Operations Management Research (2022) 15:773–792
https://doi.org/10.1007/s12063-021-00243-7

Evaluate the challenges of sustainable supply chain 4.0 implementation under the circular economy concept using new decision making approach

Lulu Xin[1] · Shuai Lang[2] · Arunodaya Raj Mishra[3]

Received: 20 June 2021 / Revised: 29 November 2021 / Accepted: 1 December 2021 / Published online: 11 May 2022

Abstract
Industry 4.0 has the potential of growing industrialization and, on the other hand, disrupting the sustainability of prevailing manufacturing supply chains through inducing great challenges such as higher resource consumption that, in turn, results in global warming and climate change. As a result, researchers working in the area of sustainable supply chain 4.0 need to make deep evaluations on the challenges arising for manufacturing supply chains contemplating the improvement of their sustainability levels and having a digital transformation toward Industry 4.0. To fill this gap, the current paper designs an innovative framework on the basis of the Stepwise Weight Assessment Ratio Analysis (SWARA) technique and the Complex Proportional Assessment (COPRAS) approach to evaluate the challenges that may arise for supply chain 4.0 in the q-Rung Orthopair Fuzzy Sets (q-ROFSs) setting. The proposed method uses an extended SWARA process to determine the criteria importance degrees considering the experts' preferences. The performance of the proposed method was assessed by conducting an empirical case study under the q-ROFSs condition. Further, a sensitivity analysis was executed to check whether the proposed method is stable enough to be relied on parameter values. Finally, the results obtained were compared to those of currently used methods to verify the obtained results' reliability. As revealed by the comparative results, the framework proposed in this article was of higher consistency and strength compared to other prevailing approaches.

Keywords Supply chain 4.0 · Industry 4.0 · Circular economy · q-rung orthopair fuzzy sets · Stepwise weight assessment ratio analysis · Complex proportional assessment

1 Introduction

The circular economy is an extensively discussed topic (Kurdve and Bellgran 2021; Velenturf and Purnell 2021) helps to identify different opportunities that could be made by Industry 4.0 and sustainable practices (Kumar et al. 2021b; Massaro et al. 2021). Industry 4.0, on the other hand, is responsible for a number of disrupting technologies that are discussed under the circular economy (Kumar et al. 2021a). Two widely recognized instances of such technologies are the internet of services (IoS) and the internet of things (IoT). The triple bottom line of sustainability (i.e., economy, environment, and society) has resulted in the 3R concept that encompasses recreating, recycling, and reusing (Daú et al. 2019; Tseng et al. 2018a). Transforming a linear concept into a circular concept brings a broader sense of motion to the process by altering it into a cycle. Ranta et al. (2018) confirmed that sustainable performances act as an alternative for the transition between two economic models. Such a cycle helps reverse the process by delivering an already transformed item to either the customer or the supplier. This way, this cycle absorbs and allows for reverse logistics.

Industry 4.0 essentially involves automation and information technology as well as a number of key technological

✉ Arunodaya Raj Mishra
arunodaya87@outlook.com

Lulu Xin
sdkjdxqd@163.com

Shuai Lang
zgsyuniversity@126.com

[1] College of Humanities and Law, Shandong University of Science and Technology, Qingdao 266590, Shandong, China

[2] School of Marxism Studies, China University of Petroleum, Shandong 266580 Qingdao, China

[3] Department of Mathematics, Government College Raigaon, Satna, MP, India

innovations in these fields (Birkel et al. 2019). Luthra and Mangla (2018) stated that Industry 4.0 creativities are big assistance for different industries in incorporating actions to have control on the environment and protect it properly. Moreover, these creativities can mitigate the risks associated with supply chains and improve their sustainability. A supply chain (SC) of high sustainability level projects, plans, and operates SCs in a way to well guarantee the market requirements; it takes into account both economic profits and social/environmental concerns simultaneously (Barbosa-Póvoa et al. 2018). At present, Industry 4.0 is one of the key topics that is receiving a great deal of attention from the academic community and practitioners (Oztemel and Gursev 2020). As Liao et al. (2017) reported, many articles published in this study area surged dramatically from 2013 to 2015. Industry 4.0, presented as the 4th Industrial Revolution (or 4IR) in Germany, in 2011, during the Hannover Fair (Ghobakhloo 2018). The abrupt enhancement of Industry 4.0 popularity is its high potential for answering significant questions such as how value is generated and carried and how firms take part in the market (Frederico et al. 2020). The term "the 4th industrial revolution" highlights the high importance of this concept compared with the other industrial revolutions witnessed previously in history, where: the first Industrial Revolution occurred between 1760 and 1860 delivered the steam engine facilitating the mechanization of production; then, the second one occurred between 1870 and 1914 led to manufacturing in huge dimensions, which was well supported by other advancements that happened like railways, electric power etc. (Mokyr and Strotz 1998); after that, the third one introduced electronics and internet and communicaton technology (ICT) that enabled automation in 1984 (Gray 1984; Fitzsimmons 1994). At the present time, Industry 4.0 is offering a range of high-tech and disruptive technologies, e.g., cyber-physical systems (CPS), the internet of things (IoT), and cloud computing (Frederico et al. 2020). This confirms that only those countries with the intention and ability to instigate Industry 4.0 plans will persist strongly in a globally competitive environment. In recent years, many researchers have attempted to find how Industry 4.0 affects other topical areas of research like sustainability, lean manufacturing, organizational structure, small and medium enterprises (SMEs), strategic management, product development, production planning and control, etc.

Industry 4.0 makes available a vigorous warehouse and reliable systems for exchanging information and communication; it also helps managers to effectively decrease the costs and increase the consumers' satisfaction (Mostafa et al. 2019). Stock et al. (2018) believe that the use of Industry 4.0 can lead to creating industrial value from a sustainability perspective. Stock et al. (2018) also highlighted the social dimension of this industry and the ways it can deliver a combination of these contributors; they emphasized the capability of Industry 4.0 in increasing value added to products and services, the possibility of providing more helpful education to employees, and harmonizing between professional and family lives of employees. A 4.0 sustainable supply chain (SSC) employs the Industry 4.0 tools to close the material and energy cycles, supporting the information flow and injecting more efficiency, intelligence, precision, and quickness into business operations. Kovacs (2019) introduced Industry 4.0 as a concept reinforcing education and provided the information required for effectively dealing with the digital economy. Such educational aspects endorse the changes occurred by Industry 4.0 to companies and their productions (Hamada 2019). Therefore, industry 4.0 has the prospective to upgrade the ways that SCs perform.

The predictions indicate that Industry 4.0 will result in an incredible development of industrialization, but, at the same time, it has the potential to interrupt the sustainability of currently-used industrialized organizations (Hermann et al. 2016; Liao et al. 2017). Furthermore, it could lead to deteriorating global climate change and enhance resource consumption rates (Tseng et al. 2018b). As a result, there is a pressing need (especially for manufacturing SCs) to adopt management practices for the production and SC systems in a way to take into consideration all the sustainability aspects (i.e., economic, environmental, and social) and exploit the digital transformation characteristics brought about by Industry 4.0. Numerous scholars have focused on the significance of incorporating sustainability into SCs (Ghadimi et al. 2019; Wang et al. 2019); while, the literature still lacks adequate practical efforts that encompass both SSC and Industry 4.0 (Ghadimi et al. 2019). In this sense, a conceptual model was introduced by Duarte and Cruz-Machado (2018), integrating the concepts of Industry 4.0 into green and lean SCs. However, numerous studies have focused on Industry 4.0-related tools, not Industry 4.0 as a whole approach. In the present article, supply chain 4.0 is addressed as an extended version of the Industry 4.0 definition, which incorporates the value chain construction practices that involve producers, retailers, traders, and end customers to harmonize supply and demand (Stefanou 1999). Luthra and Mangla (2018) mentioned that most articles conducted into Industry 4.0 focused on the manufacturing sector and overlooked the SC systems. Although numerous studies have addressed Industry 4.0, no study has clearly conceptualized Industry 4.0 considering the SC issues. The present research proposes the term "supply chain 4.0" together with an innovative conceptual model capturing the essence of Industry 4.0 in the context of SC. Inherently, Industry 4.0 can be recognized as a revolution, in this sense, as revolutions are typically evolutionary events; the current paper aims to capture the development of supply chain 4.0 from maturity levels to help the supply chain 4.0 strategies to be formulated and developed.

