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Establishment and Cluster Analysis of Performance Evaluation Index System for New Retail Enterprises Driven by Blockchain Technology

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Abstract

Over the last few years, the further transfomation of retailing derived from growing development and integration of Internet has led to the emergence of new retail mode as a tendency conforming to the demand of the consumer market. Blockchain technology as a major innovation in supply chain has a wide prospect and only little investigation about its application is available in the literature. Literature and expert opinion interpretation in index are further analyzed and modeled using fuzzy-interpretive structural modeling (FISM), Fuzzy Matriced Impacts Corises-Multiplication Appliance Classment (FMICMAC). The combined approach of both FISM and FMICMAC is applied to identify the common drivers to enhance the efficiency of new retailing in the light of efficient supply chain management. The findings in the article endorse that the traditional retailing can be made efficient by integrating the blockchain technology considering three most driving characteristics, namely, Effective Information, Interactive Reflection and Information Circulation. The study carried out in this article motivates industries to implement blockchain technology in their new retailing model. It will reduce the transaction cost, documentation work, save time and eliminate human error. The common characteristics identified in this proposed work would help in managerial decisions for the adoption of blockchain technology to ensure that the system becomes more transparent, easily traceable and finally improves the performance.

Keywords

New Retail, Blockchain Technology, Measurement, FISM, FMICMA

1. Introduction

Since the outbreak of the pneumonia epidemic, both China and the global economy have suffered an unprecedented blow. The trend of anti-globalization has intensified, and the domestic economic circulation is facing severe challenges like never before. The CPC Central Committee put forward the strategic plan of "accelerating the construction of a new development pattern with the domestic cycle as the main body and the domestic and international double cycle promoting each other", as well as putting forward new requirements for the innovation of the circulation supply chain system (Li, 2021), to cope with the internal and external pressures faced by the domestic economy. E-commerce enterprises, as the new industry with the largest scale, the most active performance and the best development momentum in the digital economy, is an important intermediary connecting the supply side and the consumption side, and is a key node for realizing the circular flow of various factors of production. Therefore, it is necessary to grasp the strategic opportunity of building a double-cycle development pattern to accelerate the transformation, development and optimization and upgrading of the industry. The value orientation of e-commerce determines its social vitality, and through the digital transformation of the e-commerce industry, it plays its radiation effect to drive and promote the transformation and upgrading of related industries.

In the present scenario, retail market is one of the aggressively expanding markets in China resulting considerable competition. Judging from the 2017-2022 statistical yearbook of China, the total online retail sales increased by 30.66% in 2017 and 28.09% in 2018, with the growth rate decreasing year by year. This trend has displayed itself in online network channel thriving whereas e-commerce slowing down. In response to this situation, "consumer-oriented" has gradually replaced "product-oriented" as a new direction of domestic retail market in China. The new retail model taking customer as the center and answering their individual needs has been followed with extensive interests. In summary, the traditional e-commerce enterprises to the new retail model enterprise transformation is the general trend. However, the question of how to carry out the transformation and upgrading in a reasonable and effective manner is an important issue that requires more research attention.

According to PwC's Strategy & "Winning Ways for Retailers in the Era of 'New Retail'", if retailers want to seize the opportunities and succeed in the market in the era of "New Retail", they need to take three steps in addition to having a deep understanding of the nature and characteristics of new retail. In addition to a deep understanding of the nature and characteristics of new retail, a three-step process is needed, including data-driven identification of consumer demand, decomposition of the consumer journey, exploration of potential solutions in each segment, and integration of resource capabilities. Therefore, constructing and evaluating the evaluation index system of new retail enterprises can effectively improve enterprise efficiency, enhance core competitiveness, and stand firmly in the era of "new retail". There are many scholars who carry out the construction of new retail evaluation index system from different perspectives or based on a certain theory. For the sake of enhance the competitiveness of enterprises, an index system based on enterprise niche theory was proposed in document (Wei & Di, 2018); Based on the technology acceptance model and the rational behavior theory, Wang et al. (2021) developed a theoretical model for the assessment of information credibility in new retailing. As a result, there is no unified system of evaluation indicators for new retail.

Taking the characteristics of the new retail model, which is a consumer-centered data-driven model, the explosive growth in the face of the volume of data has increased the burden of data processing on retail enterprises, and moreover, it has brought about security risks. Besides, blockchain technology has some outstanding characteristics, like decentralization, unchangeable information, open and transparent supply chain network, traceable data, safety and credibility, anonymity of user information and autonomy, which attract lots of scholars to apply in supplychain (Kamble et al., 2018b). In this paper, we construct a new blockchain technology-based evaluation index system for new retail enterprises and use the graph-based FISM method to establish connections among the index factors; and use the FMICMAC method was used to classify the relationships between evaluation indicators according to the strength of drivers and dependencies, and to identify the most basic and crucial indicator factors for improving the performance of new retail enterprises.

The main contribution of this paper is that we propose a new retail evaluation index system that combines the characteristics of blockchain technology to comprehensively evaluate the performance of new retail enterprises, and apply FISM-FMICMAC to this index system to screen the key factors that are the most effective in enhancing the performance of enterprises to realize transformation, so as to provide certain development ideas for the transformation of enterprises. Due to the different features and characteristics of different retail enterprises, the indicators proposed here are broad and can be modified more finely for specific enterprises. Moreover, the approach to interpretative structure modeling can be expanded by incorporating other theories, such as Bayesian network.

2. Literature Review

2.1. Retail Evaluation Application

In terms of the nature of the indicators, they can be divided into financial indicators (Xia & Zhang, 2010; Feng & Yi, 2012), non-financial indicators (Zhao, 2015; Sun et al., 2015), and a combination of both (Han et al., 2022; Zhou et al., 2018), based on whether they can be calculated using financial data or not. Mmost of the evaluations of the retail industry are based on or centered around the quantitative indicators of the 2002 Enterprise Performance Evaluation Indicator System (EPES), and have gradually strengthened the consideration of non-financial indicators, but the flexibility is still lacking. Therefore, this paper combines the features of blockchain technology to develop an indicator system that integrates quantitative and qualitative indicators. This system is well-suited to the unique characteristics of new retail enterprises.

From the perspective of evaluation index construction, generally speaking, the establishment of the evaluation index system of retail enterprise competition or performance is mostly based on five aspects, such as the retail sustainable perspective (Gleim et al., 2013; Li et al., 2022), the enterprise capability perspective (Niu et al., 2018), the perspective of combining enterprise resources and capabilities (Yu et al., 2019; Okur & Ercan, 2022), the business process perspective (Shi et al., 2017), and the customer demand perspective (Liu et al., 2018; Helm et al., 2018). However, taking customer demand as the origin is more in line with the characteristics and central concept of the new retail model, so this paper focuses on meeting consumer demand and synthesizes the internal and external factors of the enterprise for the construction of indicators.

2.2. Blockchain Technology

Blockchain emerged as a technology to support transactions in the field of cryptocurrencies (Nakamoto, 2008), as it is a fully distributed system (Risius & Spohrer, 2017). Several scholars have given different conceptual definitions based on the unique features of blockchain technology, such as "distributed digital ledger or accounting book" (Leng et al., 2018), "distributed data structure replicated and shared among network members" (Christidis & Devetsikiotis, 2016), and "digital logs of transactions" (de Leon et al., 2017).

The primary core technologies of blockchain itself include distributed ledger, in which transaction accounting is done by multiple nodes distributed in different nodes (Walport, 2016); asymmetric encryption, in which public and private keys are used to encrypt and decrypt the transaction information stored on the blockchain (Antonopoulos, 2014); consensus mechanism, in which all peers in the blockchain network must act under certain conditions and reach a collective agreement (Chen et al., 2020); and smart contracts, in which "input" information is executed completely and accurately as soon as it meets the operating conditions, and no party is granted any modification (Yli-Huumo et al., 2016).

The above core technology of blockchain is of great help to the data processing as well as security issues encountered in the transformation process of new retail enterprises. Next, discover how academics are combining blockchain technology with new retail businesses.

