the index synthesis method was used for weighting to measure the data quality index and sub-indexes of eight manufacturing enterprises in Beijing, as shown in Table 2.

Table 2. Manufacturing Data Quality Index

Enterprise	Data quality level	Data Generation	Data Acquisition
Manufacturing H	0.93（1）	0.55（6）	0.59（4）
Manufacturing E	0.89（2）	0.60（5）	0.74（1）
Manufacturing D	0.84（3）	0.73（3）	0.54（7）
Manufacturing F	0.78（4）	0.84（2）	0.55（6）
Manufacturing C	0.76（5）	0.68（4）	0.57（5）
Manufacturing A	0.74（6）	0.91（1）	0.68（3）
Manufacturing G	0.71（7）	0.30（7）	0.69（2）
Manufacturing B	0.59（8）	0.27（8）	0.47（8）

Continuation table 2

Enterprise	Pre-access processing	Architecture Construction	Data Access
Manufacturing H	0.84（2）	0.96（2）	0.69（6）
Manufacturing E	0.73（5）	0.84（3）	0.84（4）
Manufacturing D	0.95（1）	0.48（7）	0.95（1）
Manufacturing F	0.49（8）	0.64（4）	0.86（3）
Manufacturing C	0.52（7）	0.99（1）	0.40（7）
Manufacturing A	0.77（4）	0.63（5）	0.33（8）
Manufacturing G	0.64（6）	0.62（6）	0.75（5）
Manufacturing B	0.78（3）	0.40（8）	0.88（2）

Note: Rankings are in parentheses.

As can be seen from Table 2, the data quality indices of the eight manufacturing enterprises in Beijing, in descending order, are Manufacturing H, Manufacturing E, Manufacturing D, Manufacturing F, Manufacturing C, Manufacturing A, Manufacturing G, and Manufacturing B. The average data quality index is 0.78, indicating that although the data quality level of manufacturing enterprises varies, it is still at a high level overall, and the Beijing manufacturing enterprises have a good understanding of the whole data The overall use of data lifecycle process by manufacturing enterprises in Beijing is good.

From the sub-index of data quality, the data generation sub-index, the data generation quality level of 8 manufacturing enterprises in Beijing is Manufacturing A, Manufacturing F, Manufacturing D, Manufacturing C, Manufacturing E, Manufacturing H, Manufacturing G, Manufacturing B in order from high to low; the data acquisition sub-index, the data collection quality level of 8 manufacturing enterprises in Beijing is Manufacturing E, Manufacturing G, Manufacturing G, Manufacturing B in order from high to low; the pre-access processing sub-index, the data feedback quality level of 8 manufacturing enterprises in Beijing is Manufacturing A, Manufacturing H, Manufacturing C, Manufacturing F, Manufacturing D, Manufacturing B in order from high to low, Manufacturing A, Manufacturing H, Manufacturing C, Manufacturing F, Manufacturing D, Manufacturing B; pre-access processing sub-index, the quality level of data feedback of eight manufacturing enterprises in Beijing, in descending order, is Manufacturing D, Manufacturing H, Manufacturing B, Manufacturing A, Manufacturing E, Manufacturing G, Manufacturing C, Manufacturing F; architecture construction sub-index, the data space construction of eight manufacturing enterprises in Beijing, in descending order, is Manufacturing D, Manufacturing H, Manufacturing B, Manufacturing A, Manufacturing E, Manufacturing G, Manufacturing C, Manufacturing F. The quality level from high to low is Manufacturing C, Manufacturing H, Manufacturing E, Manufacturing F, Manufacturing A, Manufacturing G, Manufacturing D, Manufacturing B; the data access sub-index, the quality level of data use of 8 manufacturing enterprises in Beijing is Manufacturing D, Manufacturing B, Manufacturing F, Manufacturing E, Manufacturing G, Manufacturing H, Manufacturing C, Manufacturing A in order from high to low. It can be found that Manufacturing H is mostly at the top of all stages of the data lifecycle process, far ahead of other manufacturing industries, while Manufacturing B, on the contrary, has only a few stages of the data lifecycle process at the top, and most of the stages are at the worst level.

V. CONCLUSIONS

As the research on smart manufacturing progresses, the manufacturing multi-value chain collaborative data space becomes very important. However, how to extract proven data from manufacturing multi-value chain collaborative data space needs to be further improved. Therefore, this paper proposes a data quality scale and evaluation method based on manufacturing multi-value chain collaborative data space, which provides some research ideas for the current development of industrial big data.

The introduction of data quality evaluation scale for manufacturing enterprises can effectively reflect the value issue of data quality in manufacturing multi-value chain collaborative data space, realize quality supervision and feedback for each stage of manufacturing enterprises, continuously improve product quality and enhance the market competitiveness of enterprises. By developing and analyzing the scale for data generation, acquisition, pre-access processing, architecture construction and access stages of manufacturing enterprises, it helps to improve data quality and bring into play the potential value of data. The study also finds that the data quality level of manufacturing enterprises in Beijing is uneven but still at a high level overall, and the use of the whole life cycle process of data is good overall.

Data quality is evaluated using a combined weighting model of CRITIC model assignment method and principal component analysis assignment method, The model facilitates the elimination of subjective and chance factors, and is suitable for solving complex problems with multi-objective striping, and the problem of measuring the level of data quality for multi-value chain collaboration in manufacturing is also well suited, which is conducive to eliminating the influence of subjective factors and chance factors, and is suitable for solving the complex problem of multi-objective striping, and the problem of measuring the data quality level of multi-value chain synergy in manufacturing industry is also well suited.

ACKNOWLEDGEMENTS

This work is supported by National Key R&D Program of China (2020YFB1707801)

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