A Multianalytical Approach to Identifying Influential Factors in Data Sharing among International Construction Enterprises

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Abstract

With the advent of the data era, academia and industry have gradually recognized the pivotal role of cross-organizational data sharing in the construction sector. However, given the nature of international construction enterprises (ICEs), data sharing is often complicated by cross-border data flows, diverse standardized formats, and varying regulatory environments. Besides, existing studies have yet to investigate the factors affecting data sharing at a firm level, most identified factors are isolated and do not consider the inner relations or priorities of these elements. To bridge this gap, this study aims to construct a holistic model consisting of the influential factors in data sharing while considering their interactions and prioritization. The model derives from data collected through a literature review and semi-structured interviews with 15 experts. A multi-analytical approach comprising a two-pronged grounded theory (manpower and ChatGPT-4o), fuzzy interpretive structural modeling - matrix of cross-impact multiplications (FISM-MICMAC), and analytic network process (ANP) is employed in this paper. Our analysis demonstrates that 21 factors are organized into a seven-tier hierarchy in the

FISM model. The most significant factors include “corporate scale”, “data-sharing technical maturity”, “compliance with cross-border data flow”, “financial cost”, “corporate profit” and “corporate operation structure” based on FISM-ANP analysis. Finally, a three-stage data-sharing promotion strategy is proposed. These findings pave the way for ICE managers and policymakers to formulate strategies when sharing data and release the value of data flow to echo the sustainability paradigm within the construction sector.

Keywords: Data sharing, International construction enterprises, Grounded theory, Fuzzy interpretive structural modeling, Analytic network process

Introduction

The rapid advancement of information and communication technologies (ICTs) has propelled the construction industry into a significant phase of digitalization, underpinned by the proliferation of big data. Nevertheless, in the context of the data era, construction enterprises face persistent challenges, such as data silos among stakeholders (Ayodel and Kajimo, 2022), and insufficient data basis for decision-making (Wu et al., 2021). Therefore, a growing research inclination toward data sharing plays a crucial function in exploiting and utilizing the value of data (Wang et al., 2023), as data will be more valuable if it is owned by a growing number of entities through sharing behavior. Proposed by Ayodele and Kajimo (2022), data sharing refers to the dissemination and aggregation of construction data among organizations. Recently, researchers have demonstrated the significance of data sharing in construction industry, given the merits of facilitating decision-making (Legenvre and Hameri, 2024), improving efficiency of projects (Nezami et al., 2021), and strengthening collaboration (Bresciani et al., 2021).

According to the Engineering News-Record (ENR), the operating revenue of the top 225 international construction enterprises(ICEs) has reached US$ 82.94 billion in 2024, accounting for 6.3% of total international market. Meanwhile, as an increasing number of international standards for data exchange within the construction industry (i.e., ISO19650, ISO16739 and OpenBIM), data sharing has gradually attracted much attention as the innovation and sustainability that data brings to international construction (Wu et al., 2022). Considering the organizational attributes and operational pattern of international construction often involve collaboration among cross-border enterprises (i.e., contractors, subcontractors, suppliers, designers, etc.) (Deng et al., 2014), data sharing should be taken at a firm-level as within its specific characteristics (e.g., scales and capabilities). An international construction enterprise is a company that engages in projects across national borders (Deng et al., 2014), facing a significant gap in regulations in the host country. Therefore, compared with the general construction companies, data sharing for ICEs is more complicated. First, different countries have distinct laws and regulations regarding data usage, storage, and transmission (i.e., General Data Protection Regulation from EU), which ICEs must navigate carefully to ensure compliance. Second, considering the discrepancies of ICEs from different countries, each organization may have its own standardization and unique ways of recording and presenting data to echo their countries' requirements (Kush et al., 2020), which may make cross-border data more difficult to integrate and share. In addition, ICEs have to face the challenges introduced by cultural and linguistic variegation as they may hinder the standardization process of data sharing. Finally, the global nature of ICEs heightens data security risks as cross-border data may cover sensitive information. Therefore, it is necessary to explore the determinants and their inner relations in data sharing among ICEs to make data flow efficiently and securely. Currently, extensive research has been conducted in construction field to identify key factors in data sharing (Ayodele and Kajimo, 2022; Wang et al., 2023; Bühler et al., 2023), but there is a scarcity of research on the holistic identification of critical factors affecting data sharing among ICEs. By conducting a well-rounded audit of the existing literature, these gaps manifest in several ways. First, given the cross-border and cross-cultural nature of ICEs, previous research has not considered the affecting factors under this context, which may lead to economic and political risks for ICEs. Second, the identification of these factors in existing research is not sufficiently comprehensive and lacks a firm-level view and empirical data analysis to support the practical implications. Third, previous research treats each factor as a single entity, ignores their interaction and relative significance, the result can be relatively one-sided. Concerning these gaps, the corresponding objectives include: (1) identify and construct a factor model affecting data sharing among ICEs; (2) explore the interrelationships and powerful driving factors by which these factors can effectively promote data sharing among ICEs and (3) capture the relative weight of each factor to identify the principal determinants of data sharing among ICEs. To fulfill these objectives, a two-pronged grounded theory combining manpower and ChatGPT is employed to develop the factor model, which further serves as the foundation for the FISM-MICMAC analysis. The weight of each factor is addressed by the ANP analysis. Finally, a three-stage data-sharing promotion strategy is proposed to enhance the data flow within international construction. This research releases the following contributions to data sharing in construction industry:

(1) Considering the inherent nature of ICEs, we develop and validate a novel model to manifest

the factors affecting ICEs' data sharing to fill the existing gap; (2) Taking into account the limited resources of ICEs (e.g. labor force, capital), we elucidate and discuss the intricate conduction path and relative weight of each factor to provide ICEs' managers and government a prioritization when governing data sharing and (3) Given the attributes of changing resistance in construction industry, we offer crucial practical implications by proposing a three-stage strategy, including preparation stage, exchange stage, and utilization stage to incentivize data sharing among ICEs, thus accelerating the construction digitalization and enabling the value of data to be thoroughly unleashed within the construction industry.

Literature Review

Nature of the International Construction and Its Demand for Data Sharing

International construction is usually highly complex, unstable, and cross-border (Zhou & Liu, 2022), leading to siloed data management across diverse organizations and regions (Nezami et al., 2022). This fragmentation causes inefficiencies, redundancies, and transparency issues, especially in projects involving multinational stakeholders. Given the dynamic nature of ICPs (Deng et al., 2014), timely data exchange is crucial for managing cross-border challenges, regulatory compliance, and project efficiency. As a result, the need for effective data sharing has become increasingly prominent as a means to enhance collaboration, productivity, and innovation in global construction (Bresciani et al., 2021).

The growing adoption of digital technologies like Building Information Modeling (BIM) and Internet of Things (IoT) underscores the need for effective data sharing. These tools generate real-time data across dispersed teams, which, if shared effectively, can improve decision-making, resource allocation, and coordination. For instance, Siddiqui et al. (2021) developed a data-sharing prototype to improve BIM's capacity to record and preserve fire protection data. Despite its considerable benefits, data sharing in construction industry continues to face challenges related to trust, data ownership, and a lack of sharing standardization (Bello et al., 2021; Joyce and Javidroozi, 2024), limiting collaboration and process optimization. Thus, overcoming these barriers requires a nuanced understanding of the impactful factors that influence data-sharing among ICEs thus enabling enterprises to unlock the value of data and enable an effective digital transformation.

Data Sharing-Related Work in Construction Industry

Data sharing in the construction industry has obtained significant attention for its potential to enhance project efficiency, collaboration, and decision-making. Research has examined its challenges, drivers, and frameworks across stakeholders: Wang et al. (2023) and Ayodele and Kajimo (2022) identified key enablers and barriers through online surveys, proposing strategies to promote data sharing. Sharma et al. (2022), in a systematic review, outlined five critical data-sharing criteria, including third-party oversight, data age, provider diversity, maximum of shared data volume and anonymization measures, offering a structured approach for both academia and industry. Technological advancements have also been explored. Bühler et al. (2023) introduced a federated data-sharing platform, while Xue et al. (2022) leveraged text analysis for enhanced data management in smart construction. Jin et al. (2023) addressed interoperability challenges through standardized technical frameworks. Despite these contributions, existing studies do not fully examine what and how various factors shape enterprises' willingness to share data.

The nature of shared data in the construction industry is characterized by several attributes such as security, fragmentation and dynamism. Sensitive data, including confidential project details and financial records, requires strict access controls (Hwang et al., 2022). Multiple stakeholders and a lack of standardization cause the data fragmented, leading to interoperability challenges (Bühler et al., 2024). In digitalized environments, the dynamic nature of data requires real-time sharing to ensure continuous updates throughout project phases, improving coordination and decision-making (Ayodele and Kajimo, 2022).