The literature consists of many efforts made to convey the high significance of sustainability and environmental issues and the necessity of incorporating these issues into SCs (Belhadi et al. 2021; Hendiani et al. 2020; Rajesh 2020). Although, there are only a few studies into the ways to incorporate sustainability into the context of Industry 4.0 SCs. For that reason, there is a need for further studies to make clear the research trends in this field. Duarte and Cruz-Machado (2018) discussed this gap in the literature and managed the relationship between Industry 4.0 and green and lean SCs by designing a theoretical and conceptual model to incorporate Industry 4.0 into green and lean SCs. These efforts have provided great opportunities for realizing the digital SCs and considering the sustainability-related issues simultaneously, particularly with a focus upon the sustainable supplier assessment and selection problem, which has led to the formation of theories and practices toward the Industry 4.0 supply chains. Therefore, this study considers this domain a great opportunity for research and development.

Generally, during the process of multi-criteria decision-making (MCDM), criteria weights have been given high importance by the decision experts (DEs). Criteria weights are generally divided into objective and subjective weights (Kersuliene et al. 2010). The former is measured using the decision-matrices that are normally defined on the basis of the knowledge given by DEs (Dehnavi et al. 2015), while the latter enlightens the experts' thoughts, who concern the attributes relative significance (Karabasevic et al. 2015). To measure the subjective weights, an innovative stepwise weight assessment ratio analysis (SWARA) approach was initiated by Kersuliene et al. (2010). The advantage of SWARA is that its computational work is simpler than that of different tools such as the analytic hierarchy process (AHP) (Yang et al. 2021; He et al. 2021). Currently, to estimate the criteria weights, the analytic network process (ANP) (Saaty 1999) and AHP (Saaty 1977) are the most popular methods, while amongst the novel approaches to determining the criteria weight, the most considerable methods include SWARA, full consistency method (FUCOM) (Pamučar et al. 2018), best–worst method (BWM) (Rezaei 2015), and level -based weight assessment (LBWA) (Žižović and Pamucar 2019). Excluding SWARA, the other above-noted methods work on the basis of pairwise comparison; in addition, notable differences exist in the way of computing the criteria weights.

AHP requires to perform $n(n-1)/2$ comparisons in pairs of criteria. Executing many comparisons causes the model to be more complicated while being applied, particularly when a huge number of attributes are to be acquired into account. On the other hand, BWM quickly became so popular due to its smaller number of pair comparisons $(2n-3)$ compared to AHP. Though, numerous comparisons in pairs of criteria (which are necessary to define the limitations for the solution of nonlinear models) cause BWM to become meaningfully more complex in use. For that reason, many scholars are still avoiding the use of this model. FUCOM works on the basis of the pairwise comparisons of attributes; however, this algorithm requires to perform only $(n-1)$ comparison. It also facilitates the validation of the model by computing the error value for the obtained weight vectors by determining the Deviation form Full Consistency (DFC) (Pamucar and Ecer 2020). Finally, LBWA works on the basis of the pairwise comparisons of attributes with only $(n-1)$ comparisons.

SWARA has shown high efficiency in determining the criteria weights. In comparison to AHP that is widely used in the literature, SWARA has a higher level of consistency, and it does not require a large number of pairwise comparisons to be done. Moreover, in comparison with BWM (Rezaei 2015), in SWARA, there is no need for the solution of complex-linear objective functions, and it has a lower level of computational complexity and is more understandable. Recently, Mishra et al. (2020b) integrated the IF-SWARA-COPRAS to assess the bioenergy production model. Rani et al. (2020a) presented the integrated HF-SWARA-complex proportional assessment (COPRAS) to evaluate the sustainable supplier. Rani et al. (2020b) discussed the PF-SWARA-additive ratio assessment (ARAS) model to assess the model for treating healthcare waste. Cui et al. (2021) combined Pythagorean fuzzy SWARA with the combined compromise solution (CoCoSo) method in order to IoT adaption barriers for the circular economy. Recently, Saraji et al. (2021) suggested an integrated decision-making framework by combining SWARA and multi-objective optimization based on ratio analysis with the full multiplicative form (MULTIMOORA) with hesitant fuzzy sets (HFSs) and applied to adapt online education during COVID-19.

In MCDM problems, existing data are often not accurate but rather related to some degrees of uncertainty and ambiguity. Therefore, the fuzzy sets (FSs) doctrine, proposed by Zadeh (1965), has effectively addressed such problems. An important point while using FSs is to consider the unreliability or reliability of the problem. Hence, various generalizations of FSs have been discussed such as, intuitionistic fuzzy sets (IFSs) (Atanassov 1986), Pythagorean fuzzy sets (PFSs) (Yager 2013), q-rung orthopair fuzzy sets (q-ROFSs) (Yager 2017), Z-numbers (Zadeh 2011), probabilistic linguistic term sets (PLTSs) (Pang et al. 2016), G-numbers (Ghoushchi and Khazaeili 2019), R-numbers (Seiti et al. 2019). Zadeh (2011) introduced the concept of Z-number as an ordered pair of fuzzy numbers $Z=(M, N)$, where M is a restriction of variable and N is a measure of the reliability of M. Seiti et al. (2019) introduced a new uncertainty modeling approach, that can be used to explain or justify the errors and risks associated with fuzzy numbers in the decision- making problems. Ghoushchi and Khazaeili (2019) proposed the Importance-Necessity idea, called G-numbers, to decrease ambiguity in the MCDM process. G-numbers contain two fuzzy variables and are designated in the form of G = (I, N). The prime objective of the procedure is to lessen the uncertainty of information using I (Importance) and N (Necessity) components. I and N are linguistic variables.

Due to lack of information, the uncertain human mind, and time complexity, the decision experts (DEs) cannot provide accurate results in real MCDM problems. To conquer this concern, the theory of IFSs was pioneered by Atanassov (1986), which is portrayed by the membership grade (MG) and non-membership grade degree (NG) and satisfying that the addition of its MG and NG is restricted to unity. To overcome the drawback of IFS, Yager (2014) pioneered the PFSs concept, which the MG and NG also represent with a constraint that the square addition of MG and NG is restricted to unity. In the recent past, PFS has been proven a more influential way than IFS to handle the ambiguity in real-world decision-making situations. Therefore, many research efforts have been made related to PFSs.

