



SCIENTIFIC OASIS

Journal of Operations Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

Risk Factors Assessment of Smart Supply Chain in Intelligent Manufacturing Services Using DEMATEL Method With Linguistic q-ROF Information

Tingjun Xu¹, Haolun Wang^{1,*}, Liangqing Feng¹, Yanping Zhu¹¹ Nanchang Hangkong University, School of Economics and Management, Nanchang, China

ARTICLE INFO

Article history:

Received 14 December 2023

Received in revised form 11 January 2024

Accepted 25 January 2023

Available online 28 January 2024

Keywords:

Intelligent manufacturing service, Smart supply chain, Lq-ROFWA, DEMATEL

ABSTRACT

With the rapid development of technological informatization, competition among enterprises is gradually transitioning from being "production-centered" to being "customer-centric," making service-oriented enterprises increasingly important. In addition to this, as global manufacturing advances in the process of intelligent manufacturing (IM), there is growing attention on the integration of manufacturing and the service industry, which has garnered the interest of numerous experts and scholars in the field of intelligent manufacturing services (IMS). This article combines intelligent manufacturing enterprises, intelligent service nodes, and consumers. Based on the background of intelligent manufacturing services, it collects risk factors within the smart supply chain (SSC) that connect different service nodes. These factors were evaluated by experts using a proposed linguistic q-rung orthopair fuzzy weighted averaging (Lq-ROFWA) operator in combination with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method for aggregation operations. Finally, we obtain the conclusions that the most influential factor affecting other risk factors is the inadequate identification of core customer needs, and the most important risk factor for smart supply chains oriented to intelligent manufacturing services is the leakage of customer information. After analyzing the relevant data, we provide some theoretical and managerial implications for IM enterprises.

1. Introduction

Driven by big data in social networks, the mobile internet, and other services, market competition is gradually shifting from being "production-centered" to being "customer demand-centered." The ability to accurately and efficiently respond to customer needs has become the key factor for manufacturing companies to win in the market competition [1]. In 2020, the Ministry of Industry and Information Technology, the National Development and Reform Commission, and 15 other departments jointly issued the "Guiding Opinions on Further Promoting the Development of Service-

* Corresponding author.

E-mail address: hlwang71162@nchu.edu.cn<https://doi.org/10.31181/jopi21202417>

Oriented Manufacturing." It emphasized the development of nine major models, including industrial design services, customized services, supply chain management, shared manufacturing, inspection and testing certification services, full lifecycle management, general integration and general contracting, energy-saving and environmental protection services, and production-oriented financial services. This includes the "customer-centric" "customized services." Meanwhile, as global manufacturing continues to advance in the process of intelligent manufacturing, experts and scholars are paying increasingly more attention to the integration of manufacturing and services. Manufacturing services, as a research subject for integrated product services, encompass both productive services and manufacturing servitization. The former refers to intermediary services provided by service companies to manufacturing enterprises, while the latter refers to product service systems provided by manufacturing enterprises to end-users. [2] In the process of deepening the application of industrial internet and artificial intelligence, manufacturing services are becoming more intelligent, evolving into intelligent manufacturing services.

The DEMATEL method, through the logical relationships and direct impact matrix among various elements in a system, can calculate the influence degree of each factor on other factors as well as their vulnerability to influence. This allows for the calculation of the causality degree and centrality of each element, serving as the basis for constructing the model and determining the causal relationships among elements and the status of each element within the system. Shieh [3] and Kashyap [4] use the classical DEMATEL method to examine the factors influencing hospital service quality and the impediments to the implementation of cycles in the aluminum industry. Ibrahim Yilmaz [5] combined the Trapezoidal Fuzzy Set with DEMATEL to analyze the maintenance performance of a chemical industry company. Sun [6] combined q-ROF with DEMATEL to study the issue of strategic selection of alternative options in renewable energy systems.

Building upon existing researches, this article wants to solve the following questions: (1) What are the risk factors of SSC in IMS? (2) How to use scientific methods to evaluate risk factors? This paper's objectives are formulated as follows: First, we identify the risk factors of smart supply chains in IMS through literature research. Secondly, we propose a new risk assessment framework for IMS, integrating smart supply chains with it. Thirdly, we extend the traditional DEMATEL method and obtain a new risk assessment model.

The contribution of this article to the existing studies can be summarized as follows. Firstly, based on the existing research related to IMS, this paper considers each link in the smart supply chain as intelligent service nodes and proposes a new risk assessment framework. Secondly, we identify risk factors at different service nodes in the smart supply chain. Thirdly, although the traditional DEMATEL method can intuitively show the relationship between system elements, the evaluation process is too simple and subjective. This paper combines linguistic q-ROFS with the traditional DEMATEL method to solve the uncertainty and ambiguity in the evaluation process and provide a more flexible evaluation framework.

Section 2 provides a literature review of previous research. The new evaluation model will be introduced in Section 3. Section 4 presents a case study. Section 5 includes the discussion of the evaluation results. And some research implications will be given in Section 6. Section 7 is a conclusion of this article.

2. Literature review

2.1 Intelligent manufacturing service

As global manufacturing advances in the process of smart manufacturing, there is increasing attention on the integration of manufacturing and the service industry. More and more experts and scholars are beginning to focus on research in the field of intelligent manufacturing services. Zhang

[2] believe that intelligent manufacturing services are the result of the increasing intelligence of manufacturing services in the process of deepening the application of industrial internet and artificial intelligence. Li [1] believe that intelligent manufacturing services involve harnessing, analyzing, storing, reasoning, and applying big data resources in manufacturing through the use of next-generation information technology. This enables the perception of environmental changes both inside and outside the system, as well as scientific analysis, decision-making, and process optimization, ultimately leading to reduced manufacturing costs and improved manufacturing efficiency. In other words, it involves advanced processing and utilization of information. Giret [7] believes that within an operational system, each participant should be capable of providing specialized services to others. However, since the system can be overly complex, combining the architecture of intelligent manufacturing systems with services is essential for developing intelligent automation control and execution within manufacturing systems. Zhang et al. [8] combines service-oriented manufacturing, service and manufacturing design, and manufacturing monitoring with digital twin technology in intelligent manufacturing to establish a collaborative mechanism. Wang et al. [9] proposed a credit-driven service configuration method to handle the complex collaborative relationship between intelligent manufacturing and services. Zhang et al. [10] established an integrated framework for active discovery and optimal allocation of smart manufacturing services to promote sustainable, flexible, and collaborative production. In this way, we could perceive manufacturing resources through the application of information and communication technologies. Fei Tao et al. [11] believes that servitization has become a prominent tendency in the manufacturing industry, and proposed a framework of New IT driven service-oriented smart manufacturing (SoSM). Fei Tao et al. hopes to promote smart manufacturing by fully utilizing new IT technologies and services.

2.2 Smart supply chain

In recent years, modern information technologies such as the Internet, cloud computing, big data analysis, Internet of Things, artificial intelligence and blockchain have developed rapidly, and more and more companies have begun to implement smart supply chain changes. Experts and scholars have also conducted research on smart supply chains and smart supply chain management. Liu et al. [12] divided the management system of smart supply chain into seven parts, namely smart supply chain decision-making mechanism, collaborative supply chain operation management, integrated supply chain organization model, digital supply chain management information platform, and intelligent supply chain logistics system, proactive supply chain risk control and scientific supply chain performance evaluation. Based on the research theory of smart supply chain and SCOR supply chain model, Liu et al. [13] used methods such as literature research and comparative analysis to explain the operation process of smart supply chain and the mechanism of smart supply chain quality formation. And Liu et al. [13] designed a smart supply chain quality standard system under the guidance of the three-dimensional reference model. Liu et al. [14] selected four cases of Chinese companies developing smart supply chains, and conducted cross-analysis on these four cases to study the correlation mechanism between smart technology and smart supply chain innovation performance. AlMulhim [15] used hypothesis testing method to explore the impact of digital transformation on enterprise performance in the context of smart supply chain. Viriyasitavat et al. [16], in the context of smart supply chain, attempts to integrate blockchain technology into a service-oriented architecture to achieve seamless collaboration, cooperation, and integration of business processes on multiple platforms. Butner [17] pointed out that supply chains can not only be connected to other supply chains, but also to transportation systems, financial markets, power grids, and even natural systems such as rivers and weather. In addition, Butner [17] believes that a smarter

supply chain should have the characteristics of "Instrumented", "Interconnected" and "Intelligent". Tripathi [18] pointed out that supply chain systems are becoming increasingly complex and uncertain, and many technological innovations are making them smarter. And Tripathi [18] presented a framework to formulate transformation strategy and discusses implementation strategy in detail.

2.3 A new framework of SSC in IMS

The advantages and disadvantages of supply chain management are also key factors in assessing a company's competitiveness. Therefore, identifying risks within the supply chain system, conducting evaluations, and providing corresponding recommendations to prevent operational issues within the supply chain system are of utmost importance. However, how to reasonably summarize various risk factors is also a very important issue. Traditional supply chain management includes a series of complex activities such as planning, procurement, production, delivery and returns management, involving multiple participants and a series of decision-making processes [12]. With the continuous development and integration of intelligent technology, every participant in the traditional supply chain has undergone intelligent and technological upgrades, forming different intelligent service nodes in SSC.

Before the customer receives the product, the product generally goes through a complete supply chain system process. During the product design process, companies need to conduct research and predictions on consumer needs and preferences. Marc et al. [19] believes that accurate demand forecasting has a significant impact on the operation of the supply chain system, which will affect the company's performance. And he came up with a mathematical model that linked customer demand for a product to the risks posed by warehouse inventory levels and the operations of the production process. Suppliers need to carry out smart procurement and smart warehousing of materials. Chen et al. [20] assessed the risks of a service procurement company from the perspective of big data. He divided procurement risks into environmental risks, competition risks, moral hazards, financial risks, performance risks and internal control risks. With the development of science and technology, more and more related service companies are using automatic guided vehicles (AGV) and radio frequency identification technology (RFID) in the warehousing process. For example, Oke et al. [21] conducted research on how to safely use RFID technology in the construction industry. Bekishev et al. [22] used the FMEA method to conduct risk assessments on AGVs and other equipment; and proposed a new risk management algorithm to reduce risks. Intelligent manufacturing has an important impact on the high-quality development of the manufacturing industry. Li et al. [23] made a detailed review of the application of artificial intelligence in smart manufacturing, including new science and technology, new technology systems, etc. In order for sellers to provide services to consumers more conveniently and effectively, more and more related service companies are beginning to try to use smart transportation and smart distribution technologies. Through case analysis and literature analysis, Liu et al. [24] used intelligent models to illustrate the relationship between logistics and transportation and 5G IoT technology.

