Supply Chain Data Governance Optimization Based on Fuzzy DEMATEL-ISM

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1. Introduction

The new round of technological revolution drives the strong rise of emerging technologies, industrial digitalization has become an important engine of the fourth industrial revolution (Nar et al, 2020). In the digital era, the deconstruction and restructuring of the industrial system can catalyze the transformation and upgrading of the supply chain (Kaminski et al, 2017). At the same time, the "digital infrastructure" with industrial Internet as the core has emerged, providing key support for the collaborative innovation of supply chain (Broo, Bravo-Haro & Schooling, 2022). Under the new development pattern, the digital transformation of supply chain has become an inevitable trend of a country's economic development (Martens & Zscheischler, 2022). However, the supply chain market demand for data capacity and quality is not consistent with the state of the data, so supply chain data governance research is urgent.

Compared with other industries, the traditional manufacturing supply chain has been exposed to many problems that need to be solved under the impact of digital transformation, such as numerous data calibers, obstructed data circulation, unclear data quality and hidden data security, due to the complicated and variable nodes and significant differences in operation modes (Reinartz & Wiegand, 2019). Modern supply chain organizations are paying more and more attention to data governance, and data governance around maximizing the release of data value is a necessary way to promote the value-added of supply chain and promote the transformation and upgrading of manufacturing industry.

However, data governance parties are still facing governance dilemmas such as slow progress, low layer of governance technology and inadequate governance system (Fothergill et al, 2019). Therefore, it is necessary to explore the underlying logic behind supply chain data governance and clarify the structural mechanism of supply chain data governance. These will not only help broaden the research ideas of supply chain data governance optimization, but also facilitate the overall process of data governance. Against this background, the aim of this study is to address the below-mentioned objectives.

(1)To find out the composition of indexes for data governance in the supply chain environment.

(2)To clarify the structural system of supply chain data governance optimization..

(3)To propose the corresponding governance optimization paths to improve the effectiveness of data governance.

Furthermore, Supply chain data governance optimization is a dynamic, stable and sustainable complex cycle system (Hazen et al, 2018). It formed by the interaction of governance subject, governance technology and governance environment with data as the core and the supply chain as the carrier (Li, 2017). In view of this, the study constructs the index system of supply chain data governance ecosystem from the perspective of information ecology. We focuses on the mechanism of action among indexes in different dimensions of supply chain data governance, and determines the importance degree of each index of supply chain data governance ecosystem by applying the fuzzy DEMATEL method, and then identifies the key indexes. On this basis, the structural levels of key indexes are divided by applying the ISM method to build a multi-layer recursive explanatory structural model of supply chain data governance optimization. The model reveals the optimization structure of supply chain data governance and proposes the corresponding optimization path of supply chain data governance.

The remainder of the paper is organized as follows. In Section 2, the literature review is presented followed by Section 3 and its subsections which build a supply chain data governance ecosystem index system based on information ecology theory. Next, Section 4 presents the details of the fuzzy DEMATEL-ISM methodology and the stepwise approach that contains some steps. Thereafter, in Section 5, a multi-layer recursive explanatory structure model for supply chain data governance is proposed to analyze the governance structure in a hierarchical manner, and the data are presented in Tables 2–4, Tables A1-A3 and Fig. 2 is a explaination of the structure diagram. Section 6 proposes the corresponding optimization path followed by Section7, which concludes our study.

2. Literature review

2.1. Data governance

Data governance is a fundamental issue of economic and social governance in the digital era, and it is also the focus of scholars from all walks of life. Currently, scholars at home and abroad have formed rich research results on data governance at the levels of theoretical exploration (Jiang et all, 2021), model architecture (Nicki, Asha and Elizabeth, 2019) and practical application (Horgan, 2022), and related research perspectives are related to government governance (Zijun et al, 2022), smart campus (Villegas-Ch et al, 2019), artificial intelligence (Janssen et al, 2020), digital health (Rebekah and Lisa M 2020) and so on.

2.2. Data governance of supply chain

With the deepening of digital supply chain transformation and upgrading (Nasiri et al, 2020), some scholars gradually turn their attention to the research on data governance based on supply chain environment. The researchers who have constructed a dual-channel supply chain model to analyze the selling price of fresh agricultural products under different decision modes to solve the problem of missing data in the production and marketing process (Wei & Bo, 2022); The designs and implements a blockchain data sharing market for programmatic supply chain (Zhiyuan et al, 2021); Zou proposed a multi-attribute dynamic access control model for data services to ensure the security of data services in the supply chain (Junwei et al, 2018). Although the above studies have refined data governance to the levels of data circulation, data deficiency, data sharing and data security of supply chain, the research perspectives on supply chain data governance optimization are scattered, and most of the studies still remain in theoretical analysis, and the few quantitative analyses are limited to the operational decision of supply chain data governance (Belhadi et all, 2021) and blockchain platform construction (WL et al, 2021), etc. The research on indexes of supply chain data governance optimization based on system thinking is neglected.

2.3. Index system

At the present stage, there are abundant researches on index system, involving many fields such as medical system (Renmin, Hu & Changping, 2021), university library (Sun, Yan & Peng, 2012), urban development (Longyu et al, 2018), open government (Yupen & Bo, 2017), etc. The research objects of the index system are mostly focused on single subjects such as government, enterprises and institutions, social organizations and individuals, and few of them involve the research of complex index system in the context of supply chain data governance. In terms of system governance, supply chain data governance is characterized by diverse governance subjects, large governance scope and complex governance structure, and the existing micro-system index system cannot be directly applied to the field of supply chain data governance (Hammervoll, 2015). Therefore, it is of theoretical and practical significance to put aside the single node boundary of the existing index system, construct a multi-subject index system for supply chain data governance optimization, and explore its development path by quantifying and analyzing the mechanism of the role of indexes, in order to evaluate and improve the supply chain data governance capability.

3. Construction of index system

3.1. Selection of indexes

Supply chain data governance optimization is in line with the core idea of information ecology theory. It is based on improving the efficiency of supply chain data governance optimization, the data governance subjects establish interdependence (Jr et al, 2016). They form a benign interaction of multiple participants and build a data governance model of shared governance, thus ensuring the continuous circulation, sharing and application of data resources and services relying on technical power in a good governance environment. Therefore, constructing a supply chain data governance ecosystem index system oriented to the constituent elements of information ecology is conducive to expanding the thinking of index selection for supply chain data governance optimization and further promoting theoretical innovation of supply chain data governance optimization research. Based on this, this paper selects indexes of supply chain data governance optimization from four dimensions: data governance subject, data governance technology, data and service, and data governance environment.

3.2. Content of the index system

3.2.1. Data governance subjects

Based on the relevant stakeholders associated with supply chain data governance and relevant authoritative reports, the data governance subjects are divided into three secondary indexes: government departments, enterprises and users. The tertiary indexes that affect the optimization level of supply chain data governance are refined based on secondary indicatiors.