Nevertheless, in MCDM, some cases may occur where DEs might present the value to which an alternative O_i assures the criterion B_j is 0.9 and the value to which an alternative S_i dissatisfies, the criterion is 0.6. Therefore, PFS and IFS cannot manage this condition since $0.9 + 0.6 > 1$ and $0.9^2 + 0.6^2 > 1$. To address this problem, the notion of q-ROFSs was presented by Yager (2017). The q-ROFSs theory accomplishes a condition that the sum of the qth power of MG and NG is bounded to 1, where $q \geq 1$. q-ROFSs has the capacity of efficiently handling the above-noted instance. In q-ROFSs, the information space is more extensive compared to PFSs and IFSs corresponding to the variation of the factor q ($q \geq 1$); it is obvious that PFSs and IFSs are specific forms of q-ROFSs. Therefore, q-ROFS can be recognized as the highest flexibility and applicability method in handling the advanced level of uncertainty. In recent years, many researchers have applied the q-ROFSs environment. For instance, Yager and Alajlan (2017) examined the basic postulates of q-ROFSs and then applied for the information representation. Liu and Wang (2018) investigated a variety of q-rung orthopair fuzzy (q-ROF) geometric and arithmetic operators. Peng and Liu (2019) examined several novel formulas for q-ROF-information measures. In addition, they attempted to reveal the relationships among them. A number of the q-ROF-Bonferroni mean operators were described by Liu and Liu (2019). Pinar and Boran (2020) introduced an integrated model along with the distance measure of q-ROFSs and then applied it to the problem of supplier selection. A number of neutral aggregation operators for q-ROFSs were proposed in the study of Garg and Chen (2020). An innovative model was suggested by Tang et al. (2020) based on q-ROFS, which was capable of dealing with a three-way decision quandary. Darko and Liang (2020b) examined a number of q-ROF-Hamacher aggregation operators and also discussed their applications. A q-ROF-based decision-making framework was proposed by Krishankumar et al. (2021) as a solution to the problem of selecting renewable energy resource candidates. In the study carried out by Rani and Mishra (2020), an extended WASPAS method was tested for evaluating the fuel technologies with q-ROF-information.

Literature consists of many MCDM approaches developed to solve complex selection problems that may arise daily. Essentially, a selection problem involves four main elements: alternatives, criteria, relative significance degrees of criteria, and measures the performance of the alternatives over preferred criteria. MCDM aims to choose a desirable item from a set of possible choices considering different criteria that may even conflict with each other. Zavadskas et al. (1994) first proposed the COPRAS framework, which can be reasonably and effectively applied to information processing purposes. According to (Darko and Liang 2020a; Dhiman and Deb 2020), COPRAS offers a suitable manner to tackle MCDM-related problems effectively. The COPRAS method, which delivers more accurate information in comparison with different procedures for evaluating the benefits or cost criteria, is employed to assume both aspects of criteria. In addition, COPRAS is able to delineate the ratios simultaneously to both ideal and the worst solutions. Owing to its advantages, several researchers have employed the COPRAS approach for different purposes (Büyüközkan and Göçer 2019; Mishra et al. 2020a). As MCDM problems have become increasingly complex and uncertain, different researchers have extended the conventional COPRAS approach under a variety of uncertain environments. For example, COPRAS was discussed by Keshavarz Ghorabaee et al. (2014) in terms of its capacity in selecting optimum suppliers on interval type-2 fuzzy sets. In another project, the COPRAS approach with grey numbers was introduced by Bekar et al. (2016) to evaluate the MCDM process.

Peng and Dai (2017) suggested COPRAS, "weighted aggregated sum product assessment (WASPAS)" and "multi-attributive border approximation area comparison (MABAC)" methods under "hesitant fuzzy soft sets (HFSSs)" environment. The HF linguistic COPRAS approach was extended Zheng et al. (2018) to solve the health decision-making problem. Büyüközkan and Göçer (2019) proposed a method by combining AHP and COPRAS models within PFSs context. Rani et al. (2020c) evaluated pharmacological therapies for type-2 diabetes disease using the Pythagorean fuzzy COPRAS method. Mishra et al. (2020a) extended COPRAS on the basis of information measures in a way to assess the hazardous waste recycling facility evaluation problem under IVIFSs condition. The IF-COPRAS method associated with parametric information measures was discussed by Kumari and Mishra (2020) regarding its capacity for solving the problem of selecting the green supplier. Alipour et al. (2021) studied an integrated

SWARA and COPRAS methodology to assess the fuel cell and hydrogen components supplier selection under the PFS environment.

As noted earlier, in spite of many studies carried out in these areas, the literature still suffers from an inadequacy in terms of finding the effects, relationships, and practicality of Industry 4.0 to the supply chain perspective. This research discusses the term "supply chain 4.0" to emphasize the relationships between SC and Industry 4.0, explore the applicability and effects of Industry 4.0 on the SC context, and also identify the most important components that could shape the foundation of Industry 4.0 in the SC context. It could be accomplished by developing a conceptual supply chain 4.0 and constructing a supply chain 4.0 maturity model. Though, the literature is still introducing a number of areas with potential for being studied in the supply chain 4.0 domain. To identify all these areas, there is a need to clarify the supply chain 4.0 meaning and the development of a comprehensive perceptive of current work carried out in this area. The present study aims to understand and clarify supply chain 4.0 from an evolutionary viewpoint, consider the maturity levels, and identify the gaps that exist in the current literature to recognize the directions for future research. In this sense, the present paper attempts to bridge the existing gap by identifying the supply chain 4.0-related challenges. The current paper refers to such challenges as 'constructs'. As a result, the most important questions addressed in this research are:

RQ1. What are the challenges to the implementation of supply chain 4.0 in the era of circular economy?
RQ2. How can the evolution of supply chain 4.0 be understood and evaluated?
RQ3. What are the open research questions and research gaps related to supply chain 4.0 and its maturity?

To tackle the aforementioned concerns, the contribution of the current paper include:

- To suggest an inclusive framework for the evaluation of the challenges that arise in the implementation of supply chain 4.0 with the help of a survey approach.
- To proposing an innovative decision-making model with the use of q-ROF-SWARA-COPRAS to assess and rank the challenges to supply chain 4.0.
- To use the SWARA model to evaluate and rank the challenges that may occur to supply chain 4.0.
- To apply the COPRAS model to rank the organizations through the analysis of the challenges of supply chain 4.0.
- To compare and validate the proposed q-ROF-SWARA-COPRAS method by comparing its performance with other existing MCDM approaches.

The rest of the paper is structured in the following sections. Section 2 presented the literature review and related works of supply chain 4.0 implementation in the manufacturing sector under the circular economy. Section 3 provided the proposed q-ROF-SWARA-COPRAS approach and the basic concept of fuzzy sets. Section 4 presented the results of the study, the case study, sensitivity investigation, and comparative study. Finally, Sect. 5 discussed the conclusion of the study.

2 Literature review

The recent development of the information and communication systems has led to several key prospects for SC intelligence and autonomy to establish an appropriate stage for the development of Industry 4.0 SCs. Many researchers have addressed the sustainable supplier assessment process as a highly important SC decision. Nevertheless, this process has not yet been realized in the context of Industry 4.0 SCs, in which the foremost design principles include interconnection, technical assistance, real-time information transparency, and decentralization of members of a physical system (i.e., SC members). Because of the digitalization and automation practices, the whole structure of SC is transformable into a system of physical members that communicate and exchange their information with each other in a real-time, autonomous, and intelligent manner in line with the principles of Industry 4.0 (Hermann et al. 2016). In this regard, Schlüter and Hetterscheid (2017) maintained that the digitalization situations of different SC practices require to be accelerated; as a result, they proposed an application-oriented framework for the extraction of the significant tools in the area of Industry 4.0 mapped to different SC practices. Several tools have been offered to unfold the Industry 4.0 umbrella: big data and analytics(Cai et al. 2019; Zhang et al. 2018), autonomous robots, simulation (Buzys et al. 2018; Wei et al. 2017), IoT (Han et al. 2020; Lin et al. 2015), cybersecurity (Wei-Gang et al. 2013; Wu et al. 2013), cloud computing (Chen et al. 2016a, b), additive manufacturing and augmented reality (Shi et al. 2016a, b), Radio Frequency Identification (RFID) (Li et al. 2018; Wang et al. 2018) and real-time location system (Wang et al. 2020; Yang et al. 2020). Likewise, Oks et al. (2017) introduced an application map in order to distinguish different opportunity areas to apply the industrial cyber-physical systems of Industry 4.0. Hofmann and Rüsch (2017) examined the ways that Industry 4.0 can affect logistics management.

