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INVESTIGATING THE INTERNET-OF-THINGS (IOT) RISKS FOR SUPPLY CHAIN MANAGEMENT USING Q-RUNG ORTHOPAIR FUZZY-SWARA-ARAS FRAMEWORK

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Abstract. Modern "*Supply Chains* (*SCs*)" have recently been introduced as value networks of high complexity, and firms have focused on its efficiency as an important support for staying competitive in the market. Firms are currently capable of observing, tracking, and monitoring their products, activities, and processes throughout their value chain networks using new technologies, namely the "*Internet of Things* (*IoT*)". Though, the influencing factors of IoT are highly complex and diverse, which result in the information-intensiveness of the SCs processes. This, in turn, leads to lots of barriers to SCs. In this paper, we evaluate and rank the IoT risks for "*Supply Chain Management* (*SCM*)" by utilizing "*Stepwise Weight Assessment Ratio Analysis* (*SWARA*)" and "*Additive Ratio Assessment* (*ARAS*)" under "*q-Rung Orthopair Fuzzy Sets* (*q-ROFSs*)". A case study is presented for investigating the IoT risks for SCM in the q-ROFSs setting. Moreover, the obtained results were compared to those of some methods currently used in the literature. The outcomes of the study show that the security and privacy risks with a weight value of 0.0572 is the main IoT risk factor for the SCM and the organization-I with the utility degree 0.8208 is the best option with diverse IoT risks for SCM.

Keywords: Internet of Things (IoT), supply chain, q-rung orthopair fuzzy sets, SWARA, multi-criteria decision-making, ARAS.

JEL Classification: O14, L86, Q01, C02, D81.

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Introduction

In the context of the "*Supply Chain Management* (*SCM*)", "*Internet of things* (*IoT*)" plays the role of an active system of sensors and gateways that are digitally connected to each other for sensing and monitoring tasks. IoT has the capacity to facilitate the coordination of the SCM stakeholders through sharing the available information and resources to help them with planning, controlling, and coordinating of procedures for SCs (Li et al., 2020; Ren et al., 2017). Tu (2018) put forward to identify the factors that can impact the enterprises' goal for the implementation of IoT in their logistics and SCM processes. They showed that enterprises mainly use Industrial IoT (IIoT) for the purpose of collecting onsite real-time information. IoT clearly depicts the product flow at all steps, which starts from manufacturing and keeps on its path towards warehouse, distributors, and finally to consumers; this way, IoT brings out transparency to the whole system (Guo et al., 2021).

All items that enter a SC are tagged with "*Radio Frequency Identification* (*RFID*)" (Li et al., 2018; Wang et al., 2018). Goods are transported by means of vehicles equipped with active GPS modules. With entering or leaving warehouse or inventory by the goods, RFID scanners automatically read tags and create database entry. The delivery processes are monitored by smart IoT devices, which involve inventory and order management at the warehouse and transportation. The IoT sensors are capable of detecting the low stock of any product and automatically ordering from the manufacturers on the basis of pending demands and former order data. The information in regard to the product or the RFID reader ID can be stored by the smart active RFID tags, along with the tag ID; as a result, it could be kept secured against tapering. Note that date and timestamp are also stored by RFID reader scanning tags. The reliability of the system is established based on two key factors, i.e., on-time delivery and safe delivery (Li et al., 2013, 2018). The information gathered by the sensors are accumulated through the internet to the cloud, which offers storage, virtual resources, and computing services hosted by skilled networking firms (He et al., 2020).

Those SCs that are supported by the IoT technology can be managed remotely; they can provide improved coordination between the stakeholders. In general, the accessibility of more precise real-time information can significantly improve customer satisfaction levels and decision-making processes (Ben-Daya et al., 2019). The sensors make available some information regarding the demands, location of goods throughout the transport path, stocking details at the warehouse, delivery, etc.; this way, it indeed covers the products' whole lifecycle. In addition, it helps to manage geographically detached vendors, distributors, and customers in effective ways. On the other hand, SCs may encounter security challenges due to the contribution of numerous stakeholders as well as the undependability of IoT infrastructure.

IoT organizes physical objects into a digitally connected network in which all the objects are capable of sensing, monitoring, and making the interaction between a firm and its SC that involves factories, suppliers, distributors, retailers, and consumers (Ben-Daya et al., 2019). IoT can enhance the information exchange, visibility, and agility, which can eventually lead to data transparency; it can provide countless of data in regard to the positions, weather conditions, temperatures, and other parameters associated with the products of the firm, which could not be observed at once previous to IoT emergence (Miorandi et al., 2012). Furthermore, IoT is able to prolong the products' life cycle, draw higher customers' satisfaction levels, and enhance the quality of the products with lower costs and less volume of generated waste (Gu & Liu, 2013; Harris et al., 2015; Mathaba et al., 2017).

In spite of all the above-mentioned benefits of IoT, this technology has faced a number of consequent risks (Birkel & Hartmann, 2019; Whitmore et al., 2015). The literature is being loaded with more and more studies conducted on SCM. Researchers and practitioners working in this domain are mainly concentrated upon the potential value and applications of IoT. On the other hand, adverse effects have been often ignored, generalized, or dealt with in isolation (Strange & Zucchella, 2017). The potential risks can negatively affect the rate of adopting the technology, thereby hindering the achievement of predicted benefits; as a result, special attention is needed (Bauk et al., 2017). Due to the risks of IoT in SCM and the recently-observed increase of the studies on this subject, there is a need to pay more attention to this topic.

In another research, Musa and Dabo (2016) focused upon the use of RFID from the year 2000 to 2015. Liu et al. (2017) performed a content analysis on IoT from the technological perspective. Belinski et al. (2020) provided a systematic literature survey and research plan that covers organizational learning and Industry 4.0. Meng (2021) discussed a study to present how SC enterprisers or business can collaborate with government or community in disaster SC risk management. In addition, the literature consists of numerous reviews with a special focus upon the topics connected with IoT (Guo et al., 2021; Qi et al., 2021; Zhang et al., 2018; Zielonka et al., 2021; Wu et al., 2019, 2021a, 2021b).

"*Decision experts* (*DEs*)" cannot provide solutions to "*Multi-Criteria Decision-Making* (*MCDM*)" problems in the real world, which is mainly due to human errors, lack of knowledge, wide-spread changes and computational complexity of today's environment. To overcome these complexities and facilitate the decision-making process in these situations, the idea of "*Intuitionistic Fuzzy Sets* (*IFSs*)" was introduced by Atanassov (1986). IFS is described by two factors: the "*Belongingness Degree* (*BD*)" and "*Non-belongingness Degree* (*ND*)", and holds a constraint according to which the addition of its BD and ND is ≤ 1. Afterward, Yager (2014) put forward the notion of "*Pythagorean Fuzzy Sets* (*PFSs*)" with the aim of mending the IFS drawback. PFS is also described by BD and ND and holds a constraint that the square sum of BD and ND is ≤ 1. At the present time, because of its capability for tackling the uncertainty that generally exists in real-world MCDM problems, PFSs are a very popular tool. The literature contains many theories, methods, and applications regarding PFSs (Peng, 2019; Rani et al., 2019, 2021).

Nonetheless, the space of PFS information is very narrow with the constraint that the square sum of BD and ND should not be greater than one. To address such a situation in an effective way, the "*q-Rung Orthopair Fuzzy Sets* (*q-ROFSs*)" was suggested by Yager (2017). These sets are also described by BD and ND. The theory of q-ROFSs holds a condition that the sum of the q^{th} powers of BD and ND is ≤ 1, where $q \geq 1$. This model is capable of properly handling the above-mentioned example. Therefore, the range of the q-ROFSs is broader than PFSs and IFSs corresponding to the variation of the parameter q ($q \geq 1$). Thus, the q-ROFS has higher flexibility in handling complex uncertain information. In recent years, many researchers have focused on the q-ROFSs environment. For instance, Peng and Liu (2019) examined novel formulae for information measures under q-ROFSs and studied their relationships. Liu and Liu (2019) studied some q-ROF-Bonferroni mean operators. An innovative model based on q-ROFS was proposed by Tang et al. (2020) with the aim of addressing the 3-way decision-making problem. A decision-making framework based on q-ROF was discussed by Krishankumar et al. (2021) to obtain an effective solution for renewable energy resource decision-making problem. Cheng et al. (2021) designed an integrated MCDM method for assessing the sustainable enterprise risk management in manufacturing small and medium-sized enterprises. Further, Zeng et al. (2021) suggested a weighted induced logarithmic distance measure based method for solving MCDM problems within the context of q-ROFSs.