As an external source force driving the data governance process, the government plays an important role in the digital transformation of manufacturing industry by participating, promoting as well as regulating. The State Council's emphasizes that scientific deployment of digital government policies, innovative government governance concepts and the construction of government information systems are powerful supports for advancing the construction of the national governance system and the modernization of governance capacity (Kaur & Nand, 2021). The government's willingness to govern data is a prerequisite for the government to effectively develop and implement data governance strategies, and its willingness to govern has a significant positive impact on data governance outcomes.

Users as one of the value subjects of supply chain data governance, supply chain data governance is a means to achieve user satisfaction. In recent years, the supply chain has focused more on demand chain management and implemented supply chain reorganization around user needs. Users' demand for data use increases, and their participation in product purchase and data governance increases, which in turn drives the data governance process.

Supply chain node enterprises, operation service enterprises and industrial Internet platform enterprises are all value subjects of the governance system. The core competitiveness of enterprises is an important index to assess the current development status of the supply chain industry and the investment risk of key enterprises, while the targeted planning of governance objectives in the digital transformation of industrial enterprises is still a must for enterprises to promote the governance process.

In view of this, the secondary indexes under the data governance subject dimension are further decomposed into encouraging government policies, government data governance willingness, government service platform construction, supply chain data governance innovation concept, public participation degree, meeting user needs, enterprise core competitiveness, and effective planning of governance objectives.

3.2.2. Data governance technologies

The development of governance technology plays a core guarantee role for supply chain data governance optimization, which is an important basis for achieving sustainable development of the governance ecosystem.

Supply chain data governance optimization is closely related to factors such as data operation capability, talent availability, and information platform infrastructure. Therefore, it can be further subdivided into two secondary indexes: technology and talent, and infrastructure.

The development of next-generation information technology stimulates the urgent demand of governance system at the technical level, and the upstream and downstream subjects in the supply chain need the governance side to provide the level of data operation integrating emerging technologies such as Internet of Things, artificial intelligence and blockchain (Bhattacharyya, Mandke & Wood, 2021). Therefore, data operation ability is the key element to judge the efficiency of data governance optimization, and data governance talents with high-level operation ability can improve the efficiency of data collection and enhance the ability of independent analysis and data resources mining.

The orderly operation of the information platform can effectively solve the problems of numerous data calibers, uneven quality and data security risks, thus improving the efficiency of data governance optimization. The development and intelligent construction of infrastructure as the premise of big data integration and open sharing of industrial Internet platform, the higher the degree of its perfection, the more it can improve the efficiency of supply chain data governance optimization.

In view of this, technical support for data operation, information department personnel availability, degree of information platform development, and intelligent construction of industrial Internet are selected as the three-level indexes under the technical dimension of data governance.

3.2.3. Data and services

Data is the core element of the ecological composition of the Industrial Internet. Products as value carriers, their value-added processes interact with enterprise entity networks and resource networks in the form of data or data services (Dubey et al, 2017). The processes reflect industrial entities and integrate product value streams under resource loading, and they are precisely mapped, flowed and applied at different stages and levels. Therefore, data and services are selected as indexes for data governance optimization, respectively.

Based on the whole life cycle of the data flow process, the data governance content is divided into data management modules at the levels of metadata management, data quality, data standards, data storage and collection, and data security (Yang et al, 2022). The degree of data security risk depends on the amount of false data flow between the industrial Internet platform and the whole chain of the supply chain as well as the amount of users' personal privacy data access. As a key part of data governance, supply chain service is based on cost reduction and efficiency improvement by providing data planning, process control and financing support to the data demand side, and realizing the co-creation of emerging business models and enterprise organization models. However, with the increase of data redundancy in the service process, the demand for effective data in the supply chain is increasing, and the data ease of use and data sharing ability will form positive feedback to the supply chain market resources and affect the data circulation rate upstream and downstream of the supply chain.

In view of this, based on the current status of data governance, the three-level indexes under the data and service dimension are identified as metadata management, data quality, data specification, data storage and collection, data security and risk level, data service and innovation, data ease of use, and data sharing capability.

3.2.4. Data governance environment

The internal and external environments in the supply chain data governance ecosystem circulate with each other, forming a closed-loop circulation path with logistics, capital flow and information flow(Rla et al, 2020). Based on the complexity of the supply chain data governance ecosystem, the data governance environment is divided into two secondary indexes: the governance micro-environment and the governance macro-environment.

In the governance micro-environment, the financial demand brought by the cost of data governance stimulates the governance subject to generate financial investment in the process of data governance, and the financial investment will increase the importance of the relevant governance organization to the mechanism of professional staffing, and the professionalism of its staffing reflects the level of organization construction to a certain extent. The organizational construction of data governance includes organizational structure, departmental responsibilities, staffing, job responsibilities, competency requirements, performance management, etc (Pant, Dutta & Sarmah, 2021). It can open up the data flow between each business node and information system, and improve the efficiency of data governance optimization within the organization and between organizations.

In the macro environment of governance, proper supply chain market competition is a favorable supply chain value-added strategy that helps enhance the data governance capability of supply chain enterprises and effectively promote the data governance process. In addition, supply chain synergy can establish the synergy mechanism of node enterprises through governance strategy, data sharing, benefits and risks, and improve the data governance of the whole supply chain.

In view of this, four three-level indexes are selected in the data governance environment dimension: organization construction level, capital investment, supply chain market competition, and supply chain synergy capability. Based on the above sorting and summarizing of the index dimensions and the subordinate indexes, the supply chain data governance ecosystem index system is constructed as shown in Table 1.

Table 1

Index system for supply chain data governance ecosystem.

Dimensions (Tier 1 indexes)	Tier 1 Indexes	Secondary indexes
Data Governance Subject A1	Government Sector B1	Government Policy C1
		Government Data Governance Willingness C2
		Government service platform construction C3
		Data Governance Innovation Concept C4
	Enterprise B2	Corporate Core Competence C5
		Effective planning of governance objectives C6
	User B3	Degree of public participation C7
		Meeting the needs of users C8
Data Governance Technology A2	Technology & Talent B4	Data Operations Technical Support C9
		Information department talent staffing C10
	Infrastructure B5	Information platform development degree C11
		Industrial Internet Intelligent Construction C12
Data Governance Environment A3	Internal environment B6	Organization building level C13
		Capital investment C14
	Macro Environment B7	Supply Chain Market Competition C15
		Supply Chain Collaboration Capability C16
Data & Services A4	Data Management B8	Metadata Management C17
		Data Quality C18
		Data Specification C19
		Data storage and acquisition C20
		Data security risk level C21
	Supply Chain Services B9	Data Services and Innovation C22
		Data Ease of Use C23
		Data Sharing Capability C24

4. Research methodology

4.1 DEMATEL methodology

4.1.1. Research method selection

This study introduces the fuzzy DEMATEL model to determine the importance of each index of supply chain data governance optimization by expert scoring method. We apply fuzzy set theory for initial data processing to reduce the range limitation of data results, and improve the independence of index weights based on the improvement of the data calculation model of direct influence matrix sources. The above operations can enhance the results of subsequent key index screening and hierarchical analysis studies reliability.