Kiel et al. (2017) attempted to classify both advantages and challenges associated with the IoT, focusing on value creation sustainability. Waibel et al. (2017) examined the impacts of smart production systems from sustainability perspectives wherein each aspect of sustainability (i.e., environmental, social, economic, and technical) was assessed regarding the efficiency of resources. Manavalan and Jayakrishna (2019) made a review study on the Industry 4.0 scenarios of an SSC and provided some analyses on various IoT aspects and supply chain management. In addition, they investigated to identify the best software for planning the material resources in companies. A new model was designed by Ghadimi et al. (2019) on the basis of multi-agent systems for the automatic assessment of suppliers in the context of Industry 4.0 SCs with considering sustainable issues. Their model contained a system architecture with three layers: technical, interface, and data resources.

Luthra and Mangla (2018) reviewed the existing literature and succeeded in recognizing 18 challenges to Industry 4.0, which were categorized into four different groups: organizational, legal, strategical, and ethical. Then, they attempted to validate the identified challenges with the use of an AHP within the manufacturing sector in India. Ding (2018) also reviewed the literature with the aim of identifying the barriers to the inclusion of sustainability in the pharmaceutical SC. The barriers found were little experience and training, high expenses and long practice times, coordinating supply chains, reinforcing regulations, and unsuccessful collaboration. Furthermore, through the SSCs, called Pharma 4.0, they could identify how Industry 4.0 could be implemented in these supply chains to solve problems from sustainable viewpoints.

A conceptual agenda was suggested by Paravizo et al. (2018) to develop gamified applications in the Industry 4.0 field focusing upon sustainable manufacturing. In another study, Müller et al. (2018) introduced a search model to identify both the challenges and opportunities that may arise by the hypothetical implementation of Industry 4.0. the model was applied to 746 German manufacturing firms working in five different sectors in the German industry. Kamble et al. (2018a) also reviewed the articles linked to the concept of Industry 4.0 and constructed a reference framework of sustainability in Industry 4.0 settings through reviewing a total of 85 publications.

Kumar et al. (2018) designed a metaheuristic model to solve a sustainable, robust stochastic cellular facility layout problem. Tsai and Lu (2018) introduced a novel model applicable to planning the production and controlling with a carbon tax in an Industry 4.0 perspective. Bibaud-Alves et al. (2019) used an Industry 4.0 approach to provide a connection amongst the new product development process, sustainable development, and digital transformation. Birkel et al. (2019) designed a reference framework showing the risks in the context of Industry 4.0 to SMEs with a sustainability approach, the technical risks, the IT-related risks, and legal/political risks. Two power-aware algorithms were designed by Roda-Sanchez et al. (2018), adopting a flexible approach for the purpose of facing the sustainability challenge in Industry 4.0. Zambon et al. (2019) suggested a new structure for the management of agriculture 4.0 through virtualizing an agro-food chain.

A novel approach was proposed by Belaud et al. (2019) with the integration of Industry 4.0 into an SC to improve sustainability management to valorize agricultural 4.0 waste using big data. Considering the social aspect in the Industry 4.0 context, Stock et al. (2018) reviewed the existing literature on the basis of value creation and commenced a model for Industry 4.0 from sustainable perspectives. Chaim et al. (2018) investigated whether key performance indicators (KPIs) could be well incorporated for the evaluation of sustainability in a virtual learning setting within the environment of Industry 4.0.

Bonilla et al. (2018) designed various Industry 4.0 development scenarios to assess the challenges that arise while implementing Industry 4.0. de Sousa Jabbour et al. (2018) constructed a new model that found the synergy between Industry 4.0 and industrialized environmental sustainability activities. Meng et al. (2018) reviewed the literature taking into consideration the energy capability and sustainability in smart factories to determine the way they make the interaction between themselves. Kamble et al. (2018b) made an analysis of the energy barriers appearing while applying Industry 4.0 to the Indian manufacturing sectors. Huh and Lee (2018) carried out a number of simulations for a lower-power digital "excitement" scheme in the environment of Industry 4.0. Having reviewed the articles, Fritzsche et al. (2018) attempted to mark out the gaps in inter-governmental organizations investigating climate change and Industry 4.0 and the relationships between them. Campo et al. (2018) attempted to optimize energy in an Industry 4.0 domain with the use of IoT and considered it in real-life situations. Axelsson et al. (2018) investigated the ways to enhance efficiency and decrease waste generation during road construction projects with the use of a lean model and Industry 4.0 with a "system of systems".

Medojevic et al. (2018) evaluated the extant studies on energy management in an Industry 4.0context and, examined how to integrate both Industry 4.0 and energy management effectively, and attempted to identify the challenges that may appear in this path. Wang and Wang (2019) designed a system on the basis of "a digital twin", of Industry 4.0 to recycle electronic devices and electrical waste. Tsai (2018) introduced a mathematical model addressing environmental problems. This model took into consideration activity-based costing (ABC) and theory of constraints (TOC) and their application. Sherazi et al. (2018) proposed a method for collecting energy with a long-range wide area network (LoRaWAN) and analyzed its costs related to Industry 4.0. Tsai et al. (2019) introduced an optimization methodology in order to plan green construction with the ABC classification and Industry 4.0. For the environmental aspects, they emphasized the necessity for the improvement of energy efficiency through applying IoT to Industry 4.0. In their model, the energy consumption is monitored by the sensors in real time; the data gathered in this process can be examined and allocated by means of all the links in SC Industry 4.0.

A conceptual model was suggested by Monteleone et al. (2019), which was applicable to managing water in the context of agriculture 4.0. With an economic approach to Industry 4.0 and sustainable development, Bechtsis et al. (2017) investigated the processes of materials manipulation using the technology of automated guided vehicles (AGV). In another study, (Franciosi et al. 2018) reviewed the previous studies in regard to maintenance 4.0. Ma (2019) offered a novel model for managing the sources established for the warehouse on the basis of Industry 4.0 enablers. Nascimento et al. (2019) designed a business framework for the purpose of recycling waste based on an Industry 4.0 approach. Based on the above-presented discussions, the current paper recognized a total of 24 challenges that are; security issues (B_1); agility and flexibility (B_2); poor research and development (R&D) on Industry 4.0 adoption (B_3); unclear economic benefit of digital investments (B_4); high volatility (B_5); lack of vision and strategy (B_6); lack of governmental support and polices (B_7); lack of competency in adopting/applying new business models (B_8); lack of global standards and data sharing protocols (B_9); lack of knowledge (B_{10}); lack of digital culture (B_{11}); lack of planning (B_{12}); legal issues (B_{13}); lack of information sharing (B_{14}); overconfidence in suppliers (B_{15}); low management support and dedication (B_{16}); lack of integration (B_{17}); financial constraints (B_{18}); low understanding of Industry 4.0 implications (B_{19}); lack of collaboration and coordination (B_{20}); lack of infrastructure and internet-based networks (B_{21}); poor existing data quality (B_{22}); silver bullet chase (B_{23}) and profiling and complexity issues (B_{24}).