The DEs often provide high significance to the criteria weights in the decision-making process. The attribute weights are divided into "*objective and subjective*" weights (Yang et al., 2021; He et al., 2021). The former is measurable with the help of decision-matrices; objective weights are defined by means of information given by the DEs (Dehnavi et al., 2015). In contrast, subjective weights reflect the DEs' opinions, who describe the relative importance of the criteria (Karabasevic et al., 2016a). To measure the subjective weights, the "*Stepwise Weight Assessment Ratio Analysis* (*SWARA*)" approach was initiated by Keršulienė et al. (2010). Compared to diverse tools such as AHP, the computational operations of SWARA are simpler. The "*Analytic Network Process* (*ANP*)" (Saaty, 1999) and AHP (Saaty, 1980) are the most commonly employed methods to predict the criteria weights; although, amongst the novel criteria weighting procedures, SWARA (Keršulienė et al., 2010), "*Level Based Weight Assessment* (*LBWA*)" (Žižović & Pamucar, 2019),"*Full Consistency Method* (*FUCOM*)" (Pamucar et al., 2018), and "*Best-Worst Method* (*BWM*)" (Rezaei, 2015) are worth considering. Apart from SWARA, the other methods work on the basis of pairwise comparisons; though, considerable differences still exist in how they calculate the criteria weights. In AHP, $n(n-1)/2$ comparisons are required to be made in pairs of criteria. Note that making many comparisons results in higher complexity of the model implementation, particularly when there are many criteria to be taken into account. BWM became extensively utilized in a short time. In comparison with AHP, it has a smaller number of pair comparisons ($2n-3$). On the other hand, the existence of lots of comparisons in pairs of attributes, which define the limitations for the solution of nonlinear model, has caused the use of BWM to be of high complexity. For that reason, numerous scholars do not show any tendency to use it. FUCOM works on the basis of the pairwise comparisons of criteria, where there is a need only for the ($n-1$) comparison in the model. FUCOM aids in validating the model by computing the error value for considered weights by "Deviation from Full Consistency (DFC)" (Pamucar & Ecer, 2020). LBWA works based on the pairwise comparisons of criteria, in which there is a need only for the ($n-1$) comparison in the model. SWARA can effectively measure the criteria weights. In comparison to AHP, SWARA does not need many pairwise comparisons and also is more consistent. In addition, unlike BWM (Rezaei, 2015), SWARA does not involve the solution of complex-linear objective functions; it has lesser assessment intricacy and is easier to recognize than BWM. Mishra et al. (2020b) integrated SWARA with COPRAS with the aim of evaluating the bioenergy production processes with IFSs. He et al. (2021) put forward an interval-valued Pythagorean fuzzy SWARA based decision support system for assessing community-based tourism from sustainable perspective.

During the past few decades, MCDM was taken into consideration as a key process of people's daily lives. In real-life situations, it is not easy to solve MCDM problems (Cavallaro, 2010). Because of the increasing complexity and widespread alterations to today's environments, the conventional MCDM methods are generally inapplicable to the MCDM problems. The additive ratio assessment (ARAS) method (Zavadskas & Turskis, 2010) provides the argument that the phenomenon of complex domains could be tackled by simple relative comparisons. ARAS makes use of the concept of an optimality degree in order to achieve prioritization. The most important benefits of ARAS include: 1) direct and proportional relation with attribute weights (Iordache et al., 2019); 2) having the ability to solve complex problems

(Mishra et al., 2021); 3) involving some simple and direct steps for the assessment of a number of options or choices based on their performance in comparison with the chosen evaluation criteria that obtained suitable, sensible, and comparatively-accurate results (Zavadskas & Turskis, 2010). Most situations where the conventional ARAS has been recently utilized have been aimed at personnel evaluation purposes (Karabasevic et al., 2016a), the ranking of firms on the basis of indicators of corporate social accountability (Karabasevic et al., 2016b), and the evaluation of drug selections for COVID-19 (Mishra et al., 2021). Recently, this approach has been elaborated in various uncertain fields. A popular instance is the ARAS Grey model (Turskis & Zavadskas, 2010), which was extended on interval-valued triangular fuzzy numbers (Stanujkic, 2015). ARAS was used by Mishra et al. (2020a) for the assessment and selection of desired IT personnel for a firm on IFSs. Büyüközkan and Güler (2020) made use of two methods, i.e., SAW and ARAS, and then considering the results obtained, they evaluated and selected smart watch options.

The considered review studies contributed significantly to Internet of Things and its relevant topics; however, some significant knowledge gaps motivated the current research. Some of these studies focus on a specific topic, and some address IoT as a topic amongst many other subtopics. Some of the studies considered in this research have overlooked the field of SCM and its associated risks. Therefore, to classify the most imperative IoT risks in SCM, a survey approach has been regulated based on the literature review and experts' interviews. To doing so, a comprehensive framework including several risks related to IoT in the area of SCM has been developed in manufacturing companies. To analysis the IoT risk framework, an integrated decision-making approach has been proposed using SWARA and ARAS methods under q-ROFSs. Based on above-mentioned discussions, the main contributions of this study are as

- To conduct a survey approach utilizing expert interviews and literature review to investigate the IoT risks for the supply chain management.
- To propose an innovative approach to decision-making by means of the SWARA-ARAS method from q-rung orthopair fuzzy perspective to prioritize the organizations and analysis the main IoT risks for the supply chain management.
- The SWARA model is used to assess and prioritize the IoT risks for the supply chain management.
- The ARAS method from q-rung orthopair fuzzy perspective is discussed to prioritize the organization, analysis and evaluate the IoT risks for the supply chain management.
- To comparison and validation of the proposed q-ROF-SWARA-ARAS approach using other extant decision-making models.

The next sections are structured as: Section 1 presents the literature review related to the risks of IoT for the SCM. Section 2 firstly presents the fundamental ideas of q-ROFSs and then proposes an integrated SWARA-ARAS method under q-rung orthopair fuzzy environment. Section 3 presents the implementation results of the current method on a case study and further performed the sensitivity and comparative analyses. At last, the last Section confers the concluding remarks of this work.

1. Literature review

1.1. IoT risk in SCM

The effective factors of IoT are highly complex and diverse, resulting in an information-intensive SCM process and, in turn, lots of obstacles for companies and their SCs (Birkel & Hartmann, 2019). Furthermore, despite the fact that the significance of the exchange between SC associates and the significance of risk information has been well recognized in the literature, only limited research has been carried out with a focus on the cohesion of information requests and processing capacities in the SCM setting (Fan et al., 2017; Rogers et al., 1999).

A consequent risk for the IoT growth can be the shift of the providers' perspectives from a rather linear SC to an ecosystem (Birkel & Hartmann, 2019) wherein one platform plays the role of the architect of the structure and the setter of the benchmarks. This can result in the dominance of one supplier and also the formation of winner-takes-all markets (Rymaszewska et al., 2017). Such a problem can also be the case for firms in addition to smart capabilities, resulting in indistinct planned differences and zero-sum competitions. The problems stated sporadically comprise higher financial complexity and the indefinite effects of IoT on SCs (Neirotti et al., 2018). Thus, the substantial impacts of IoT on SCs and the macro-environment may result in numerous widespread risks.

The uncertainty in the adoption of technology and surveillance and suspicion to companies are consequent risks that emerge from privacy concerns. Societal risks are prevalent dealing with the adverse effects upon persons' lives, together with the rise of injuries rates (Ahmed et al., 2017) and missing of simple jobs, which occurs due to the increase of automation (Dweekat et al., 2017). More than 50% of the identified articles have addressed the security-related issues and recognized them as the origin of many other risks at diverse stages. Security has been conferred from several points of view (Khan & Salah, 2018), including the absence of transport encryption, non-secured web interfaces, or deficient authorization, which cause the IoT system to be susceptible to attacks (Karkouch et al., 2016). To moderate potential risks, many scholars have attempted to develop distinctive protocols, verification, and authorization to access control and trusted communications, security through transparency or hardware-based security at chipset stage (Díaz et al., 2016).