As Legenvre and Hameri (2024) emphasized, effective data sharing necessitates a system-level analysis to address technological, organizational, and regulatory interdependencies. However, existing studies fail to systematically identify key determinants of data-sharing behavior or examine their interactions within an integrated model. Additionally, the relative significance of these factors remains unclear, complicating managerial decision-making. Methodological limitations concerning objectivity and robustness also persist. For instance, Ayodele and Kajimo (2022) provided insights into data-sharing policies but rely on web-based surveys and Likert-scale ratings, introducing potential biases. Wang et al. (2023) classified data-sharing barriers and strategies but rely on government reports and literature, limiting applicability to evolving industry challenges. These gaps highlight the need for a comprehensive, empirical, and multi-analytical (qualitative and quantitative analysis) approach. This study addresses these limitations by developing a model of influential data-sharing factors based on a two-pronged grounded theory (manpower and ChatGPT). The model's intrinsic relationships and critical factors are further analyzed using FISM-MICMAC, while ANP quantifies factor significance. Finally, a three-stage strategy is proposed to enhance data sharing, facilitating an efficient release of data value within the international construction.

Research Methods

Research Design Flow

The purpose of this study is to construct a factor model of data sharing across ICEs by considering the coupling effects, integrating three methods, including a two-pronged grounded theory (TP-GT), fuzzy interpretive structural modeling - matrix of cross-impact multiplications applied to classification method (FISM-MICMAC) and analytic network process (ANP). The research design is shown in **Figure 1**.

Proposed by Glaser and Strauss, grounded theory aims to explore a phenomenon or seek a novel perspective on a familiar situation (Charmaz, 2015). It has been extensively adopted in establishing a factor model in construction industry. For instance, using GT, Sun et al. (2022) identified 53 factors leading to the early termination of PPP projects; Xue et al. (2023) investigated 21 risk factors for large airport operational readiness. By integrating raw data from interviews and articles, researchers can establish a model during the process of coding, categorizing, connecting, and testifying. Compared to software development, coding in this context refers to the systematic process of analyzing qualitative data by identifying key themes, patterns, and relationships (Corbin and Strauss, 2014). Notably, in parallel to manpower, our study introduces a novel approach, ChatGPT-4o, to conduct the coding process synchronously. ChatGPT is a generative artificial intelligence released by OpenAI in 2022 (Byrne, 2023). In fact, it has been confirmed the ability to perform grounded theory effectively by Zhou et al. (2024) and Sinha et al. (2024). The integration of manpower and ChatGPT can reduce subjective errors to a certain extent and offers a more holistic model. Particularly, this study employs the temporary chat, a mode that prevents ChatGPT from retaining or recalling raw data from previous interactions once each conversation ends, to mitigate bias from previously inputted data (Khan et al., 2025). Therefore, to enhance the AI coding efficiency while minimizing potential bias, each conversation is limited to the input of 2-3 sentences before initiating a new coding process. Considering the following quantitative analysis, this section can also avoid a certain degree of subjectivity by referring to the results of the GT, which includes an entire factor model validated by a theoretical saturation test.

Secondly, data sharing in the construction sector involves multiple stakeholders (Ayodele and Kajimo, 2022), which complicates the relationships within the model. Consequently, the application of FISM intends to map a multilevel hierarchy system of the inter-relationships of the identified factors. This method has proven to be an effective tool for revealing the interpretive logical linkages of different factors, particularly at the organizational level (Jiang et al., 2019). Compared with ISM, FISM provides a more detailed elaboration on the strength of influence between factors through fuzzy logic and reduces the subjective bias of experts (Jain and Raj, 2021). To further identify the dependent and independent factors, the MICMAC technique categorized these factors into four clusters according to their driving and dependence powers. This integration of FISM and MICMAC is proved functionally in identifying the efficient pathway within the complex system (Gu and Guo, 2024).

Although the inter-relationships have been identified, it is still challenging to obtain the priority using the same approach. To overcome this dilemma, ANP is applied to further obtain the factor weight considering their coupling effects. As an advanced form of AHP, ANP is commonly employed to rank factors under the bi-directional relationship context (Kumar et al., 2021). Several established methods, such as AHP and DEMATEL, are used for determining weights.

However, they have notable limitations. For example, AHP assumes that factors are isolated, making it unsuitable for analyzing intricate network structures (Chen et al., 2024). Conversely, DEMATEL emphasizes causal relationships among factors but struggles to provide prioritization (Vaz-Patto et al., 2024). In this case, the ANP technique provides a competitive edge in prioritizing groups of factors by accounting for bi-directional relationships within the established factor model to help managers order these determinants.

According to Liu et al. (2024), there is no uniformity in the number of samples required for the ISM and ANP, the sample needs to be focused more on quality than quantity (Yu et al., 2020). The amount of experts in FISM and ANP analysis varies from 5 to 15 (Sun et al., 2024; Afzali and Adelzade, 2024; Gu and Guo, 2024). Herein, 10 experts with extensive experience and knowledge in this field were invited to answer the questionnaire proposed by FISM and ANP methods, which is consistent with the sample sizes of previous studies Yu et al. (2020) and Kumar et al. (2021).

Validation

The validity and reliability of this research were ensured through multiple steps. First, an extensive literature review was conducted to confirm the model saturation. Theoretical saturation was continuously assessed by multiple researchers until a consensus was reached, ensuring the model’s robustness. For quantitative analysis, the expression validity of the questionnaire is verified by professors and Ph.D. students in relevant fields to ensure clarity before distribution to experts. Moreover, data inconsistencies in expert evaluations regarding interrelationships and factor importance were resolved through iterative discussions. For example, if two experts contend that Factor 1 greatly influences Factor 2, Factor 1 has no significant impact on Factor 1. Another 2 experts argue that Factors 1 and 2 exhibit an equally bi-directional influence, with each significantly affecting the other. Meanwhile, two experts assert that Factor 2 drives Factor 1, whereas Factor 1 doesn't impact Factor 2. In this case, a new round of discussions is conducted until a consensus is reached, following the principle outlined by Yu et al. (2020). Additionally, if pairwise comparison results yielded a consistency ratio (C_R) above 0.1, experts are asked to reassess their judgments until the C_R falls below this threshold, ensuring the validity of the ANP results. Finally, research findings were sent to experts via email for validation of the logical coherence and consistency of the GT, FISM, and ANP results. Necessary modifications were made based on expert feedback to enhance the reliability, robustness and applicability of the findings.

Data Analysis and Results

Phase I: Construction of Influential Factors Model Based on Two-Pronged Grounded Theory

1) Data Collection

The selection of data collection targets is a pivotal step of grounded theory, which is a decisive link to ensure the quality of the original data (Sun et al., 2024). Whereas the subject of this study is ICEs, promoting data sharing requires the cooperation of government, practitioners and scholars in this field. To be more specific, ICE's managers with technological experience, academics and governmental managers with certain knowledge are selected as our respondents. Subsequently, a total of 15 personnel were interviewed during the semi-structured interview stage and the duration of interviews varied from 30 to 60 minutes. The basic information of respondents is shown in **Table 1**. However, due to the limited number of interviews, relevant documents such as articles and data-sharing policies are reviewed to conjunct with interviews, ensuring the richness of the original statements.

2) Coding Process

This article employs a two-pronged approach, including the manpower and ChatGPT-4o to execute the coding. In this process, researchers are expected to collect, code, and analyze data simultaneously, rather than postponing analysis until all data has been gathered, as the ongoing analysis allows researchers to adjust the questions in time, which is in line with Luo et al. (2024). Innovatively, ChatGPT is introduced to coding the text corpus subsidiarily. According to Byrne (2023), the structure of GT process can derive a clear and specific prompt for GPT to generate an accurate response. The coding results at each stage were integrated and adjusted based on the results received from both human and GPT, allowing for a more objective and complete result. The prompts for GPT coding were adapted and refined based on Zhou et al. (2024), as presented in Tables 2 and 3. Meanwhile, AI-assisted coding results were cross-validated and refined by researchers to mitigate potential biases, ensuring the integration of ChatGPT-4o adheres strictly to AI ethics principles of transparency, reliability, and human oversight (Hosseini et al., 2024).