2.3. Blockchain Technology Application in New Retail

In the field of new retail, practice often precedes theory, and more and more enterprises have successfully explored in practice, which triggers more scholars to think deeply, combining with other theories to make the research in this area more fulfilling and full, such as the theory of empowerment: blockchain can empower new retail from the supply chain side, logistics side, and transaction side in the three fields (Yang & Niu, 2019); combining with representative literature to conduct scientific measurement analysis, four key paths for blockchain to empower new retail were proposed (Liu & Tang, 2021). Some scholars also try to explore the new retail ecological map, Yang and Niu (2019) simply portrayed the aspect of online and offline integration and interoperability; Xu and Guo (2021) defined the connotation of the new retail ecosystem and the four major mechanisms of action in a more detailed way, and put forward the corresponding enhancement strategies.

Therefore, the application of blockchain technology in the field of new retail requires further research and practice, not only to continue the qualitative analysis at the theoretical level, but also to combine with mathematical models and other means of quantitative analysis to promote the successful transformation of new retail. For this reason, this paper fills this gap, and constructs a relatively novel indicator evaluation system with an in-depth understanding of the characteristics of blockchain technology and how it is reflected in the new retail model.

Not only that, but there is little about the application of explanatory structural modeling to retail evaluations, which will be covered in 4.2.

3. Indicators

After several reforms and advancements, we discover that customer scale is the cornerstone and fundamental guarantee for the long-term development of retail enterprises. As the era of shopping is an era of trust-based consumption, it is critical to build a foundation of trust and improve consumer satisfaction. Blockchain, as a "trust-making machine" (Berkeley, 2015), is a bridge to build trust. In the customer expectation theory proposed by Anderson et al. (1994), customers' expectations are derived from three dimensions: their experience with the retailer, the reputation of the retailer, and the confidence they have in the retailer's future products. On the basis of this and the ecological niche theory, the following 13 relevant indicators are proposed in this paper.

R1 Product Quality

The product is the physical object that connects the entire supply chain. The quality of products is crucial for the long-term success of retail enterprises operating under the new retail mode. Improving product quality is the key to enhancing enterprise competitiveness. Blockchain technology offers the possibility to share and tamper-proof product information at each link, which can help prevent illegal traders from fabricating counterfeit product information to some extent. Chia et al. (2019) designed "Fakeout" using blockchain technology to provide customers with a unique blockchain code to verify the authenticity of products. In quality-sensitive industries, manufacturers are highly attuned to the quality preferences of consumers for new products, particularly when they have their own distribution channels (Zhang et al., 2019). Huang et al. (2020) demonstrated that the spontaneous information sharing actions of retailers can motivate upstream firms to increase their investments in order to gain higher spillovers. Therefore, blockchain can not only enhance consumers' trust in products but also encourage upstream manufacturers to prioritize improving product quality by offering a platform for information sharing.

R2 Effective Information

The most notable adoption of blockchain technology is to maintain the authenticity and validity of information, covering the safety and security of product information, logistics information, transaction information, and consumers' personal information. Thang and Tan (2003) argued that customer perceived risk and satisfaction are inversely proportional, and only if security is increased, customer satisfaction will raise. In pursuit of a more transparent market, blockchain technology has been employed for the development of reputation systems (Soska et al., 2016). The authenticity and security of information are the biggest guarantees of blockchain-based new retail models, which also provide the strongest competitive advantage compared to other retail models.

R3 Brand Loyalty

Loyalty is the most valuable asset of a company's brand, with greater market share resulting from customer loyalty (Chaudhuri & Holbrook, 2001). Blockchain technology supports companies to give sufficient product as well as reputation guarantees to consumers and decreases the degree of consumer sensitivity to price. As revealed by Batra et al. (2012), attitude strength (holding more certain and confident attitudes) is associated with higher brand likability for more preferred brands compared to less preferred brands. In other words, the brand reputation constructed by blockchain will continuously enhance both its brand loyalty and stabilize consumers' propensity to consume the brand.

R4 Scene Experience

The reason why new retail is "new" is that its value creation is no longer limited to exchange value and use value, rather it is more about the degree of scenario value creation and the ability to create it. Technology has now become the most compelling driving force in shaping consumer experience and service delivery Lu et al. (2019). Scenarios inspire emotions and experiences form word-of-mouth. Blockchain technology enables the rapid and precise identification of consumer needs, consumption habits, and preferences through data analysis. This analysis allows for the creation of relevant scenarios that can shape emotional resonance and increase brand loyalty.

R5 Payment Experience

The core blockchain technology-distributed ledger is regarded as having a disruptive impact, with a trust-based ecosystem helping to revolutionize transactions, processes, and business models, improve the consumer payment experience, and extend the existing functionality of general ledger accounting by integrating it with digital cryptography (Gomber et al., 2018). This decentralized nature enables new retail to achieve point-to-point transactions from the source to the end, the so-called straight-through production and sales. No third-party trust endorsement is required, which shortens the distance between consumers and the manufacturing end, speeds up payments, and provides the opportunity to accurately grasp consumer preferences. This offers the possibility of personalized services.

R6 Digital Experience

New retailing is a product of digital transformation. Digital transformation means that new technologies, including blockchain, are utilized to attain dramatic business improvements that enhance customer experience, streamline operations, or create new business models (Warner & Wäger, 2018). Consumers expect product customization for a better experience, and the cost and technical challenges of product customization pose a dilemma for new retail. The solution to this dilemma requires a deeper integration of digital technologies.

Blockchain technology allows for the sharing of consumer data to drive digital consumption and enhance data security. For example, DTC (Directer to Customer), new social retail, and interest-based e-commerce provide retailers with real-time data analysis and diagnostics of the customer experience. This allows them to make further adjustments to merchandise selection, discount pricing, and other detailed marketing strategies in real time, based on consumers' personalized preferences. It also enables them to issue comprehensive strategies for optimizing products to meet these needs. Smart contracts can automatically process associated transaction operations, avoiding the delays and errors of manual efforts and saving consumers' time. This enables consumer goods brands to scale quickly, gain insights into all aspects of their operations, and eliminate blind spots, ultimately providing a better consumer experience.

R7 Logistics Service

Logistics services are a necessity for Internet retailing, a value-added service for traditional retailing, and moreover, a key component of new retailing. Given the competition in the retail industry, the quality of logistics services directly impacts customer demand for products (Fu & Liao, 2017). In addition to meeting the basic requirements of goods availability, speed and quality are key elements that enhance competitiveness. At present, the area primarily covered by new retail is instant products, such as fresh food, medicine, flowers, etc. The increasing number of consumers purchasing instant products on a daily basis indicates a growing demand and expectation for timely fulfillment (Liu et al., 2023). Blockchain technology plays an important role in solving the problem of logistics information asymmetry. It enables open, transparent, and shared information, reduces the delay in information transmission in all aspects of logistics operations, and ensures the accuracy of information. This, in turn, promotes the achievement of "good offline performance and efficient completion of the closed loop".

R8 After-sales Service

The smart contract of blockchain technology can be used to implement new retail and automatically handle after-sales related business processing. This reduces the time cost for both enterprises and consumers, enables timely response, traces the relevant responsible links, and provides a satisfactory solution to consumers. As a result, the lower the perceived risk of after-sales service by the customer, the higher the consumer's willingness to purchase (Lee et al., 2000). Furthermore, providing quality after-sales service will minimize the likelihood of returns, complaints, and other negative behaviors. This will help establish a reliable brand image and motivate consumers to continue making purchases.

R9 Interactive Reflection

In the management perspective, consumer engagement increases loyalty and satisfaction (Ma et al., 2022). Therefore, new retailers aim to interact with consumers and foster greater engagement. In general, most of the data obtained on the platform represents incomplete explicit information about consumers. Only through frequent interactions between retailers and consumers can they uncover more information about their hidden needs in order to provide more precise services. Both the "information reach" initiated by the platform and the "information search" initiated by the user have a significant positive impact on the final transaction, indicating that the more frequent two-way interaction of information can foster more dynamic purchasing behavior of consumers (Liu et al., 2023).