3 Proposed research method

The COPRAS and SWARA have shown high efficiency in preference ordering of the options and determining the subjective weights of the criteria, respectively. The literature consists of a few studies that have applied a combination of COPRAS and SWARA to various domains; although, no study has integrated these two in the q-ROFSs environment. To the best of the authors' reviews, the present paper is the first effort made to develop an integrated q-ROF-SWARA-COPRAS method with the aim of evaluating the challenges to supply chain 4.0. This method is also applicable to a number of decision-making problems, e.g., the COVID-19 medication selection, selection of technology for treating medical waste, third-party reverse logistics providers, and others. Here, we show the basic idea about the q-ROFSs and then discuss the methodology.

3.1 Basic concepts

This section briefly presents elementary conceptions on q-ROFSs and similarity measures.

Definition 1 (Yager 2017). Consider $\Xi = \{z_1, z_2, \dots, z_n\}$ be a fixed set. A q-ROFS 'M' on Ξ is described as follows:

$$M = \{(z_i, \mu_M(z_i), \nu_M(z_i)) | z_i \in \Xi\}.$$

Here, μ_M and ν_M signify the MG and the NG of $z_i \in \Xi$, respectively, $\mu_M(z_i) \in [0,1] \nu_M(z_i) \in [0,1], 0 \le (\mu_M(z_i))^q + (\nu_M(z_i))^q \le 1$, with $q \ge 1$. The indeterminacy degree is presented by $\pi_M(z_i) = \sqrt[q]{1 - (\mu_M(z_i))^q - (\nu_M(z_i))^q}, \forall z_i \in \Xi$. The pair $(\mu_M(z_i), \nu_M(z_i))$ is referred as q-ROF number (q-ROFN), denoted by $\sigma = (\mu_\sigma, \nu_\sigma)$.

Definition 2 For three q-ROFNs $\sigma = (\mu_\sigma, \nu_\sigma)$, $\sigma_1 = (\mu_{\sigma_1}, \nu_{\sigma_1})$ and $\sigma_2 = (\mu_{\sigma_2}, \nu_{\sigma_2})$, the operations can be given by (Liu and Wang 2018).

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

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

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

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

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

Definition 3 (Liu and Wang 2018). Let $\sigma = (\mu_\sigma, \nu_\sigma)$ be a q-ROFN. Then, score and accuracy values of σ are presented as $\mathbb{S}(\sigma) = \mu_\sigma^q - \nu_\sigma^q$ and $\hbar(\sigma) = \mu_\sigma^q + \nu_\sigma^q$, respectively wherein $\mathbb{S}(\sigma) \in [-1, 1]$ and $\hbar(\sigma) \in [0, 1]$.

Definition 4 Assume that $\sigma = (\mu_\sigma, \nu_\sigma)$ be a q-ROFN. Then, the improved score and uncertainty functions are presented as.

$$\begin{aligned} \mathbb{S}^*(\sigma) &= \frac{1}{2}(\mathbb{S}(\sigma) + 1), \ \mathring{\hbar}(\sigma) \\ &= 1 - \hbar(\sigma) \text{ such that } \mathbb{S}^*(\sigma), \ \mathring{\hbar}(\sigma) \in [0, 1]. \end{aligned} \tag{1}$$

For any two q-ROFNs $\sigma_1 = (\mu_{\sigma_1}, \nu_{\sigma_1})$ and $\sigma_2 = (\mu_{\sigma_2}, \nu_{\sigma_2})$,

(i) If $\mathbb{S}^*(\sigma_1) > \mathbb{S}^*(\sigma_2)$, then $\sigma_1 > \sigma_2$,
(ii) If $\mathbb{S}^*(\sigma_1) = \mathbb{S}^*(\sigma_2)$, then

(a) if $\hbar^{\circ}(\sigma_1) > \hbar^{\circ}(\sigma_2)$, then $\sigma_1 > \sigma_2$;
(b) if $\hbar^{\circ}(\sigma_1) = \hbar^{\circ}(\sigma_2)$, then $\sigma_1 = \sigma_2$.

Definition 5 (Liu et al. 2019). For two q-ROFNs $\sigma_1 = (\mu_{\sigma_1}, \nu_{\sigma_1})$ and $\sigma_2 = (\mu_{\sigma_2}, \nu_{\sigma_2})$, the q-ROF-distance measure for σ_1 and σ_2 is presented as.

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

3.2 Proposed q-ROF-SWARA-COPRAS approach

Zavadskas et al. (1994) developed COPRAS as an effective method that can provide an optimum outcome related to the compromising decision-making technique. COPRAS is mainly applied to decision-making purposes in deterministic circumstances. This is because decision-making processes typically deal with uncertain situations, and q-ROFS effectively addresses uncertainty and the vagueness of available information. Therefore, this section develops a modified COPRAS method under the q-ROFSs environment for solving decision-making applications and is named the q-ROF-COPRAS method. The calculation steps for the q-ROF-SWARA-COPRAS framework are given by (see Fig. 1).

Step 1: Generate a q-ROF-decision matrix (q-ROF-DM)

A group of ℓ DEs $A = \{A_1, A_2, ..., A_\ell\}$ determine the sets of m options $O = \{O_1, O_2, ..., O_m\}$ and n criteria $B = \{B_1, B_2, ..., B_n\}$, respectively. Owing to the ambiguity of human's mind, lack of data, and imprecise knowledge about the options, the DEs allocate q-ROFNs to estimate his/her decision on alternative O_i by means of a criterion B_j. Assume that $\mathbb{Z}^{(k)} = \left(\xi_{ij}^{(k)}\right)_{m\times n}$ is the q-ROF-DM suggested by experts, where $\xi_{ij}^{(k)}$ refer to the assessment of an alternative O_i over a criterion B_j in form of q-ROFN given by kth DE.

Step 2: Compute the weights of DEs

To compute the kth DM, let $A_k = (\mu_k, \nu_k, \pi_k)$ be the q-ROFN. Now, the process for expert weight determination is obtained by

$$\varpi_k = \frac{\left(\mu_k^q + \pi_k^q \times \left(\frac{\mu_k^q}{\mu_k^q + \nu_k^q}\right)\right)}{\sum_{k=1}^{\ell}\left(\mu_k^q + \pi_k^q \times \left(\frac{\mu_k^q}{\mu_k^q + \nu_k^q}\right)\right)}, \; k = 1(1)\ell. \tag{3}$$

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

Step 3: Aggregate all the individual opinions

To generate the aggregated-q-ROF-decision-matrix (A-q-ROF-DM), q-rung orthopair fuzzy weighted arithmetic (q-ROFWA) operator is used and then $\breve{\mathbb{Z}} = \left(\breve{\xi}_{ij}\right)_{m\times n}$, where

$$\begin{aligned}\breve{\xi}_{ij} &= q - ROFWA_{\varpi}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, ..., \xi_{ij}^{(\ell)}\right) \\ &= \left(\sqrt[q]{1 - \prod_{k=1}^{\ell}\left(1 - \mu_k^q\right)^{\varpi_k}}, \prod_{k=1}^{\ell}\left(\nu_k\right)^{\varpi_k}\right).\end{aligned} \tag{4}$$

Step 4: Estimate the criteria weights using SWARA model.

The implementation steps for computing the criteria weights are:

Step 4.1: Estimate the score values $\mathbb{S}^*\left(\breve{\xi}_{kj}\right)$ of q-ROFNs using Eq. (1).

Step 4.2: Prioritize the attributes. The attributes are ranked using the DE's opinions from maximum considerable to minimum considerable attribute.

Step 4.3: Obtain the comparative significance of the average degree. The significance degree is estimated from the criteria that are ranked in second place, and the subsequent comparative significance is calculated by relating criterion B_j to criterion B_{j-1}.

Step 4.4: Obtain the comparative coefficient κ_j as follows:

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

where s_j indicates the significance degree (Kersuliene et al. 2010).