Open coding: This stage is conducted word by word and sentence by sentence, ensuring an unbiased approach free from research preconceptions and personal cognitive stereotypes (Yu et al., 2020). In this paper, NVivo 15 and ChatGPT-4o were used for conceptualization separately, and 45 initial sub-categories were finally formed. Due to the space constraints, only representative sentences from respondents for open coding results and the prompt pattern *I* applied in ChatGPT-4o are given in **Table 2**.

Axial coding: builds on open coding by further exploring and identifying the relationships between conceptual categories. Phrases or words retrieved from open coding with similar concepts are clustered together in the subsequent categories. Therefore, 21 sub-categories are further identified.

Selective coding: This stage facilitates the identification of core categories with shared attributes, resulting in a structured framework comprising core categories, subcategories, and conceptual categories. Based on the referencing of the axial coding, eventually, 6 core categories were identified. The results of axial and selective coding and prompt patterns *II* and *III* are listed in **Table 3**.

3) Theoretical Saturation Test

To fully identify the factors, the paper examines whether there are new categories emerge from further data collection. 1/4 of the data from the text corpus was stochastically selected for the saturation testing and the results indicate that the model cannot reflect any new conceptual categories. Meanwhile, the same progress was conducted by a Ph.D. student from the research group, which validated the reliability of the testing results. Based on the results and modifications of grounded theory, the model of factors influencing data sharing among ICEs is integrated and constructed, as shown in **Figure 2**.

Phase II: Exploration of Interrelationship within Factors Based on FISM and MICMAC Analyses

After model construction, FISM-MICMAC is utilized to build a hierarchy illustrating the interactions based on grounded theory. As mentioned in the methodology section, the relationships are iteratively refined until a consensus is reached, forming the basis for the subsequent MICMAC analysis. Building upon established procedures (Gu and Guo, 2024), this section follows the steps below.

1) Fuzzy Adjacency and Correlation Matrix Construction

Using the nominal group technique, the study assessed contextual relationships among 21 factors by analyzing them in pairs to construct a fuzzy adjacency matrix. This matrix represents logical relationships between influencing factors as a directed graph. $\mathbf{A_E}$ is the adjacency matrix judged by the $\mathbf{E_{th}}$ expert; the number of experts is $\boldsymbol{m}$. $\boldsymbol{N}$ is the matrix formed by the average number of elements according to all adjacency matrices, which equals $\frac{1}{m}\sum_{E=1}^{m} N_E$. In the current study, the degree of impact between the influencing factors ($\mathbf{x}_{ij}$) was categorized referring to the criteria shown in Equation (1). The resulting fuzzy adjacency matrix $\boldsymbol{N}$ is presented in **Table 4**.

$$X_{ij} = \begin{cases} 0.00, & F_i \text{ has no influence on } F_j \\ 0.25, & F_i \text{ has few influence on } F_j \\ 0.50, & F_i \text{ has moderate influence on } F_j \\ 0.75, & F_i \text{ has high influence on } F_j \\ 1.00, & F_i \text{ has greatly influence on } F_j \end{cases} \quad (1)$$

Based on the matrix $\boldsymbol{N}$, to retrieve the correlation strength, equation (2) is applied to transform the fuzzy adjacency matrix to a relation matrix $\mathbf{B}=b_{ij(n\times n)}$

$$y_{ij} = \begin{cases} \frac{x_{ij}}{x_i+x_j-x_{ij}}, i \neq j \\ 0 \quad , \ i = j \end{cases} \quad (2)$$

Where b_{ij} is the fuzzy impact of factor i on factor j; x_i is the sum of i_{th} row of the fuzzy correlation matrix **N**; x_j is the sum of the j_{th} column of the matrix **N**; $i, j = 1, 2, \ldots, n$.

2) Intercept Coefficient Assignation and Binary Adjacency Matrix Creation

The fuzzy correlation matrix is then converted to a binary adjacency matrix with a 0-1 binary transformation; while λ is the intercept coefficient to set the threshold for 0-1 conversions.

Following equation (3) If the impact exceeds the threshold, the value in the correlation matrix is converted to 1, otherwise, it will be converted to 0. The binary adjacency matrix $\boldsymbol{Z}=z_{ij(n\times n)}$ can be obtained accordingly.

$$z_{ij} = \begin{cases} 1, y_{ij} \geq \lambda \\ 0, y_{ij} < \lambda \end{cases} \qquad (3)$$

The intercept coefficient selection influences model hierarchy. A diminutive value of λ creates an excessively intricate model, while a large value of λ cannot accurately reflect factor interactions. Existing selection methods include expert judgment and mean value, which can be subjective. According to the λ strategy of Gu and Guo (2024) ($\lambda = \mu + 0.5\sigma$), it might not be applicable in this study as the model only has two layers when λ=0.028. Building on this foundation, the value of λ was increased by 0.01. Ultimately, the model achieved optimal interpretability at a value of 0.034, corresponding to seven layers.

3) Reachability Matrix

The adjacency matrix captures only the direct effects between factors within the network system, excluding any indirect relationships resulting from transitivity. Therefore, the reachability matrix is calculated as Equation (4):

$$(\boldsymbol{Z}+\boldsymbol{E})^{\boldsymbol{k-1}} \neq (\boldsymbol{Z}+\boldsymbol{E})^{\boldsymbol{k}} = (\boldsymbol{Z}+\boldsymbol{E})^{\boldsymbol{k+1}} = \boldsymbol{M} \qquad (4)$$

Where **Z** is binary adjacency matrix, E is identity matrix, $\mathbf{(Z+E)^k}$ is the intermediate reachability matrix with n intermediates, and **M** is the reachability matrix shown in **Table 5**.

4) Level Partitions and Diagram Development

Regarding the reachability matrix, the reachability and antecedent sets for each factor can be identified. The reachability set, P(F_i), comprises the factor itself along with other factors it influences, while the antecedent set, Q(F_i), includes the factor itself and those factors that influence it. The intersection set, L, represents the overlap between the reachability and antecedent sets. The calculations for these sets are detailed in Equations (5), (6), and (7). Subsequently, as illustrated in **Figure 3**, a diagram reflecting the interrelationships in the model is proposed.

$$\boldsymbol{P}(\boldsymbol{F_i}) = \{\boldsymbol{F_j} | \boldsymbol{m_{ij}} = 1\}, \boldsymbol{i} = 1,2,3,\ldots,n;\ \boldsymbol{j} = 1,2,3,\ldots,n \quad (5)$$

$$\boldsymbol{Q}(\boldsymbol{F_i}) = \{\boldsymbol{F_j} | \boldsymbol{m_{ji}} = 1\}, \boldsymbol{i} = 1,2,3,\ldots,n;\ \boldsymbol{j} = 1,2,3,\ldots,n \quad (6)$$

$$\boldsymbol{L} = \{\boldsymbol{F_j} | \boldsymbol{P}(\boldsymbol{F_i}) \cap \boldsymbol{Q}(\boldsymbol{F_i}) = \boldsymbol{P}(\boldsymbol{F_i})\}, \boldsymbol{i} = 1,2,3,\ldots,n;\ \boldsymbol{j} = 1,2,3,\ldots,n \quad (7)$$

5) *Factor Categorization Using MICMAC Technique*

The MICMAC technique is then applied to classify the factors into a few clusters based on their driving *(DR_i)* and dependence powers *(DE_i)*, calculated through Equations (8) and (9).

$$\boldsymbol{DR}_i = \textstyle\sum_{j=1}^{n} \boldsymbol{m_{ij}},\ (i = 1,2,3,\ldots,n) \quad (8) \qquad \boldsymbol{DE_j} = \textstyle\sum_{i=1}^{n} \boldsymbol{m_{ij}},\ (i = 1,2,3,\ldots,n) \quad (9)$$

As noted by Yu et al. (2020), a power is classified as strong if it surpasses the average factor level; otherwise, it is deemed weak. Utilizing MICMAC analysis, all identified factors were classified into four distinct quadrants based on their driving power and dependence power, as illustrated in **Figure 4**.

Driving Factors: Nine factors, i.e., A_2, A_3, D_3, E_1, E_2, D_4, C_3, D_2, B_1, were classified in the driving quadrant, indicating strong influence but low dependence. These factors form the foundation of the FISM model and require greater attention as they are crucial for effective data sharing across ICEs.

Linkage Factors: Factors A_4, A_5, A_6, C_1, C_2, and D_1 exhibit both strong driving and dependence powers, making them highly sensitive to external influences. Their feedback effects necessitate careful consideration when implementing data sharing among ICEs to ensure stability and effectiveness.

Autonomous Factors: Factors D_5 and F_2 exhibit low driving and dependence power, indicating minimal influence and insulation from other variables. Their limited impact on the overall system suggests they can be addressed with relative ease in data-sharing mechanisms among ICEs.