R10 Information Circulation

Various channels are used to interact with consumers, through which data and information related to consumer behavior and evaluation can be obtained. These pieces of information are interconnected under blockchain technology. They aim to portray the characteristics of consumers as accurately as possible through data collection, correlation, and analysis. This, in turn, provides decision-making support to reduce service blind spots and optimize the quality of products and services. Ultimately, it enhances the shopping experience for consumers. For consumers, it is possible to reduce their information costs, which include comparison costs and search costs, to a certain extent in order to attract consumers and encourage them to make more purchases (Liu et al., 2023).

R11 Cost Effect

"The supply chain of the 'new retail' model is free from the distribution link in the conventional model, making it challenging to control costs." With digitalization backup, cost management may be effectively improved and enhanced.

In terms of retail business activities, operation and logistics and distribution are the key points for cost control. In addition to reducing distribution costs, retail enterprises can enhance their bargaining power by comparing multiple manufacturers and thereby reduce the purchase price to some extent. Lee et al. (2000) concluded that the acquisition of consumer information helps retailers to better understand market trends. This, in turn, enables them to effectively organize their inventory and set reasonable sales prices. With blockchain technology support, real changes in market demand and timely access to logistics information are useful for strategic planning of inventory, higher product turnover, and lower storage costs.

In addition, the integrated management of offline and online largely saves the investment of repeated management costs. Besides, whether it is online marketing or offline experience, the improvement of customer acquisition ability of one party can be driven by the flow of the other party, which decreases the cost of customer acquisition. Certainly also the smart contract technology saves many intermediate manual operation links, etc., all of which effectively bring down the cost with the application of blockchain technology.

R12 Flexibility Effect

The integration of online and offline channels under the new retail model alleviates the risk of demand forecasting (Ma et al., 2022). The ever-changing consumer expectations in different time and space necessitate the implementation of flexible manufacturing. To obtain the data information regarding these dynamic expectations, blockchain technology can be utilized to establish a flexible and responsive supply chain system that aligns with consumer expectations and enables the ability to sense demand. This involves gathering consumer data from both online and offline sources, thereby enhancing the speed of response in new retail and achieving accurate positioning. The flexibility effect additionally includes accurate projection from data, scientific and reasonable setting of incoming and outgoing goods, improving effective supply and controlling lower inventory.

R13 Integration Effect

New retail can break through the pain points of real economy development by combining technological innovation, among which technological innovation can be manifested in technology integration innovation, i.e. deep integration and cross-application of blockchain technology with big data, Internet of Things, artificial intelligence, etc. For instance, blockchain and Internet of Things (IoT) technology fusion, blockchain technology solves the problems of long ecological chain and high information asymmetry in the field of IoT, treats the collected data as digital assets, guarantees the security and consistency of data information, and improves the application value of data (Zhang et al., 2020).

The integration of blockchain technology in other areas of new retailing is also promising, for example, in supply chain finance, where an equal and collaborative trading platform is constructed from multiple dimensions of efficiency, cost, and trust, realizing real-time data reconciliation and reducing the trouble of financing difficulties.

In the following, the inter-influence relationships among the proposed 13 relevant indicators will be studied by performing cluster analysis to determine the influence relationships among the indicators.

4. Methodology and Research Design

4.1. Data Collection

The ISM methodology is built on the consensus from a group of experts' opinions through different techniques, such as nominal technique, questionnaire, face-to-face discussion, etc., to establish pairwise contextual relationships among variables (Toktaş-Palut et al., 2014). With this in mind, a questionnaire was designed to collect the opinions of each expert on the contextual and mutual relationships among the indicators listed in part 3. The first section of the questionnaire contained general information about the experts' profiles and the professional roles and backgrounds they belong to. The second section examined the contextual interactions between the identified indicators. The experts were requested to give their written opinions individually to avoid the influence of one opinion on another. These opinions were then aggregated and analyzed to develop the final contextual and mutual relationships matrix. The selected group of suitable experts, who are knowledgeable in the field of Blockchain technology and the new retail model, was found to be small. However, the number of respondents participating in the ISM methodology should not be too many (Govindan et al., 2013a). Thus, a total number of three experts from the field of new retail and blockchain technology were involved. The three experts involved in this study have at least 10 years of academic experience in universities. One expert has approximately 14 years of research experience, another has around 17 years of research experience, and the third expert has over 20 years of academic experience. The three professors have published numerous papers both internationally and nationally. They stay updated on current events and make significant contributions to the development of new theories in the field of retail. Therefore, the evaluation of the three scholars mentioned above can be considered reliable and trustworthy.

4.2. ISM Methodology

A method of Integrated Structural Modeling (ISM) for analyzing structural problems in complex socioeconomic systems was developed by Professor Walter Felter in 1974 (Warfield, 1974a; Warfield, 1974b). The fundamental principle of ISM is to determine the various factors that affect the system and their interrelationships through the practical experience and knowledge of experts. It utilizes the matrix of a relation in graph theory and computer technology to process information about the factors and their interrelationships, clarifying the correlation and hierarchy among factors. This allows for the identification of the main (key) factors and their internal links. Referring to the literature (Babu et al., 2020), the basic process of the ISM model is shown in **Figure 1**.

Step 1: The first step is to identify the key variables that are relevant to the research problem through a literature review.

Step 2: From the identified variables in Step 1, a contextual relationship is established among the variables. Pairs of variables will be examined to determine their relationship.

Step 3: To develop a structural self-interaction matrix (SSIM) for variables, which indicates pairwise relationships among variables in the system.

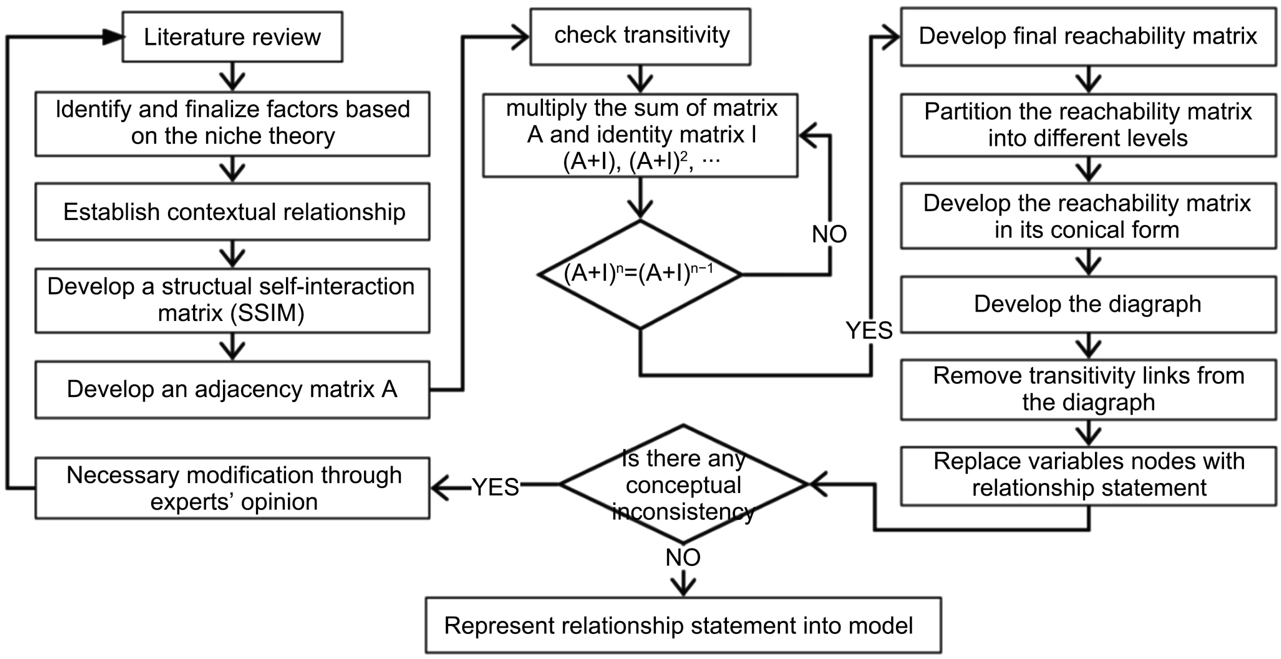

Figure 1. Basic flow chart of ISM model.