When the presented challenges are combined, many technological risks will arise. The attack-related risks are the main risks that may emerge, which have far-reaching consequences for people, companies, and SC networks (Qiu et al., 2015). In the majority of cases, there is an unbalanced information exchange between SC parties, which results in information irregularity. Therefore, the other risks from the increase of data exchange include the threat of being punished for unfair behaviors, the loss of information advantages, the expose of distribution channels, skipping SC stages, and the decrease of bargaining power. A portion of every network coordination demands high expenses for the management of the complicated heterogeneous network, which includes managing the enterprise relationships and data exchange processes (Lee & Lee, 2015). The objective of such expenses is to stay resilient against SC disruptions and also to avoid the decline of the network efficiency due to deficient management (Ochoa et al., 2017). The adoption and implementation of different technologies is an obstacle to the constant orchestration of SCs (Khan & Salah, 2018). It may result in the problem of dependency that can, in turn, bring about different risks (Friedewald & Raabe, 2011).

Opportunism addresses the problems that may arise due to malicious behaviors. Such behaviors (e.g., data manipulation, data misuse, financial penalties, and customer preference and favoritism) have negative impacts on both companies and consumers (Cavalcante et al., 2016a). Every company has to cope with different risks that may range from data management to human resources. The literature has emphasized the significance of complex data management for companies since it is taken into account as both challenge and risk (Parry et al., 2016). In strategic management, the risk is extensively prevalent and involves the risks that arise because of the adaption of decision models, the accomplishment of improper plans through undeveloped technologies, and complicated system management. In the context of operational management, the adoption of IoT may induce some risks such as imprecise risk detection, work intensification, loss of goods, delivery failure, etc (Qiu et al., 2015).

The financial risks involve the expenses of the maintenance of managerial IoT organizations, IoT-related operating costs, and technological developments (Birkel & Hartmann, 2019). Subsequent risks cover the adverse impacts on the company's stock price (De Cremer et al., 2017). The most addressed risks are related to attacks; this has directly resulted from the security issues with disturbing impacts upon both companies and SCs. The potential consequences scope is ranged from data leakage to physical damages to employees. Though, due to the high complexity of this issue, we can see that the literature suffers from a deficiency in quantifying the effects of attack-related risks with respect to companies and SCs (Birkel & Hartmann, 2019). The second mostly-discussed risk is network coordination, which plays an important role in SCM and IoT (De Cremer et al., 2017). To effectively address such challenges, there is a need for communication, trust management, and technological frameworks of high efficiency; in addition, it is necessary to carry out multidisciplinary research involving as many disciplines as possible. This has also been suggested by (Thomas, 2014).

For the alleviation of the opportunistic behaviors risks and distrust risks and also for the promotion of practical applications, there is a need for further research into delineated and incomplete information exchange between companies. In every IoT-based system, trust plays the role of a critical enabler. The IoT adoption results in changing value establishment in close association with the last customer; this needs relationships to be set both inside and across industries.

The most durable relationship continues among the attack-associated risks, the absence of permissible guidelines, high costs, reliance-related problems, and the complexity of the system use. It can be unexpected for a number of categories such as competition and asymmetry of information, low data quality and data exchange, and unknown productivity and lack of knowledge; although, it reflects single perspective approaches. Discussing the risks and relations can open a wide area of research and provide good opportunities for the contribution of knowledge. As a result, the current paper carried out a survey approach for the purpose of identifying the key risks, with the review of the existing literature and considering experts' opinions. This way, the present study also developed a comprehensive framework. Table 1 summarizes the IoT-related risks in the SCM context in the case of manufacturing firms.

Table 1. Considered IoT risks for SCM

IoT risks	References
Creation of zero-sum competition (r_1)	Bauk et al. (2017); Birkel and Hartmann (2019)
Economic risks (r_2)	Leone (2017); Strous et al. (2021)
Uncertain technology adoption (r_3)	Ahmed et al. (2017); Friedewald and Raabe (2011)
Surveillance and distrust (r_4)	Dutton (2014); Grieco et al. (2014)
Social risks (r_5)	Dweekat et al. (2017); Eling and Schnell (2016)
Security and privacy risks (r_6)	Ho-Sam-Sooi et al. (2021); Strous et al. (2021)
Low data quality (r_7)	Jing et al. (2014); Karkouch et al. (2016)
Technological risks (r_8)	Li et al. (2015); Lowry et al. (2017)
Political risks (r_9)	(Kshetri, 2017); Leone (2017)
Asymmetry of information (r_{10})	Docherty et al. (2018); Eurich et al. (2010)
Distrust and trust management (r_{11})	De Cremer et al. (2017); Díaz et al. (2016)
Complex network coordination (r_{12})	Bogle (2017); Yee-Loong Chong et al. (2015)
Dependencies and consequences (r_{13})	Gu et al. (2017); Docherty et al. (2018)
Opportunism (r_{14})	Cavalcante et al. (2016b); De Cremer et al. (2017)
Competition (r_{15})	Ghanbari et al. (2017); Jing et al. (2014)
Complex data management (r_{16})	Badia-Melis et al. (2018); Bardaki et al. (2012)
Strategic management (r_{17})	Bauk et al. (2017); Boos et al. (2013)
Operational management (r_{18})	Cavalcante et al. (2016b); Gu et al. (2017)
Financial-related (r_{19})	Badia-Melis et al. (2018); Bardaki et al. (2012)
Human resources (r_{20})	Yee-Loong Chong et al. (2015); Gubbi et al. (2013)

2. Proposed research method

2.1. Preliminaries

In the current part of study, some basic concepts of q-ROFSs are presented.

Definition 1. A q-rung orthopair fuzzy set B on a universal set $C=\{c_1,c_2,...,c_n\}$ is described as follows (Yager, 2017):

$$B=\left\{\left\langle c_i,\mu_B\left(c_i\right),\nu_B\left(c_i\right)\right\rangle \middle| c_i\in C\right\},$$

where $\mu_B:C\to[0,1]$ and $\nu_B:C\to[0,1]$ show the BD and ND of an object $c_i\in C$, respectively, with the constraints $0\le\mu_B(c_i)\le 1$, $0\le\nu_B(c_i)\le 1$, $0\le(\mu_B(c_i))^q+(\nu_B(c_i))^q\le 1$, $q\ge 1$, $\forall c_i\in C$. The indeterminacy degree is presented by $\pi_B(c_i)=\sqrt[q]{1-(\mu_B(c_i))^q-(\nu_B(c_i))^q}$, $\forall c_i\in C$. For ease, $\langle\mu_B(c_i),\nu_B(c_i)\rangle$ is said to be a *"q-Rung Orthopair Fuzzy Number (q-ROFN)"* and is signified by $\sigma=(\mu_\sigma,\nu_\sigma)$.