Dependent Factors: Factors defined by weak driving power but strong dependence power, i.e., A_1, B_3, F_1, and B_2, typically occupy the upper levels in the model. Addressing these factors effectively requires resolving the issues associated with the factors positioned at lower levels of the FISM hierarchy.

However, the hierarchy structure shows that factors within the same quadrant are placed at the same level, which might be unfeasible or create confusion for managers when making decisions on data sharing. Hence, to prioritize these factors, the method of ANP is employed to retrieve the ranking.

Phase III: Determination of Critical Factors Weights Based on Analytic Network Process

1) Establish the ANP Network Structure

The ANP network structure illustrates the relationships among factors across multiple levels, with these interconnections represented by arcs or bidirectional arrows (Sun et al., 2024). In this study, the analytical structure is derived from the influence diagram produced by the FISM method and constructed using Super Decisions software, to operationalize the motivational factors model analyzed in phases I and II. The overview of the structure is presented in **Figure 5** by using Super Decisions V3.2.

2) Construct the Pairwise Comparison Matrix and Consistency Check

In this process, 10 experts are engaged to assess the relative importance of factors through pairwise comparisons, utilizing Saaty's nine-point scale and further developing a pairwise comparison matrix. **Figure 6** shows the pairwise comparison example in the data collection technique. Aggregately, 6 weighting matrixes and 126-factor matrixes were delivered to the experts for further data analysis.

The consistency index ($\boldsymbol{C_i}$) and consistency ratio ($\boldsymbol{C_R}$) are employed to evaluate the consistency of the pairwise comparison matrix, as calculated using Equations (10)-(11). Pairwise comparisons with a $\boldsymbol{C_R}$ value below 0.1 are deemed acceptable, which has been confirmed and illustrated in **Table 6**.

$$\boldsymbol{C_i} = \frac{\boldsymbol{\lambda_{max} - N}}{\boldsymbol{N-1}} \qquad (10) \qquad\qquad \boldsymbol{C_R} = \frac{CI}{RI} \qquad (11)$$

where CI denotes the consistency index, $\lambda_{\max}$ is the principal eigenvalue of the comparison matrix, and N is the size of the square comparison matrix.

3) Develop the Unweighted Supermatrix

Using the control layer A as the main criterion and element C_{jl} ($l=1,2,3,...,n_j$) within B_j as the sub-criterion, a judgment matrix is obtained from progress 2. The results are further utilized to develop an unweighted supermatrix through the sorting vector $w_{i1}^{(jl)}, w_{i2}^{(jl)}, \ldots, w_{in_i}^{(jl)}$, notation W_{ij} is shown in Equation (12). Where the column vector of $\mathbf{W_{ij}}$ is the ordering vector of the degree of influence of the elements C_{i1}, C_{i2}, ..., C_{in_i} in B_i on the elements C_{ji}, ...,C_{jn_j} in B_j. If the elements in B_j are not influenced by the elements in B_i, then $\mathbf{W_{ij}}$=0. The unweighted supermatrix **W** under criterion A is obtained accordingly as presented in Equation (13), shown in **Table 7**.

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & w_{i1}^{(j2)} & \cdots & w_{i1}^{(jn_j)} \\ w_{i2}^{(j1)} & w_{i2}^{(j2)} & \cdots & w_{i2}^{(jn_j)} \\ & & \vdots & \\ w_{in_i}^{(j1)} & w_{in_i}^{(j2)} & \cdots & w_{in_i}^{(jn_j)} \end{bmatrix} \qquad (12) \qquad\qquad W =$$

$$
\begin{array}{c}
1 \\ \vdots \\ n_1 \\ 1 \\ \vdots \\ n_2 \\ 1 \\ \vdots \\ n_N
\end{array}
\begin{bmatrix}
w_{11} & w_{12} & \cdots & w_{1N} \\
w_{21} & w_{22} & \cdots & w_{2N} \\
 & & \vdots & \\
w_{N1} & w_{N2} & \cdots & w_{N3}
\end{bmatrix} \quad (13)
$$

4) Derive the weighted supermatrix

The unweighted supermatrix is initially developed without accounting for inter-cluster impacts. To accurately assess multi-level factors, it is necessary to derive the weighted supermatrix. Treating each cluster as a variable, pairwise comparisons are conducted to determine the clusters' relative importance, resulting in the relative weight matrix **R**, as calculated using Equation (14). The unweighted supermatrix **W** is then integrated with the relative weight matrix **R** to produce the weighted supermatrix $\mathbf{W_0}$, as defined by Equation (15). Matrix **R** and $\mathbf{W_0}$ are shown in **Tables 8 and 9**, respectively.

$$
\mathrm{A} = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N_1} & \cdots & a_{NN} \end{bmatrix} \quad (14) \qquad \mathrm{W}_0 = a_{ij}\, W_{ij}\ (i = 1, \ldots, N;\ j = 1, \ldots, N) \quad (15)
$$

5) Calculate the Limit Supermatrix and weight retrieval

Through the application of the power method with equation (16), the weighted supermatrix W_0 is iteratively stabilized until the matrix product converges to a unique solution, resulting in the limit supermatrix W_l. In this matrix, each row represents the weight value of the corresponding factor.

$$
W_l = W^{\infty} = \lim_{t \to \infty} W^t \quad (16)
$$

Finally, the limit supermatrix W_l and the weight of each factor are obtained in **Table 10**. Furthermore, the priorities of the top ten factors are listed in **Table 11**.

Discussion

Driven by the potential capabilities of data, enterprises are striving to enhance data flow within the construction industry through data sharing (Wang et al., 2023). While existing studies indeed identified pertinent factors (Ayodele and Kajim, 2022), a notable research gap remains in comprehensively analyzing their interactions and the relative weight of these factors under an international context. The current research illustrated the efficiency of a multi-analytical approach combining *TP-GT-FISM (MICMAC)-ANP* techniques to analyze the determinants in data sharing among ICEs.

The findings from the FISM-ANP analysis revealed a generally consistent pattern. The developed FISM model is structured as a seven-tiered system. The root influencing factors (Levels VII and VI), located at the bottom levels, are likely to exert a significant impact on other factors. In this study, variables such as corporate scale (***Rank3***), corporate profit (***Rank2***), financial cost (***Rank4***), corporate operational structure (***Rank8)***, and peer competition (***Rank18***) are positioned at the base level, driving the dynamics of all remaining factors from Level V onward. These factors closely align with the results obtained from the ANP analysis. To enhance the adoption of data-sharing practices, greater emphasis must be placed on addressing these determinants. According to (Teece, 2007), a firm's size is a critical organizational attribute determining the most relevant performance gains captured and plays a crucial role in shaping its resource-sharing behavior. Conti et al. (2024) validated a positive correlation between a firm's data-sharing intention and its productivity. Large enterprises, with greater resources such as advanced technology and financial capacity, are better equipped to implement data-sharing, enhancing compliance with international regulations and fostering trust by leveraging their industrial reputation (supported by Expert 1,6). In contrast, small- and medium-sized enterprises (SMEs) may face resource constraints, leading to less standardization. While large enterprises may prioritize long-term partnerships and strategic collaboration, SMEs might focus on immediate benefits, balancing the risks and costs of sharing data with their need to remain competitive (supported by Expert 2,11). Therefore, the government could provide subsidies, grants, or tax incentives to SMEs to invest in data-sharing infrastructure. For instance, according to the policy on "Accelerating the Development and Utilization of Data Resources" proposed by the State Council of China in 2024, companies engaging in data sharing will receive a subsidy for research & development costs and tax deductions. Besides, the government can encourage collaboration through public-private partnerships (Geddes, 2017) or consortia (Todeva and Knoke, 2005) to help them build trust and engage in long-term strategic relationships with larger enterprises. Besides, the operational structure of the ICEs should be reconsidered by the managers. While centralized structures enable standardization through clear hierarchies and unified decision-making but limit adaptability to local conditions, decentralized structures enhance flexibility and responsiveness by tailoring practices to local needs, fostering trust and stronger relationships, which is supported by (Kharel and Acharya, 2023). However, this approach may risk inconsistencies and fragmentation, requiring robust coordination (Bakos and Dumitrașcu, 2021) to ensure its security and efficiency. Despite the low ranking achieved by peer competition in ANP analysis, it is still a major impediment to data-sharing in construction industry (Wijayarathne et al., 2024). As proposed by Yu et al. (2023), the firms' willingness to share data decreases as market competition increases, and will refuse to share when the condition is fierce. Hence, government should respond by establishing regulations to coordinate the competitors into a data consortium (Tang et al., 2024) and investing in secure platforms to protect sensitive data. Besides, data sharing incurs monetary costs for ICEs in investments and compliance, which can also deter their participation. However, firms are more inclined to participate in data-sharing initiatives when the expected profits substantially outweigh the costs (Krafft et al., 2021), highlighting the role of government-provided financial subsidies in incentivizing such collaboration.