4.1.2. Initial weight determination

In order to determine the initial weights of supply chain data governance and construct the original DEMATEL data, this study designed the index importance scoring table for supply chain data governance optimization. 8 experts were contacted for their opinions to determine the importance of the indexes. The experts who participated in the questionnaire survey covered academic professors, industrial Internet industry operators and department heads of supply chain enterprises who studied related topics. At the same time, senior users were invited to participate in the scoring. The questionnaire was distributed and collected online.

The study uses triangular fuzzy numbers in fuzzy mathematics to reflect the results of experts' judgments on the importance of indexes, which are easier to obtain ideal solutions from group decisions than traditional methods. The triangular fuzzy numbers refer to the fuzzy numbers on the set of real numbers with the affiliation function of fuzzy numbers. Denote the triangular fuzzy number as, where and denote the upper and lower limits of the fuzzy value, respectively, and is the approximation of the fuzzy value.

Table 2

Comparison table of triangular fuzzy number.

Score	Scoring semantic representation	Corresponding triangular fuzzy number (r
0	Index i has no impact on the evaluation objectives	(0,0,0.25)
1	Low impact of index i on evaluation objectives	(0,0.25,0.5)
2	Index i has a medium impact on the evaluation objective	(0.25,0.5,0.75)
3	High degree of influence of index i on evaluation objectives	(0.5,0.75,1.00)
4	Index i has a very high degree of influence on the evaluation objectives	(0.75,1.00,1.00)

4.1.3. Data deblurring process

In order to reflect the overall influence degree of each index on the governance system and to clarify the specific values of the expert scoring results, the integrated fuzzy values need to be defuzzified. The defuzzification process takes the distribution pattern, shape and height of the fuzzy numbers into consideration. According to Table 2, the results of the above expert survey scoring table are transformed into triangular fuzzy numbers, and the comprehensive fuzzy value of the degree of influence is obtained based on equations (1)-(3). Where, indicates the number of experts who participated in the questionnaire; indicates the serial number of experts who provided data.

Since the CFCS (Converting Fuzzy data into Crisp Scores) method can effectively distinguish two fuzzy numbers with the same exact value (Lina, Guotao & Jue, 2021). Therefore, in this study, CFCS method is used for defuzzification, and the combined fuzzy values are regarded as the weight values of indexes for the governance system, as follows.

Step 1 . Fuzzy number normalization.

Step 2. The upper limit value is normalized to the lower limit value.

Step 3. Calculate the weight value.

Among them, .

4.1.4. Direct relation matrix

According to the initial fuzzy weights of indexes for supply chain data governance optimization, the DEMATEL model is introduced to optimize the initial index weights, so as to weaken the subjective determination of data results caused by expert scoring.

In view of the wide scope of supply chain data governance under the industrial Internet, the complexity of the correlation between relevant stakeholders, the interference of the overlapping influence of indexes when experts score, and the difficulty of ensuring the independence of indexes, the study optimizes the data sources based on the original DEMATEL method, and points the experts' scoring to a single evaluation target, which circumvents the tedious operational problems caused by experts due to the importance of multiple indexes for two-by-two comparison. It also reduces the chance of misjudgment due to the lack of independence among the elements. The direct relation matrix is set as to characterize the influence of the indexon, and the data source is the ratio of the initial fuzzy weights of each index, i.e.. Where,[1,24]. Therefore, the final direct relation matrix is established (Table A1).

4.1.5. Integrated relationship matrix

The direct relation matrix is normalized according to Equation (10) to obtain the normalization matrix .

Where,denotes the number of indexes. In order to represent the degree of direct and indirect influence among the indexes of supply chain data governance, Matlab software is further used to calculate the integrated relationship matrix of based on Equation(11) (Table A2). Where is the unit matrix.

4.1.6. Influence index ranking analysis

After determining the integrated relationship matrix , the influence degree of each factor, the influenced degree , the centrality degree (+), and the reason degree (-) are calculated according to equations(12)-(13), where the influence degree indicates the comprehensive influence degree of each index in the comprehensive influence matrix on all other indexes; the influenced degree indicates the comprehensive influence degree of each column of indexes inon other indexes; the centrality degree indicates the importance degree of indexes in the whole evaluation system; the reason degree is used to portray the contribution degree of an index to the formation of the evaluation system, that is, the degree of interrelationship between the index and other indexes.

where is the element of the row and column of the integrated relationship matrix.

Table 3

Ranking of influence index of each indexes.

Indexes	Degree of influence	Degree of being influenced	Centrality +	Ranking	Reason degree -	Ranking	Cause Properties
C1	2.188	2.187	4.374	24	0.001	13	Causal factors
C2	2.385	2.004	4.389	18	0.381	9	Causal factors
C3	2.080	2.301	4.381	21	-0.220	14	Resulting factors
C4	1.651	2.895	4.546	5	-1.245	22	Resulting factors
C5	2.602	1.838	4.441	8	0.764	5	Causal factors

Indexes	Degree of influence	Degree of being influenced	Centrality +	Ranking	Reason degree -	Ranking	Cause Properties
C6	1.973	2.423	4.396	17	-0.450	16	Resulting factors
C7	1.544	3.091	4.635	3	-1.547	23	Resulting factors
C8	2.494	1.919	4.413	12	0.574	7	Causal factors
C9	3.118	1.531	4.649	2	1.586	1	Causal factors
C10	1.759	2.718	4.476	6	-0.959	21	Resulting factors
C11	2.367	2.020	4.387	20	0.347	11	Causal factors
C12	2.602	1.838	4.441	8	0.764	4	Causal factors
C13	1.973	2.423	4.396	14	-0.450	17	Resulting factors
C14	1.436	3.323	4.759	1	-1.886	24	Resulting factors
C15	1.973	2.423	4.396	14	-0.450	17	Causal factors
C16	2.477	1.931	4.407	13	0.546	8	Causal factors
C17	2.264	2.114	4.378	23	0.150	12	Causal factors
C18	2.385	2.004	4.389	18	0.381	9	Causal factors
C19	1.866	2.564	4.430	10	-0.699	20	Resulting factors
C20	2.080	2.301	4.381	21	-0.220	14	Resulting factors
C21	2.711	1.764	4.475	7	0.947	3	Causal factors
C22	2.570	1.860	4.430	11	0.710	6	Causal factors
C23	1.973	2.423	4.396	14	-0.450	17	Resulting factors
C24	3.011	1.587	4.597	4	1.424	2	Causal factors

(1) Analysis of main indexes

Based on the analysis of supply chain data governance ecosystem perspective, the system governance system mainly consists of four indexes: data governance subject, governance technology, governance environment, and data and services. By analyzing the main indexes A and B, the index ranking of index centrality and cause degree is integrated to obtain the mean value of cause degree of A-level indexes (listed in the order of cause degree) as A2, A4, A1, A3, and the centrality degree as A3, A2, A1, A4, respectively. It can be seen that the cause factors of the first-level indexes are data governance technology and data and services; the result elements are data governance subject and data governance environment. The centrality of data governance technology as the cause factor ranks second, indicating that data governance technology dominates the governance system and has a high degree of influence on other indexes. The centrality of data governance environment is in the first place, and because it is the result element, it indicates that data governance environment also plays an important role in the governance system, but it is less stable and vulnerable to other indexes. The data governance subject as the governance subject of the supply chain data governance ecosystem is classified as the result element, which reflects that the current governance situation of the data governance subject is more and more passive, and the governance behavior needs to rely on data governance technology, data and services as support.