Definition 2. Let $\sigma=(\mu_\sigma,\nu_\sigma)$, $\sigma_1=(\mu_{\sigma_1},\nu_{\sigma_1})$ and $\sigma_2=(\mu_{\sigma_2},\nu_{\sigma_2})$ be the q-ROFNs. Then, the operational laws on q-ROFNs is given by (Liu & Wang, 2018)

(1) (1) $\sigma^c=(\nu_\sigma,\mu_\sigma)$;

(2) $\sigma_1 \oplus \sigma_2 = \left(\sqrt[q]{\mu_{\sigma_1}^q + \mu_{\sigma_2}^q - \mu_{\sigma_1}^q \mu_{\sigma_2}^q}, \nu_{\sigma_1} \nu_{\sigma_2} \right);$

(3) $\sigma_1 \otimes \sigma_2 = \left(\mu_{\sigma_1} \mu_{\sigma_2}, \sqrt[q]{\nu_{\sigma_1}^q + \nu_{\sigma_2}^q - \nu_{\sigma_1}^q \nu_{\sigma_2}^q} \right);$

(4) $\lambda \sigma = \left(\sqrt[q]{1 - \left(1 - \mu_\sigma^q\right)^\lambda}, \nu_\sigma^\lambda \right), \ \lambda > 0;$

(5) $\sigma^\lambda = \left(\mu_\sigma^\lambda, \sqrt[q]{1 - \left(1 - \nu_\sigma^q\right)^\lambda} \right), \ \lambda > 0.$

Definition 3. Let $\sigma = \left(\mu_\sigma, \nu_\sigma\right)$ be a q-ROFN. Then, Liu & Wang (2018) defined the score and accuracy values of σ, which as

$$\mathbb{S}\left(\sigma\right) = \mu_\sigma^q - \nu_\sigma^q \text{ and } \hbar\left(\sigma\right) = \mu_\sigma^q + \nu_\sigma^q \text{ where } \mathbb{S}\left(\sigma\right) \in \left[-1,1\right] \text{ and } \hbar\left(\sigma\right) \in \left[0,1\right].$$

The normalized score and uncertainty values of q-ROFNs are given by

$$\mathbb{S}^*\left(\sigma\right) = \frac{1}{2}\left(\mathbb{S}\left(\sigma\right) + 1\right), \text{ and } \hbar^\circ\left(\sigma\right) = 1 - \hbar\left(\sigma\right) \text{ such that } \mathbb{S}^*\left(\sigma\right), \hbar^\circ\left(\sigma\right) \in \left[0,1\right]. \tag{1}$$

Definition 4. Let $\sigma_1 = \left(\mu_{\sigma_1}, \nu_{\sigma_1}\right)$ and $\sigma_2 = \left(\mu_{\sigma_2}, \nu_{\sigma_2}\right)$ be q-ROFNs, then, the distance measure on σ_1 and σ_2 is given by

$$d\left(\sigma_1, \sigma_2\right) = \frac{1}{2}\left(\left|\mu_{\sigma_1}^q - \mu_{\sigma_2}^q\right| + \left|\nu_{\sigma_1}^q - \nu_{\sigma_2}^q\right| + \left|\pi_{\sigma_1}^q - \pi_{\sigma_2}^q\right| \right). \tag{2}$$

2.2. Proposed q-ROF-SWARA-ARAS approach

In the current section, we propose a hybrid decision-making method, called as q-ROF-SWARA-ARAS, for solving MCDM problems from q-rung orthopair fuzzy perspective. The procedural steps of the q-ROF-SWARA-ARAS framework are presented:

Step 1. Create a decision matrix

A committee of DEs $\left\{e_1, e_2, \ldots, e_l\right\}$ is created to find the best option from a set of alternatives $P = \left\{P_1, P_2, \ldots, P_m\right\}$ by means of attribute/criterion set $r = \left\{r_1, r_2, \ldots, r_n\right\}$. Let $M = \left(\zeta_{ij}^{(k)}\right)_{m \times n}$, $i = 1(1)m$, $j = 1(1)n$ denotes the *"q-ROF-decision matrix* (*q-ROF-DM*)*"* given by DEs, in which $\zeta_{ij}^{(k)}$ presents the evaluation of an alternative P_i over a criterion r_j in the form of q-ROFNs for k^{th} DE.

Step 2. Derive the DEs weights (λ_k)

The determination of the DEs' weights is a vital concern in the MCDM process. To do this, assume $e_k = \left(\mu_k, \nu_k\right)$ be a q-ROFN, then the weight of k^{th} expert is given by

$$\varpi_k = \frac{\mu_k^q\left(2 - \mu_k^q - \nu_k^q\right)}{\sum_{k=1}^{\ell}\left[\mu_k^q\left(2 - \mu_k^q - \nu_k^q\right)\right]}. \tag{3}$$

Clearly, $\varpi_k \geq 0$ and $\sum_{k=1}^{\ell} \varpi_k = 1.$

Step 3. Construct the aggregated q-ROF-DM (A-q-ROF-DM)

During the MCDM process, it is significant to combine the distinct decision opinions into one matrix. Here, the q-rung orthopair fuzzy weighted aggregated operator is utilized and then obtained the A-q-ROF-DM $\mathbb{N} = \left(\tilde{\zeta}_{ij}\right)_{m\times n}$, where

$$\tilde{\zeta}_{ij} = q - ROFWA_{\varpi}\left(\zeta_{ij}^{(1)}, \zeta_{ij}^{(2)}, \ldots, \zeta_{ij}^{(\ell)}\right) = \left(\sqrt[q]{1 - \prod_{k=1}^{\ell}\left(1-\mu_k^q\right)^{\varpi_k}}, \prod_{k=1}^{\ell}\left(\nu_k\right)^{\varpi_k}\right). \tag{4}$$

Step 4. Determination of the criteria weights using the SWARA approach

The procedure for computing the criteria weights is discussed as

Step 4.1. Predict the crisp values. The score values $\mathbb{S}^*\left(\tilde{\zeta}_{ij}\right)$ of q-ROFNs are calculated with the use of Eq. (2).

Step 4.2. Prioritize the attribute. The prioritization of the attributes is done based on the DE's preferences from the highly important to the lower important attributes.

Step 4.3. Evaluate the comparative significance of the mean value. The significance degree can be predicted considering the attribute placed in the second spot, and the subsequent comparative significance is calculated by making a comparison between the attribute r_j and attribute r_{j-1}.

Step 4.4. Assess the comparative factor κ_j as follows:

$$\kappa_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1, \end{cases} \tag{5}$$

wherein s_j symbolizes the significant value.

Step 4.5. Calculate the weights. The reassessed weight ρ_j is presented as

$$\rho_j = \begin{cases} 1, & j = 1 \\ \dfrac{\rho_{j-1}}{\kappa_j}, & j > 1. \end{cases} \tag{6}$$

Step 4.6. Compute the normalized weight. The attribute weights are normalized as

$$w_j = \frac{\rho_j}{\sum_{j=1}^{q}\rho_j}. \tag{7}$$

Step 5. Define optimal rating of alternative

The best rating of option can be obtained as

$$\mathbb{R}_0 = \begin{cases} \max\tilde{\zeta}_{ij}, & j \in r_b \\ \min\tilde{\zeta}_{ij}, & j \in r_n \end{cases}, \tag{8}$$

wherein r_b and r_n are the benefit and cost attributes, respectively.

Step 6. Normalize the A-q-ROF-DM

In the MCDM procedure, the A-q-ROF-DM $\mathbb{N} = \left(\tilde{\zeta}_{ij}\right)_{m\times n}$ is transformed into normalized A-q-ROF-DM (NA-q-ROF-DM) $\widehat{\mathbb{N}} = \left(\varsigma_{ij}\right)_{m\times n}$ such that

$$\varsigma_{ij} = \left(\widehat{\mu}_{ij}, \widehat{\nu}_{ij}\right) = \begin{cases} \tilde{\zeta}_{ij} = \left(\mu_{ij}, \nu_{ij}\right), & j \in R_b \\ \left(\tilde{\zeta}_{ij}\right)^c = \left(\nu_{ij}, \mu_{ij}\right), & j \in R_n. \end{cases} \tag{9}$$

Step 7. Make weighted NA-q-ROF-DM (WNA-q-ROF-DM)

The WNA-q-ROF-DM $\widehat{\mathbb{N}}_w = \left(\tilde{\varsigma}_{ij}\right)_{m\times n}$ is assembled as below:

$$\tilde{\varsigma}_{ij} = \overset{n}{\underset{j=1}{\oplus}} w_j \varsigma_{ij} = \left(\sqrt{1 - \prod_{j=1}^{n}\left(1-\widehat{\mu}_{ij}^{q}\right)^{w_j}}, \prod_{j=1}^{n}\left(\widehat{\nu}_{ij}\right)^{w_j} \right). \tag{10}$$

Step 8. Evaluation of the score value of option

By employing Eq. (1), the score values of WNA-q-ROF-decision matrix $\mathbb{N}_w = \left(\tilde{\varsigma}_{ij}\right)_{m\times n}$ are computed by

$$\mathbb{S}^*\left(\tilde{\varsigma}_{ij}\right) = \frac{1}{2}\left(\left(\tilde{\mu}_{ij}^{q} - \tilde{\nu}_{ij}^{q}\right) + 1\right). \tag{11}$$

Step 9. Evaluate the *"Overall Performance Rating* (*OPR*)*"* and *"Utility Degree* (*UD*)*"*

The OPR can be assessed using the expression

$$\Upsilon_i = \sum_{j=1}^{n} \mathbb{S}^*\left(\tilde{\varsigma}_{ij}\right). \tag{12}$$

The suitable option has the higher OPR, whilst the worst option has the minimum value of Υ_i. Hence, the prioritization of the options can be obtained using Υ_i.