Therefore, this article will focus on intelligent manufacturing services and, from a perspective of smartness, take intelligent manufacturing enterprises as an example to identify potential risks in the operations of each collaborating enterprise and in the process of engaging with consumers. It will also conduct assessments and analyses to ensure the efficient and smooth operation of every stage (intelligent service node) within the entire smart supply chain system. As shown in Figure 1, the smart service nodes will be referenced according to the elements in the Supply-Chain Operations Reference-model (SCOR), such as planning, procurement, production, distribution, and sales, and will correspond to intelligent forecasting nodes, smart procurement nodes, smart warehousing nodes,

intelligent manufacturing nodes, smart transportation nodes, smart distribution nodes, and external environment.

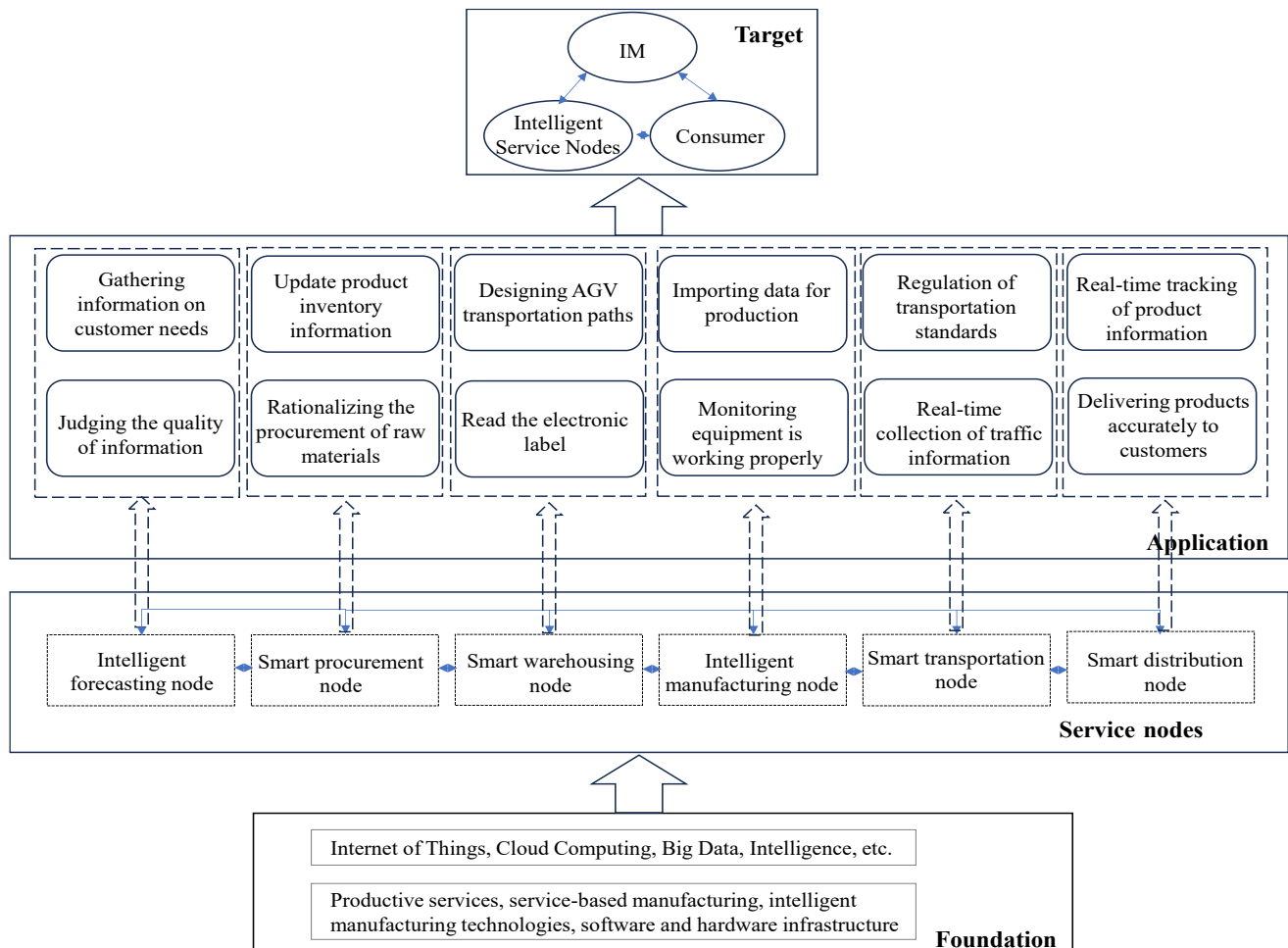


Fig. 1. The hierarchical framework of intelligent manufacturing services

2.4 Risk factors of SSC

Based on the different intelligent service nodes in Figure 1, in this section we will collect and summarize the risk factors that affect the smart supply chain by literature research.

Before the product put into production, the product needs to be designed, and the company needs to design according to the preferences of consumers. At this stage, there exists a prediction risk. This includes the miscellaneous data sources of product designing requirements and the short timeliness of maintenance [1]. Besides, inadequate identification of customer core needs will also have an impact on the performance and quality of the entire supply chain. Then, the analysis of the market situation is inaccurate. The competition of enterprises should not only be managed internally, but also be analyzed externally, including the market and competitors [25].

As one of the important stages in the supply chain system, suppliers are involved in the smart storage of goods and the smart procurement with other collaborative enterprises. Smart storage is the product of warehouse automation. It works together through automation and Internet technologies to improve the productivity and efficiency of the warehouse, minimize the number of labor and reduce errors at the same time. With the development and progress of information technology, many enterprises apply radio frequency identification (RFID) and automatic guided vehicle (AGV) to warehouse management. If these technologies are not mature or have problems in the application process, they will cause huge losses to the enterprise. For example, the RFID chip may

be attacked in the process of reading, and the electronic tag is misread. In addition, the AGV path error may cause car collision and other risks, which increases the losses of enterprises.

The risk of smart procurement refers to the possibility that some technologies of suppliers or suppliers' networks may be damaged by unexpected conditions in the process of obtaining some resources to meet the needs of consumers. This possibility is hidden in every stage of procurement. For example, the procurement information cannot be symmetrical in time [20] and the information in the purchaser's database is not updated in time [20]. Besides, Weak traceability and supervision [22] may lead to obvious material loss and poor control of material quality during procurement and transportation.

Nowadays, more and more manufacturers are integrating intelligent manufacturing technology into their production processes. Intelligent manufacturing is an advanced production method based on the deep integration of new generation information technology and advanced manufacturing technology, running through various manufacturing activities such as design, production, management, and service. It has characteristics such as self-awareness, decision-making, execution, adaptation, and self-learning, aiming to improve the quality, efficiency, and core competitiveness of the manufacturing industry. In various stages of the intelligent manufacturing process, there are also different risks. For example, the industrial control equipment is difficult to be safely controlled and data fusion of incorrect information [26]. Besides, the loss of production data [26] will also lead to abnormal production. Isolated and disconnected systems [27] are also the problems of many manufacturing enterprises. More and more enterprises invest in ERP, WMS, MES and other systems for production management, but each system is isolated, resulting in disordered production lines and low efficiency. A large number of data packets are injected, resulting in network congestion [27]. When a large number of data packets are poured into the manufacturing process, it will cause network congestion, and even paralysis in serious cases, which will have a huge impact on production. The system control network is attacked [28]. There are a wide variety of execution equipment, control equipment and sensor equipment in the intelligent manufacturing system, and there are widespread security vulnerabilities. The introduction of Internet technology will expose the equipment to the network and make it easier to be attacked through the Internet.

Smart transportation mainly relies on the rapid development of the Internet of things in recent computer technology efficiently, and even applies to the entire traffic management system. However, the real-time performance of traffic information is not up to standard [24], and the lack of accumulation of smart logistics technologies [29] has become a factor hindering the development of smart transportation system. At present, the amount of traffic information collection cannot support smart transportation, active transportation and all-round traffic information services, which will greatly affect the efficiency of transportation. In addition, the imperfect institutionalization of transportation management is also a significant risk.

The seller is responsible for direct communication with consumers and delivery. But there are still some risks affecting the consumer satisfaction. During the delivery of goods, the privacy of customers is easy to leak [27]. When customers' privacy is leaked, it will endanger customers' safety and affect customers' satisfaction. Then, the tracking ability of distribution information is poor [30], and the information of goods cannot be tracked in time, which will lead to low distribution efficiency and security risks. In addition, the poor or affected GPS signal [30] will also affect the efficiency of goods distribution. GPS technology can track the driving status, driving path and other information of transportation vehicles in real time. If GPS is affected, it will not be able to feed back the problems in the process of order in time.

In addition to the five stages mentioned above, the operation of the whole supply chain system is also affected by external links. This paper mainly puts forward two external risks: first, the

adjustment of industrial policies [31] has greatly affected the development of the industry, and different policies will directly affect the operation level and economic benefits of enterprises. Secondly, natural disasters or emergencies [31] will also hinder the normal operation of the supply chain system. Natural disasters mainly include meteorological disasters, geological disasters, marine disasters, diseases and other irresistible factors. Emergencies include large-scale diseases, epidemic situations, etc.

In order to better show the risk factors involved in different stages, this section classifies and summarizes them as shown in Table 1.

Table 1

The risk factors of smart supply chain in intelligent manufacturing services

	Risk categories	Details of risks	Relevant Literatures
Risk factors of SSC in IMS	Product designing	FR1: Inaccurate market situation analysis	[25]
		FR2: Inadequate identification of customer core needs	[25]
		FR3: Miscellaneous sources of customer demand data	[1]
		FR4: Short message maintenance and fast failure	[1]
	Supplier	SP1: Purchase information cannot be symmetrical in time	[20]
		SP2: The purchaser's database information was not updated in time	[20]
		SP3: Weak traceability and supervision of procurement	[22]
		SS1: Misreading of electronic labels	[21]
		SS2: RFID chip is attacked	[21]
		SS3: The path route of AGV is error	[22]
	Manufacture	IM1: Industrial control equipment is difficult to be safely controlled	[26]
		IM2: Fusion of wrong data	[26]
		IM3: Data loss	[26]
		IM4: Isolation of the system	[27]
		IM5: Net jam because of massive data packets injection	[27]
		IM6: System control network is attacked	[28]
	Logistics provider	ST1: The real-time performance of traffic information is not up to standard	[24]
		ST2: Low level of intelligent logistics technology	[29]
		ST3: Imperfect institutionalization of transportation management	[29]
	Seller	SD1: Poor tracking ability of distribution information	[30]
		SD2: The privacy is leaked	[27]
		SD3: Poor GPS signal or affected	[30]
	Environment	ER1: Adjustment of industrial policies	[31]
		ER2: Natural disasters or emergencies	[31]

2.5 Methods for risk evaluation

Risk management is the process of identifying, assessing and responding to potential risks. It involves a comprehensive analysis and assessment of risks and taking appropriate measures to reduce or control the occurrence and impact of risks. Risk management is important for organizations to make informed decisions in uncertain environments and reduce potential risks and losses.