Step 4.5: Compute the weights. The recalculated weight is given by

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

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: Sum the criteria values with different types of criteria

In the present step, each alternative is articulated with its sum of maximizing criterion τ_i and minimizing criterion ι_i. To obtain the values of τ_i and ι_i, the following procedures are implemented

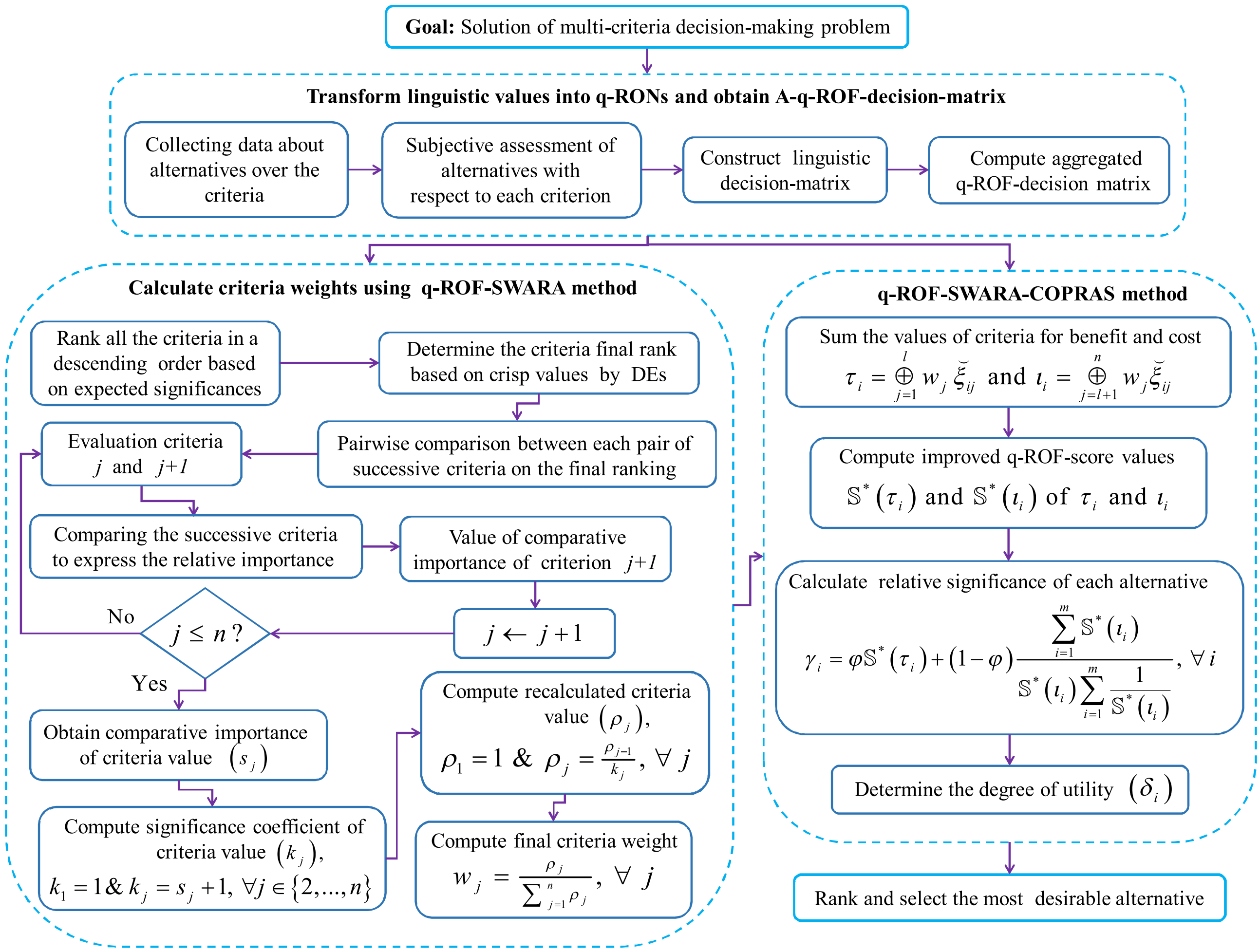

Fig. 1 Flowchart of proposed q-ROF-SWARA-COPRAS framework

$$\tau_i = \underset{j=1}{\overset{l}{\oplus}} w_j \breve{\xi}_{ij}, \quad \forall\, i. \tag{8}$$

$$\iota_i = \underset{j=l+1}{\overset{n}{\oplus}} w_j \breve{\xi}_{ij}, \quad \forall\, i. \tag{9}$$

In formulae (8) and (9), l and n denote the beneficial and total no. of criteria and w_j is weight value.

Step 6: Evaluation of the relative degree (RD) of each option.

The RD of each alternative is computed by means of the following:

$$\gamma_i = \varphi \mathbb{S}^*\left(\tau_i\right) + (1-\varphi)\frac{\min_i \mathbb{S}^*\left(\iota_i\right) \sum_{i=1}^{m} \mathbb{S}^*\left(\iota_i\right)}{\mathbb{S}^*\left(\iota_i\right) \sum_{i=1}^{m} \frac{\min_i \mathbb{S}^*\left(\iota_i\right)}{\mathbb{S}^*\left(\iota_i\right)}}, \forall\, i, \tag{10}$$

In this formula, $\mathbb{S}^*\left(\tau_i\right)$ and $\mathbb{S}^*\left(\iota_i\right)$ are the score values of τ_i and ι_i, respectively, and $\varphi \in [0,\ 1]$ signifies the strategy value of decision expert.

Another form of Eq. (10) is presented as

$$\gamma_i = \varphi \mathbb{S}^*\left(\tau_i\right) + (1-\varphi)\frac{\sum_{i=1}^{m} \mathbb{S}^*\left(\iota_i\right)}{\mathbb{S}^*\left(\iota_i\right) \sum_{i=1}^{m} \frac{1}{\mathbb{S}^*\left(\iota_i\right)}}, \quad \forall\, i. \tag{11}$$

Step 7: Create a priority degree of alternatives.

Note that the priority degree of alternatives is determined by taking into consideration the relative values of accessible candidates. It can be computed as

$$E^* = \max_i \gamma_i. \tag{12}$$

Step 8: Evaluate the utility degree (UD).

Now, the procedure for the evaluation of the UD is described by

$$\delta_i = \frac{\gamma_i}{E^*} \times 100\,\%,\ \forall i. \tag{13}$$

Here, γ_i and E^* are given by Steps 6−7.

The introduced q-ROF-COPRAS framework helps in the evaluation of the direct and proportional dependence of UDs and the relative significance of all the alternatives concerning the criterion set. After that, COPRAS marks out the best option among a set of various alternatives with considering the set of multiple criteria.

4 Results and discussion

4.1 Case study

Applying Industry 4.0 to the SC in manufacturing firms is more difficult in comparison with the other industry sectors (Kleindorfer et al. 2005; Yadav et al. 2020). According to Majumdar and Sinha (2019), the SC performance of the service and healthcare sectors is much better than the manufacturing industries. Because of the presence of tangible goods in the automotive industry, it is not easy to apply sustainability to their existing supply chain structure in an effective way (Gimenez et al. 2012). The organization for the future plans to expand their business to the international context, which necessitates the adoption of a sustainable perspective in their prevailing SC. The managers of the case organization want to make sure of the effective supply chain 4.0 implementation in the manufacturing sector under the circular economy concept; as a result, they came to a decision to examine the method developed by the authors before their actual implementation. To this end, a team was created consisting of three decision experts, including one project manager, one supervisor from the production department, one assistant manager from sales and distribution, and one senior manager from the purchase area. All of these decision experts had experienced the activities related to SC for more than 20 years. In addition, two out of the six experts had the practice of managing the international SC activities for 10 years. Before gathering data, approval was taken from the ethics board of the university and also the case organization indicating that the data gathered will be applied to developing a framework, and the outcomes of the research will be delivered to the case organization with the aim of facilitating supply chain 4.0 implementation in the manufacturing sector under the circular economy concept. The created decision panel was used in three phases through holding brainstorming sessions. The challenges were taken out from the existing studies and presented prior to the expert group. In the first phase, the SC 4.0 challenges were finalized to develop the frame for supply chain 4.0 implementation in the manufacturing sector under the circular economy concept, and later 24 challenges were recognized through previous researches.