To obtain the suitable option(s), it is not only essential to analyze the best option but also significant to obtain the relative significance of obtained choices with the most desirable rating. Hence, the UD $\mathbb{Q}_i$ of an alternative P_i is computed by

$$\mathbb{Q}_i = \frac{\Upsilon_i}{\mathbb{R}_0}. \tag{13}$$

Clearly, $\mathbb{Q}_i \in [0, 1]$ and can be preferred in descending ranking, which is the essential preference order.

Step 10. Choose the most desirable one

The highest UD $\mathbb{Q}_i$ of each option P_i is the best one. Therefore, the suitable option is evaluated using the procedure

$$\Upsilon^* = \left\{\Upsilon_i \mid \max_i \mathbb{Q}_i;\ i = 1(1)m\right\}, \tag{14}$$

Step 11. End.

3. Results and discussion

3.1. Case study

In the current part of the study, to recognize the key IoT risks in SCM, a comprehensive survey model by means of the current literature review and interviews with experts has been carried out. In total, 20 IoT risks including, the creation of zero-sum competition, economic risks, uncertain technology adoption, surveillance and distrust, social risks, security and privacy risks, low data quality, technological risks, political risks, asymmetry of information, distrust, and trust management, complex network coordination, dependencies and consequences, opportunism, competition, complex data management, strategic management, operational management, financial-related and human resources related to SCM are identified using a survey study. In the next stage, to evaluate the selected IoT risks in the manufacturing sector, a decision team of three DEs has been created. The procedural steps of the proposed method are as follows:

Steps 1 and 2. Assume that the DEs' weights are presented in the form of q-ROFNs, presented by {(0.90, 0.40, 0.5266), (0.75, 0.65, 0.6720), (0.80, 0.60, 6479)}. Now, Table 1 presents the q-ROF-DM $\mathbb{Z}^{(k)} = \left(\xi_{ij}^{(k)}\right)_{m\times n}, k = 1,2,3.$

Since DEs' importance degrees as provided by the experts, are in terms of q-ROFNs. Now, the weights $\lambda_k : 1,2,3$ of DMs are evaluated by employing Eq. (3) and given as {ϖ_1 = 0.3659, ϖ_2 = 0.2808, ϖ_3 = 0.3533}. Table 2 shows the grades in terms of *"Linguistic Values* (*LVs*)*"* of DEs to measure the options related to IoT risks for SCM.

Table 2. Ratings of options and IoT risks in terms of LVs

LVs	q-ROFNs
Absolutely Significant (AS)	(0.95,0.20)
Very Significant (VS)	(0.90,0.40)
Significant (S)	(0.80,0.60)
Moderately Significant (MS)	(0.75,0.65)
Average (A)	(0.60,0.70)
Moderately Insignificant (MI)	(0.50,0.75)
Insignificant (I)	(0.40,0.80)
Very Insignificant (VI)	(0.30,0.90)
Absolutely Insignificant (AI)	(0.20,0.95)

Table 3. LVs of alternative under different evaluate the IoT risks by DEs

	P_1	P_2	P_3	P_4
r_1	(S,A,S)	(A,MS,VI)	(MS,MS,A)	(S,S,A)
r_2	(A,VS,MS)	(A,S,S)	(S,A,MS)	(S,MS,MS)
r_3	(MS,VS,S)	(VS,MS,VS)	(MS,A,S)	(A,A,MS)
r_4	(MS,A,MS)	(VS,A,MS)	(MS,MI,MS)	(MI,A,S)
r_5	(A,MS,S)	(MS,S,S)	(S,MI,A)	(S,A,A)
r_6	(VI,MI,I)	(A,VI,I)	(VI,MS,A)	(VI,I,MS)
r_7	(MI,A,I)	(I,VI,I)	(A,MI,A)	(I,MI,A)
r_8	(S,MS,VS)	(A,S,MS)	(MI,A,MS)	(I,A,MS)
r_9	(MS,A,S)	(A,MS,S)	(A,MI,S)	(I,MI,S)
r_{10}	(MI,I,A)	(I,MI,VI)	(I,A,MI)	(I,I,MI)
r_{11}	(MI,I, I)	(MS,MI,I)	(MS,I,A)	(MS,MI,A)
r_{12}	(MI,I,MI)	(MI,A,MI)	(S,I,A)	(MS,I,A)

End of Table 3

	P_1	P_2	P_3	P_4
r_{13}	(MI,VI,VI)	(I,MI,I)	(MI,A,MI)	(MI,VI,MI)
r_{14}	(MI,A,S)	(MI,MS,S)	(MS,VS,MS)	(A,VS,S)
r_{15}	(VS,MS,A)	(MI,VS,S)	(A,MI,VS)	(A,A,MS)
r_{16}	(MI,I,VI)	(A,I,VI)	(MS,A,VS)	(MS,A,S)
r_{17}	(MS,MI,A)	(I,VS,MI)	(MS,MI,A)	(MS,I,A)
r_{18}	(MS,VS,S)	(A,VS,S)	(A,VI,MI)	(A,VI,MI)
r_{19}	(ML,A,S)	(MS,VS,S)	(MI,MS,A)	(MI,S,A)
r_{20}	(MS,VS,S)	(A,MS,A)	(MS,S,A)	(MS,MS,A)

Step 3. The LVs ratings of options, which are depicted in Table 3, provided by three decision experts have been combined using Eq. (4) and constructed an A-q-ROF-DM $A = \left(\xi_{ij}\right)_{m \times n}$, portrayed in Table 4.

Table 4. A-q-ROF-DM for IoT risks for SCM

	P_1	P_2	P_3	P_4
r_1	(0.762, 0.627, 0.678)	(0.612, 0.749, 0.705)	(0.709, 0.667, 0.703)	(0.751, 0.634, 0.686)
r_2	(0.782, 0.583, 0.687)	(0.749, 0.635, 0.687)	(0.742, 0.645, 0.687)	(0.770, 0.631, 0.663)
r_3	(0.805, 0.581, 0.656)	(0.880, 0.448, 0.612)	(0.741, 0.645, 0.687)	(0.666, 0.682, 0.729)
r_4	(0.762, 0.627, 0.678)	(0.806, 0.556, 0.674)	(0.705, 0.677, 0.698)	(0.677, 0.680, 0.722)
r_5	(0.731, 0.649, 0.695)	(0.783, 0.618, 0.657)	(0.684, 0.675, 0.720)	(0.699, 0.662, 0.718)
r_6	(0.409, 0.820, 0.724)	(0.484, 0.787, 0.736)	(0.605, 0.752, 0.708)	(0.584, 0.776, 0.693)
r_7	(0.508, 0.753, 0.762)	(0.377, 0.827, 0.725)	(0.576, 0.714, 0.763)	(0.516, 0.749, 0.762)
r_8	(0.836, 0.532, 0.643)	(0.727, 0.653, 0.696)	(0.517, 0.699, 0.804)	(0.629, 0.716, 0.727)
r_9	(0.741, 0.645, 0.687)	(0.731, 0.649, 0.695)	(0.681, 0.676, 0.721)	(0.647, 0.710, 0.719)
r_{10}	(0.508, 0.734, 0.780)	(0.410, 0.819, 0.725)	(0.507, 0.753, 0.762)	(0.441, 0.782, 0.758)
r_{11}	(0.443, 0.781, 0.578)	(0.613, 0.728, 0.727)	(0.641, 0.707, 0.726)	(0.652, 0.695, 0.729)
r_{12}	(0.477, 0.764, 0.764)	(0.533, 0.736, 0.559)	(0.675, 0.687, 0.717)	(0.641, 0.707, 0.726)
r_{13}	(0.400, 0.842, 0.697)	(0.434, 0.786, 0.757)	(0.533, 0.736, 0.767)	(0.462, 0.789, 0.743)
r_{14}	(0.677, 0.680, 0.722)	(0.716, 0.666, 0.697)	(0.811, 0.567, 0.658)	(0.798, 0.567, 0.677)
r_{15}	(0.800, 0.559, 0.679)	(0.787, 0.581, 0.681)	(0.763, 0.586, 0.708)	(0.666, 0.682, 0.729)
r_{16}	(0.420, 0.815, 0.728)	(0.480, 0.794, 0.730)	(0.803, 0.559, 0.675)	(0.741, 0.645, 0.687)
r_{17}	(0.652, 0.695, 0.729)	(0.708, 0.644, 0.723)	(0.652, 0.695, 0.729)	(0.641, 0.707, 0.726)
r_{18}	(0.824, 0.551, 0.648)	(0.798, 0.567, 0.677)	(0.512, 0.770, 0.743)	(0.512, 0.770, 0.743)
r_{19}	(0.677, 0.680, 0.722)	(0.824, 0.551, 0.648)	(0.631, 0.703, 0.738)	(0.659, 0.687, 0.730)
r_{20}	(0.824, 0.551, 0.648)	(0.654, 0.686, 0.735)	(0.728, 0.652, 0.695)	(0.709, 0.667, 0.703)