Step 4: An adjacency matrix is developed from the SSIM and checked for transitivity, resulting in the creation of the final reachable matrix. In the ISM model, transitivity is a fundamental assumption. This means that if variable A is related to B and B is related to C, then A is necessarily related to C. After incorporating transitivity, the final reachability matrix is obtained.

Step 5: Identify reachable sets, antecedent sets, and intersection sets. Partition the final reachability matrix into different levels.

Step 6: From the final reachable matrix, a conical matrix is developed by clustering the variables of the same level.

Step 7: A digraph is drawn based on the relationship given in the final reachable matrix. The final digraph is obtained by removing the transitive links.

Step 8: In the final digraph is converted into an ISM model. The developed ISM model is reviewed for conceptual inconsistencies, and necessary modifications are made.

There is actually competition in the supply chain supporting the new retail model. The ISM is widely applied to the supply chain (SC), especially in exploring the factors that enable supply chain sustainability (SCS). This exploration has significant implications for studying the long-term development of the new retail model. Reference (Yadav et al., 2020) employed an integrated ISM-DEMATEL (Decision-making Trial and Evaluation Laboratory) approach in an Indian agricultural supply chain (ASC) to model the significant challenges of adopting blockchain (BC) technology in the supply chain. An ISM approach was also adopted by Ghode et al. (2020) to evaluate the elements of technical, organizational, and environmental factors that influence blockchain adoption in supply chains. Many more applications are listed in the table below. Nonetheless, ISM is rarely addressed in the new retail space. This paper aims to fill this gap, making it an innovative contribution.

More literature related to the use of ISM methods in research is listed in Table 1. Using the ISM method requires several steps. First, the factors to be evaluated need to be obtained using a specific method (column 1). Next, the relationship or weight between these factors is determined (column 2). Then, ISM modeling is performed to complete the hierarchical division (column 3). Finally, the division results are analyzed (column 4).

As shown in the table, literature surveys and expert questionnaires were commonly used to obtain the factors to be evaluated and their respective weights. ISM, when combined with other strategies, was often used in modeling and analysis to improve the objectivity and rationality of the results. In this document, we introduce the fuzzy concept to account for the strong subjectivity of expert evaluation. Additionally, we utilize the FISM to enhance the scientificity and rationality of the influence relationships among evaluation indicators.

Table 1. Relevant ISM literature for sub-process steps.

Identification	Relationship	Model	Analysis	Application	Resource
Literature	Balanced score card + Expert	ISM	Analytic Network Process (ANP)	Healthcare industry	Jalil et al. (2021)
Literature + principal components analysis	Expert	ISM	MICMAC	SCS in wood industry	Paul et al. (2022)
Literature + Expert	Fuzzy analytic hierarchy process	ISM	MICMAC	E-commerce logistics	Jiang et al. (2019)
Questionnaire	Literature + Expert + Grey relational analysis (GRA)	ISM	/	SCS	Yang et al. (2021)
Literature + Expert		ISM + DEMATEL	/	E-waste management	Kumar & Dixit (2018)
Literature + Expert		ISM + DEMATEL	MICMAC	BC in ASC	Kamble et al. (2019)
Literature + Expert	Intervaltype-2trapezoidal fuzzy number + improved Hesitant Fuzzy Linguistic Term Set	ISM + DEMATEL	K-means	BC in power data trasing	Chen et al. (2022)
Literature + Expert		ISM	FMICMAC	Manufacturing industry	Kamble et al. (2018a)
Literature + Expert		FISM	FMICMAC	Cold SC	Sharma et al. (2021)
Literature		FISM	FMICMAC + FANP	BC in SCS	Yadav & Singh (2020)

The FMICMAC method, which combines fuzzy mathematics and fuzzy matrix theory, is applied to cluster analysis of evaluation indexes based on driving force and dependency strength. This method can more accurately depict the strength of relationship association under complex systems.

A brief review of the FISM method follows.

4.3. FISM Methodology

In 1965, Professor Zadeh, an American computer and control expert, proposed the theory of fuzzy sets in his paper (Zadeh, 1965). This theory utilized mathematical methods to investigate fuzzy phenomena and established a new discipline known as fuzzy mathematics. Since the elements in a fuzzy set can take any real number between the values of 0 and 1, it is more suitable than classical set theory for describing problems involving fuzziness. After recent developments, fuzzy mathematics has been widely applied in various fields, including engineering construction (Kutlu & Ekmekçioğlu, 2012), management decision making (Govindan et al., 2013b), and risk assessment (Taylan et al., 2014).

In the ISM modeling process, only the existence and some influence relationship (between on a 0 - 1 scale scale) is considered. The difference between FISM and ISM is that the established adjacency matrix can take any value on the interval [0, 1]. This allows for more expressive and realistic representation when dealing with uncertainty and fuzziness problems.

4.3.1. Fuzzy Sets and Affiliation Functions

Any mapping on the closed interval of the argument domain X to [0, 1]: μ_A: X $\to$ [0, 1], x $\to$ μ_A (x), identifies a fuzzy set $\tilde{A}$ on X. Then, we can write μ_A as the affiliation function of $\tilde{A}$ and write μ_A as the affiliation degree of X to the fuzzy set $\tilde{A}$. The fuzzy set $\tilde{A}$ is completely inscribed by μ_A. The larger μ_A is, the greater the degree of x's affiliation to the fuzzy set $\tilde{A}$. On the closed interval [0, 1] it can be written as

$$\mu_A(X) = \begin{cases} 1, & \text{when } x \in \mu_A \\ 0 < \mu_A < 1, & \text{when x belong to the } \mu_A \text{ to a certain extent} \\ 0, & \text{when } x \notin \mu_A \end{cases} \tag{1}$$

If the fuzzy set is defined on all real numbers, the affiliation function of the fuzzy set is called fuzzy distribution. Common fuzzy distributions are matrix type, trapezoidal type, kth parabolic type, normal distribution type, etc. The triangular type fuzzy distribution function used in this paper is

$$\mu_A = \begin{cases} 1, & x \le a \\ b - x/b - a, & a \le x \le b \\ c - x/c - b, & b \le x \le c \\ 0, & x > c \end{cases} \tag{2}$$

4.3.2. Triangular Fuzzy Number

Out of many types of fuzzy functions, the triangular fuzzy number can better express and handle fuzzy information, while the operation process is simple and convenient, so it has been widely used in supplier performance evaluation (Kutlu & Ekmekçioğlu, 2012), multi-attribute decision making methods (Govindan et al., 2013b), and risk assessment (Taylan et al., 2014). The triangular fuzzy number $\tilde{F}$ is denoted as $\tilde{F} = (l, m, u)$, and its geometric meaning is shown in **Figure 2** (Feng, 2023).

In the picture above, l and u denote the upper and lower bounds of x affiliation degree respectively, when $x = m$, the affiliation degree is maximum, and when x is outside l and u, the affiliation degree is 0, which means it does not belong to the fuzzy number $\tilde{F} = (l, m, u)$ at all.

According to the operation rules of fuzzy sets, suppose there are two fuzzy numbers $\tilde{F}_1 = (l_1, m_1, u_1)$ and $\tilde{F}_2 = (l_2, m_2, u_2)$, and the formula of algebraic operation between them is as follows:

$$\tilde{F}_1 \oplus \tilde{F}_2 = (l_1 + l_2, m_1 + m_1, u_1 + u_2) \tag{3}$$

$$\tilde{F}_1 \ominus \tilde{F}_2 = (l_1 - l_2, m_1 - m_1, u_1 - u_2) \tag{4}$$

$$\tilde{F}_1 \otimes \tilde{F}_2 = (l_1 l_2, m_1 m_1, u_1 u_2) \tag{5}$$

$$\tilde{F}_1 \div \tilde{F}_2 = (l_1/l_{12}, m_1/m_2, u_1/u_2) \tag{6}$$

$$\lambda \tilde{F}_1 = (\lambda l_1, \lambda m_1, \lambda u_1) \tag{7}$$

4.3.3. Trigonometric Fuzzy Number Conversion of Linguistic Variables

It is rather difficult to describe variables with specific values in some fuzzy and uncertain environments, for example, to evaluate a person's basketball skills, using linguistic variables can obviously achieve a better representation. In latest years, many scholars have performed relevant studies on the link between the levels of linguistic variables and the conversion of triangular fuzzy numbers, and in this paper, five levels of linguistic variables (very low, low, medium, high, and very high) are used with reference to the literature (Li, 1999), and the variables and the corresponding triangular fuzzy numbers are shown in **Table 2**.