According to the comparison of the centrality of B-level indexes, technology and tools, internal environment, users and supply chain services are ranked high, among which the internal environment and users are more influenced, resulting in their centrality ranking among the top, that is, technology and tools and supply chain services are the key factors affecting the governance system, while internal environment and users are in a passive position in the system.

(2) Causal elements and centrality analysis

C-level indexes can more accurately and comprehensively assess the optimization effectiveness of supply chain data governance ecosystem. Based on the positive and negative comparison of C-level indexes, we can find that the supply chain data governance ecosystem index system consists of 13 cause elements and 11 result indexes, and the order of index centrality is C14, C9, C7, C24, C4, C10, C21, C12, C5, C19, C22, C8, C16, C15, C13, C23, etc. Combining the cause elements and centrality, it can be seen that C9, C24, C21, C12, C5, C22, C8 and C16 are the key impact indexes in the governance system, which can directly shape the governance effectiveness fluctuations and have a greater impact on other indexes.

Among them, data operation technical support has the greatest direct impact among all indexes, indicating that data technical support in the process of governance is a key bearing index for the effectiveness of governance optimization, and improving the level of data operation technology of supply chain enterprises and industrial Internet can guarantee the perfection of data governance infrastructure, effectively resist the problems of data circulation, storage, collection, exchange and sharing to upstream and downstream subjects of supply chain and industrial Internet platform through supply chain. It helps to enhance the intelligent construction of industrial Internet and strengthen the core competitiveness of enterprises, construct a good service and innovation environment for the information platform, and promote the sustainable development of supply chain data governance ecosystem.

(3) Resulting elements and centrality analysis

Combining the result factors and centrality, it can be found that the cause degree of C14, C7, C4, and C6 become negative and their are affected to a greater degree. This suggests that they are vulnerable to fluctuations in the governance system. Although their centrality is high, they are not counted in the screening of key indexes in this study due to the low ranking of the influence degree of the indexes.

C13, C15 and C23 are ranked in the middle in terms of centrality and reason and they are influenced by a greater degree. They are the easiest governance points and also belong to the key indexes. Data governance subjects should focus on these four indexes in the governance process. Therefore, in order to effectively improve the effectiveness of data governance optimization, it is necessary to collaborate with all value subjects in the governance system. Each subject should not only reasonably plan the data governance optimization system and improve data governance organization construction, but also open up the data flow of each business node and information system and enhance the core competitiveness of supply chain node enterprises and industrial Internet enterprises.

4.1.7. Cause-and-effect four-quadrant diagram analysis

Based on the data in Table 3, the inter-index causality diagram for supply chain data governance optimization is established by quadrant determination method with centrality as the x-axis and causality as the y-axis, and the values of each index are plotted one by one in the diagram (Fig. 1). Among them, since the median indicates the sample distribution based on the middle value, the set of values can be stratified equivalently. Therefore, the median x=4.41, which corresponds to the centrality of 24 indexes, is added to the graph as the internal auxiliary axis z. The purpose is to visualize the centrality and causality of indexes, so as to visually observe the distribution pattern of indexes and reasonably screen the key indexes.

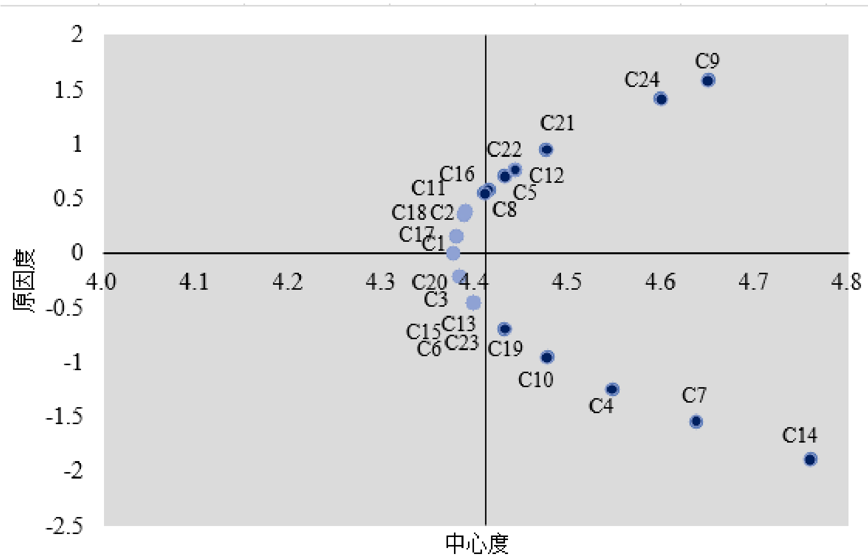

Fig. 1. Four quadrant diagram of cause and effect.

According to the distribution law of indexes in the four quadrants of cause and effect diagram, it can be concluded that C9, C24, C21, C12, C22, C8, C5 in the first quadrant have a centrality greater than 4.41, which belong to the driving indexes with a relatively large degree of influence on the supply chain data governance ecosystem and play a direct driving role in the sustainable development of the governance system; C16, C11, C2, C18, C17, C17 These six indexes have a higher degree of cause although their centrality is lower than 4.41, and they can be used as support indexes for optimizing the governance system and show a stronger indirect driving effect on the governance system. Although C13, C15 and C15 are in the third quadrant, they should be included in the selection of key indexes for the optimization of the supply chain data governance ecosystem because their centrality is close to 4.41 and the absolute value of the cause degree is larger. Based on the aforementioned influence degree analysis, the six indexes in the fourth quadrant were excluded.

In summary, through the comparison and analysis of impact index ranking and cause-effect four-quadrant diagram, 16 key indexes for supply chain data governance ecosystem optimization are finally screened out, namely C1, C2, C5, C8, C9, C11, C12, C13, C15, C16, C17, C18, C21, C22, C23, C24. to further study the structural system of supply chain data governance ecosystem indexes and provide quantitative thinking for the design of optimization paths.