In the mid-level, four elements are identified as the driving influencing factors (Levels V and IV), including mechanisms for resolving data-sharing disputes (***Rank10***), change resistance in industry (***Rank15***), financial incentives (***Rank11***) and data-sharing technical maturity (***Rank1***). Clear protocols, such as arbitration frameworks (Dithebe et al., 2023) or smart contracts (Gurgun and Koc, 2022), reduce the risks of conflicts and build trust among stakeholders. These mechanisms ensure fair resolution and confidence building, ultimately fostering collaboration and improving the willingness to participate in data sharing, leading to the demand for more elaborate international standardized protocols (i.e., ISO 19650) for data-sharing practices. Parallels to D_3, the stagnation in adopting technology within the construction industry is also a brake on data sharing (Iacovidou et al., 2021). Referring to Solove and Hartzog (2022), outdated practices induce data breaches and data silos. Thus, a tailored incentive policy should be taken by government to stimulate technological infrastructure improvement. Compared to general incentives, governments should customize the policy by introducing an optimal allocation coefficient considering their data-sharing volume, data quality and risk taken, which is in line with Tang et al. (2024). It is worth noting that whilst data-sharing technical maturity isn’t the most fundamental factor in the FISM model, it ranks first in ANP analysis. The outcome is also supported by the findings of (Yu and He, 2021; Xue et al., 2022; Nezami et al., 2022; Bühler et al., 2023). Data-sharing technique with a high maturity level ensures seamless integration across diverse systems and security issues (Nezami et al., 2022), especially for ICEs. A maturity platform enables cost-efficient, real-time analysis and timely completion (Bühler et al., 2023). For instance, Huang et al. (2024) verified the integration of blockchain and data alliance can enhance collaborative revenue. Government should support employees' technical training and collaboration with research institutions to develop specified solutions.

At the third level, six factors are identified as mediating influencing factors. These include compliance with cross-border data flow (***Rank5***), corporate reputation and status (***Rank6***), misconduct of data sharing (***Rank7***), political environment (***Rank9***), trust and collaboration (***Rank12***), and data ethics and security (***Rank17***). As one of the priority issues discussed in the G20 meeting, the cross-border data flow has been increasingly discussed in recent years (Li et al., 2022). Notably, the attitude of data flows varies from one country to another: the United States remains an open door to the cross-border flow, whereas the EU and China are extremely strict regarding the outbound data, especially sensitive data (i.e., face, fingerprint, national topography). These data regulations (i.e., CLOUD Act, GDPR, Data Security Law of the PRC) may cost firms a great fortune. For instance, Amazon and Uber have been fined \$887 million and \$324 million, respectively, after being accused by the EU's data protection agency of violating relevant provisions of the GDPR. Consequently, the cross-border data-sharing regulations should be focused on the following criteria by ICEs (Sharma et al., 2022; Li et al., 2022): (1) sharing should be managed by an independent third party (i.e., data brokers); (2) aggregation must prevent identification of individual provider’s data; (3) implement data localization strategies where necessary. Similar to A_2, a solid reputation often drives the ICE to foster trust and collaboration, enhance credibility and attract partnerships. globally. However, it can also be damaged by the misconduct of data sharing, such as data leakage and malicious tampering, to usurp profit. To resolve this dilemma, a solid penalty cost can be fined by governments (Tang et al., 2024). The political environment should be carefully considered by ICE managers when sharing data. For instance, a strong government tie fosters trust, enhances cooperation, and provides firms with the necessary approvals to key projects (Deng et al., 2014). Moreover, political tensions (i.e., trade disputes) may hinder the process of data sharing as government may impose bans on certain software, limiting data exchange internationally. As mentioned by Yu et al. (2020), data ethics must be considered to protect privacy and prevent misuse. This suggests that the data provider must consistently deliver data exchange plans and communicate with owners for data ethics assessment, such as the UK Data Ethics Framework (Yan et al., 2025).

Factors A_1***(Rank20)*** on the second level and Factors B_2***(Rank14)***, B_3***(Rank13)***, D_5***(Rank21)***, F_1***(Rank19)***, and F_2***(Rank16)*** on the first level are identified as influencing results, these factors are highly affected by the senior factors or have no strong driving power to affect the other factors, which is consistent with the MICMAC analysis. While as a dependent element, Tang et al. (2024) indeed demonstrated the willingness to share data has a profound impact on their sharing behaviors through an evolutionary game model. As mentioned repeatedly by several experts in the GT process, it is crucial to conduct data quality check before sharing. For example, the quality control checks for models containing semantic information (e.g., Revit) should include but are not limited to (Yan et al., 2025): (1) Verification of whether the model accurately represents real-world conditions, potentially requiring on-site validation. (2)

Evaluation of whether each element is modeled as a complete, singular unit to enable seamless analysis, and (3) Validation of the completeness and accuracy of parameters for each element across disciplines (i.e., serial number and unit of measurement). According to Yu et al. (2020), top priority should be given to the bottom level (i.e., A_2, D_3) or comprising a large proportion of factors (i.e., B_1), and a long-term perspective should be taken to these top-level factors.

Data Sharing Promotion Strategies for ICEs

This section developed a three-stage framework to stimulate data sharing among ICEs, including the preparation stage, exchange stage, and utilization stage, as shown in **Figure 7**.

In the preparation stage, rather than being isolated as an individual, companies should cooperate as a data consortium under the regulation and mobilization of government, especially for SMEs. This requires a clear legal agreement, confidence-building and consistent revenue allocation schedules. Managers should analyze the political environment before sharing data while being clear about data quality and sovereignty. Meanwhile, governments should invest in or financially subsidize data-sharing techniques, such as standardized protocols and compatibility of API interfaces for different countries.

During the data exchange stage, organizations' operational structure should be customized to the local context. For instance, if local (host country) laws mandate strict data sovereignty requirements (i.e., all project data must be stored within the country), the firm may establish localized data storage solutions to comply with regulations while maintaining smooth data exchange. In addition, a new department (Data compliance department) may need to emerge in ICEs to avoid financial losses for violating the data regulations (i.e., GDPR, RCEP, CPTPP).

In the data utilization stage, demonstrating the tangible value of shared data is critical. ICEs can achieve this by improving decision-making, project efficiency, and collaboration. Evaluations for feedback on sharing performance can serve as in refining data-sharing processes and fostering stronger collaborative relationships among data-sharing entities.

It is noteworthy that four elements are indispensable. Firstly, a tailored incentive policy should be established by the government. As the policy considers the data volume, quality and risk taken contributed by ICE, it ensures a fair and equitable allocation. Government can streamline the sharing process, such as reducing associated administrative and legal procedures to minimize its sharing costs. According to Crain (2018), the data broker manages the secure data transfer between entities and ensures transparency and compatibility by employing standardized formats and robust validation. As a mediator, they can establish trust and ensure clarity between data-sharing entities. Identity authentication is also necessary to make modifications traceable (Liao et al., 2025). The entire process should be kept under real-time surveillance by the government to ensure that data is collected and used legally.

Theoretical and practical implications

This research contributes to both theoretical and managerial implications. First, this research not only identified influential factors but also explored the interactions within the model and further determined weights. The findings align with previous studies and underscore the crucial role of government and technical maturity. Researchers can benefit from these findings to develop conceptual or analytical models for data-sharing-related concepts. The model can also aid researchers, through the interactions and prioritization within the model, to help them understand the future focus in this field. Moreover, to the best of our knowledge, this is the first paper that integrates ChatGPT-4o into grounded theory in the construction sector. Researchers may use GPT solely for coding to simplify the GT process and improve efficiency in the future. Given the practical implications, first, ICE managers can develop strategies based on priorities and interactions from FISM and ANP analysis for a more targeted allocation of resources to the data-sharing process. This insight matters especially when the budget for data-sharing investments is tightened. The government can formulate rational policies to coordinate data sharing among enterprises of various scales and create incentives in a fair manner by considering their risk-taking, data-sharing volume and contribution. In addition, the concept of the data broker can be introduced by government into construction sector, as it ensures fairness and transparency during data sharing.