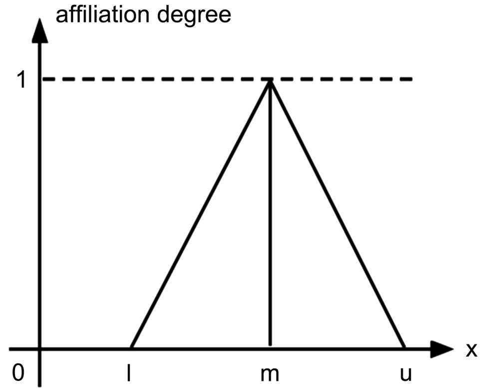

Figure 2. Triangular fuzzy number affiliation function.

Table 2. Triangular fuzzy number linguistic variables.

Language variable levels	Triangular fuzzy number
Very low (VL)	(0, 0, 0.25)
Low (L)	(0, 0.25, 0.5)
Medium (M)	(0.25, 0.5, 0.75)
High (H)	(0.5, 0.75, 1)
Very high (VH)	(0.75, 1, 1)

5. Modeling Analysis

In this section, we will complete the construction of an explanatory structure model for FISM. This model is based on the basic ISM process combined with triangular fuzzy numbers. According to the modeling process described in this paper, **Figure 3** is specifically constructed.

5.1. Build a Triangular Fuzzy Matrix of Linguistic Variables for Expert Opinion

Several experts were invited to determine the linguistic variables of the inter-influence relationships among the factors $\left(R_1, R_2, \cdots, R_{13}\right)$ of the established 13 categories of new retail enterprise performance evaluation. The results were then converted into triangular fuzzy numbers based on the corresponding relationships in the table. Define the triangular fuzzy number of the determination result of R_i to R_j given by the kth expert is converted to $\tilde{d}_{ij}^k = \left(\tilde{a}_{ij}^k, \tilde{b}_{ij}^k, \tilde{c}_{ij}^k\right)$, and the triangular fuzzy moment of the influence relationship of each factor is:

$$\tilde{D}^k = \left[\tilde{d}_{ij}^k\right]_{13\times13} = \begin{bmatrix} \tilde{d}_{11}^k & \tilde{d}_{12}^k & \cdots & \tilde{d}_{113}^k \\ \tilde{d}_{21}^k & \tilde{d}_{22}^k & \cdots & \tilde{d}_{213}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{131}^k & \tilde{d}_{132}^k & \cdots & \tilde{d}_{1313}^k \end{bmatrix} \tag{8}$$

Build a Fuzzy Adjacency Matrix

In order to establish the fuzzy adjacency matrix, the above triangular fuzzy matrix needs to be defuzzified first. The commonly used defuzzification methods include the maximum subordination method, the center of gravity method, the weighted average method, etc. Among them, the maximum subordination method lacks consideration of non-maximum values, and the rest are mostly calculated using the weighting principle, which can be quite tedious. In this paper, we adopt the area-mean method, which is easier to operate and applicable to most of the fuzzy matrices while preserving all the decision values, by defuzzifying $\tilde{D}^k\left(K = 1, 2, \cdots, 13\right)$ for defuzzification, the defuzzified matrix is obtained and represented as $\tilde{H}^k = \left[\tilde{h}_{ij}^k\right]_{13\times13}$, where:

$$\tilde{h}_{ij}^k = \left(\tilde{a}_{ij}^k + 2\tilde{b}_{ij}^k + \tilde{c}_{ij}^k\right)/4 \tag{9}$$

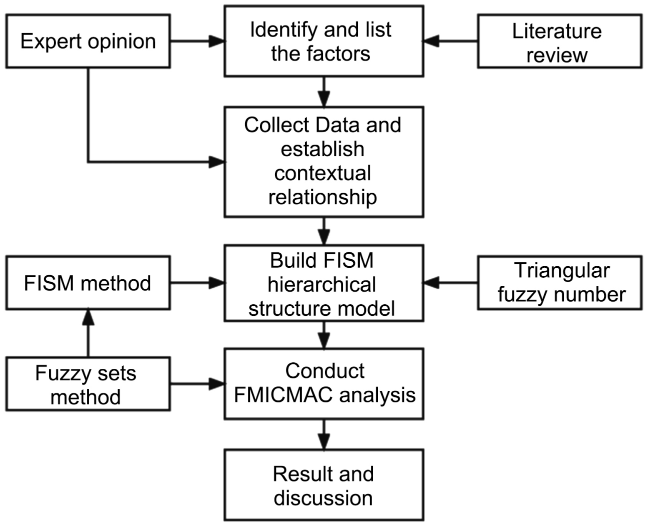

Figure 3. Flowchart of the modeling process in this paper.

The fuzzy adjacency matrix $\tilde{H} = \left[\tilde{h}_{ij}\right]_{13\times13}$ can be established by combining the opinions of the experts and defining the kth expert to have a weight w^k. Where:

$$\tilde{h}_{ij} = \sum\nolimits_{k=1}^{13} w^k \tilde{h}_{ij}^k \tag{10}$$

Here, three experts were selected, and it was assumed that all experts had the same weight of 1/3. The results of the first expert's determination of the linguistic variables of the interactions between the two factors of the new retailing indicators are shown in Table 3.

Take the first column of the table as an example, "VL, L, M, H, VH" indicate that the expert believes that the direct influence of factors R_3 (brand loyalty), R_8 (after-sales service), R_9 (interactive reflection), R_{10} (information circulation), R_2 (information effectiveness) on R1 (product quality) is expressed as "very low, low, medium, high, very high", while factor R1 has no influence with itself, and the same meaning for other positions.

After the steps of Equation (7) and Equation (8), the linguistic variables of the first expert can be converted into triangular fuzzy numbers and defuzzified to obtain the fuzzy adjacency matrix H for the conversion of the linguistic variables of the first expert, and the results are shown in Table 4.

Similarly, $\tilde{H}^2$ and $\tilde{H}^3$ can be obtained in turn. The obtained $\tilde{H}^1$, $\tilde{H}^2$ and $\tilde{H}^3$ are passed through the steps of Equation (9) to obtain the final fuzzy adjacency matrix $\tilde{H} = \left[\tilde{h}_{ij}\right]_{13\times13}$ as shown in Table 5.

5.2. Calculation of Cut and Reachable Matrices

5.2.1. Calculate the Cut Matrix

The resulting fuzzy adjacency matrix $\tilde{H}$ is converted into a 0 - 1 matrix $H = \left[h_{ij}\right]_{13\times13}$ by setting some threshold value. After setting λ to take some value on the interval [0, 1], the conversion is performed according to the following formula.

Table 3. Self-interaction matrix for the first expert evaluation.

R_j \ R_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}
R_1	0	VL	VH	VL	VL	VL	VL	VL	M	VL	H	VL	VL
R_2	VH	0	VH	M	H	VH	H	H	VH	VH	H	H	VH
R_3	VL	VL	0	VL	VL	VL	L	L	VL	VL	VL	L	VL
R_4	VL	VL	VH	0	VL	M	VL	VL	H	L	M	M	VL
R_5	VL	VL	H	VL	0	M	VL	VL	L	L	H	VL	VL
R_6	VL	VL	H	H	VH	0	L	L	M	L	M	M	VL
R_7	H	VL	H	VL	VL	VL	0	H	M	M	M	L	VL
R_8	L	VL	H	VL	VL	VL	M	0	VH	L	M	L	VL
R_9	M	H	M	H	L	L	M	VH	0	M	M	H	VL
R_{10}	H	H	M	H	VL	M	H	H	H	0	H	VH	VL
R_{11}	L	L	L	L	L	L	H	L	L	L	0	M	VL
R_{12}	VH	L	H	H	M	M	M	H	H	H	L	0	VL
R_{13}	H	H	M	H	H	H	H	H	H	VH	H	H	0

Table 4. Fuzzy adjacency matrix of the combined experts.