Govindan [32] used the traditional DEMATEL method to prioritize the risks faced by third-party logistics service providers through threshold comparison, and analyzed the impact between different risk categories. Rajesh [33] studied risk drivers in electronic supply chains. They used the gray-DEMATEL method to determine and construct a causal relationship graph between risk drivers. Sreedevi [34] conducted a research on supply chain flexibility using structural equation modeling to mitigate supply risk, manufacturing process risk, and delivery risk in the supply chain. Rostamzadeh [35] constructed a new research framework for sustainable supply chain risk management and combined fuzzy TOPSIS and fuzzy Criteria Importance Through Inter-criteria Correlation (CRITIC) methods to analyze and study 44 risk factors. Based on the Failure mode and effects analysis (FMEA) method, Wan [36] combines rough sets with the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method to deal with fuzzy information and the issue of risks' weights. Hansen [37] conducts research on climate risks affecting agricultural poverty alleviation through a range of risk-reducing agricultural production technologies and practices and interventions. Abdel-Basset et al. [38] proposed a combination of plithogenic multi-criteria decision-making approach based on the TOPSIS and CRITIC methods and conducted an important ranking of factors in sustainable supply chain risk management. Munir [39] used a covariance-based structural equation model to test the proposed hypotheses and explore the connection between supply chain integration and supply chain risk management to improve the operational performance of enterprises. Liu [40] used hierarchical cluster analysis method to identify risk factors in smart supply chain and established a risk assessment index system to reduce potential losses in intelligent manufacturing. Lin [41] conducted detailed research on risk prediction and assessment using machine learning methods such as Artificial neural networks (ANNs) Support vector machine (SVM) Random forest (RF) and Bayesian network (BN) under different fuzzy set theory environments. Based on the current situation of China's intelligent manufacturing industry, Li [42] constructed an evaluation index system for intelligent manufacturing system supplier selection, and used the PLS-SEM method to establish an evaluation model for intelligent manufacturing system supplier selection risk. Seker [43] regarded the spread of the epidemic as a multi-complex decision-making problem and combined the interval-valued q-rung orthopair fuzzy set with the COmplex PROportional Assessment (COPRAS) method. And the risks of epidemic spread were assessed from social, technical, economic and governmental aspects. Cheng et al. [44] assessed and identified the risks of factors affecting the historical concentration of microcystin in Taihu Lake, China, through sampling and chemical element analysis. Reshad [45] integrates the TOPSIS and VIKOR methods to identify and assess the obstacles to sustainable supply chain risk management, and proposes strategies to overcome the obstacles. Lima et al. [46] proposed a theoretical framework on risk and uncertainty management in sustainable supply chains to help scholars and practitioners understand the challenges of circular economy implementation. Bekishev [22] identifies potential hazards associated with AGV/AMR robots, and in order to simplify and increase work efficiency, this article proposes a risk management algorithm suitable for high-tech projects. Minguito et al. [47] used the Gray Relational Analysis (GRA) method to verify the effectiveness of the FMEA method in identifying priority issues related to supply chain risks.

This article summarizes the previous literature in Table 2 below:

Table 2
Summary of previous literatures

No.	Authors (Year)	Values	Research Methods	Application
1	Govindan et al. [32]	Real value	DEMATEL	The interrelationships of third party logistics service providers and customers
2	Rajesh et al. [33]	Grey value	Grey-DEMATEL	Causality of risk drivers in electronic supply chains
3	Sreedevi et al. [34]	Real value	Structural equation modeling	The moderating role of supply chain flexibility in risk mitigation
4	Rostamzadeh et al. [35]	Triangular fuzzy value	Fuzzy TOPSIS- CRITIC	Sustainable supply chain risk management
5	Wan et al. [36]	Rough fuzzy vale	Rough-TOPSIS FMEA	Risk Assessment in Intelligent Manufacturing Process
6	Hansen et al. [37]	Real value	Risk-reducing agricultural production technologies and practices	Impact of climate risk management on crop production
7	Abdel-Basset et al. [38]	Triangular neutrosophic value	Plithogenic TOPSIS- CRITIC model	Sustainable supply chain risk management
8	Munir et al. [39]	Real value	Structural equation modeling	The operational performance of companies
9	Liu et al. [40]	Real value	The hierarchical clustering analysis	Smart Supply Chain Risk Assessment in Intelligent Manufacturing
10	Lin et al. [41]	Fuzzy values	ANNs, SVM, RF, BN	The application of machine learning methods in risk prediction and assessment
11	Li et al. [42]	Real value	PLS-SEM (Least squares structural equation model)	Risk Assessment in Supplier Selection for Intelligent Manufacturing
12	Seker et al. [43]	Interval-valued q-ROF	COPRAS	Risk assessment to overcome the pandemic
13	Cheng et al. [44]	Real value	Sediment sampling, Geochemical element analysis	Risk assessment and identification of factors influencing the historical concentrations of microcystin
14	Reshad et al. [45]	Real value	TOPSIS, VIKOR	Evaluating barriers and strategies to sustainable supply chain risk management
15	Lima et al. [46]	Real value	Delphi	Risk and uncertainty management in circular supply chains
16	Bekishev et al. [22]	Real value	FMEA	Risk Analysis for the Implementation of AGV/AMR Robotic T echnologies
17	Minguito et al. [47]	Real value	FEMA, GRA	Identifying priority issues relating to the supply chain risks
18	This article	Lq-ROF value	Lq-ROF-DEMATEL	Risk factors assessment of SSC in IMS

2.6 Research gaps and Research objectives

The research gaps are summarized as follows: (1) In the existing literature, supply chains or smart supply chains are directly used as the research object to conduct risk factor analysis (e.g., Liu et al., 2021). Currently, there are no articles that use smart manufacturing services as a background or research system. (2) Although the classic DEMATEL method is often used in factor analysis research (e.g., Govindan et al., 2016), it cannot handle the uncertainty of information in the evaluation process.

Considering the aforementioned research gap, this paper aims to identify the risk factors of SSC in IMS and adopt a scientific and comprehensive method to conduct risk assessment. Firstly, this article draws on the SCOR model to propose corresponding intelligent service nodes and a framework for identifying risk factors. Secondly, we combine linguistic q-ROFS with the classic DEMATEL method to analyze the risk factors of each smart service node. In order to solve the uncertainty and ambiguity in the evaluation process, this article introduces q-ROFS; in addition, combining linguistic set with q-ROFS can make the evaluation process more flexible.

3. Methodology

3.1 Linguistic q-rung orthopair fuzzy sets

In order to deal with the linguistic fuzzy decision-making problem efficiently, Liu and Liu [49] combined linguistic term sets with q-rung orthopair fuzzy sets to obtain a new hybrid evaluation set, which is the Linguistic q-rung orthopair fuzzy sets (Lq-ROFS).

Definition 1 [48]. Suppose $X = \{x_1, x_2, \dots, x_n\}$ is a finite set, and $S = \{s_1, s_2, \dots, s_t\}$ is a linguistic term set. Then the linguistic q-rung orthopair fuzzy set A defined on X can be expressed as:

$$A = \{\langle x, s_u(x), s_v(x) \rangle | x \in X\} \quad (1)$$

where $s_u(x), s_v(x) \in S_{[0,t]}$, $s_u(x)$ and $s_v(x)$ represent the degree of linguistic membership and the degree of linguistic non-membership, respectively. For any $x \in X$, the condition $u^q + v^q \leq t^q$ ($q \geq 1$) is always established, then, $a = (s_u, s_v)$ can be called as the linguistic q-rung orthopair fuzzy number (Lq-ROFN), and we can regard $X_{[0,t]}$ as the set of all Lq-ROFNs on the basis of $S_{[0,t]}$. Besides, the degree of linguistic indeterminacy for A can be defined as $\pi_A(x) = S_{\sqrt[q]{t^q - u^q - v^q}}$.

With the change of the value of the parameter q , the Lq-ROFS will also degenerate into other forms. When $q = 1$, the Lq-ROFS will degenerate into the linguistic intuitionistic fuzzy set (LIFS), and when $q = 2$, the Lq-ROFS will degenerate into the linguistic Pythagorean fuzzy set (LPyFS).

Definition 2 [49]. Let $a_1 = (s_{u1}, s_{v1})$, $a_2 = (s_{u2}, s_{v2}) \in X_{[0,t]}$ be any two Lq-ROFNs, where $\lambda > 0$, then the foundational operational rules of Lq-ROFNs are as follows:

$$a_1 \oplus a_2 = \left(S_{\left(\frac{u_1^q + u_2^q - \frac{u_1^q u_2^q}{t^q}}{t^q} \right)^{\frac{1}{q}}}, S_{\frac{v_1 v_2}{t}} \right) \quad (2)$$

$$a_1 \otimes a_2 = \left(S_{\frac{u_1 u_2}{t}}, S_{\left(\frac{v_1^q + v_2^q - \frac{v_1^q v_2^q}{t^q}}{t^q} \right)^{\frac{1}{q}}} \right) \quad (3)$$

$$\lambda a_1 = \left(S_{\left(t^q - t^q \left(1 - \frac{u_1^q}{t^q} \right)^\lambda \right)^{\frac{1}{q}}}, S_{\left(\frac{v_1}{t} \right)^\lambda} \right) \quad (4)$$

$$a_1^q = \left(s, \left(\frac{u_1}{t} \right)^{\frac{1}{q}}, s, \left(\frac{v_1}{t^q - t^q \left(1 - \frac{v_1}{t^q} \right)^{\frac{1}{q}}} \right)^{\frac{1}{q}} \right) \quad (5)$$

Definition 3 [49]. Let $a_1 = (s_{u1}, s_{v1})$, $a_2 = (s_{u2}, s_{v2}) \in X_{[0,t]}$ be any two Lq-ROFNs, then the standardized Hamming distance for a_1 and a_2 is shown below:

$$d(a_1, a_2) = \frac{|u_1^q - u_2^q| + |v_1^q - v_2^q| + |\pi_1^q - \pi_2^q|}{2t^q} \quad (6)$$

Definition 4 [49]. Let $a = (s_u, s_v) \in X_{[0,t]}$ be a Lq-ROFN, then the score function $S(a)$ and accurate function $H(a)$ are defined as follows:

$$S(a) = \sqrt[q]{\frac{t^q + u^q - v^q}{2}} \quad (7)$$

$$H(a) = \sqrt[q]{u^q + v^q} \quad (8)$$

Definition 5 [49]. Let $a_1 = (s_{u1}, s_{v1})$, $a_2 = (s_{u2}, s_{v2}) \in X_{[0,t]}$ be any two Lq-ROFNs,

(1) if $S(a_1) > S(a_2)$, then $a_1 > a_2$, which means a_1 is better than a_2 .