Conclusions

As techniques continue to mature and evolve, the construction industry is ushering in its data era. Data sharing has hence commenced to capture the attention as it can enhance decision-making efficiency, collaboration, and rationalize the allocation of resources. However, as yet, no comprehensive exploration and analysis of factors affecting data sharing under ICE context has been conducted. In this study, based on the experts' interviews and literature review, a two-pronged grounded theory is used to develop a holistic model comprising 21 factors. The model is further used as the foundation for FISM analysis to explore the inter-relations within the model and identify the powerful factors by MICMAC analysis. Moreover, ANP is employed to solve the weight of each factor. The results of FISM and ANP showed a similar pattern. It was found that corporate scale, data-sharing technical maturity, corporate profit, financial cost, and compliance with cross-border data flow have a strong impact on ICE data sharing. Although peer competition obtained a low ranking in ANP, it indeed has been confirmed to have a strong driving power from the MICMAC analysis. Finally, a three-stage data-sharing promotion strategy is proposed to accelerate the data flow within the construction sector. These findings can provide valuable insights for policymakers and practitioners to develop strategies for data sharing, thereby expediting the application of the sustainability paradigm in the construction sector.

This study has certain limitations. First, it relies on insights from construction sector, limiting generalizability to other industries. Future research should explore similar phenomena across sectors for comparative analysis. Second, the FISM and ANP methods primarily depend on expert judgment, which may inherently reflect their individual experiences, interests, or potential biases. Consequently, variations in decision-making across experts are to be expected. To address these limitations, future research could incorporate larger datasets and employ advanced statistical techniques and sensitivity analyses.

Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1. Basic information on interview sample targets.

Profile	***Category***	***Frequency***	***Percentage***
Gender	Male	13	86.67%
	Female	2	12.33%
Occupation	ICEs' Practitioners	12	80.00%
	Academia	2	13.33%
	Government personnel	1	6.67%
Education	Bachelor	8	53.33%
	Master	3	20.00%
	Doctorate	4	26.67%
Working region (for practitioners)	Southeast Asia	2	16.67%
	Middle East	5	41.67%
	Africa	3	25.00%
	Europe	1	8.33%
	Northen America	1	8.33%
Working overseas experience	0-5 years	4	26.67%
	6-10 years	8	53.33%
	>10 years	3	20.00%
Position level	Deputy manager	1	6.67%
	Department Manager	5	33.33%
	Others(e.g., General Stuff)	6	40.00%
	Full Professer	1	6.67%
	Associate Professor	1	6.67%
	Department Head	1	6.67%

Table 2. Partical open coding results for data sharing

Representative content	***Two-prolonged open coding results***		***Sub-Initial No.***	***Child Node (Concept)***
	Manpower	***ChatGPT-4o***		
If we see it as critical to achieving our business goals, like improving project efficiency or strengthening partnerships, we’re more inclined to do it. (*P2, P4, P5*)	Data-sharing inclination	Action driven by perceived value	$A1_1$	Behavioral intent toward sharing
I think in today's era of rapid information development, the interflow of data is a very meaningful thing. We should be open to data sharing. (*P7, P10*)	Positive attitude toward data sharing	Advocacy for openness in data sharing	$A1_2$	Openess to data sharing
Companies with high business turnover are usually more cautious about sharing data because of the large amounts of sensitive data. (*P2, P11*)	Business turnover	High business turnover	$A2_1$	Business turnover
For organisations with larger workforces, they typically have more in-house resources and technical capabilities to analyse and manage data. (*P1, P6*)	Workforce size	Impact of workforce size	$A2_2$	Employee size
Companies with higher ratings tend to provide data that is more authoritative and persuasive. (*P7, P8*)	Status of the company	Impact of high company ratings	$A5_1$	Companies’ rating
When data is shared, its authenticity is the basis for ensuring that projects are delivered securely and in a timely manner. (*P1, P12*)	Data authenticity	Importance of data authenticity	$B3_1$	Data authenticity
When data crosses borders, it should be mindful of sensitive data that relates to countries and individuals so as not to infringe on local data regulations. (*R1, P4, P11*)	Compliance with local data laws	Compliance with local data regulations	$C1_1$	Compliance with local data regulations
If companies have a strained relationship with the local government, they may face stricter scrutiny and restrictions, affecting the sharing and flow of data. (*G1, P5, R2*)	Tensions with the Government	Impact of strained relationships	$D1_1$	Situation with the Government
Sharing data can light up a company's bottom line and thus make it less competitive. (*P1, P3*)	Declining competitiveness	Impact of data sharing on competition	$D3_1$	Reduction of competitiveness
It is possible that some religions, like Islam, emphasise respect for individual and collective privacy. (*R1, R2*)	Religional influence	Influence of religion on practices	$F1_1$	The religional impact

Prompt Pattern I for ChatGPT-4o Open Coding:

You are an expert specializing in grounded theory. I want to identify key concepts/themes from qualitative interview transcripts for open coding in grounded theory.
Here is an excerpt from one of the interviews:
[Insert text]
Please analyze the following text line by line and suggest initial codes for grounded theory analysis.
Please note if two or more themes are same or similar, please provide a same concept for them. Thank you!

Note: **P** refers to Practitioner, **G** refers to Government Employee, **R** refers to Researcher.

Table 3. Results of axial and selective coding

Child Node (Concept)	***Two-prolonged axial coding results***		***Parent Node***	***Core Node (Manpower&GPT)***
	Manpower	***ChatGPT-4o***		
Behavioral intent toward sharing; Openess to data sharing	Willingness to share data	Willingness to share data	***W***illingness to share data	***Firm-Specific Factors***
Business turnover; Employee size	Corporate scale	Corporate resources and capacity	***C***orporate scale	
Firm hierarchical structure; Decision-makeing process	Coporate operation strcuture	Firm governance and decision-making	***C***oporate operation mechanism	
Mutual trust and collaboration; Reliability	Trust and collaboration	Trust and collaboration	***T***rust and collaboration	
Companies' rating; Good image	Corporate status	Reputation and Trust	***C***orporate reputation and status	
Misinterpret; Criticize; Falsify; Beforehand use data	Misconduct of data sharing	Data sharing misuse	***M***isconduct of data sharing	***Technological Factors***
Technical interoperability; data sharing standards; Common data environment	Data-sharing technology	Technical compatibility	***D***ata-sharing technical maturity	
Data content; Data type; Data structure	Data type and format	Data characteristics	***D***ata type and format	
Data accuracy; Data validation; Data authenticity and operability; Data timeliness	Data quality	Data quality	***D***ata quality	
Cross-boder regulation; Compliance with local data laws	Adherence to national regulations on cross-border data flows	Legal and Regulatory Compliance	***C***ompliance with cross-border data flow	***Legal and Regulatory Factors***
Data ownership; Intellectual property propection; Data security and confidentiality	Data ethics	Data security and protection	***D***ata ethics and security	
Enterprise response mechanisms when risks occur; Effectiveness and timeliness of dispute resolution methods	Dispute resolution mechanisms	Risk and Conflict Management	***M***echanisms for resolving data-sharing disputes	
Situation with the government; Political stability; Government intervention	Political environment	Political and Governmental Environment	***P***olitical environment	***Social Factors***
Government financial support;	Incentives policies	Governmental Financial Support	***F***inancial incentives	

Governmental incentives		and Incentives		
Competition among peers; Intense market environment	Peer competition	Market Competition	***P***eer competitions	
Slower to embrace new technologies; Reluctance to adopt new technologies	Change resistance	Reluctance to Adopt New Technologies	***C***hange resistance in industry	
Data are exchanged in a form that meets the requirements of the other party; Data has to be recognised by the other party	Data recognition by clients	Data Compatibility and Recognition	***C***lient's satisfaction	
Costs of technology introduction; Costs of setting up the data exchange platform	Sharing cost	Costs of technology implementation	***F***inancial cost	***Financial Factors***
Increased benefits lead to reduced costs; Company revenue surplus; Profit from sharing	Financial profit	Financial benefits of data-sharing	***C***oporate profit	
Cultural diversity; Religious sensitivity	Cultural and religious diversity	Cultural and social diversity	***C***ultural and religious diversity	***Cultural Factor***s
Different language; Daily communication variety	Language diversity	Communication diversity	***L***anguage distinctions	

Prompt Pattern II for ChatGPT-4o Axial Coding:

You are an expert specializing in grounded theory. The child nodes related to the influential factors of data sharing are provided for you. Please conduct the axial coding process for the child nodes (subcategories). Please list each parent node for abstracting child nodes and explain it.

Here are the child nodes retrieved from the open cpoding process:

[Insert text]

Please note if two or more themes are same or similar, please provide a same concept for them. Thank you!