R_j \ R_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}
R_1	0.00	0.06	1.00	0.06	0.06	0.06	0.06	0.06	0.50	0.06	0.75	0.06	0.06
R_2	1.00	0.00	1.00	0.50	0.75	1.00	0.75	0.75	1.00	1.00	1.00	0.75	1.00
R_3	0.06	0.06	0.00	0.06	0.06	0.06	0.25	0.25	0.06	0.06	0.06	0.25	0.06
R_4	0.06	0.06	1.00	0.00	0.06	0.50	0.06	0.06	0.75	0.25	0.50	0.50	0.06
R_5	0.06	0.06	0.75	0.06	0.00	0.50	0.06	0.06	0.25	0.25	0.75	0.06	0.06
R_6	0.06	0.06	0.75	0.75	1.00	0.00	0.25	0.25	0.50	0.25	0.50	0.50	0.06
R_7	0.75	0.06	0.75	0.06	0.06	0.06	0.00	0.75	0.50	0.50	0.50	0.25	0.06
R_8	0.25	0.06	0.75	0.06	0.06	0.06	0.50	0.00	1.00	0.25	0.50	0.25	0.06
R_9	0.50	0.75	0.50	0.75	0.25	0.25	0.50	1.00	0.00	0.50	0.50	0.75	0.06
R_{10}	0.75	0.75	0.50	0.75	0.06	0.50	0.75	0.75	0.75	0.00	0.75	1.00	0.06
R_{11}	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.25	0.25	0.00	0.50	0.06
R_{12}	1.00	0.25	0.75	0.75	0.50	0.50	0.50	0.75	0.75	0.75	0.25	0.00	0.06
R_{13}	0.75	0.75	0.5	0.75	0.75	0.75	0.75	0.75	0.75	1.00	0.75	0.75	0.00

Table 5. Fuzzy adjacency matrix of the combined experts.

R_j \ R_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}
R_1	0.00	0.06	0.92	0.21	0.06	0.06	0.12	0.29	0.35	0.06	0.75	0.06	0.12
R_2	0.92	0.00	0.83	0.67	0.75	0.75	0.75	0.75	1.00	1.00	0.83	0.67	1.00
R_3	0.37	0.06	0.00	0.21	0.21	0.21	0.35	0.44	0.29	0.21	0.52	0.19	0.12
R_4	0.19	0.06	0.92	0.00	0.21	0.35	0.12	0.12	0.58	0.19	0.67	0.50	0.29
R_5	0.06	0.06	0.83	0.21	0.00	0.44	0.06	0.29	0.35	0.27	0.75	0.12	0.37
R_6	0.12	0.29	0.58	0.67	0.83	0.00	0.35	0.35	0.44	0.44	0.67	0.58	0.37
R_7	0.58	0.21	0.75	0.12	0.06	0.29	0.00	0.52	0.52	0.35	0.67	0.19	0.29
R_8	0.42	0.21	0.83	0.12	0.29	0.29	0.44	0.00	0.52	0.19	0.67	0.12	0.06
R_9	0.58	0.75	0.58	0.67	0.35	0.35	0.58	0.83	0.00	0.75	0.44	0.92	0.29
R_{10}	0.52	0.83	0.42	0.35	0.21	0.52	0.92	0.58	0.83	0.00	0.52	1.00	0.29
R_{11}	0.58	0.27	0.42	0.35	0.35	0.35	0.52	0.35	0.35	0.35	0.00	0.35	0.29
R_{12}	9.75	0.25	0.58	0.67	0.27	0.35	0.27	0.29	0.83	0.60	0.27	0.00	0.29
R_{13}	0.58	0.75	0.50	0.75	0.83	0.83	0.75	0.52	0.92	0.92	0.75	0.75	0.00

$$h_{ij} = \begin{cases} 1, & \tilde{h}_{ij} \geq \lambda \\ 0, & \tilde{h}_{ij} < \lambda \end{cases} \tag{11}$$

Call H the cut matrix of λ for the fuzzy matrix. The selection of λ value is the key to the transformation of the cut matrix and the subsequent hierarchical division of each factor of the system. A higher value indicates a strong relationship between individual factors within the system, and a lower value indicates a weaker fuzzy relationship. Therefore, the selection of appropriate λ values is extremely important for the construction of FISM.

So far, in fuzzy mathematical studies, the value of λ still lacks a uniform quantitative guideline and relies more on subjective assessments by experts from various industries or is determined by the average value of the non-fuzzy relational matrix of system factors (Kavilal et al., 2017). Shakerian et al. (2020) sets this threshold at 0.175 based on expert recommendations, and Wang et al. (2018) sets the threshold at 0.65 with reference to the results of the runs and in combination with expert recommendations.

In this paper, λ = 0.5, 0.6, 0.7 were selected and three different FISM frameworks were calculated, and λ = 0.6, was adopted as the more reasonable after expert discussion, and the conversion is shown in **Table 6** below.

Table 6. λ = 0.6 fuzzy cut matrix.

R_i / R_j	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}
R_1	0	0	1	0	0	0	0	0	0	0	1	0	0
R_2	1	0	1	1	1	1	1	1	1	1	1	1	1
R_3	0	0	0	0	0	0	0	0	0	0	0	0	0
R_4	0	0	1	0	0	0	0	0	0	0	1	0	0
R_5	0	0	1	0	0	0	0	0	0	0	1	0	0
R_6	0	0	0	1	1	0	0	0	0	0	1	0	0
R_7	0	0	1	0	0	0	0	0	0	0	1	0	0
R_8	0	0	1	0	0	0	0	0	0	0	1	0	0
R_9	0	1	0	1	0	0	0	1	0	1	0	1	0
R_{10}	0	1	0	0	0	0	1	0	1	0	0	1	0
R_{11}	0	0	0	0	0	0	0	0	0	0	0	0	0
R_{12}	1	0	0	1	0	0	0	0	1	1	0	0	0
R_{13}	0	1	0	1	1	1	1	0	1	1	1	1	0

The cut matrix calculated in the above table can be considered as the adjacency matrix of the relationships between the influences of the factors of new retailing, which will be denoted as A.

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

5.2.2. Calculating the Reachable Matrix

The reachable matrix is a matrix form to describe the degree that can be reached between the nodes in a directed adjacency graph after a certain length of pathway. Using the operational properties of a Boolean matrix, a Boolean operation is performed on the adjacency matrix A to obtain the reachable matrix D, which is calculated as follows,

$$D = \left[d_{ij}\right]_{13\times 13} = (A+I)^{k+1} = (A+I)^{k} \neq (A+I)^{k-1} \neq \cdots \neq (A+I) \tag{12}$$

where $k = 1,2,3,\cdots$, I is the only unit matrix that is identical to A, and

$$d_{ij} = \begin{cases} 1, & e_i \text{ reachable } e_j \\ 0, & e_i \text{ unreachable } e_j \end{cases}.$$

The reachable matrix D can be obtained by performing Boolean operations on A according to Equation (11), and the above steps are programmed in MATLAB software to calculate the results as follows.

$$D = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

5.3. Hierarchy Division

Reachable set: the set of other elements reachable, denoted as

$$R(e_i) = \left\{ e_j \in E \middle| d_{ij} = 1 \right\} \tag{13}$$

Antecedent set: the set of other elements reachable by, denoted as

$$R(e_i) = \left\{ e_j \in E \middle| d_{ij} = 1 \right\} \tag{14}$$

Highest set: the set whose intersection of the reachable set and the antecedent set is still the reachable set, denoted as

$$Q(e_i) = \left\{ e_j \in E \middle| R(e_i) \cap S(e_i) = R(e_i) \right\} \tag{15}$$

After the steps of Equation (12) and Equation (13), the resulting reachable matrix D can be decomposed to determine the reachable set R antecedent set S, and their intersection R ∩ S.