(2) if $S(a_1) = S(a_2)$, then

if $H(a_1) > H(a_2)$, then $a_1 > a_2$, which means a_1 is better than a_2 .

if $H(a_1) = H(a_2)$, then $a_1 = a_2$, which means a_1 is equal to a_2 .

Definition 6. Let $a_i = (s_{ui}, s_{vi}) \in X_{[0,t]}$ ($i = 1, 2, \dots, n$) be a Lq-ROFNs set, taking any $q > 0$, the value of the aggregation after applying the weighted linguistic q-rung orthopair fuzzy averaging operator (WLq-ROFA) is still Lq-ROFN, and the aggregation value is as follows:

$$WLq-ROFA(a_1, a_2, \dots, a_n) = \left\langle s, \left(\frac{\prod_{i=1}^n (t^q)^{w_i} - \prod_{i=1}^n (t^q - (u_i)^q)^{w_i}}{\prod_{i=1}^n (t^q)^{w_i}} \right)^{\frac{1}{q}}, s, \frac{\prod_{i=1}^n (v_i)^{w_i}}{\sqrt[q]{\prod_{i=1}^n (t^q)^{w_i}}} \right\rangle \quad (9)$$

3.2 Lq-ROF-DEMATEL

In this section, we will fuse the Lq-ROFS with the Decision-making Trial and Evaluation Laboratory (DEMATEL) method to analyze the risk factors of the smart supply chain for intelligent manufacturing services.

Step 1. Constructing the initial direct influence matrix

Each expert will compare the interactions of each of the two risk factors based on the linguistic term set $S = \{s_0 = \text{super low}, s_1 = \text{very low}, s_2 = \text{low}, s_3 = \text{medium}, s_4 = \text{high}, s_5 = \text{very high}, s_6 = \text{super high}\}$. The e th expert's evaluation for the degree to which risk factor i affects risk factor j is represented as $a_{ij}^e = (s_{uij}^e, s_{vij}^e)$, where, $i, j = 1, 2, \dots, n$; $e = 1, 2, \dots, k$. Then, the initial direct influence matrix can be expressed as $A^e = \langle a_{ij}^e \rangle_{n \times n} = \langle s_{uij}^e, s_{vij}^e \rangle_{n \times n}$.

Step 2. Calculation of expert weights

In the process of risk assessment, the evaluations of experts are very important. In this step, we will apply the similarity measure between linguistic fuzzy matrices to calculate the weights of each expert.

Based on the initial direct influence matrix of k experts, the total average initial influence matrix A^* is obtained by combining Eq. (2) and Eq. (4) as follow:

$$A^* = \langle a_{ij}^* \rangle_{n \times n} = \begin{bmatrix} 0 & \langle s_{u_{12}}^*, s_{v_{12}}^* \rangle & \dots & \langle s_{u_{1n}}^*, s_{v_{1n}}^* \rangle \\ \langle s_{u_{21}}^*, s_{v_{21}}^* \rangle & 0 & \dots & \langle s_{u_{2n}}^*, s_{v_{2n}}^* \rangle \\ \dots & \dots & \dots & \dots \\ \langle s_{u_{n1}}^*, s_{v_{n1}}^* \rangle & \langle s_{u_{n2}}^*, s_{v_{n2}}^* \rangle & \dots & 0 \end{bmatrix}$$

where, $a_{ij}^* = \frac{1}{k} \sum_{e=1}^k a_{ij}^e$.

Then, the standardized Hamming distance for each expert's initial direct influence matrix and the total average initial influence matrix can be calculated by using Eq. (6). The similarity measure will be obtained as follow:

$$SM(A^e, A^*) = \frac{\sum_{i=1}^n \sum_{j=1}^n d(a_{ij}^e, (a_{ij}^*)^c)}{\sum_{i=1}^n \sum_{j=1}^n (d(a_{ij}^e, a_{ij}^*) + d(a_{ij}^e, (a_{ij}^*)^c))} \quad (10)$$

where, $(a_{ij}^*)^c = (s_{vij}^*, s_{uij}^*)$, and $0 \leq SM(A^e, A^*) \leq 1$.

Finally, we can use the obtained similarity measure to calculate the weight of each expert, as shown below

$$w_e = \frac{SM(A^e, A^*)}{\sum_{e=1}^k SM(A^e, A^*)}, e = 1, 2, \dots, k. \quad (11)$$

Step 3. Calculation of aggregated direct influence matrix

This paper will use Eq. (9) to aggregate the initial direct influence matrix of each expert, and the aggregated direct influence matrix $\hat{A}$ will be calculated as follow:

$$\hat{A} = \begin{bmatrix} 0 & \langle s_{u_{12}}^{agg}, s_{v_{12}}^{agg} \rangle & \dots & \langle s_{u_{1n}}^{agg}, s_{v_{1n}}^{agg} \rangle \\ \langle s_{u_{21}}^{agg}, s_{v_{21}}^{agg} \rangle & 0 & \dots & \langle s_{u_{2n}}^{agg}, s_{v_{2n}}^{agg} \rangle \\ \dots & \dots & \dots & \dots \\ \langle s_{u_{n1}}^{agg}, s_{v_{n1}}^{agg} \rangle & \langle s_{u_{n2}}^{agg}, s_{v_{n2}}^{agg} \rangle & \dots & 0 \end{bmatrix}$$

Step 4. Standardization of the aggregated direct influence matrix

In this step, we will divide the aggregated direct influence matrix $\hat{A}$ into two submatrix, linguistic membership direct influence matrix X^u and linguistic non-membership direct influence matrix X^v . The formula of standardization is $X = A \times S$, where $S = \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}}$. And the submatrix can be represented as follows:

$$X^u = \begin{bmatrix} 0 & s_{u_{12}} & \dots & s_{u_{1n}} \\ s_{u_{21}} & 0 & \dots & s_{u_{2n}} \\ \dots & \dots & \dots & \dots \\ s_{u_{n1}} & s_{u_{n2}} & \dots & 0 \end{bmatrix}, \quad X^v = \begin{bmatrix} 0 & s_{v_{12}} & \dots & s_{v_{1n}} \\ s_{v_{21}} & 0 & \dots & s_{v_{2n}} \\ \dots & \dots & \dots & \dots \\ s_{v_{n1}} & s_{v_{n2}} & \dots & 0 \end{bmatrix}$$

Step 5. Identification of the total relationship matrix

The standardized linguistic membership and non-membership direct influence matrix are obtained in step4. And in this step, we will use $T = X(I - X)^{-1}$ to calculate the total relationship matrix of the standardized submatrix, where I is the identity matrix. Then, we will aggregate the two sub-matrices, and the final total relationship matrix can be shown as follow:

$$T = \begin{bmatrix} \langle s_{u_{11}}^T, s_{v_{11}}^T \rangle & \langle s_{u_{12}}^T, s_{v_{12}}^T \rangle & \dots & \langle s_{u_{1n}}^T, s_{v_{1n}}^T \rangle \\ \langle s_{u_{21}}^T, s_{v_{21}}^T \rangle & \langle s_{u_{22}}^T, s_{v_{22}}^T \rangle & \dots & \langle s_{u_{2n}}^T, s_{v_{2n}}^T \rangle \\ \dots & \dots & \dots & \dots \\ \langle s_{u_{n1}}^T, s_{v_{n1}}^T \rangle & \langle s_{u_{n2}}^T, s_{v_{n2}}^T \rangle & \dots & \langle s_{u_{nn}}^T, s_{v_{nn}}^T \rangle \end{bmatrix}$$

After the total relationship matrix T is obtained, the score function of each group of linguistic fuzzy sets in the matrix can be calculated by Eq. (7), and the score function matrix of the total relation matrix is obtained as follow:

$$T^* = \begin{bmatrix} S(a_{11}) & S(a_{12}) & \dots & S(a_{1n}) \\ S(a_{21}) & S(a_{22}) & \dots & S(a_{2n}) \\ \dots & \dots & \dots & \dots \\ S(a_{n1}) & S(a_{n2}) & \dots & S(a_{nn}) \end{bmatrix}$$

Step 6. Calculation of the importance and contribution

According to the score function matrix T^* , we can obtain the impact degree r_i and the affected degree c_j of each risk factor. r_i represents the sum of the i -th row in the matrix T^* , then r_i summarizes the direct and indirect impact of risk factor i on other risks (i.e. the impact degree of risk factor i). c_j represents the sum of the j -th column in matrix T^* , then c_j summarizes the direct and indirect impact of other risk factors on risk factor j (i.e. the affected degree of risk factor j). And when $i=j$, $(r_i + c_j)$ quantifies the importance of the influence that risk factor i has in the system, and $(r_i - c_j)$ quantifies the contribution of criterion i as a cause or effect criterion in the system.

$$r_i = \left[\sum_{j=1}^n S(a_{ij}) \right]$$

$$c_j = \left[\sum_{i=1}^n S(a_{ij}) \right]$$

Step 7. Determination of the threshold value and drawing network directed graph

Since the matrix T^* represents the interaction between any two risk factors, it is necessary to set a threshold to filter some negligible effects. In this way, the threshold value is compared with the values of different elements in matrix T^* . And only when it is greater than the threshold value, can the arrow be used in the directed graph to indicate that the risk factor i has an impact on the risk factor j . In this study, the threshold value is set as the average value of the elements in the matrix T^* , and the value of $(r + c, r - c)$ will be put into the coordinate system.

4. Application

At present, there are few articles that combine "service + manufacturing" and "intelligent + manufacturing" to do some researches. Due to the intelligent, technical and directional characteristics of intelligent manufacturing services, the stable operation of smart supply chain system is one of the key elements of intelligent manufacturing services. In other words, intelligent manufacturing services need the support of smart supply chain system. Therefore, for intelligent manufacturing services, this study takes intelligent manufacturing enterprises as an example to collect and analyze the risk factors in the whole smart supply chain system. In this paper, the risk factors are analyzed mainly through the scoring of evaluators. The evaluators are mainly experts and scholars in the fields of intelligent manufacturing services, smart supply chain and risk management. In addition, there are also experienced employees in relevant departments of the enterprise.

In this section, we invite five experts to evaluate the collected risk factors, and use the Lq-ROF-DEMATEL model in Section 3 to calculate and analyze the evaluation results of the experts, and finally give the corresponding theoretical and practical suggestions. The details of the five experts are shown in Table 3.

Table 3

The details of the invited experts.