Step 1–2: Assume that the DEs' weights are given in terms of q-ROFNs, presented by {(0.85, 0.45, 0.6655), (0.70, 0.65, 0.7258), (0.75, 0.60, 0.7128)}. Now, Table 1, adopted from Krishankumar et al. (2021), describes the significance value of DEs and supply chain 4.0 in linguistic values (LVs) and is now converted into q-ROFNs.

Since DEs' importance degrees as provided by the specialists, are in the form of q-ROFNs. Now, the final weights of DEs are evaluated by employing Eq. (4) and given as $\{\varpi_1 = 0.4171, \varpi_2 = 0.2661, \varpi_3 = 0.3168\}$. Table 2 defines the LVs of DEs to evaluate the options over the related challenges for supply chain 4.0 implementation in the manufacturing sector.

Step 3: Evaluation made by three DEs have been combined by Eq. (5) for alternatives over the challenges of supply chain 4.0 into an A-q-ROF-DM $\breve{\mathbb{Z}} = \left(\breve{\xi}_{ij}\right)_{m \times n}$, and is presented in Table 3.

Step 4: For estimating the weight of various challenges wth SWARA, the DEs' opinion is highly significant, which is discussed in Table 4. From Eqs. (5)−(7), the DEs ranked all the considered challenges from the first to the last ones. Then, all challenges' weights are discussed in Table 5 as w_j column. Table 5 displays that the weight of the challenges of supply chain 4.0 is given by

w_j = (0.0402, 0.0429, 0.0357, 0.0399, 0.0343, 0.0489, 0.0429, 0.0418, 0.0385, 0.0443, 0.0397, 0.0416, 0.0409, 0.0435, 0.0434, 0.0414, 0.0392, 0.0432, 0.0421, 0.0467, 0.0446, 0.0445, 0.0382, 0.0416)

Here, Fig. 2 illustrates the weight values of different challenges of supply chain 4.0 with respect to the goal. Lack of vision and strategy (B_6) with a weight value of 0.0489 has become the most critical challenge of supply chain 4.0. lack of collaboration and coordination (B_{20}) with a weight value of 0.0467 is the second most crucial challenge of supply

Table 1 Ratings of options and challenges in the term of LVs

LVs	q-ROFNs
Absolutely high (AH)	(0.95,0.20)
Very high (VH)	(0.90,0.50)
High (H)	(0.80,0.60)
Medium high (MH)	(0.75,0.65)
Average (A)	(0.60,0.70)
Medium low (ML)	(0.50,0.75)
Low (L)	(0.40,0.80)
Very low (VL)	(0.30,0.90)
Absolutely low (AL)	(0.20,0.95)

Table 2 LVs of options over various challenges by DEs

	O_1	O_2	O_3	O_4
B_1	(MH,A,H)	(A,ML,VL)	(H, MH,A)	(H,H,A)
B_2	(A,VH,H)	(ML,MH,H)	(H,A,MH)	(H,ML,MH)
B_3	(H,VH,H)	(VH,H,VH)	(ML,A,H)	(ML,A,MH)
B_4	(ML,A,H)	(VH,A,H)	(ML,ML,MH)	(ML,A,H)
B_5	(ML,MH,H)	(ML,H,H)	(MH,ML,A)	(MH,A,A)
B_6	(VL,MH,L)	(A,VL,L)	(VH,H,A)	(VH,H,MH)
B_7	(ML,MH,L)	(L,VL,L)	(A,MH,A)	(H,MH,A)
B_8	(H,VH,VH)	(A,H,VH)	(ML,A,MH)	(ML,A,H)
B_9	(H,A,H)	(A,VH,H)	(A,ML,H)	(L,ML,H)
B_{10}	(L,L,A)	(L,VL,VL)	(L,A,ML)	(L,ML,ML)
B_{11}	(ML,L, L)	(MH,L,L)	(MH,H,A)	(MH,MH,A)
B_{12}	(ML,L,ML)	(ML,A,ML)	(H,VH,A)	(MH,VH,A)
B_{13}	(ML,VL,VL)	(L,ML,L)	(ML,A,ML)	(ML,VL,ML)
B_{14}	(ML,A,H)	(ML,MH,H)	(MH,VH,MH)	(A,VH,H)
B_{15}	(VH,MH,A)	(ML,VH,H)	(A,ML,VH)	(A,A,MH)
B_{16}	(ML,L,VL)	(A,L,VL)	(MH,A,VH)	(MH,A,H)
B_{17}	(ML,ML,A)	(L,VL,ML)	(MH,ML,A)	(MH,L,A)
B_{18}	(MH,VH,H)	(A,VH,H)	(A,VL,ML)	(A,VL,ML)
B_{19}	(ML,A,H)	(MH,VH,H)	(ML,MH,A)	(ML,H,A)
B_{20}	(MH,H,H)	(A,MH,A)	(ML,VL,A)	(ML,L,A)
B_{21}	(MH,L,H)	(A,A,MH)	(ML,L,A)	(ML,L,MH)
B_{22}	(MH,MH,H)	(A,ML,A)	(ML,ML,A)	(L,VL,A)
B_{23}	(H,L,MH)	(A,MH,A)	(MH,L,A)	(ML,ML,MH)
B_{24}	(MH,A,H)	(MH,ML,A)	(ML,MH,A)	(L,L,A)

chain 4.0. Lack of infrastructure and internet-based networks (B_{21}) has third with significance value 0.0446, poor existing data quality (B_{22}) has fourth with weight value 0.0445, lack of knowledge (B_{10}) with significance value 0.0443 has fifth most important challenge challenges of supply chain 4.0. lack of information sharing (B_{14}) with significance value 0.0435; overconfidence in suppliers (B_{15}) with significance value 0.0434; financial constraints (B_{18}) with significance value 0.0432; lack of governmental support and polices (B_7) and agility and flexibility (B_2) with significance value 0.0429; low understanding of Industry 4.0 implications (B_{19}) with significance value 0.0421; lack of competency in adopting/applying new business models (B_8) with significance value 0.0418; lack of planning (B_{12}) and profiling & complexity issues (B_{24}) significance value 0.0416; low management support and dedication (B_{16}) with significance value 0.0414; legal issues (B_{13}) with significance value 0.0409; security issues (B_1) with significance value 0.0402; unclear economic benefit of digital investments (B_4) with significance value 0.0399; Lack of digital culture (B_{11}) with significance value 0.0397; lack of integration (B_{17}) with significance value 0.0392; lack of global standards and data sharing protocols (B_9) with significance value 0.0385; silver bullet chase (B_{23}) with significance value 0.0382; poor research and development (R&D) on Industry 4.0 adoption (B_3) with significance value 0.0357; high volatility (B_5) with significance value 0.0343 are considered crucial challenges of supply chain 4.0.