4.2. ISM methodology

4.2.1. Building the reachable matrix

Based on the 16 key indexes screened above, the overall impact matrix is established. Given that the comprehensive impact matrix obtained by DEMATEL method does not consider the impact of indexes themselves, the comprehensive impact matrix formed by the 16 key indexes is added with the unit matrix to obtain the overall impact matrix , and then determine the reachable matrix of supply chain data governance (=), which is used to portray whether there is a pathway between the fixed points of the directed graph, if there is a pathway between indexes f_i and f_j , then =1; otherwise, then =0, expressed as follows.

Where, is the threshold value. It is set up with the aim of eliminating less influential indexes, thus simplifying the hierarchical structure of the indexes. To eliminate the subjective dependence of data sources, the study relies on the mean of the combined impact matrixμ with varianceσ for λ In order to eliminate the subjective dependence of the data source, the study relies on the mean and variance of the composite impact matrix. Matlab calculates = 0.091, = 0.019, then = + = 0.11. According to the formula, we obtain the reachable matrix of supply chain data governance optimization indexes (Table A3).

4.2.2. Hierarchy of indexes

According to the reachability matrix, the indexes are divided into a hierarchy, and the index reachable set, the prior set , and the common set are obtained. If=, then is extracted as the first hierarchical index set. The results of the first level decomposition are as follows.

Table 4

First level reachable set and prior set.

Indexes			
C1	1	1,5,9,12,21,22,24	1
C2	2,13,15,23	2,9,24	2
C5	1,5,13,15,23	5,9,24	5
C8	8,13,15,23	8,9,24	8
C9	1,2,5,8,9,11,12,13,15,16,17,18,22,23	9	9
C11	11,13,15,23	9,11,24	11
C12	1,12,13,15,23	9,12,24	12
C13	13	2,5,8,9,11,12,13,16,18,21,22,24	13
C15	15	2,5,8,9,11,12,15,16,18,21,22,24	15
C16	13,15,16,23	9,16,24	16
C17	17	9,17,21,24	17
C18	13,15,18,23	9,18,24	18
C21	1,13,15,17,21,23	21	21
C22	1,13,15,22,23	9,22,24	22
C23	23	2,5,8,9,11,12,16,18,21,22,23,24	23
C24	1,2,5,8,11,13,12,13,15,16,17,18,22,23,24	24	24

The first level of supply chain data governance ecosystem indexes includes 5: C1, C13, C17, C15 and C23. After the indexes of the first level are determined, the ranks of the matrix where the indexes of the first level are located are eliminated, and the next level is divided in the same way. Similarly, the eight indexes in the second tier are C2, C5, C8, C11, C12, C16, C18, and C22, and the indexes in the third tier are C9, C21, and C24.

5. Supply chain data governance optimization structure analysis

5.1. Constructing a multi-layer recursive explanatory structure model

According to the hierarchical division of each index, a multi-layer recursive explanation structure model of supply chain data governance ecosystem is established as shown in Fig. 2, which divides the data governance optimization structure into three layers, namely, governance surface layer, governance middle layer and governance root layer. The model is characterized by layers advancing and complementing each other to promote supply chain data governance optimization in a systematic and orderly manner and achieve sustainable development of the whole domain of the governance system.

The middle layer of data governance plays a transitional role in the sustainable development of the supply chain data governance ecosystem, and its structure is complex, with relatively relaxed control of the middle layer by the governance body and a large governance difficulty factor. Whereas the data governance surface layer can produce direct effect advantages, the data governance root layer starts with the logic of the governance bottom layer to optimize the governance system with maximum intensity. Integrating the data governance surface layer with the root layer structure can efficiently and rapidly achieve sustainable development of the supply chain data governance ecosystem.

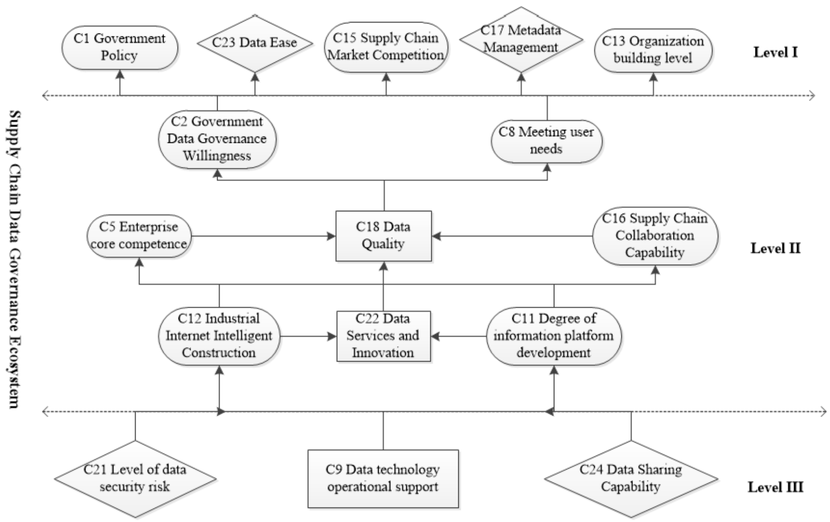

Figure. 2. A multi-layer recursive explanatory structure model for supply chain data governance.

5.2. Data governance optimization structure hierarchy analysis

5.2.1. Data governance surface layer

The surface-layer indexes of data governance are the direct elements to evaluate the process of data governance, of which five indexes involve the governance subject, data, governance environment and governance technology of the governance system. They also indicate the comprehensiveness and rationality of the surface-layer governance system. Effective data use and metadata management are not only the basic elements to improve the efficiency of data governance optimization, they are also the indexes that can most easily show the governance results. The government department policy, the organization of enterprise data department and the competing environment of supply chain can directly influence the process of supply chain data governance optimization.

5.2.2. Data governance middle layer

The middle layer of data governance is supported by the root layer metrics, which act on the surface layer metrics, and the impact is indirectly penetrated into the supply chain data governance ecosystem. Data quality, as the core element of the middle layer of data governance, is an important yardstick to assess the results of data governance optimization. The supply chain requires high accuracy and timeliness of data, and each participant in the supply chain needs to make plans and risk decisions through real-time data in the processes of production, distribution, procurement and after-sales. The improvement of data quality not only increases the user's consumer experience and trust, but also promotes the overall governance process of the supply chain.

Along with the root layer data operation technology to support the whole process of governance, the construction of information platform needs to rely on advanced technology development capability as support, and the sustainable development of industrial Internet also needs to integrate increasingly mature artificial intelligence, Internet of Things, cloud computing and other information technology(Shuangming et al, 2018). Since the orderly and safe flow of data is the premise of the intelligent construction and orderly operation of the platform, the development and construction of the information platform is positively influenced by the data sharing ability and data security, and acts on the collaborative development of each node enterprise in the supply chain and promotes the healthy competition in the supply chain market. Enterprises are driven by economic interests to enhance their core competitiveness by improving their data service and innovation capabilities, and then realize the personalized needs of those being served.