Number of experts	Profile	Professional expertise	Years of experience
1	Supply chain manager	Supply chain management	Ten years
1	IM manager	IM development experience	Ten years
3	Three experts from academia	IMS technology and the SSC field	One professor with ten years of experience; two associate professors with six years of experience

Step 1. Firstly, the five experts will compare the degree of influence of 24 risk factors using Lq-ROFS to get the initial direct influence matrix. Each expert will evaluate each of the two risk factors based on their own experience and in accordance with the linguistic term in Section 3.2. The initial direct influence matrix of the first expert is shown below as an example.

Matrix 1. The initial direct influence matrix

(Detailed matrix information will be shown in the Appendix)

$$A^1 = \langle a_{ij}^1 \rangle_{24 \times 24} = \begin{bmatrix} (s_0, s_0) & (s_4, s_3) & \dots & \dots & (s_2, s_1) & (s_2, s_1) \\ (s_5, s_4) & \dots & \dots & \dots & \dots & (s_2, s_1) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ (s_2, s_1) & \dots & \dots & \dots & \dots & (s_2, s_1) \\ (s_2, s_1) & (s_2, s_1) & \dots & \dots & (s_3, s_5) & (s_0, s_0) \end{bmatrix}$$

Step 2. After obtaining the initial influence matrices of the five experts, the total averaging initial influence matrix A^* is calculated and show in Matrix 2. Then, Eq. (10) and (11) are used to obtain the similarity measure (SM) between each expert's evaluation matrix and the total averaging matrix, as well as the weights (w^e) of the five experts, as shown in Table 4 below:

Matrix 2. the total averaging initial influence matrix A^*

$$A^* = \begin{bmatrix} (s_{0.000}, s_{0.000}) & (s_{3.828}, s_{4.282}) & \dots & \dots & (s_{1.979}, s_{1.320}) & (s_{1.341}, s_{1.149}) \\ (s_{5.863}, s_{4.573}) & \dots & \dots & \dots & \dots & (s_{1.341}, s_{1.149}) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ (s_{2.091}, s_{1.741}) & \dots & \dots & \dots & \dots & (s_{1.734}, s_{2.048}) \\ (s_{1.979}, s_{1.821}) & (s_{1.979}, s_{1.888}) & \dots & \dots & (s_{1.979}, s_{2.993}) & (s_{0.000}, s_{0.000}) \end{bmatrix}$$

Table 4

The weights (w^e) of five experts

	1	2	3	4	5
Expert					
SM (A^e, A^*)	0.5089	0.5305	0.5331	0.5223	0.5224
w^e	0.1944	0.2027	0.2037	0.1996	0.1996

Step 3. - Step 4. After obtaining the evaluation weights of the five experts, we aggregate the evaluation matrices of the five experts using the WLq-ROFA operator. The aggregated direct influence matrix A^{agg} is obtained, and then the elements in the matrix A^{agg} are divided into two, forming a membership sub-matrix as well as a non-membership sub-matrix, respectively. Finally, the normalized matrices are obtained as Matrix 3 - 4.

Matrix 3-4. The normalized matrices

$$X^u = \begin{bmatrix} 0.0000 & 0.0636 & \dots & \dots & 0.0328 & 0.0222 \\ 0.0975 & \dots & \dots & \dots & \dots & 0.0222 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0.0348 & \dots & \dots & \dots & \dots & 0.0288 \\ 0.0329 & 0.0328 & \dots & \dots & 0.0327 & 0.0000 \end{bmatrix}$$

$$X^v = \begin{bmatrix} 0.0000 & 0.0592 & \dots & \dots & 0.0182 & 0.0158 \\ 0.0631 & \dots & \dots & \dots & \dots & 0.0158 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0.0240 & \dots & \dots & \dots & \dots & 0.0284 \\ 0.0251 & 0.0261 & \dots & \dots & 0.0410 & 0.0000 \end{bmatrix}$$

Step 5. We compute the total relationship matrix of the two sub-matrices separately and combine them to obtain the total relation matrix T as shown in Matrix 5. After obtaining the total relationship matrix, the effects between the risk elements are equally enlarged, and finally the score function matrix T^* of the total relationship matrix is calculated using Eq. (7) as shown in Matrix 6:

Matrix 5. The total relation matrix T

$$T = \begin{bmatrix} (s_{0.284}, s_{0.134}) & (s_{0.300}, s_{0.197}) & \dots & \dots & (s_{0.224}, s_{0.128}) & (s_{0.225}, s_{0.126}) \\ (s_{0.384}, s_{0.190}) & \dots & \dots & \dots & \dots & (s_{0.232}, s_{0.124}) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ (s_{0.292}, s_{0.164}) & \dots & \dots & \dots & \dots & (s_{0.217}, s_{0.149}) \\ (s_{0.284}, s_{0.165}) & (s_{0.245}, s_{0.174}) & \dots & \dots & (s_{0.205}, s_{0.159}) & (s_{0.184}, s_{0.121}) \end{bmatrix}$$

Matrix 6. The score function matrix T^*

$$T^* = \begin{bmatrix} 4.9208 & 4.8305 & \dots & \dots & 4.9310 & 4.9334 \\ 4.8400 & \dots & \dots & \dots & \dots & 4.9380 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 4.8752 & \dots & \dots & \dots & \dots & 4.8980 \\ 4.8739 & 4.8615 & \dots & \dots & 4.8831 & 4.9424 \end{bmatrix}$$

Step 6. After obtaining the score function matrix T^* , we will calculate the impact degree (r_i), the affected degree (c_j), the degree of center ($r_i + c_j$) and the degree of cause ($r_i - c_j$), as shown in Table 5 below:

Table 5
The center and cause degree of risk factors

Risk factors	r_i	c_j	$r_i + c_j$	$r_i - c_j$	Risk factors	r_i	c_j	$r_i + c_j$	$r_i - c_j$
FR1	117.49	115.75	233.25	1.74	IM3	115.58	115.28	230.86	0.30
FR2	117.62	115.43	233.05	2.20	IM4	115.12	116.28	231.40	-1.16
FR3	115.59	115.02	230.61	0.57	IM5	114.96	116.01	230.97	-1.04
FR4	116.00	114.41	230.41	1.59	IM6	114.72	116.46	231.17	-1.74
SP1	115.67	114.50	230.18	1.17	ST1	116.03	115.86	231.88	0.17
SP2	115.60	114.86	230.46	0.74	ST2	116.38	117.26	233.64	-0.88
SP3	115.09	115.56	230.65	-0.48	ST3	116.34	116.66	233.00	-0.32
SS1	116.08	116.86	232.94	-0.78	SD1	116.00	115.93	231.94	0.07
SS2	115.69	116.76	232.44	-1.07	SD2	117.31	117.07	234.38	0.24
SS3	116.08	116.36	232.44	-0.27	SD3	116.06	116.82	232.88	-0.76
IM1	115.07	115.92	230.99	-0.84	ER1	117.06	116.74	233.81	0.32
IM2	115.42	115.59	231.01	-0.16	ER2	117.07	116.67	233.73	0.40

Step 7. When the degree of center ($r_i + c_j$) and the degree of cause ($r_i - c_j$) are used as horizontal and vertical coordinates respectively, we can correspond each of the 24 risk factors to the axes, as shown in Figure 2:

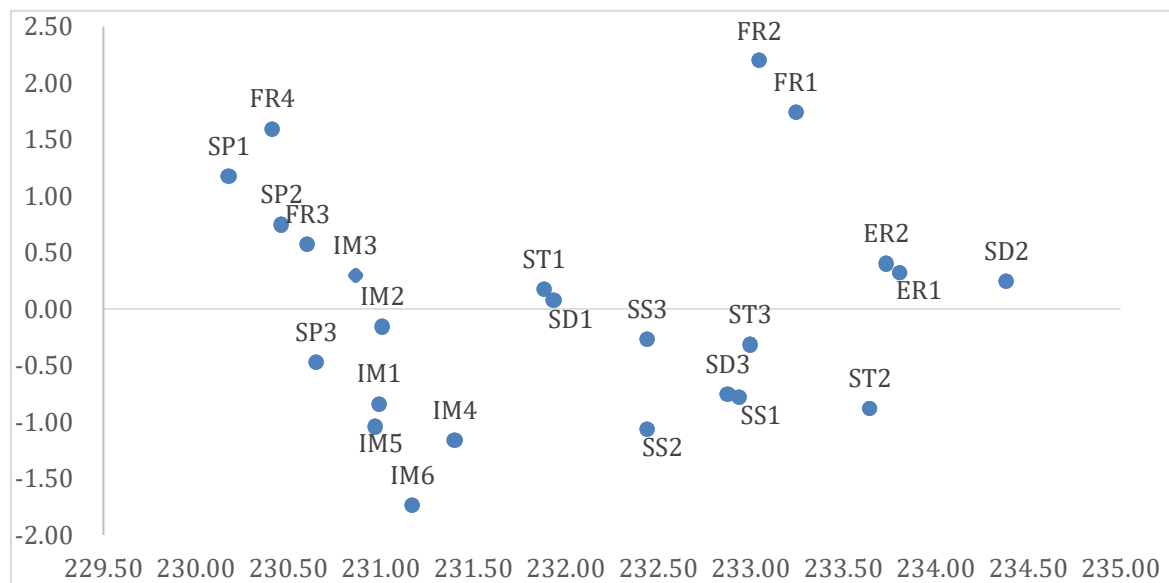


Fig. 2. Distribution of risk factors

We will use the average (4.8334) of the values in the score function matrix T^* as a threshold to determine the direction of the arrows in the directed graph by comparing these values of risk factors. And the network directed graph will be drawn for each stage (as shown in Figures 3 to 8). Besides, we can find, based on the network directed graph, that there are unidirectional and bidirectional arrows for the influence between risk factors. The unidirectional arrow indicates a single effect between two factors, while the bidirectional arrow indicates that two risk factors have a reciprocal effect.

5. Discussion

In this section, we will analyze the risk factors in the conjunction with the risk network directed graphs at different stages and the relevant data obtained.