The structure of the first level of division is shown in **Table 7**.

Table 7. Intersection of reachable set and antecedent set and the first level of division.

R_i	R (R_i)	S (R_i)	R (R_i) ∩ S (Ri)	Level
R_1	1, 3, 11	1, 2, 7, 8, 9, 10, 12, 13	1	
R_2	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_3	3	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 13	3	I
R_4	3, 4, 11	2, 4, 6, 9, 10, 12, 13	4	
R_5	3, 5, 11	2, 5, 6, 9, 10, 12, 13	5	
R_6	3, 4, 5, 6, 11	2, 6, 9, 10, 12, 13	6	
R_7	1, 3, 7, 11	2, 7, 9, 10, 12, 13	7	
R_8	1, 3, 8, 11	2, 8, 9, 10, 12, 13	8	
R_9	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{10}	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{11}	11	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	11	I
R_{12}	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{13}	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	

According to the definition of the highest set in Equation (14), the reachable matrix D is gradually divided into layers, and the first layer of division contains the factors $L_1 = \{R_3, R_{11}\}$.

The results of the second level of division are shown in Table 8.

Repeating the above steps, the second layer contains the factors of $L_2 = \{R_1, R_4, R_5\}$. The results of the third layer division are shown in Table 9.

Likewise, the factors contained in the third layer can be obtained as $L_3 = \{R_6, R_7, R_8\}$; The fourth layer of factors in Table 10 are: $L_4 = \{R_2, R_9, R_{10}, R_{12}, R_{13}\}$.

5.4. Hierarchy Model Diagram

The hierarchical framework as a FISM model is obtained using the input from the final reachable matrix according to the division level. The relationship between variables i and j is represented by an arrow from i to j and vice versa. After removing the indirect chains, the final FISM model was developed. The expert checked this FISM model for any conceptual inconsistencies. The final FISM hierarchical model diagram is constructed in this paper based on the reachable matrix D above, as shown in **Figure 4**.

Table 8. Intersection of reachable set and antecedent set and the second level of division.

R_i	$R(R_i)$	$S(R_i)$	$R(R_i) \cap S(R_i)$	Level
R_1	1	1, 2, 7, 8, 9, 10, 12, 13	1	II
R_2	1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_4	4	2, 4, 6, 9, 10, 12, 13	4	II
R_5	5	2, 5, 6, 9, 10, 12, 13	5	II
R_6	4, 5, 6	2, 6, 9, 10, 12, 13	6	
R_7	1, 7	2, 7, 9, 10, 12, 13	7	
R_8	1, 8	2, 8, 9, 10, 12, 13	8	
R_9	1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{10}	1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{12}	1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{13}	1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	

Table 9. Intersection of reachable set and antecedent set and the third level of division.

R_i	$R(R_i)$	$S(R_i)$	$R(R_i) \cap S(R_i)$	Level
R_2	2, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_6	6	2, 6, 9, 10, 12, 13	6	III
R_7	7	2, 7, 9, 10, 12, 13	7	III
R_8	8	2, 8, 9, 10, 12, 13	8	III
R_9	2, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{10}	2, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{12}	2, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	
R_{13}	2, 6, 7, 8, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	

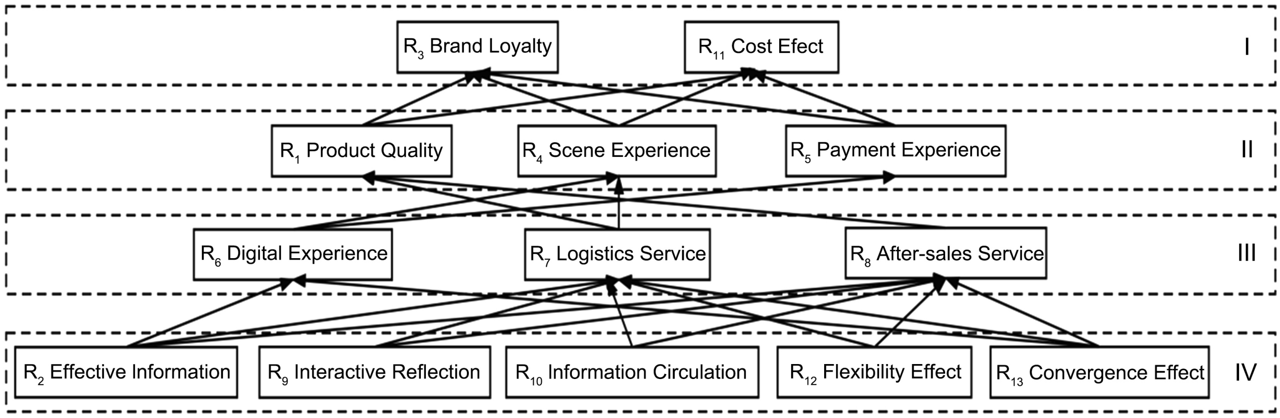

Figure 4. FISM hierarchy.

Table 10. Intersection of reachable set and antecedent set and the fourth level of division.

R_i	R (R_i)	S (R_i)	R (R_i) ∩ S (R_i)	Level
R_2	2, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	IV
R_9	2, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	IV
R_{10}	2, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	IV
R_{12}	2, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	IV
R_{13}	2, 9, 10, 12, 13	2, 9, 10, 12, 13	2, 9, 10, 12, 13	IV

6. FMICMAC Analysis

MICMAC analysis, proposed by Duperrin and Godet, applies the principles of the matrix multiplicative property (Duperrin & Godet, 1973). This analysis allows the influence matrix to reach a steady state for observing the identification of driving and dependent variables in the influence system. This method is a complement and extension of the ISM technique to identify the driving and dependent factors of the influencing variables. This allows for the targeting of the management and intervention priorities (Govindan et al., 2012). On the other hand, the FMICMAC model introduces the theory of fuzzy mathematics and fuzzy matrices based on the MICMAC model, and the FMICMAC model can more accurately reflect the strength of relational associations under complex systems.

6.1. FMICMAC Data Processing

When performing FMICMAC analysis, in addition to considering the current reachability, the analysis also takes into account the probability of reachability between factors. Qualitatively, the reachability probability P_{ij} between factors is considered, with values ranging from 0 to 1. The values for the fuzziness selection are shown in **Table 11**.

Table 11. Table of fuzzy reachable probability values.

Reachable probability	None (N)	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)	Fully Possible (F)
Standards	0	0.1	0.3	0.5	0.7	0.9	1

Similarly, using 1/3 as the weights assigned to the experts, the probability matrices determined by the three different experts are normalized. These matrices are then multiplied with the adjacency matrix A obtained above to obtain the fuzzy relational matrix, which is denoted as matrix M.

$$M = \begin{bmatrix} 0.00 & 0.00 & 0.77 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.10 & 0.10 & 0.10 \\ 0.50 & 1.00 & 0.10 & 0.50 & 0.50 & 0.50 & 0.63 & 0.63 & 0.70 & 0.70 & 0.10 & 0.70 & 0.10 \\ 0.00 & 0.10 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.00 & 0.10 & 0.57 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.70 & 0.10 & 0.10 & 0.30 & 0.10 \\ 0.10 & 0.10 & 0.57 & 0.10 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.10 & 0.10 & 0.03 & 0.70 & 0.70 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.10 & 0.10 & 0.77 & 0.70 & 0.10 & 0.10 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.10 & 0.10 & 0.77 & 0.10 & 0.10 & 0.10 & 0.10 & 1.00 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.70 & 0.70 & 0.00 & 0.63 & 0.10 & 0.10 & 0.10 & 0.70 & 1.00 & 0.70 & 0.10 & 0.10 & 0.10 \\ 0.10 & 0.10 & 0.00 & 0.10 & 0.10 & 0.10 & 0.70 & 0.10 & 0.70 & 1.00 & 0.10 & 0.70 & 0.10 \\ 0.70 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 1.00 & 0.10 & 0.10 \\ 0.70 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 1.00 & 0.10 \\ 0.10 & 0.63 & 0.10 & 0.70 & 0.70 & 0.70 & 0.10 & 0.63 & 0.10 & 0.10 & 0.10 & 0.10 & 1.00 \end{bmatrix}$$

In order to obtain a steady-state fuzzy relational matrix that represents the stability of the driving forces and dependencies of each factor in the system, we consider the convergence of the fuzzy relational matrix M. Matrix multiplication is performed according to the definition of fuzzy operators, $P^2 = PP$, $P^3 = P^2P$. For a sequence $\{P^n\}$, $n = 1, 2, 3, \cdots, k$, this matrix either converges or diverges. If there exists a positive integer c such that n ≥ c when $P^n = P^c$, then it is defined that the sequence $\{P^n\}$, $n = 1, 2, 3, \cdots, k$ converges. According to the definition, the convergent fuzzy direct relational matrix N can be calculated using Matlab programming. The driving and dependence values of each influencing factor can be obtained by performing horizontal and vertical summation. These values are presented in Table 12.