However, users, as users and governors of data, have their personal data needs met as a reflection of supply chain value realization. Stimulating the motivation of user data governance can promote the sustainable development of the governance system. As the leading force of supply chain data governance, the government is committed to the construction of a quality management system for the whole life cycle of data, and enhancing the government's willingness for data governance is a prerequisite for promoting the overall planning and policy implementation of supply chain big data by government departments. The government can develop an effective data governance system through active governance policies, promote the transformation of data content into high-value streams, and provide a positive driving force for the sustainable operation of the governance system.

5.2.3. Data governance root cause layer

The root indexes of supply chain data governance are the decisive indexes of the optimization effect of supply chain data governance. The degree of data security risk, data technology operational support and data sharing capability have the greatest impact on the sustainability of the governance ecosystem.

It can be seen that the data operation technology supports the steady development of the whole governance system. Improving data operation technology from the root is more conducive to the intelligent construction of supply chain collaboration and industrial Internet. At the same time, advanced data technology can simplify the data service process and pursue the principle of cost and efficiency priority while continuously improving quality and maintaining data user satisfaction, so as to reshape the core competitiveness of each node enterprise in the supply chain from three aspects: cost reduction, efficiency increase and quality improvement. The development of cloud-based supply chain under the industrial Internet has also exposed problems such as data security crisis and obstructed data circulation in the process of achieving end-to-end digital transformation. Due to the trusted data interaction environment in the supply chain system, the open and transparent supply chain personal privacy data and false circulation data are exposed to users and supply chain node enterprises, which hinders the sustainable development of the supply chain data governance ecosystem. At the same time, the persistent problem of poor circulation data transmission efficiency throughout the supply chain also leads to the reduction of data validity and affects the convergence and sharing of data upstream and downstream of the supply chain.

Therefore, data technology support, data security and data sharing are not only the core issues of supply chain data governance that need to be solved urgently, but also the underlying governance logic that runs through the whole governance system.

6. Path design

6.1. Complete governance policies and improve the supply chain data security environment

With the existing security risk issues of supply chain data as a data governance gap to optimize the governance system, government departments, as the key nodes of data storage and circulation, are the key to improving the supply chain data security environment. The improvement of risk prevention and privacy protection capability can not only guarantee the steady operation of the whole supply chain, but also escort the implementation of other optimization links. To this end, the government should be aware of security risks, and while giving full play to the advantages of the relevant system and policy dividends, it should be alert to data security risks, adjust the mechanism behind industrial data through the top-level design of "digital government", and build a scientific and reasonable data security policy system. In addition, enterprises should monitor the security of data systematically and comprehensively, not only to prevent external hacking attacks, but also to prevent internal staff from improper operation of data, and to establish a perfect security tracking system while reinforcing the underlying design.

6.2. Enhance data sharing capability and increase effective data throughput

Timely, high quality and comprehensive data resources can stimulate the full release of data value and thus promoting the sustainable development of supply chain data governance ecosystem. On the one hand, the main body of the supply chain should establish a perfect data information sharing mechanism, emphasizing the value creation and sharing among supply chain node enterprises with different property rights, and enterprises should build an information sharing platform under the premise of considering cost factors, rebuild data circulation channels, accelerate information sharing among supply chain nodes, and enhance data ease of use. On the other hand, enterprises should pay attention to the construction of smart supply chain. They should take user value enhancement as a guide to enhance the intelligence of enterprise supply chain through collaborative innovation mode and integration of advanced technologies such as Internet of Things, artificial intelligence and block chain. The aim to realize the ability of supply chain visualization, perceptibility and regulation, to promote supply chain autonomy and control, and to promote the orderly development of supply chain data governance.

6.3. Enhance data technology support and pay attention to organization construction and talent allocation

Data operation technology support plays a decisive role in the sustainable development of supply chain data governance ecosystem. The main body of supply chain governance should pay attention to the research on the precision technology of big data, improve the data operation ability of each main body of the supply chain, analyze the circulation data of the supply chain through big data technology, excavate the law and value behind the figures, and provide decision basis for data producers and users. In addition, each department of the governance organization needs to establish a data governance talent team with a clear division of labor. A special data governance team should be established in the supply chain to classify and manage the data in the industrial Internet, strengthen the training of data-driven professional talents in the industrial Internet, enhance the analysis and problem-solving ability of the governance personnel, and ensure the input of high-end talents in the data governance market.

7. Conclusions and limitations

This paper identifies the causal attributes of indexes for supply chain data governance optimization through fuzzy DEMATEL model and screens out 16 key indexes. Based on this, the ISM model is used to further visualize the hierarchical structure of key indexes, reveal the mechanism of the indexes in depth, and systematically analyze the supply chain data governance optimization structure. The findings of the study aim to enhance the sustainable development of the supply chain data governance ecosystem and provide managers with an adaptive choice of supply chain data governance optimization path. In order to ensure the authority and objectivity of the study, there are still shortcomings in the selection of data samples for expert scoring, and the number and type of samples should be expanded in the future to make the research results more representative.

Appendix A. Appendices

* Table A1 Direct relation matrix () for indexes.

* Table A2 Integrated relationship matrix () for indexes.

* Table A3 Reachable matrix () for indexes.

Table A1

Direct relation matrix () for indexes.