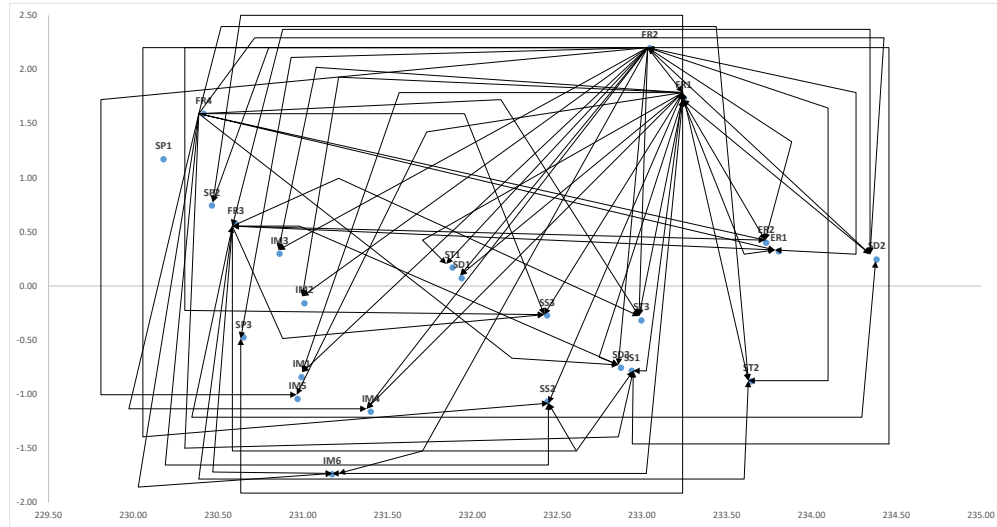


Fig. 3. The network directed graph of forecasting risk

First, we will analyze the risk factors among different service nodes according to Figures 3 to 8. Based on the forecasting risk directed graph of the product design process, we can find that FR1 and FR2 as risks related to the market and consumer demand affect each stage of the supply chain system. And as the smart supply chain is an important system to break down the barriers between smart manufacturing service nodes, we need to analyze the risk factors affecting its operation. Inaccurate analysis of the market situation means that the supply chain system is unable to accurately predict changes and trends in market demand, leading to possible deviations in production planning, inventory management and logistics arrangements, increasing the risk of supply chain operations. Beside inadequate identification of customers' core requirements may result in the supply chain system failing to meet customer expectations, and product quality and delivery time may not be in line with market demand, thus reducing customer satisfaction.

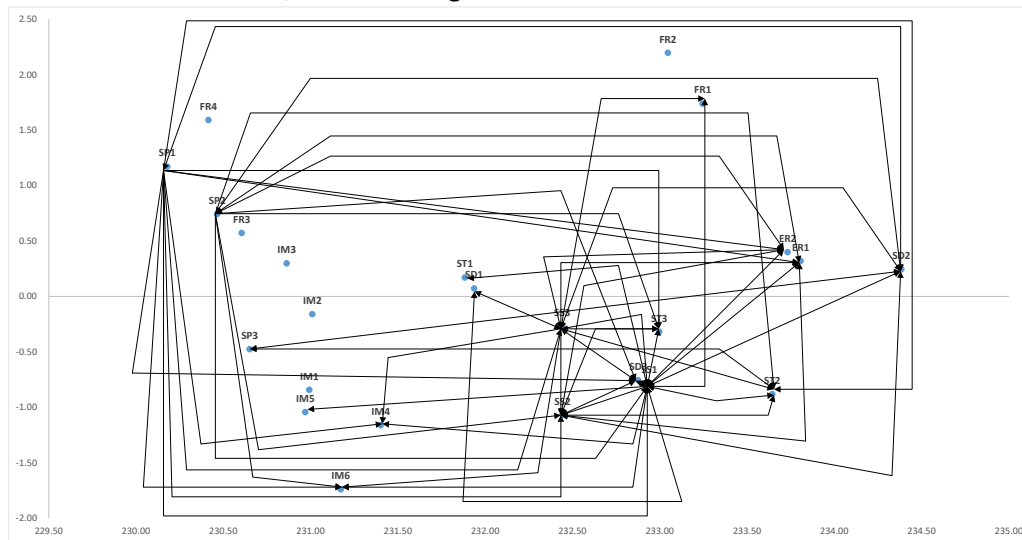


Fig. 4. The network directed graph of SP and SS

SP1 and SP2 mainly unilaterally affect the warehousing service nodes and transportation service nodes. If the procurement information is not symmetrical in time, the providers of warehousing services and transportation services will not be able to accurately know the quantity, specification, delivery time and other key information of the goods. This may lead to forecasting and planning errors, and the inability to make reasonable warehousing and transportation arrangements, affecting the timeliness and efficiency of services.

Besides, if the database information is not updated in time, there may be a backlog or shortage of goods, affecting the normal operation of the supply chain.

SS1 and SS3 affect the manufacturing service nodes and the transportation service nodes. Electronic label misreading may lead to wrong production process and operation. If the information on the electronic label is incorrectly read or cannot be read, it may lead to errors in the process on the production line, thus delaying the production schedule and delivery time. Misreading of critical information (e.g., specifications, part numbers, etc.) on electronic labels may lead to non-compliance with product specifications and quality problems. AGV path errors will result in abnormal action or downtime of automated equipment. If an AGV encounters a path error while performing a task, there may be interruptions in equipment operation, production line downtime, etc., which in turn affects the operational efficiency and capacity of the entire intelligent manufacturing system.

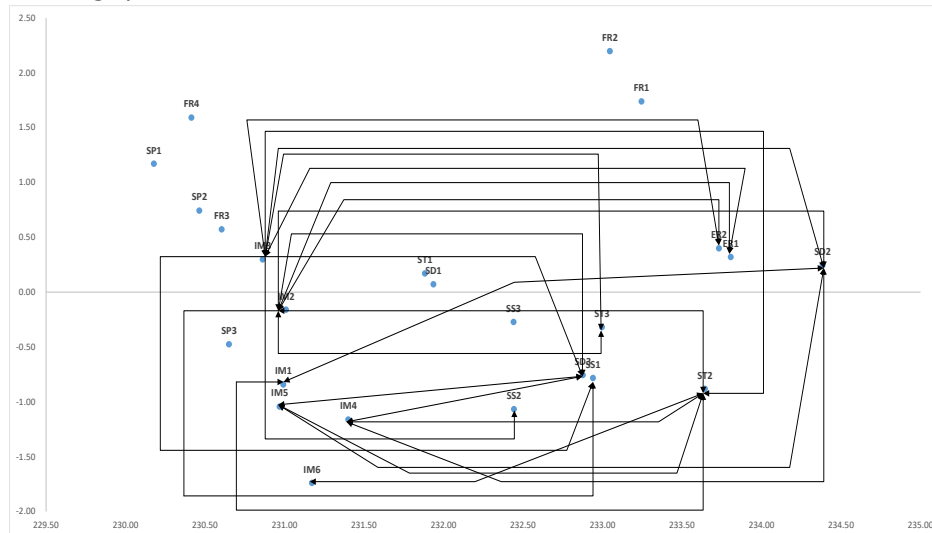


Fig. 5. The network directed graph of IM

As shown in Figure 5, IM1-IM6 have less impact on other service nodes. However, if there is a problem in the manufacturing process, it will lead to a decrease in the efficiency of the subsequent transportation and distribution service nodes.

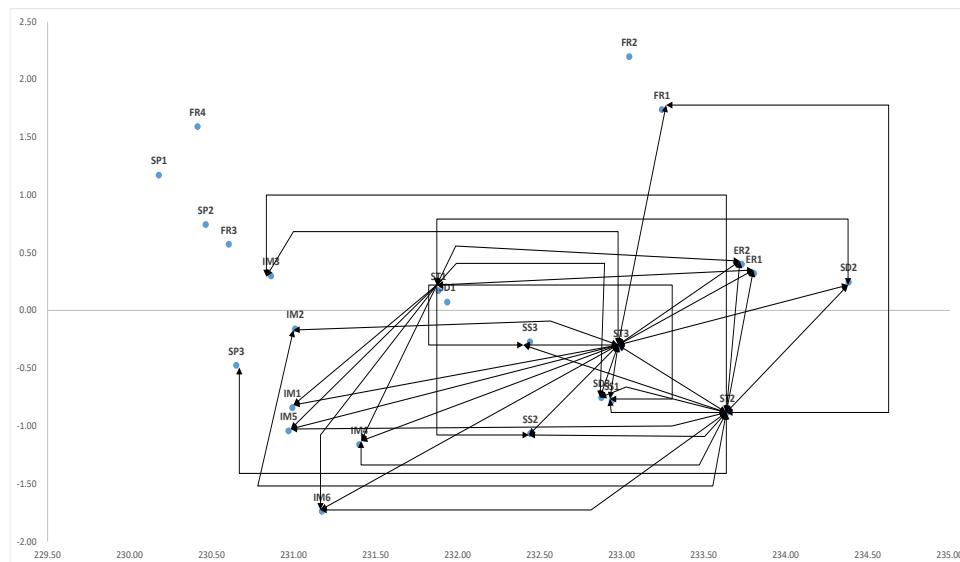


Fig. 6. The network directed graph of ST

For the risk that exists in the logistics intelligent service node, it is mainly reflected in the lack of information technology and intelligent equipment. This type of risk mainly affects the warehouse service

nodes and the manufacturing service nodes, and is mainly reflected in situations such as cargo crushing or out-of-stocks.

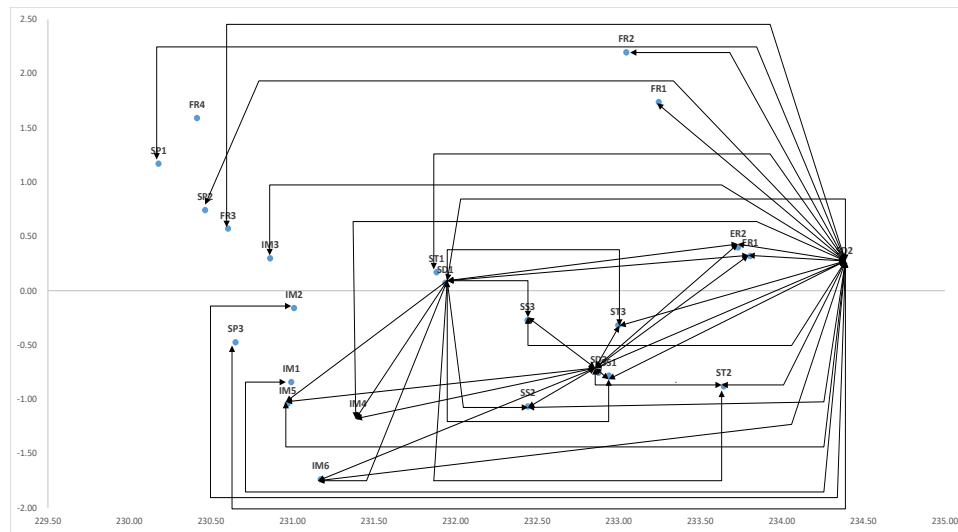


Fig. 7. The network directed graph of SD

Regarding the sales service node, the main issue lies in the problem of privacy leakage. Privacy leakage problems can lead to a crisis of trust between intelligent manufacturing service companies, and at the same time, customers may also experience reduced satisfaction due to information leakage.

The external environment and other service nodes mutually influence each other, in other words, they have a complementary relationship. Some business phenomena can lead to the establishment of new policies, and policies can also impact the development of businesses.