Table 5. Weights of the IoT risks for supply chain management

Risk factor	e_1	e_2	e_3	A-q-ROFNs	Crisp degrees $\mathbb{S}^*\left(\tilde{\xi}_{kj}\right)$
r_1	A	MS	MI	(0.631, 0.703, 0.738)	0.4526
r_2	MS	A	MS	(0.718, 0.664, 0.696)	0.5390
r_3	MI	MI	I	(0.470, 0.767, 0.763)	0.3261
r_4	MS	A	MI	(0.647, 0.698, 0.730)	0.4654
r_5	VI	MI	MI	(0.449, 0.802, 0.733)	0.2875
r_6	MS	MS	S	(0.769, 0.632, 0.664)	0.6016
r_7	MI	MS	S	(0.716, 0.666, 0.697)	0.5356
r_8	MS	A	I	(0.633, 0.714, 0.726)	0.4446
r_9	MI	A	MI	(0.533, 0.736, 0.767)	0.3768
r_{10}	S	MS	MI	(0.719, 0.649, 0.708)	0.5487
r_{11}	I	MI	MS	(0.608, 0.730, 0.728)	0.4181
r_{12}	A	A	MS	(0.666, 0.682, 0.729)	0.4895
r_{13}	S	MI	I	(0.651, 0.707, 0.718)	0.4613
r_{14}	S	MI	MI	(0.664, 0.691, 0.722)	0.4816
r_{15}	MS	MS	I	(0.680, 0.699, 0.700)	0.4862
r_{16}	MI	S	MI	(0.636, 0.704, 0.733)	0.4539
r_{17}	I	MS	MI	(0.586, 0.738, 0.735)	0.4001
r_{18}	MI	MS	MS	(0.689, 0.685, 0.706)	0.5029
r_{19}	A	MI	MS	(0.649, 0.695, 0.731)	0.4689
r_{20}	A	A	S	(0.696, 0.663, 0.719)	0.5228

Table 6. Significance degree of IoT risks for supply chain management using SWARA method

Risk factor	Crisp degrees	Comparative importance of attributes (s_j)	Coefficient (k_j)	Reassessed weight (ρ_j)	Final weight (w_j)
r_6	0.6016	–	1.0000	1.0000	0.0572
r_{10}	0.5487	0.0529	1.0529	0.9498	0.0543
r_2	0.5390	0.0097	1.0097	0.9407	0.0538
r_7	0.5356	0.0034	1.0034	0.9375	0.0536
r_{20}	0.5228	0.0128	1.0128	0.9256	0.0529
r_{18}	0.5029	0.0199	1.0199	0.9075	0.0519
r_{12}	0.4895	0.0134	1.0134	0.8955	0.0512
r_{15}	0.4862	0.0033	1.0033	0.8926	0.0510
r_{14}	0.4816	0.0046	1.0046	0.8885	0.0508
r_{19}	0.4689	0.0127	1.0127	0.8774	0.0502
r_4	0.4654	0.0035	1.0035	0.8743	0.0500
r_{13}	0.4613	0.0041	1.0041	0.8707	0.0498
r_{16}	0.4539	0.0074	1.0074	0.8643	0.0494
r_1	0.4526	0.0013	1.0013	0.8632	0.0493
r_8	0.4446	0.0080	1.0080	0.8563	0.0489
r_{11}	0.4181	0.0265	1.0265	0.8342	0.0477
r_{17}	0.4001	0.0180	1.0180	0.8194	0.0468
r_9	0.3768	0.0233	1.0233	0.8007	0.0458
r_3	0.3261	0.0507	1.0507	0.7621	0.0436
r_5	0.2875	0.0386	1.0386	0.7338	0.0419

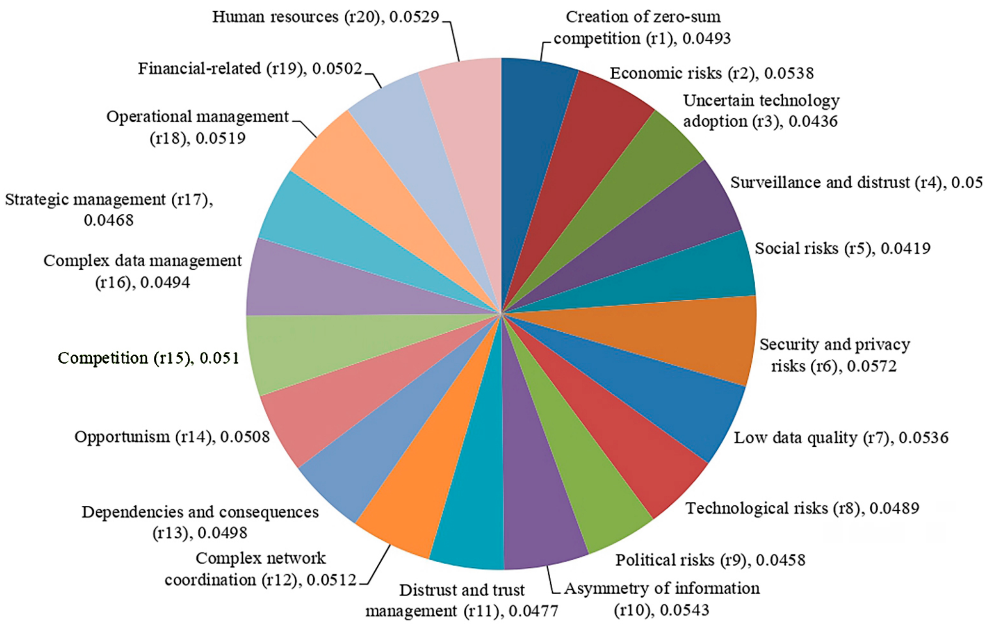

Figure 1. Significance values/weight of different IoT risks for supply chain management

Step 4. To estimate the weight of each challenge using the SWARA tool, DEs play an important role (see Table 5). The DEs were asked to choose the importance of each IoT risk. Using Eqs (5)–(7), DEs ordered all the available attributes from the first attribute to the last one. On the basis of the SWARA method, the IoT risk with the maximum importance was ranked the 1st, whereas that of the least significant barrier was ranked as the last one. DEs find the total prioritization was predicted. Table 6 presents all IoT risk weights under the w_j column. This table demonstrates that the weight of the IoT risks for SCM is given by

w_j = (0.0493, 0.0538, 0.0436, 0.0500, 0.0419, 0.0572, 0.0536, 0.0489, 0.0458, 0.0543, 0.0477, 0.0512, 0.0498, 0.0508, 0.0510, 0.0494, 0.0468, 0.0519, 0.0502, 0.0529).