Indexes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	0.00	0.92	1.05	1.32	0.84	1.11	1.41	0.88	0.70	1.24	0.92	0.84	1.11	1.51	1.11	0.88	0.97
C2	1.09	0.00	1.15	1.44	0.92	1.21	1.53	0.96	0.77	1.35	1.01	0.92	1.21	1.65	1.21	0.96	1.05
C3	0.95	0.87	0.00	1.26	0.80	1.05	1.34	0.84	0.67	1.18	0.88	0.80	1.05	1.44	1.05	0.84	0.92
C4	0.76	0.70	0.80	0.00	0.64	0.84	1.07	0.67	0.53	0.94	0.70	0.64	0.84	1.15	0.84	0.67	0.73
C5	1.19	1.09	1.25	1.57	0.00	1.31	1.67	1.04	0.84	1.47	1.10	1.00	1.31	1.80	1.31	1.05	1.15
C6	0.90	0.83	0.95	1.19	0.76	0.00	1.27	0.79	0.64	1.12	0.84	0.76	1.00	1.37	1.00	0.80	0.87
C7	0.71	0.65	0.75	0.94	0.60	0.79	0.00	0.62	0.50	0.88	0.66	0.60	0.79	1.07	0.79	0.63	0.69
C8	1.14	1.04	1.20	1.50	0.96	1.26	1.60	0.00	0.80	1.41	1.05	0.96	1.26	1.72	1.26	1.01	1.10
C9	1.42	1.30	1.49	1.87	1.20	1.57	2.00	1.25	0.00	1.76	1.31	1.20	1.57	2.15	1.57	1.26	1.37
C10	0.81	0.74	0.85	1.06	0.68	0.89	1.14	0.71	0.57	0.00	0.75	0.68	0.89	1.22	0.89	0.71	0.78
C11	1.08	0.99	1.14	1.43	0.91	1.20	1.52	0.95	0.76	1.34	0.00	0.91	1.20	1.63	1.20	0.96	1.05
C12	1.19	1.09	1.25	1.57	1.00	1.31	1.67	1.04	0.84	1.47	1.10	0.00	1.31	1.80	1.31	1.05	1.15
C13	0.90	0.83	0.95	1.19	0.76	1.00	1.27	0.79	0.64	1.12	0.84	0.76	0.00	1.37	1.00	0.80	0.87
C14	0.66	0.61	0.70	0.87	0.56	0.73	0.93	0.58	0.47	0.82	0.61	0.56	0.73	0.00	0.73	0.58	0.64
C15	0.90	0.83	0.95	1.19	0.76	1.00	1.27	0.79	0.64	1.12	0.84	0.76	1.00	1.37	0.00	0.80	0.87
C16	1.13	1.04	1.19	1.49	0.95	1.25	1.59	0.99	0.80	1.40	1.05	0.95	1.25	1.71	1.25	0.00	1.09
C17	1.03	0.95	1.09	1.37	0.87	1.15	1.46	0.91	0.73	1.28	0.96	0.87	1.15	1.57	1.15	0.92	0.00
C18	1.09	1.00	1.15	1.44	0.92	1.21	1.53	0.96	0.77	1.35	1.01	0.92	1.21	1.65	1.21	0.96	1.05
C19	0.85	0.78	0.90	1.13	0.72	0.95	1.20	0.75	0.60	1.06	0.79	0.72	0.95	1.29	0.95	0.76	0.83
C20	0.95	0.87	1.00	1.26	0.80	1.05	1.34	0.84	0.67	1.18	0.88	0.80	1.05	1.44	1.05	0.84	0.92
C21	1.24	1.13	1.30	1.63	1.04	1.37	1.74	1.09	0.87	1.53	1.14	1.04	1.37	1.87	1.37	1.09	1.20
C22	1.17	1.08	1.23	1.55	0.99	1.30	1.65	1.03	0.83	1.45	1.08	0.99	1.30	1.77	1.30	1.04	1.13
C23	0.90	0.83	0.95	1.19	0.76	1.00	1.27	0.79	0.64	1.12	0.84	0.76	1.00	1.37	1.00	0.80	0.87
C24	1.37	1.26	1.44	1.81	1.16	1.52	1.93	1.21	0.97	1.70	1.27	1.16	1.52	2.07	1.52	1.21	1.33

Table A2

Integrated relationship matrix () for indexes.

Indexes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	0.06	0.08	0.10	0.12	0.08	0.10	0.13	0.08	0.06	0.11	0.08	0.08	0.10	0.14	0.10	0.08	0.09
C2	0.10	0.06	0.10	0.13	0.08	0.11	0.14	0.09	0.07	0.12	0.09	0.08	0.11	0.15	0.11	0.09	0.10
C3	0.09	0.08	0.06	0.11	0.07	0.10	0.12	0.08	0.06	0.11	0.08	0.07	0.10	0.13	0.10	0.08	0.08
C4	0.07	0.06	0.07	0.06	0.06	0.08	0.10	0.06	0.05	0.09	0.06	0.06	0.08	0.10	0.08	0.06	0.07
C5	0.11	0.10	0.11	0.14	0.06	0.12	0.15	0.09	0.08	0.13	0.10	0.09	0.12	0.16	0.12	0.10	0.10
C6	0.08	0.08	0.09	0.11	0.07	0.06	0.12	0.07	0.06	0.10	0.08	0.07	0.09	0.12	0.09	0.07	0.08
C7	0.06	0.06	0.07	0.08	0.05	0.07	0.06	0.06	0.05	0.08	0.06	0.05	0.07	0.10	0.07	0.06	0.06
C8	0.10	0.09	0.11	0.14	0.09	0.11	0.15	0.06	0.07	0.13	0.10	0.09	0.11	0.16	0.11	0.09	0.10
C9	0.13	0.12	0.14	0.17	0.11	0.14	0.18	0.11	0.06	0.16	0.12	0.11	0.14	0.19	0.14	0.11	0.12
C10	0.07	0.07	0.08	0.10	0.06	0.08	0.10	0.06	0.05	0.06	0.07	0.06	0.08	0.11	0.08	0.06	0.07
C11	0.10	0.09	0.10	0.13	0.08	0.11	0.14	0.09	0.07	0.12	0.06	0.08	0.11	0.15	0.11	0.09	0.09
C12	0.11	0.10	0.11	0.14	0.09	0.12	0.15	0.09	0.08	0.13	0.10	0.06	0.12	0.16	0.12	0.10	0.10
C13	0.08	0.08	0.09	0.11	0.07	0.09	0.12	0.07	0.06	0.10	0.08	0.07	0.06	0.12	0.09	0.07	0.08
C14	0.06	0.06	0.06	0.08	0.05	0.07	0.08	0.05	0.04	0.07	0.06	0.05	0.07	0.06	0.07	0.05	0.06
C15	0.08	0.08	0.09	0.11	0.07	0.09	0.12	0.07	0.06	0.10	0.08	0.07	0.09	0.12	0.06	0.07	0.08
C16	0.10	0.09	0.11	0.14	0.09	0.11	0.14	0.09	0.07	0.13	0.09	0.09	0.11	0.16	0.11	0.06	0.10
C17	0.09	0.09	0.10	0.12	0.08	0.10	0.13	0.08	0.07	0.12	0.09	0.08	0.10	0.14	0.10	0.08	0.06
C18	0.10	0.09	0.10	0.13	0.08	0.11	0.14	0.09	0.07	0.12	0.09	0.08	0.11	0.15	0.11	0.09	0.10
C19	0.08	0.07	0.08	0.10	0.07	0.09	0.11	0.07	0.05	0.10	0.07	0.07	0.09	0.12	0.09	0.07	0.07

Indexes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C20	0.09	0.08	0.09	0.11	0.07	0.10	0.12	0.08	0.06	0.11	0.08	0.07	0.10	0.13	0.10	0.08	0.08
C21	0.11	0.10	0.12	0.15	0.09	0.12	0.16	0.10	0.08	0.14	0.10	0.09	0.12	0.17	0.12	0.10	0.11
C22	0.11	0.10	0.11	0.14	0.09	0.12	0.15	0.09	0.07	0.13	0.10	0.09	0.12	0.16	0.12	0.09	0.10
C23	0.08	0.08	0.09	0.11	0.07	0.09	0.12	0.07	0.06	0.10	0.08	0.07	0.09	0.12	0.09	0.07	0.08
C24	0.12	0.11	0.13	0.16	0.10	0.14	0.18	0.11	0.09	0.15	0.11	0.10	0.14	0.19	0.14	0.11	0.12

Table A3

Reachable matrix () for indexes.