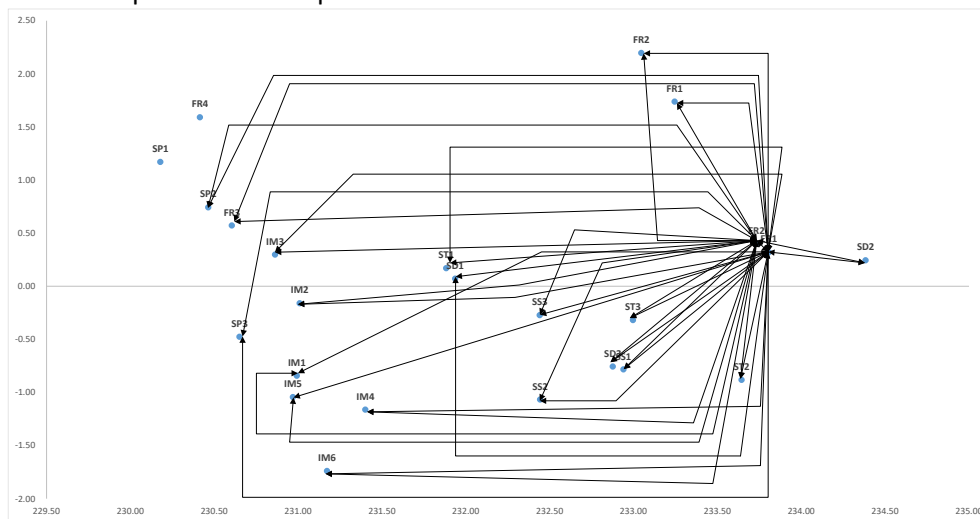


Fig. 8. The network directed graph of ER

Then, according to the values of the impact degree (r_i) shown in Table 3, we will find that FR2 (insufficient identification of core customer needs) is the factor with the highest impact on other risk factors. For customer-centric intelligent manufacturing service enterprises, customer demands are the prerequisite for all operations. Failing to accurately comprehend customer requirements and preferences makes it challenging for a business to establish appropriate product positioning. This can potentially result in unreasonable product designs, redundant or missing functionalities, thus affecting the market competitiveness of the product. Furthermore, failing to fully understand the core needs of customers, a business may be unable to grasp market changes and potential opportunities, impacting the company's innovation capability and product development direction. This could potentially result in the company lagging behind its competitors in technology and missing out on market opportunities. Therefore, this article proposes to integrate customer opinions and ideas into

every service node of the smart supply chain system, enhancing customer satisfaction and overall production efficiency in all aspects.

According to the degree of center ($r_i + c_j$) shown, the factor with the highest level of importance is SD2 (The privacy is leaked). As the level of intelligence in the supply chain system gradually increases, enterprises inevitably need to assess and control such network information data. Improper handling may potentially lead to the leakage of a significant amount of sensitive information, such as supplier information, customer data, transaction records, and more. If the system is subjected to an attack, hackers may steal this data for illegal purposes, leading to issues such as the leakage of company and personal privacy, as well as trade secrets. Furthermore, the source and continuity of information data are also essential factors that deserve attention. To address such issues, it is necessary to conduct research on the quality of information, which is one of the challenges that needs to be resolved after the intelligence of the supply chain system is enhanced.

6. Research implications

6.1 Theoretical implications

This article has the following theoretical significance for the research field of risk assessment of IMS. First, this paper identifies the risk factors in smart supply chain in IMS that will affect the operation of the system. Risk factors include intelligent forecasting nodes, smart procurement nodes, smart warehousing nodes, intelligent manufacturing nodes, smart transportation nodes, smart distribution nodes, and external environment. Comprehensive factor analysis provides relevant insights for both smart manufacturing services and smart supply chains. Secondly, this paper combines linguistic q-ROFS with the classic DEMATEL method to solve the problems of uncertainty and ambiguity in the field of evaluation research.

6.2 Managerial implications

In Section 5, we analyzed the assessment results of risk factors. Based on the series of results obtained, we will provide some managerial implications from both the internal and external perspectives of the intelligent manufacturing service system.

- (1) When a business is unable to efficiently and accurately gather sufficient customer information, there are several ways to improve data collection. This can be done through enhancing the website, survey methods, and customer feedback channels to increase the sources of data. In this way, we could ensure a more comprehensive acquisition of customer information. Additionally, existing data can be synthesized, and data mining and analysis techniques can be employed to infer potential missing information, allowing for a better understanding of customer needs and behavior. Furthermore, businesses can offer value-added services. This means that companies can provide personalized recommendations, professional advice, discounts, or reward programs to encourage customers to voluntarily share information.
- (2) When customer information is leaked, we should quickly find the source of the information leak, shut down the affected system, repair the vulnerability, suspend related services and take emergency measures quickly. Second, we should investigate and identify vulnerabilities: Look inside the system to identify vulnerabilities and security issues that lead to data breaches. Subsequently, steps are taken to fix these vulnerabilities to prevent future information leaks. In addition, companies should provide compensation and additional security measures to customers to restore their trust.
- (3) Regarding risks encountered in the intelligent manufacturing process, companies should ensure the security of industrial control equipment, including regularly updating the software and firmware of the equipment, configuring strong passwords and access control policies, and using anti-virus software and other protective measures. In addition, intelligent manufacturing companies must ensure good connectivity with other service nodes. We can establish a unified information platform to integrate information from various nodes to achieve data sharing and business process collaboration.
- (4) In addition to internal management of the system, enterprises should also strengthen their ability to adapt to the external environment. We can establish a dedicated team responsible for monitoring policy changes related to intelligent manufacturing and intelligent manufacturing services. Corporate executives should identify opportunities arising from policy changes and actively exploit these

opportunities to promote corporate development. For example, the government may provide funding, subsidies, or R&D support to promote innovation in intelligent manufacturing. In addition, companies should maintain sufficient flexibility and be able to quickly adjust their business models and strategies to adapt to policy changes.

7. Conclusion

This paper takes the integration of "intelligent manufacturing" and "service-oriented manufacturing" as the research object, starting from the smart supply chain system, and studies the risk issues of smart service nodes in the smart supply chain oriented to smart manufacturing services. By combining the Lq-ROFS and the traditional DEMATEL method, a new Lq-ROF-DEMATEL analysis system was constructed to conduct a comparative analysis of 24 risk factors. Finally, it was concluded that the risk factors that affect the smart supply chain to a high degree include insufficient identification of customers' core needs, improper processing of network information data, leakage of customer privacy, and the impact of the policy environment. There are two shortcomings of this article: first, the identification of risk factors mainly comes from literature search, without objective screening and analysis; second, the q-ROFS is two dimensions, and there is still room for expansion. Therefore, future work is mainly to use models to screen risk factors, and secondly, to combine the larger-dimensional fuzzy environment with the DEMATEL method to study the influence between factors.

Author Contributions

Conceptualization, T.X., H.W. and L.F.; methodology, T.X.; software, T.X.; validation, H.W., L.F. and Y.Z.; formal analysis, T.X.; investigation, T.X.; resources, T.X.; data curation, T.X.; writing—original draft preparation, T.X.; writing—review and editing, T.X.; visualization, T.X.; supervision, H.W. and L.F.; project administration, H.W. and L.F.; funding acquisition, H.W. and L.F. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by the National Natural Science Foundation, China (No. 72361026, 71862025), Jiangxi Social Science Foundation Project (20MJ0), the Humanities and Social Sciences Foundation of Ministry of Education of the People's Republic of China (No. 19YJC630164), the Postdoctoral Science Foundation of Jiangxi Province (No. 2019KY14) and Jiangxi Provincial "Double Thousand Plan" Philosophy and Social Science Leading Talent Project (jxsq2019203008).

Data Availability Statement

There is no data in this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

References

- [1] Li, X., & Zhou, D. (2020). Product Design Requirement Information Visualization Approach for Intelligent Manufacturing Services. *China Mechanical Engineering*, 31(7), 871-881. <https://doi.org/10.3969/j.issn.1004-132X.2020.07.013>

- [2] Zhang, W., Wang, X. K., Shi, Y. J., Gu, X. J., Wang, J., & Tian, J. H. (2023). Construction technology of intelligent manufacturing service systems driven by industrial big data. *SCIENTIA SINICA Technologica*, 53(7), 1084-1096. <https://doi.org/10.1360/SST-2022-0372>
- [3] Shieh, J. I., Wu, H. H., & Huang, K. K. (2010). A DEMATEL method in identifying key success factors of hospital service quality. *Knowledge-Based Systems*, 23(3), 277-282. <https://doi.org/10.1016/j.knosys.2010.01.013>
- [4] Kashyap, A., Kumar, C., Kumar, V., & Shukla, O. J. (2022). A DEMATEL model for identifying the impediments to the implementation of circularity in the aluminum industry. *Decision Analytics Journal*, 5, 100134. <https://doi.org/10.1016/j.dajour.2022.100134>
- [5] Yilmaz, I., Erdebilli, B., Naji, M. A., & Mousrij, A. (2023). A Fuzzy DEMATEL framework for maintenance performance improvement: A case of Moroccan Chemical Industry. *Journal of Engineering Research*, 11(1), 100019. <https://doi.org/10.1016/j.jer.2023.100019>
- [6] Sun, L., Peng, J., Dinçer, H., & Yüksel, S. (2022). Coalition-oriented strategic selection of renewable energy system alternatives using q-ROF DEMATEL with golden cut. *Energy*, 256(1), 124606. <https://doi.org/10.1016/j.energy.2022.124606>
- [7] Giret, A., Garcia, E., & Botti, V. (2016). An engineering framework for Service-Oriented Intelligent Manufacturing Systems. *Computers in Industry*, 81, 116-127. <https://doi.org/10.1016/j.compind.2016.02.002>
- [8] Zhang, L., Feng, L., Wang, J., & Lin, K. Y. (2022). Integration of Design, Manufacturing, and Service Based on Digital Twin to Realize Intelligent Manufacturing. *Machines*, 10(4), 275. <https://doi.org/10.3390/machines10040275>
- [9] Wang, S., Zhang, Y., Qian, C., & Zhang, D. (2021). A framework for credit-driven smart manufacturing service configuration based on complex networks. *International Journal of Computer Integrated Manufacturing*, 35(10-11), 1107-1132. <https://doi.org/10.1080/0951192X.2021.1879400>
- [10] Zhang, G., Chen, C. H., Zheng, P., & Zhong, R. Y. (2020). An integrated framework for active discovery and optimal allocation of smart manufacturing services. *Journal of Cleaner Production*, 273(10), 123144. <https://doi.org/10.1016/j.jclepro.2020.123144>
- [11] Tao, F., & Qi, Q. (2017). New IT driven service-oriented smart manufacturing: framework and characteristics. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(1), 81-91. <https://doi.org/10.1109/TSMC.2017.2723764>
- [12] Liu, Z., Qin, X., Cheng, Q., & Tang, Y. (2021). Thoughts on Smart Supply Chain Management System. *Supply Chain Management*, 9, 5-15. <https://doi.org/10.19868/j.cnki.gylgl.2021.09.001>
- [13] Liu, W., Zeng, Y., & Qiao, X. (2022). Preliminary Study on Quality Standard System of Smart Supply Chain. *Supply Chain Management*, 9, 5-19. <https://doi.org/10.19868/j.cnki.gylgl.2022.09.001>
- [14] Liu, W., Long, S., & Wei, S. (2022). Correlation mechanism between smart technology and smart supply chain innovation performance: A multi-case study from China's companies with Physical Internet. *International Journal of Production Economics*, 245, 108394. <https://doi.org/10.1016/j.iipe.2021.108394>
- [15] AlMulhim, A. F. (2021). Smart supply chain and firm performance: the role of digital technologies. *Business Process Management Journal*, 27(5), 1353-1372. <https://doi.org/10.1108/BPMJ-12-2020-0573>
- [16] Viriyasitavat, W., Bi, Z., & Hoonsopon, D. (2022). Blockchain technologies for interoperation of business processes in smart supply chains. *Journal of Industrial Information Integration*, 26, 100326. <https://doi.org/10.1016/j.jii.2022.100326>
- [17] Butner, K. (2010). The smarter supply chain of the future. *Strategy & leadership*, 38(1), 22-31. <https://doi.org/10.1108/10878571011009859>
- [18] Tripathi, S., & Gupta, M. (2020). Transforming towards a smarter supply chain. *International Journal of Logistics Systems and Management*, 36(3), 319-342. <https://doi.org/10.1504/IJLSM.2020.108694>
- [19] Marc, I., & Berlec, T. (2023). Inventory Risk Decision-Making Techniques Using Customer Behaviour Analysis. *Journal of Mechanical Engineering*, 69(7-8), 317-325. <http://dx.doi.org/10.5545/sv-jme.2023.577>
- [20] Chen, J., Xiao, Y., & Zhu, B. (2021). Procurement risk evaluation from a big-data perspective: A case study of a procurement service company. *Systems Engineering Theory & Practice*, 41(3), 596-612. <https://doi.org/10.12011/SETP2019-1219>
- [21] Oke, A. E., Kineber, A. F., Akindede, O., & Ekundayo, D. (2023). Determining the stationary barriers to the implementation of radio frequency identification (RFID) technology in an emerging construction industry. *Journal of Engineering, Design and Technology*. <https://doi.org/10.1108/JEDT-07-2022-0348>
- [22] Bekishev, Y., Pisarenko, Z., & Arkadiev, V. (2023). FMEA Model in Risk Analysis for the Implementation of AGV/AMR Robotic Technologies into the Internal Supply System of Enterprises. *Risks*, 11(10), 172. <https://doi.org/10.3390/risks11100172>