Prompt Pattern III for ChatGPT-4o Selective Coding:

You are an expert specializing in grounded theory. The parent nodes related to the influential factors of data sharing are provided for you. Please conduct the selective coding process for the parent nodes (categories). Please list the core category and explain it.

Here are the parent nodes retrieved from the axial cpoding process:

[Insert text]

Please note if two or more themes are same or similar, please provide a same concept for them. Thank you!

Table 4. Fuzzy adjacency matrix ***N*** of factors affecting data sharing among ICEs.

Factor	*A₁*	*A₂*	*A₃*	*A₄*	*A₅*	*A₆*	*B₁*	*B₂*	*B₃*	*C₁*	*C₂*	*C₃*	*D₁*	*D₂*	*D₃*	*D₄*	*D₅*	*E₁*	*E₂*	*F₁*	*F₂*
A_1	0.00	0.38	0.35	0.48	0.40	0.65	0.65	0.73	0.68	0.50	0.50	0.63	0.50	0.50	0.43	0.50	0.53	0.48	0.38	0.35	0.38
A_2	0.55	0.00	0.90	0.40	0.88	0.65	0.78	0.53	0.50	0.63	0.65	0.63	0.75	0.65	0.68	0.78	0.40	0.50	0.40	0.40	0.38
A_3	0.68	0.38	0.00	0.35	0.38	0.40	0.43	0.35	0.38	0.40	0.40	0.50	0.38	0.43	0.40	0.78	0.40	0.53	0.50	0.43	0.40
A_4	0.80	0.40	0.40	0.00	0.75	0.78	0.55	0.50	0.75	0.78	0.78	0.78	0.50	0.53	0.65	0.55	0.43	0.43	0.40	0.40	0.40
A_5	0.53	0.38	0.40	0.78	0.00	0.65	0.40	0.40	0.65	0.68	0.43	0.55	0.78	0.40	0.65	0.53	0.40	0.40	0.40	0.65	0.53
A_6	0.95	0.40	0.43	0.80	0.70	0.00	0.55	0.58	0.95	0.95	0.95	0.70	0.65	0.45	0.43	0.68	0.65	0.58	0.55	0.40	0.40
B_1	0.80	0.38	0.40	0.40	0.40	0.75	0.00	0.65	0.90	0.88	0.75	0.75	0.50	0.43	0.38	0.65	0.50	0.65	0.53	0.38	0.38
B_2	0.78	0.40	0.38	0.48	0.38	0.50	0.63	0.00	0.73	0.63	0.60	0.48	0.35	0.38	0.35	0.48	0.48	0.48	0.35	0.38	0.38
B_3	0.68	0.38	0.38	0.50	0.65	0.63	0.63	0.63	0.00	0.63	0.63	0.50	0.50	0.40	0.38	0.50	0.50	0.38	0.38	0.38	0.38
C_1	0.55	0.40	0.35	0.48	0.63	0.63	0.48	0.63	0.78	0.00	0.75	0.65	0.78	0.53	0.38	0.53	0.53	0.63	0.48	0.38	0.35
C_2	0.65	0.35	0.38	0.48	0.50	0.75	0.60	0.60	0.53	0.73	0.00	0.60	0.60	0.40	0.40	0.50	0.63	0.50	0.38	0.38	0.38
C_3	0.65	0.35	0.40	0.65	0.53	0.75	0.78	0.75	0.75	0.75	0.73	0.00	0.48	0.53	0.38	0.50	0.53	0.50	0.38	0.50	0.38
D_1	0.53	0.35	0.40	0.53	0.63	0.60	0.35	0.35	0.38	0.75	0.75	0.50	0.00	0.40	0.40	0.38	0.50	0.63	0.63	0.50	0.35
D_2	0.90	0.38	0.38	0.75	0.38	0.75	0.75	0.73	0.75	0.75	0.73	0.73	0.50	0.00	0.50	0.73	0.48	0.63	0.50	0.35	0.35
D_3	0.65	0.38	0.43	0.65	0.65	0.78	0.55	0.53	0.53	0.40	0.40	0.53	0.40	0.40	0.00	0.78	0.38	0.78	0.78	0.40	0.40
D_4	0.78	0.38	0.65	0.38	0.53	0.53	0.88	0.78	0.63	0.63	0.60	0.63	0.53	0.78	0.53	0.00	0.65	0.53	0.63	0.38	0.38
D_5	0.63	0.35	0.48	0.50	0.63	0.48	0.53	0.53	0.55	0.53	0.53	0.53	0.65	0.48	0.48	0.60	0.00	0.50	0.50	0.40	0.40
E_1	0.68	0.38	0.43	0.53	0.35	0.38	0.63	0.63	0.63	0.60	0.60	0.63	0.53	0.63	0.53	0.78	0.53	0.00	0.90	0.40	0.38
E_2	0.78	0.63	0.50	0.40	0.75	0.78	0.78	0.68	0.78	0.78	0.80	0.78	0.55	0.80	0.78	0.78	0.53	0.50	0.00	0.40	0.40
F_1	0.80	0.38	0.40	0.63	0.65	0.63	0.63	0.78	0.65	0.73	0.75	0.75	0.78	0.50	0.53	0.53	0.50	0.63	0.63	0.00	0.63
F_2	0.73	0.33	0.33	0.58	0.48	0.45	0.58	0.70	0.50	0.60	0.60	0.60	0.63	0.48	0.50	0.48	0.48	0.60	0.60	0.60	0.00

Table 5. Reachability matrix ***M*** of factors affecting data sharing among ICEs.

Factor	A_1	A_2	A_3	A_4	A_5	A_6	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	D_4	D_5	E_1	E_2	F_1	F_2	DR_p
A_1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	***2***
A_2	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0	1	0	***15***
A_3	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0	1	0	***14***
A_4	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
A_5	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
A_6	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
B_1	1	0	0	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***11***
B_2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	***1***
B_3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	***1***
C_1	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
C_2	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
C_3	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	0	***12***
D_1	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	1	0	***10***
D_2	1	0	0	1	1	1	0	1	1	1	1	0	1	1	0	0	0	0	0	1	0	***11***
D_3	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	***16***
D_4	1	0	0	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0	1	0	***13***
D_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	***1***
E_1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	***16***
E_2	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	***16***
F_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	***1***
F_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	***1***
DE_p	***16***	***1***	***2***	***15***	***15***	***15***	***8***	***17***	***16***	***15***	***15***	***1***	***15***	***7***	***3***	***6***	***1***	***3***	***3***	***16***	***1***	

Table 6. The $\boldsymbol{C_R}$ value of each pairwise comparison.

C_R	A_1	A_2	A_3	A_4	A_5	A_6	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	D_4	D_5	E_1	E_2	F_1	F_2
A	0.0182	0.0088	0.0442	0.0000	0.0304	0.0695	-	0.0000	0.0291	0.0000	0.0175	0.0516	0.0000	0.0000	0.0515	0.0270	0.0000	-	0.0622	0.0000	0.0000
B	0.0088	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0088	0.0000	0.0000	0.0000
C	0.0516	0.0000	0.0516	0.0000	0.0516	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0516	0.0000	0.0000	0.0000
D	0.0307	0.0290	0.0088	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
E	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7. The unweighted supermatrix $\boldsymbol{W}$ of affecting factors for data sharing among ICEs.