Indexes	C1	C2	C5	C8	C9	C11	C12	C13	C15	C16	C17	C18	C21	C22	C23	C24
C1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0	1	0	0	0	0	1	1	0	0	0	0	0	1	0
C8	0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0
C9	1	1	0	1	1	1	0	1	1	1	1	1	0	1	1	0
C11	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
C12	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0
C13	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
C16	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0
C17	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
C18	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C21	1	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0
C22	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	0
C23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
C24	1	1	0	0	0	1	0	1	1	1	1	1	0	0	1	1

References

Belhadi A, Kamble S S, Venkatesh M, et al. Behavioral mechanisms influencing Sustainable Supply Chain Governance decision-making from a dyadic buyer-supplier perspective[J]. International Journal of Production Economics, 2021, 236(4):108136.

Broo D G, Bravo-Haro M, Schooling J. Design and implementation of a smart infrastructure digital twin[J]. Automation in Construction, 2022, 136:104171-.

Bhattacharyya S S, Mandke P, Wood L C. Exploratory Study of the Role of Emerging Technologies in Outsourcing of Supply Chain Functions[J]. International journal of applied logistics, 2021(11-2).

Dubey R, Luo Z, Gunasekaran A, et al. Big Data and Predictive Analytics in Humanitarian Supply Chains: Enabling Visibility and Coordination in the Presence of Swift Trust[J]. The International Journal of Logistics Management, 2017, 29(2):485-512.

Fothergill B T, Knight W, Stahl B C, et al. Responsible Data Governance of Neuroscience Big Data[J]. Frontiers in Neuroinformatics, 2019, 13.

He Lina, Wang Guotao, Liu Jue. Supply chain risk management based on hesitant fuzzy DEMATEL and risk house[J]. Computer Integrated Manufacturing Systems,2021,27(05):1459-1468.DOI:10.13196

Hammervoll T, Hammervoll T. Governance of Value Creation in Supply Chain Relationships[J]. Supply Chain Forum An International Journal, 2015, 12(2):116-126.

Horgan L. The Everyday of Future-Avoiding: Administering the Data-Driven Smart City[J]. Information & Culture, 2022, 57.

Hazen E L, Scales K L, Maxwell S M, et al. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries[J]. Science Advances, 2018, 4(5):eaar3001.

Jiang G, Cai X, Feng X, et al. Effect of data environment and cognitive ability on participants' attitude towards data governance[J]. Journal of Information Science, 2021(1):016555152110190.

Junwei Zou et al. Multi-attribute-Based Access Control Policy for Supply Chain Data Service [J]. Chinese Journal of Electronics, 2018, 27(6) : 1283-1290.

Jr R, Morgan T R, Lindsey-Hall K, et al. A global exploration of Big Data in the supply chain[J]. International Journal of Physical Distribution & Logistics Management, 2016, 46(8):710-739.

Kaminski A M, Genschick S, Kefi A S, et al. Commercialization and upgrading in the aquaculture value chain in Zambia[J]. Aquaculture, 2017:355-364.

Kaur P, Nand P. Towards Transparent Governance by Unifying Open Data[J]. IAENG Internaitonal journal of computer science, 2021(4 Pt.2):48.

Li X. Research on China's Social Governance Mode Transformation and Upgrading in Supply-Side Reform Field—From the Perspective of Public Management[J]. Chinese Studies, 2017, 06(3):188-200.

Mina Nasiri et al. Managing the digital supply chain: The role of smart technologies [J]. Technovation, 2020, 96-97(prepublish): 102121-102121.

Marijn Janssen et al. Data governance: organizing data for trustworthy Artificial Intelligence [J]. Government Information Quarterly, 2020, 37(3).

Martens K, Zscheischler J. The Digital Transformation of the Agricultural Value Chain: Discourses on Opportunities, Challenges and Controversial Perspectives on Governance Approaches[J]. Sustainability, 2022, 14.

Nar Z M, Nuhu A A, Zeeshan Q, et al. Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0[J]. Sustainability, 2020, 12.

Pant P, Dutta S, Sarmah S P. Intangible supply chain complexity, organizational structure and firm performance[J]. The International Journal of Logistics Management, 2021, ahead-of-print(ahead-of-print).

Qu Y, Lu YJ, Liu ZYY, Yang MX. Research on weight calculation method based on AHP-EMATEL method[J]. Practice and understanding of mathematics,2016,46(07):38-46.

Renmin, Hu, Changping. Research on collaborative health data governance system under the strategy of "Health China 2030"[J]. Library Intelligence Work,2021,65(01):102-109.5.

Reinartz W, Wiegand N, Imschloss M. The impact of digital transformation on the retailing value chain - ScienceDirect[J]. International Journal of Research in Marketing, 2019, 36(3):350-366.

Rla B, Zxa B, Yh C, et al. Improving high-tech enterprise innovation in big data environment: A combinative view of internal and external governance[J]. International Journal of Information Management, 2020, 50:575-585.

Shi Longyu et al. Standardization of the Evaluation Index System for Low-Carbon Cities in China: A Case Study of Xiamen[J]. Sustainability, 2018, 10(10) : 3751-3751.

Sun M, Yan JX, Peng Y. Research on the weight values of service quality evaluation indexes of university libraries based on triangular fuzzy numbers[J]. Library Information Work,2012,56(17):89-92+108.

Shuangming W, Jianwei S, Shiqiu F, et al. Research on the Construction of Sports Resources Information Platform Based on Big Data[J]. International Journal of Advanced Network Monitoring and Controls, 2018, 3(2):28-32.

Sun Z, Liang X, Xuelu X U. The New Round of Technological Revolution and Industrial Re-revolution Strategy in The Western Industrialized Countries[J]. Journal of Audit & Economics, 2016.

William Villegas-Ch et al. Application of a Big Data Framework for Data Monitoring on a Smart Campus [J]. Sustainability, 2019, 11(20) : 5552-5552.

WI A, Xiao L A, Fan X A, et al. Exploring smart construction objects as blockchain oracles in construction supply chain management[J]. Automation in Construction, 129.

Yupen Zhao and Bo Fan. The moderating effect of external pressure on the relationship between internal organizational factors and the quality of open government data[J]. Government Information Quarterly, 2017, 34(3) : 396-405.

Yang C, Liu Y, Zhao F, et al. Provable data deletion from efficient data integrity auditing and insertion in cloud storage[J]. Computer Standards & Interfaces, 2022, 82:103629-.

Zijun Mao et al. Government data governance framework based on a data middle platform [J]. Aslib Journal of Information Management, 2022, 74(2) : 289-310.

Zhou W, Zhao TS, Xu SM, Liu W. Modeling of influencing factors of safety behavior of construction workers based on DEMATEL and ISM. Journal of Civil Engineering and Management 34(6): 126-132.

Zhang Heping,Chen Qihai. A comprehensive evaluation study of journals based on factor analysis-DEMATEL weighting method[J]. Journal of Intelligence,2017,36(11):180-185.

Zhao Yupan and Fan Bo. Effect of an agency's resources on the implementation of open government data [J]. Information & Management,2021,58(4).