According to the values obtained for the two-dimensional axes, the factors are then classified into four different quadrants: spontaneous, dependent, independent, and connected. This is illustrated in Figure 5. In the following section, the influencing factors are analyzed separately based on the characteristics of the quadrants they belong to.

6.2. FMICMAC Analysis

The 13 factors in this paper are classified into spontaneous factors, dependent factors, and independent factors through FMICMAC analysis.

Table 12. Converged fuzzy direct relational matrix.

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	Driving
R_1	1	0	1	0	0	0	0	0	0	0	1	0	0	3
R_2	1	1	1	1	1	1	1	1	1	1	1	1	1	13
R_3	0	0	1	0	0	0	0	0	0	0	0	0	0	1
R_4	0	0	1	1	0	0	0	0	0	0	1	0	0	3
R_5	0	0	1	0	1	0	0	0	0	0	1	0	0	3
R_6	0	0	1	1	1	1	0	0	0	0	1	0	0	5
R_7	0	0	1	0	0	0	1	0	0	0	1	0	0	4
R_8	0	0	1	0	0	0	0	1	0	0	1	0	0	4
R_9	1	1	1	1	1	1	1	1	1	1	1	1	1	13
R_{10}	1	1	1	1	1	1	1	1	1	1	1	1	1	13
R_{11}	0	0	0	0	0	0	0	0	0	0	1	0	0	1
R_{12}	1	1	1	1	1	1	1	1	1	1	1	1	1	13
R_{13}	1	1	1	1	1	1	1	1	1	1	1	1	1	13
Dependence	6	5	12	7	7	6	6	6	5	5	12	5	5	

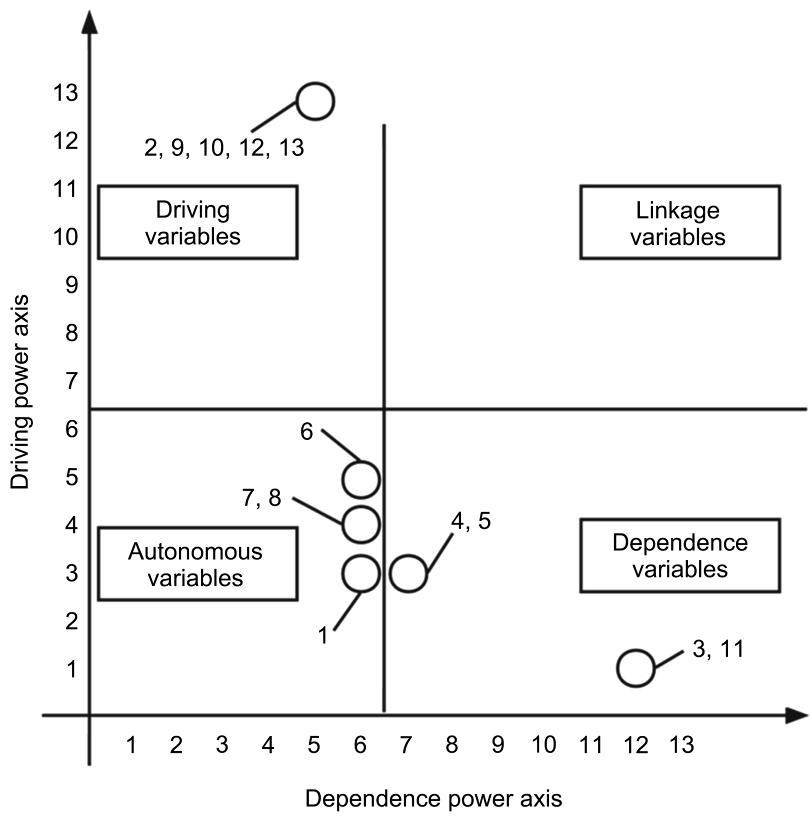

Figure 5. Blockchain-based new retail evaluation metrics FMICMAC matrix.

1) The spontaneous factors include R_1 (product quality), R_6 (digital experience), R_7 (logistics service), and R_8 (after-sales service). Spontaneous factors have a low correlation with other factors, as they are relatively stable and often directly impact the performance of new retail. These factors typically require separate attention and improvement.

2) Independent factors are R_2 (effective information), R_9 (interactive reflection), R_{10} (information circulation), R_{12} (flexibility effect), and R_{13} (integration effect), which have strong driving force and low dependency and tend to exist at the bottom of the structural model. In addition, these factors are the deepest and most direct factors that will have high productivity on new retail performance, requiring focused attention when conducting performance evaluation.

(3) The dependency factors include R_3 (brand loyalty), R_4 (scene experience), R_5 (payment experience), and R_{11} (cost effect). These factors have a lower driving force but a higher dependency compared to other factors.

Combining the results of the FISM stratification and the findings of the FMICMAC analysis, the following inferences can be drawn:

Five independent factors are seated at the bottom of the FISM framework, all related to the efficiency and quality of information delivery. Technology convergence drives efficient information transfer which in turn provides the guarantee of communication for flexible manufacturing, making it a breakthrough for the performance improvement of enterprises under the new retail model. By solving the problem of real-time information sharing, blockchain technology acts from the bottom layer of FISM model upward layer by layer, penetrating and driving, and the middle layer also plays a role in carrying the force of the top and bottom, and then building a complete hierarchical model. Blockchain can bridge the information flow barrier in each link of the supply chain, and its tamper-evident feature also improves the security and validity of information. Therefore, by breaking the information silos, the operational efficiency of the whole supply chain links is improved.

Spontaneous factor is located in the middle of the hierarchical framework, which is the products and services directly experienced by customers. With the goal of facilitating the seamless exchange of information, digital transformation is being promoted to optimize the entire supply chain through data integration. This will help minimize losses in circulation within and between enterprises, ultimately leading to a restructuring of the value chain. This is mainly reflected in three aspects: product, logistics and after-sales, such as special ordering, real-time tracking of logistics information, and traceability of problem responsibility.

Dependency factors are positioned in the middle and upper layers of the FISM model, effectively enhanced with the addition of lower layer factors. New logistics bridges online e-commerce and offline brick-and-mortar stores to make effective interoperability, thus providing a strong logistics guarantee for the scenario experience; digitalization enhances the security and reliability of the payment process; personalized products win customers' word-of-mouth and improve brand loyalty; decentralized blockchain technology saves a host of unnecessary cost expenditures.

7. Conclusion

New retailing is an inevitable product of the integration and development of retail industry and Internet technology, the trend of transformation in response to the needs of the consumer market. In this paper, a new performance evaluation index system is proposed by investigating the application of blockchain technology in new retail logistics, supply chain and transaction process, on the basis of customer expectation theory and ecological niche theory, using a kind of hierarchical analysis based on FISM model to discover the causal relationship between each index, and FMICMAC clustering of all the indexes according to the driving force and dependency, dividing them into different categories and analyzing. The results indicate that the efficiency of information flow is the key to whether new retail companies can reshape their competitive advantage. Blockchain technology, with its decentralization and other characteristics, can enable efficient information flow and facilitate successful digital transformation of enterprises. This paper provides a reliable theoretical foundation for new retail enterprises to address their critical weaknesses and improve their performance.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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