Here, Figure 1 illustrates the significance values or weights of diverse IoT risks for supply chain management with respect to the goal. Security and privacy risks (r_6) with a weight value of 0.0572 have come out to be the prime IoT risks for the SCM. Asymmetry of information (r_{10}) with a weight value of 0.0543 is the second main IoT risk for SCM. Economic risks (r_2) have third with weight value 0.0538, low data quality (r_7) has fourth with a weight value of 0.0536, human resources (r_{20}) with a significance value of 0.0529 has fifth main IoT risks for supply chain management, and others are considered crucial IoT risks for the supply chain management.

Step 5. Afterward, the optimum performance rating of options to use the IoT risks for supply chain management is determined using Eq. (8). The obtained optimal performance ratings of rank the organizations and analysis the IoT risks for supply chain management are

P_0 = {(0.762, 0.627, 0.678), (0.782, 0.583, 0.687), (0.880, 0.448, 0.612), (0.806, 0.556, 0.674), (0.783, 0.618, 0.657), (0.605, 0.752, 0.708), (0.576, 0.714, 0.763), (0.836, 0.532, 0.643), (0.741, 0.645, 0.687), (0.508, 0.734, 0.780), (0.652, 0.695, 0.729), (0.675, 0.687, 0.717), (0.533, 0.736, 0.767), (0.811, 0.567, 0.658), (0.800, 0.559, 0.679), (0.803, 0.559, 0.675), (0.708, 0.644, 0.723), (0.824, 0.551, 0.648), (0.824, 0.551, 0.648), (0.824, 0.551, 0.648)}.

Steps 6–7. As all attributes are of beneficial type thus, there is no requirement to N-A-q-ROF-DM. By Eq. (9)–Eq. (10), the WNA-q-ROF-DM is discussed in Table 7.

Table 7. WNA-q-ROF-DM for options over different IoT risks for SCM

	P_0	P_1	P_2	P_3	P_4
r_1	(0.305, 0.977, 0.337)	(0.305, 0.977, 0.337)	(0.234, 0.986, 0.307)	(0.278, 0.980, 0.332)	(0.299, 0.978, 0.338)
r_2	(0.325, 0.971, 0.366)	(0.325, 0.971, 0.366)	(0.307, 0.976, 0.347)	(0.303, 0.977, 0.344)	(0.318, 0.976, 0.340)
r_3	(0.365, 0.966, 0.371)	(0.316, 0.977, 0.333)	(0.365, 0.966, 0.371)	(0.282, 0.981, 0.321)	(0.248, 0.983, 0.323)
r_4	(0.331, 0.971, 0.363)	(0.306, 0.977, 0.339)	(0.331, 0.971, 0.364)	(0.277, 0.981, 0.329)	(0.264, 0.981, 0.336)
r_5	(0.300, 0.980, 0.316)	(0.274, 0.982, 0.318)	(0.300, 0.980, 0.316)	(0.252, 0.984, 0.318)	(0.259, 0.983, 0.322)
r_6	(0.242, 0.984, 0.322)	(0.159, 0.989, 0.309)	(0.190, 0.986, 0.322)	(0.242, 0.984, 0.323)	(0.233, 0.986, 0.310)
r_7	(0.224, 0.982, 0.346)	(0.196, 0.985, 0.334)	(0.144, 0.990, 0.301)	(0.225, 0.982, 0.346)	(0.199, 0.985, 0.335)
r_8	(0.348, 0.970, 0.359)	(0.348, 0.970, 0.360)	(0.286, 0.979, 0.334)	(0.193, 0.983, 0.353)	(0.240, 0.984, 0.324)
r_9	(0.330, 0.980, 0.283)	(0.287, 0.980, 0.326)	(0.282, 0.980, 0.328)	(0.258, 0.982, 0.328)	(0.290, 0.984, 0.278)
r_{10}	(0.170, 0.987, 0.325)	(0.197, 0.983, 0.346)	(0.157, 0.989, 0.304)	(0.196, 0.985, 0.335)	(0.170, 0.987, 0.325)
r_{11}	(0.249, 0.983, 0.328)	(0.163, 0.988, 0.312)	(0.231, 0.985, 0.317)	(0.244, 0.984, 0.324)	(0.248, 0.983, 0.329)
r_{12}	(0.265, 0.981, 0.334)	(0.180, 0.986, 0.326)	(0.203, 0.984, 0.335)	(0.265, 0.981, 0.335)	(0.249, 0.982, 0.331)
r_{13}	(0.201, 0.985, 0.332)	(0.149, 0.991, 0.281)	(0.162, 0.988, 0.315)	(0.201, 0.985, 0.332)	(0.173, 0.988, 0.309)
r_{14}	(0.336, 0.972, 0.355)	(0.265, 0.981, 0.338)	(0.284, 0.980, 0.334)	(0.336, 0.972, 0.355)	(0.328, 0.972, 0.362)
r_{15}	(0.330, 0.971, 0.366)	(0.330, 0.971, 0.367)	(0.322, 0.973, 0.359)	(0.309, 0.973, 0.366)	(0.261, 0.981, 0.340)
r_{16}	(0.328, 0.972, 0.361)	(0.156, 0.990, 0.297)	(0.179, 0.989, 0.303)	(0.328, 0.972, 0.361)	(0.294, 0.979, 0.334)
r_{17}	(0.273, 0.980, 0.341)	(0.247, 0.983, 0.327)	(0.273, 0.980, 0.341)	(0.247, 0.983, 0.327)	(0.242, 0.984, 0.322)
r_{18}	(0.347, 0.970, 0.361)	(0.386, 0.970, 0.315)	(0.331, 0.971, 0.365)	(0.195, 0.987, 0.319)	(0.195, 0.987, 0.319)
r_{19}	(0.343, 0.971, 0.357)	(0.264, 0.981, 0.336)	(0.343, 0.971, 0.357)	(0.243, 0.982, 0.334)	(0.256, 0.981, 0.337)
r_{20}	(0.042, 0.969, 0.448)	(0.349, 0.969, 0.602)	(0.258, 0.980, 0.345)	(0.294, 0.978, 0.342)	(0.023, 0.979, 0.396)

Table 8. Overall performance degree of organization of weighted evaluation matrix

	P_0	P_1	P_2	P_3	P_4
r_1	0.048	0.048	0.027	0.040	0.046
r_2	0.059	0.059	0.050	0.048	0.052
r_3	0.074	0.050	0.074	0.039	0.032
r_4	0.060	0.048	0.060	0.039	0.037
r_5	0.043	0.037	0.043	0.032	0.034
r_6	0.031	0.019	0.024	0.031	0.028
r_7	0.032	0.026	0.017	0.032	0.027
r_8	0.065	0.065	0.042	0.029	0.031

End of Table 8

	P_0	P_1	P_2	P_3	P_4
r_9	0.047	0.041	0.040	0.035	0.035
r_{10}	0.028	0.028	0.018	0.026	0.022
r_{11}	0.033	0.020	0.028	0.031	0.033
r_{12}	0.037	0.023	0.027	0.037	0.034
r_{13}	0.026	0.014	0.020	0.026	0.020
r_{14}	0.060	0.038	0.042	0.060	0.059
r_{15}	0.061	0.061	0.057	0.054	0.037
r_{16}	0.059	0.017	0.020	0.059	0.044
r_{17}	0.040	0.032	0.040	0.032	0.031
r_{18}	0.065	0.073	0.060	0.024	0.024
r_{19}	0.063	0.037	0.063	0.033	0.036
r_{20}	0.045	0.066	0.038	0.046	0.031
Overall performance rating	0.978	0.8026	0.7890	0.755	0.692
Utility degree	–	0.8208	0.8068	0.7722	0.7080
Ranking		1	2	3	4

Steps 8–10. Next, using Eq. (11)–Eq. (12), we compute the score value and overall performance degrees of the weighted evaluation matrix of organizations to evaluate the IoT risks for supply chain management and are presented in Table 8. By Eq. (13), the UD $\mathbb{Q}_i$ is estimated by $\mathbb{Q}_1=0.8208$, $\mathbb{Q}_2=0.8068$, $\mathbb{Q}_3=0.7722$ and $\mathbb{Q}_4=0.7080$. Based on the UD $\mathbb{Q}_i$, the prioritization of the organizations to evaluate the IoT risks for SCM is $P_1 \succ P_2 \succ P_3 \succ P_4$, and thus from Eq. (14), the organization-I (P_1) is the best option with diverse IoT risks for SCM.