W	A_1	A_2	A_3	A_4	A_5	A_6	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	D_4	D_5	E_1	E_2	F_1	F_2
A_1	0.000	0.000	0.000	0.000	0.000	0.281	0.000	0.000	0.157	0.000	0.000	0.000	0.000	0.000	0.000	0.282	0.000	0.000	0.189	0.000	0.000
A_2	0.302	0.000	0.431	0.000	0.368	0.298	0.377	0.000	0.211	0.000	0.195	0.311	0.000	0.000	0.310	0.192	0.000	0.464	0.277	1.000	0.000
A_3	0.104	0.540	0.000	0.000	0.150	0.000	0.085	0.000	0.000	0.500	0.220	0.493	0.000	0.000	0.000	0.000	0.000	0.175	0.236	0.000	0.000
A_4	0.265	0.000	0.207	0.000	0.200	0.245	0.300	0.000	0.128	0.000	0.281	0.000	0.000	0.000	0.338	0.271	1.000	0.157	0.000	0.000	0.000
A_5	0.187	0.297	0.138	0.667	0.000	0.176	0.000	0.000	0.296	0.000	0.141	0.196	0.667	0.000	0.181	0.132	0.000	0.204	0.150	0.000	0.000
A_6	0.141	0.163	0.224	0.333	0.282	0.000	0.238	0.000	0.209	0.500	0.163	0.000	0.333	0.000	0.171	0.123	0.000	0.000	0.148	0.000	0.000
B_1	0.540	0.000	0.000	0.500	0.000	0.667	0.000	1.000	0.000	1.000	0.667	1.000	0.000	1.000	0.000	0.500	0.000	0.540	1.000	0.000	0.000
B_2	0.163	0.000	0.000	0.000	0.000	0.000	0.250	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.163	0.000	0.000	0.000
B_3	0.297	0.000	0.000	0.500	1.000	0.333	0.750	0.000	0.000	0.000	0.333	0.000	0.000	0.000	0.000	0.500	0.000	0.297	0.000	0.000	0.000
C_1	0.413	0.000	0.413	0.333	0.413	0.400	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.584	0.667	0.000	0.000
C_2	0.327	0.000	0.260	0.333	0.260	0.400	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.184	0.000	0.000	0.000
C_3	0.260	0.000	0.327	0.333	0.327	0.200	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.232	0.333	0.000	0.000
D_1	0.114	0.327	0.540	0.000	0.333	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.500	0.000	0.000	0.250	0.000	0.000	0.000
D_2	0.266	0.260	0.163	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.000	0.750	1.000	0.000	0.000
D_3	0.320	0.000	0.297	0.000	0.000	0.500	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000
D_4	0.164	0.413	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D_5	0.138	0.000	0.000	0.000	0.667	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000
E_1	0.667	0.500	1.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.333	0.000	0.000	0.500	0.500	0.750	0.000	0.000	1.000	0.000	0.000
E_2	0.333	0.500	0.000	1.000	0.000	0.500	1.000	0.000	0.000	0.000	0.667	0.000	0.000	0.500	0.500	0.250	0.000	1.000	0.000	0.000	0.000
F_1	0.500	0.000	0.500	0.000	0.000	1.000	0.000	0.000	0.000	0.500	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F_2	0.500	0.000	0.500	0.000	0.000	0.000	1.000	1.000	1.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000

Tables 8. The relative weight matrix ***R*** for data sharing among ICEs.

R	***A***	***B***	***C***	***D***	***E***	***F***
A	0.333	0.187	0.237	0.191	0.250	0.500
B	0.099	0.214	0.177	0.104	0.126	0.000
C	0.160	0.144	0.160	0.223	0.161	0.000
D	0.170	0.155	0.196	0.203	0.195	0.500
E	0.177	0.237	0.149	0.191	0.181	0.000
F	0.060	0.064	0.080	0.087	0.087	0.000

Tables 9. The weighted supermatrix W_0 of affecting factors for data sharing among ICEs.

W_0	A_1	A_2	A_3	A_4	A_5	A_6	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	D_4	D_5	E_1	E_2	F_1	F_2
A_1	0.000	0.000	0.000	0.000	0.000	0.094	0.000	0.000	0.063	0.000	0.000	0.000	0.000	0.000	0.000	0.078	0.000	0.000	0.052	0.000	0.000
A_2	0.101	0.000	0.159	0.000	0.161	0.099	0.071	0.000	0.085	0.000	0.050	0.107	0.000	0.000	0.101	0.053	0.000	0.127	0.076	1.000	0.000
A_3	0.035	0.264	0.000	0.000	0.066	0.000	0.016	0.000	0.000	0.139	0.057	0.169	0.000	0.000	0.000	0.000	0.000	0.048	0.065	0.000	0.000
A_4	0.088	0.000	0.076	0.000	0.087	0.082	0.056	0.000	0.051	0.000	0.073	0.000	0.000	0.000	0.110	0.075	0.461	0.043	0.000	0.000	0.000
A_5	0.062	0.145	0.051	0.289	0.000	0.059	0.000	0.000	0.119	0.000	0.036	0.067	0.307	0.000	0.059	0.037	0.000	0.056	0.041	0.000	0.000
A_6	0.047	0.080	0.083	0.144	0.123	0.000	0.045	0.000	0.084	0.139	0.042	0.000	0.154	0.000	0.056	0.034	0.000	0.000	0.041	0.000	0.000
B_1	0.054	0.000	0.000	0.064	0.000	0.066	0.000	0.769	0.000	0.208	0.128	0.257	0.000	0.353	0.000	0.076	0.000	0.075	0.138	0.000	0.000
B_2	0.016	0.000	0.000	0.000	0.000	0.000	0.053	0.000	0.459	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000	0.000
B_3	0.029	0.000	0.000	0.064	0.130	0.033	0.160	0.000	0.000	0.000	0.064	0.000	0.000	0.000	0.000	0.076	0.000	0.041	0.000	0.000	0.000
C_1	0.066	0.000	0.073	0.069	0.087	0.064	0.000	0.000	0.000	0.000	0.174	0.000	0.539	0.000	0.000	0.000	0.000	0.103	0.117	0.000	0.000
C_2	0.052	0.000	0.046	0.069	0.055	0.064	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.539	0.032	0.000	0.000	0.000
C_3	0.042	0.000	0.058	0.069	0.069	0.032	0.144	0.000	0.000	0.189	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041	0.059	0.000	0.000
D_1	0.019	0.082	0.102	0.000	0.074	0.000	0.000	0.000	0.000	0.231	0.000	0.284	0.000	0.000	0.174	0.000	0.000	0.053	0.000	0.000	0.000
D_2	0.045	0.065	0.031	0.000	0.000	0.085	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.148	0.000	0.160	0.214	0.000	0.000
D_3	0.054	0.000	0.056	0.000	0.000	0.085	0.000	0.000	0.000	0.000	0.213	0.000	0.000	0.000	0.000	0.148	0.000	0.000	0.000	0.000	0.000
D_4	0.028	0.103	0.000	0.000	0.000	0.000	0.155	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D_5	0.023	0.000	0.000	0.000	0.149	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.174	0.000	0.000	0.000	0.000	0.000	0.000
E_1	0.118	0.130	0.197	0.000	0.000	0.089	0.000	0.000	0.000	0.000	0.054	0.000	0.000	0.323	0.163	0.207	0.000	0.000	0.198	0.000	0.000
E_2	0.059	0.130	0.000	0.230	0.000	0.089	0.237	0.000	0.000	0.000	0.108	0.000	0.000	0.323	0.163	0.069	0.000	0.198	0.000	0.000	0.000
F_1	0.030	0.000	0.033	0.000	0.000	0.060	0.000	0.000	0.000	0.047	0.000	0.116	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F_2	0.030	0.000	0.033	0.000	0.000	0.000	0.064	0.231	0.138	0.047	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 10. The limit supermatrix $\boldsymbol{W_l}$ of factors affecting data sharing among ICEs.

W_l	A_1	A_2	A_3	A_4	A_5	A_6	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	D_4	D_5	E_1	E_2	F_1	F_2
A_1	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.000
A_2	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.000
A_3	0.059	0.059	0.059	0.059	0.059	0.059	0.058	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.000
A_4	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.000
A_5	0.068	0.069	0.069	0.068	0.068	0.068	0.068	0.068	0.068	0.069	0.068	0.069	0.069	0.068	0.068	0.068	0.068	0.068	0.068	0.069	0.000
A_6	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.000
B_1	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.000
B_2	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.026	0.026	0.025	0.025	0.025	0.025	0.026	0.025	0.025	0.025	0.025	0.025	0.025	0.000
B_3	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.000
C_1	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.000
C_2	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.000
C_3	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.051	0.000
D_1	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.000
D_2	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.049	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.000
D_3	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.019	0.019	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.000
D_4	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.000
D_5	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.000
E_1	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.000
E_2	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.000
F_1	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.000
F_2	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.000
Rank	***20***	***3***	***8***	***12***	***6***	***7***	***1***	***14***	***13***	***5***	***17***	***10***	***9***	***11***	***18***	***15***	***21***	***4***	***2***	***19***	***16***

Table 11. Priorities of the top ten factors.

Factors	***Limiting Value***	***Ranking***
Data-sharing technical maturity (B_1)	*0.09870*	*1*
Coporate profit (E_2)	*0.08958*	*2*
Corporate scale (A_2)	*0.08148*	*3*
Financial cost (E_1)	*0.07334*	*4*
Compliance with cross-border data flow (C_1)	*0.07207*	*5*
Corporate reputation and status (A_5)	*0.06849*	*6*
Misconduct of data sharing (A_6)	*0.06044*	*7*
Corporate operation structure (A_3)	*0.05852*	*8*
Political environment (D_1)	*0.05711*	*9*
Mechanisms for resolving data-sharing disputes (C_3)	*0.05097*	*10*