- [23] Li, B., Hou, B., Yu, W., Lu, X., & Yang, C. (2017). Applications of artificial intelligence in intelligent manufacturing: a review. *Frontiers of Information Technology & Electronic Engineering*, 18(1), 86-96. <https://doi.org/10.1631/FITEE.1601885>
- [24] Liu, Y., & Zheng, J. (2022). Intelligent management of supply chain logistics based on 5g LoT. *Cluster Computing*, 25, 2271–2280. <https://doi.org/10.1007/s10586-021-03487-x>
- [25] Zheng, K., Huo, X., Jasimuddin, S., Zhang, Z., & Battaia, O. (2023). Logistics distribution optimization: Fuzzy clustering analysis of e-commerce customers' demands. *Computers in Industry*, 151, 103960. <https://doi.org/10.1016/j.compind.2023.103960>
- [26] Qi, Q., Xu, Z., & Rani, P. (2023). Big data analytics challenges to implementing the intelligent Industrial Internet of Things (IIoT) systems in sustainable manufacturing operations. *Technological Forecasting & Social Change*, 190, 1–15. <https://doi.org/10.1016/j.techfore.2023.122401>
- [27] Kaur, B., Dadkhah, S., Shoeleh, F., Neto, E. C. P., Xiong, P., Iqbal, S., Lamontagne, P., Ray, S., & Ghorbani, A. (2023). Internet of Things (IoT) security dataset evolution: Challenges and future directions. *Internet of Things*, 22, 1-23. <https://doi.org/10.1016/j.iot.2023.100780>
- [28] Fodor, G., Dahlman, E., Mildh, G., Parkvall, S., Reider, N., Miklós, G., & Turányi, Z. (2012). Design aspects of network assisted device-to-device communications. *IEEE Communications Magazine*, 50(3), 170-177. <https://doi.org/10.1109/MCOM.2012.6163598>
- [29] Weibull, K., Lidestam, B., & Prytz, E. (2022). Potential of Cooperative Intelligent Transport System Services to Mitigate Risk Factors Associated With Emergency Vehicle Accidents. *Transportation research record*, 2677(3), pp.999-1015. <https://doi.org/10.1177/03611981221119459>
- [30] Wei, X., Sun, C., Lyu, M., Song, Q., & Li, Y. (2022). ConstDet: Control Semantics-Based Detection for GPS Spoofing Attacks on UAVs. *Remote Sensing*, 14(21), 5587. <https://doi.org/10.3390/rs14215587>
- [31] Xu, M., Cui, Y., Hu, M., Xu, X., Zhang, Z., Liang, S., & Qu, S. (2019). Supply chain sustainability risk and assessment. *Journal of Cleaner Production*, 225, 857-867. <https://doi.org/10.1016/j.jclepro.2019.03.307>
- [32] Govindan, K., & Chaudhuri, A. (2016). Interrelationships of risks faced by third party logistics service providers: A DEMATEL based approach. *Transportation Research Part E*, 90, 177-195. <https://doi.org/10.1016/j.tre.2015.11.010>
- [33] Rajesh, R., & Ravi, V. (2017). Analyzing drivers of risks in electronic supply chains: a grey–DEMATEL approach. *The International Journal of Advanced Manufacturing Technology*, 92, 1127-1145. <https://doi.org/10.1007/s00170-017-0118-3>
- [34] Sreedevi, R., & Saranga, H. (2017). Uncertainty and supply chain risk: The moderating role of supply chain flexibility in risk mitigation. *International Journal of Production Economics*, 193, 332-342. <https://doi.org/10.1016/j.ijpe.2017.07.024>
- [35] Rostamzadeh, R., Ghorabae, M. K., Govindan, K., Esmaili, A., & Nobar, H. B. K. (2018). Evaluation of sustainable supply chain risk management using an integrated fuzzy TOPSIS- CRITIC approach. *Journal of Cleaner Production*, 175(20), 651-669. <https://doi.org/10.1016/j.jclepro.2017.12.071>
- [36] Wan, N., Li, L., Ye, C., & Wang, A. B. (2019). Risk Assessment in Intelligent Manufacturing Process: A Case Study of An Optical Cable Automatic Arranging Robot. *IEEE Access*, 7, 105892–105901. <https://doi.org/10.1109/ACCESS.2019.2932756>
- [37] Hansen, J., Hellin, J., Rosenstock, T., Fisher, E., Cairns, J., Stirling, C., Lamanna, C., Etten, J., Rose, A., & Campbell, B. (2019). Climate risk management and rural poverty reduction. *Agricultural Systems*, 172, 28-46. <https://doi.org/10.1016/j.agsy.2018.01.019>
- [38] Abdel-Basset, M., & Mohamed, R. (2020). A novel plithogenic TOPSIS- CRITIC model for sustainable supply chain risk management. *Journal of Cleaner Production*, 247(20), 119586. <https://doi.org/10.1016/j.jclepro.2019.119586>
- [39] Munir, M., Jajja, M. S. S., Chatha, K. A., & Farooq, S. (2020). Supply chain risk management and operational performance: The enabling role of supply chain integration. *International Journal of Production Economics*, 227, 107667. <https://doi.org/10.1016/j.ijpe.2020.107667>
- [40] Liu, C., Ji, H., & Wei, J. (2021). Smart Supply Chain Risk Assessment in Intelligent Manufacturing. *Journal of Computer Information Systems*, 62(3), 609-621. <https://doi.org/10.1080/08874417.2021.1872045>
- [41] Lin, S. S., Shen, S. L., Zhou, A., & Xu, Y. S. (2021). Risk assessment and management of excavation system based on fuzzy set theory and machine learning methods. *Automation in Construction*, 122, 103490. <https://doi.org/10.1016/j.autcon.2020.103490>
- [42] Li, S., Huang, K., Liu, Y., Ge, F., & Liu, S. (2022). Risk Assessment in Supplier Selection for Intelligent Manufacturing Systems Based on PLS-SEM. *Applied Science*, 12(8), 3998. <https://doi.org/10.3390/app12083998>
- [43] Seker, S., Bağlan, F. B., Aydin, N., Deveci, M., & Ding, W. (2023). Risk assessment approach for analyzing risk factors to overcome pandemic using interval-valued q-rung orthopair fuzzy decision making method. *Applied Soft Computing*, 132, 109891. <https://doi.org/10.1016/j.asoc.2022.109891>

- [44] Cheng, C., Steinman, A. D., Zhang, K., Lin, Q., Xue, Q., Wang, X., & Xie, L. (2023). Risk assessment and identification of factors influencing the historical concentrations of microcystin in Lake Taihu, China. *Journal of environmental sciences*, 127, 1-14 <https://doi.org/10.1016/j.jes.2022.03.043>
- [45] Reshad, A. I., & Biswas, T., Agarwal, R., Paul, S. K., Azeem, A. (2023). Evaluating barriers and strategies to sustainable supply chain risk management in the context of an emerging economy. *Business strategy and the environment*, 1-20. <https://doi.org/10.1002/bse.3367>
- [46] Lima, F. A. D., & Seuring, S. (2023). A Delphi study examining risk and uncertainty management in circular supply chains. *International journal of production economics*, 258, 108810. <https://doi.org/10.1016/j.ijpe.2023.108810>
- [47] Minguito, G., & Banluta, J. (2023). Risk management in humanitarian supply chain based on FMEA and grey relational analysis. *Socio-economic planning sciences*, 87(B), 101551. <https://doi.org/10.1016/j.seps.2023.101551>
- [48] Lin, M., Li, X., & Chen, L. (2020). Linguistic q-rung orthopair fuzzy sets and their interactional partitioned Heronian mean aggregation operators. *International Journal of Intelligent Systems*, 35(2), 217-249. <https://doi.org/10.1002/int.22136>
- [49] Liu, P., & Liu, W. (2019). Multiple-attribute group decision-making based on power Bonferroni operators of linguistic q-rung orthopair fuzzy numbers. *International Journal of Intelligent Systems*, 34(4), 652-689. <https://doi.org/10.1002/int.22071>