3.2. Comparison with other models

This subsection examines the efficiency of the proposed q-ROF-SWARA-ARAS methodology. To this end, q-rung orthopair fuzzy information based TOPSIS (Liu et al., 2019), COPRAS (Krishankumar et al., 2019), and WASPAS (Rani & Mishra, 2020) approaches were utilized to find a solution to above-mentioned problem. The process of the q-ROF-COPRAS operation is discussed as

Steps 1–4. These steps are completely comparable to steps 1 to 4 of the aforementioned model.

Step 5. Combine the benefit and cost criteria in A-q-ROF-DM with the use of Eq. (4). Remember that all criteria are of the benefit-type; for that reason, the assessment index was analyzed for each alternative to maximize the risk preference $\alpha_i = \bigoplus_{j=1}^{n} w_j \tilde{\varsigma}_{ij},\ i=1(1)m.$ Hence, we obtain $\lambda_1 = 0.2835$, $\lambda_2 = 0.2853$, $\lambda_3 = 0.2661$ and $\lambda_4 = 0.2620$. And the priority of organizations as $\lambda_2 \succ \lambda_1 \succ \lambda_3 \succ \lambda_4$. Thus, the organization P_2 is the best candidate among set of four options.

Step 6. Find the "UD" $\hbar_i = \frac{\lambda_i}{\lambda_{\max}} \times 100\%$, to evaluate the IoT risks for SCM. Then, we obtain $\hbar_1 = 99.37\%$, $\hbar_2 = 100.00\%$, $\hbar_3 = 93.27\%$ and $\hbar_4 = 91.83\%$.

Consequently, the present study applies various currently-used approaches to the same instance to compare with the outcomes assessed by the proposed method (see Figure 2). In comparison with the TOPSIS, COPRAS and WASPAS approaches, q-ROF-SWARA-ARAS has the following advantages:

a) The q-ROF-SWARA-ARAS works based on a broader norm of *"Additive Ratio Assessment (ARAS)"* with q-ROFNs to select the organizations to evaluate the IoT risks for SCM problems in comparison to q-ROF-COPRAS (Utility degree), q-ROF-WASPAS (Utility degree), q-ROF-TOPSIS (Compromise programming), q-ROF-WSM and q-ROF-WPM methods.

b) For the q-ROF-TOPSIS (Liu et al., 2019) procedure, an important task is the estimation of the distance between each alternative over given criteria with the q-ROF-IS, which is time-taking and decreases the accuracy of the results, while the computation procedure of the q-ROF-SWARA-ARAS framework is simple and straightforward with the determination of higher effectiveness.

c) The developed method only evaluates q-ROF-IS, whereas q-ROF-TOPSIS requires to obtain both q-ROF-IS and q-ROF-AIS, and the q-ROF-WASPAS model (Rani & Mishra, 2020) utilizes q-ROFWAO and q-ROFWGO. To conclude, it can be said that for MCDM methods with more criteria or options, q-ROF-SWARA-ARAS is capable of, to some extent, increasing the operational effectiveness with higher operability.

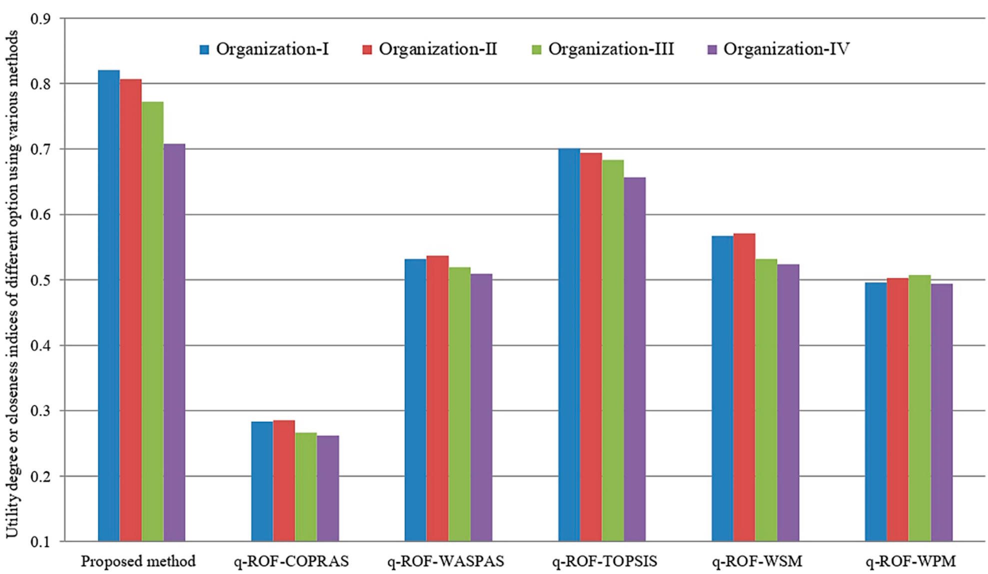

Figure 2. Utility degree of each organization to evaluate the IoT risks for SCM with extant methods

Conclusions

The current paper was primarily aimed at identifying, ranking, analyzing, and evaluating different "*Internet-of-Things* (*IoT*)" risks for "*Supply Chain Management* (*SCM*)" using an integrated MCDM approach. At first, to recognize the key IoT risk factors for SCM, a survey study by means of literature review and experts' opinions has been presented. For this purpose, a comprehensive framework including 20 risk factors, which included the formation of zero-sum competition, uncertain technology adoption, economic risks, technological risks, surveillance and distrust, security and privacy risks, social risks, low quality of data, political risks, asymmetry of information, distrust and trust management, complex network coordination, dependencies and consequences, opportunism, competition, complex data management, operational management, strategic management, financial-related and human resources was developed in regard to the execution of IoT technologies for SCM. In the next step, an integrated MCDM framework has been proposed to rank, analysis and evaluate the selected IoT risk factors using two important decision-making approaches, including SWARA and ARAS under the q-ROFSs setting.

In this study, for the purpose of determining the accurateness of the experts' outlooks regarding the weights, the SWARA approach was applied, and the ARAS approach was used to an optimal degree with the aim of evaluating the priority ordering of the candidate organizations with respect to a set of IoT risk factors for SCM. The outcomes of this study found that the security and privacy risks (0.0572) was the most important IoT risk factors for supply chain management followed by, asymmetry of information (0.0543), economic risks (0.0538), low data quality (0.0536), human resources (0.0529), operational management (0.0519), etc. The study proposed a comprehensive framework of the IoT risks in SCM through the analysis of the concerns before and after the assessment. Due to the concurrent presence of various levels, the present paper provided insights into both soft factors (e.g., trust issues or privacy concerns) and hard factors (e.g., costs or technological maturity). In addition, the relationships between the levels and categories were identified, and the risks were revealed indifference to the few applications. The rest of the unknown benefits are a reflection of the initial phase of IoT in SCM in spite of the robust interest and disruptive nature.

As a result, there is a need to further analyze the relationships amongst the challenge and risk categories and find target-oriented solutions. In addition, it is highly necessary to give support to companies and provide a suitable stage for the effective utilization of IoT. The risks identified provide managers with a valued insight into IoT and the issues associated with this relatively new technology. The framework proposed in this study provides a holistic view, offers practical correlations, links organizational, environmental, strategic, and further dimensions, and supports constructive use of IoT. To respond the varying structure of the supply network, there is a requirement for effective collaboration, communication, and data exchange. To establish closer relations in the SC context and manage the distrust of society, it is essential to recover trust management, especially in the organizational contexts. Such problematic areas result in a extensive inter-organizational task definition for the SC executives. Though, due to the concentration upon the technical challenges, this paper also exposes the inadequate decision-making effect upon definite features of IoT in the setting of SCM.

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