Steps 5–8: In the process of assessment of challenges of supply chain 4.0, all risk factors are the benefit types. Hence, the RD γ_i of each option is equal to $\mathbb{S}^*(\tau_i)$, i.e., $\mathbb{S}^*(\tau_i) = \gamma_i$. Using (8)–(12), the values of τ_i,γ_i and δ_i of $O_i\,(i = 1(1)4)$ are computed over the challenges $B_j\,(j = 1(1)24)$, and specified in Table 6. From Table 6, the prioritization of the organization candidates is $O_1 \succ O_3 \succ O_2 \succ O_4$ and thus, O_1 is the best site for organizations.

4.2 Comparative study

The result of the q-ROF-SWARA-COPRAS method was compared with the results of another approach. To demonstrate the efficacy and the unique advantages of the introduced method, the q-ROF-TOPSIS model (Liu et al. 2019) and q-ROF-WASPAS (Rani and Mishra 2020) are employed to tackle the same problem.

4.2.1 q-ROF-TOPSIS method

Steps 1–4: Similar to the aforementioned technique.

Step 5: Define the q-rung orthopair fuzzy ideal solution (q-ROF-IS) and q-rung orthopair fuzzy anti-ideal solution (q-ROF- AIS).

Let ζ^+ and ζ^- symbolize the q-ROF-IS and q-ROF-AIS and are estimated by

$$\zeta^+ = \left(\mu_\zeta^+, \nu_\zeta^+\right) = \begin{cases} \max\limits_i \ \mu_{ij}, & \text{for benefit criterion } B_b \\ \min\limits_i \ \nu_{ij}, & \text{for cost criterion } B_n \end{cases}, \tag{14}$$

$$\zeta^- = \left(\mu_\zeta^-, \nu_\zeta^-\right) = \begin{cases} \min\limits_i \ \mu_{ij}, & \text{for benefit criterion } B_b \\ \max\limits_i \ \nu_{ij}, & \text{for cost criterion } B_n \end{cases}. \tag{15}$$

Step 6: Estimate the distance measures from options to q-ROF-IS and q-ROF-AIS, respectively.

Using Eq. (2), we estimate the discrimination $dis\left(O_i, \zeta^+\right)$ between the alternative O_i and q-ROF-IS ζ^+.

$$dis\left(O_i, \zeta^+\right) = \frac{1}{2}\sum_{j=1}^{n}\left[w_j\left(\left|\mu^q_{\breve{\xi}_{ij}} - \left(\mu_\zeta^+\right)^q\right| + \left|\nu^q_{\breve{\xi}_{ij}} - \left(\nu_\zeta^+\right)^q\right| + \left|\pi^q_{\breve{\xi}_{ij}} - \left(\pi_\zeta^+\right)^q\right|\right)\right] \tag{16}$$

Table 3 A-q-ROF-DM for different challenges of supply chain 4.0

	O_1	O_2	O_3	O_4
B_1	(0.740, 0.646, 0.687)	(0.514, 0.772, 0.739)	(0.741, 0.644, 0.689)	(0.756, 0.630, 0.682)
B_2	(0.789, 0.610, 0.656)	(0.704, 0.673, 0.703)	(0.746, 0.641, 0.684)	(0.736, 0.653, 0.686)
B_3	(0.835, 0.572, 0.613)	(0.881, 0.525, 0.556)	(0.665, 0.686, 0.726)	(0.634, 0.704, 0.735)
B_4	(0.665, 0.686, 0.726)	(0.828, 0.579, 0.620)	(0.615, 0.717, 0.736)	(0.665, 0.686, 0.726)
B_5	(0.704, 0.673, 0.703)	(0.723, 0.659, 0.696)	(0.661, 0.691, 0.725)	(0.676, 0.679, 0.723)
B_6	(0.546, 0.795, 0.694)	(0.496, 0.781, 0.738)	(0.822, 0.584, 0.625)	(0.842, 0.570, 0.601)
B_7	(0.584, 0.737, 0.737)	(0.379, 0.825, 0.726)	(0.652, 0.686, 0.737)	(0.741, 0.644, 0.689)
B_8	(0.868, 0.540, 0.574)	(0.797, 0.604, 0.649)	(0.505, 0.704, 0.806)	(0.665, 0.686, 0.726)
B_9	(0.743, 0.625, 0.702)	(0.789, 0.610, 0.656)	(0.673, 0.679, 0.725)	(0.632, 0.718, 0.723)
B_{10}	(0.486, 0.767, 0.757)	(0.349, 0.857, 0.690)	(0.501, 0.756, 0.761)	(0.464, 0.770, 0.762)
B_{11}	(0.448, 0.779, 0.578)	(0.617, 0.734, 0.718)	(0.731, 0.651, 0.693)	(0.714, 0.665, 0.699)
B_{12}	(0.478, 0.763, 0.764)	(0.532, 0.736, 0.560)	(0.802, 0.600, 0.645)	(0.783, 0.621, 0.655)
B_{13}	(0.410, 0.834, 0.705)	(0.432, 0.786, 0.757)	(0.532, 0.736, 0.767)	(0.464, 0.787, 0.744)
B_{14}	(0.665, 0.686, 0.726)	(0.704, 0.673, 0.703)	(0.808, 0.606, 0.630)	(0.789, 0.610, 0.656)
B_{15}	(0.812, 0.584, 0.642)	(0.776, 0.627, 0.658)	(0.751, 0.641, 0.679)	(0.660, 0.684, 0.732)
B_{16}	(0.429, 0.808, 0.733)	(0.493, 0.785, 0.734)	(0.797, 0.610, 0.643)	(0.740, 0.646, 0.687)
B_{17}	(0.537, 0.734, 0.766)	(0.420, 0.809, 0.735)	(0.661, 0.691, 0.725)	(0.651, 0.703, 0.722)
B_{18}	(0.820, 0.572, 0.639)	(0.789, 0.610, 0.656)	(0.520, 0.765, 0.744)	(0.520, 0.765, 0.744)
B_{19}	(0.665, 0.686, 0.726)	(0.820, 0.591, 0.623)	(0.624, 0.706, 0.739)	(0.651, 0.692, 0.732)
B_{20}	(0.781, 0.620, 0.658)	(0.652, 0.686, 0.737)	(0.507, 0.770, 0.744)	(0.519, 0.747, 0.763)
B_{21}	(0.722, 0.670, 0.686)	(0.660, 0.684, 0.732)	(0.519, 0.747, 0.763)	(0.603, 0.729, 0.733)
B_{22}	(0.767, 0.634, 0.664)	(0.578, 0.713, 0.763)	(0.537, 0.734, 0.766)	(0.473, 0.791, 0.736)
B_{23}	(0.729, 0.664, 0.683)	(0.652, 0.686, 0.737)	(0.651, 0.703, 0.722)	(0.615, 0.717, 0.736)
B_{24}	(0.740, 0.646, 0.687)	(0.661, 0.691, 0.725)	(0.624, 0.706, 0.739)	(0.486, 0.767, 0.757)

and the discrimination $dis(O_i, \zeta^-)$ between the alternative O_i and q-ROF-AIS ζ^- is described by

$$dis(O_i, \zeta^-) = \frac{1}{2}\sum_{j=1}^{n}\left[w_j\left(\left|\mu^q_{\breve{\xi}_{ij}} - \left(\mu^-_{\zeta}\right)^q\right| + \left|\nu^q_{\breve{\xi}_{ij}} - \left(\nu^-_{\zeta}\right)^q\right| + \left|\pi^q_{\breve{\xi}_{ij}} - \left(\pi^-_{\zeta}\right)^q\right|\right)\right]. \tag{17}$$

Step 7: Appraise the relative closeness index (RCI).

The RCI of each candidate can be determined using Eq. (18):

$$RC(O_i) = \frac{dis(O_i, \zeta^-)}{dis(O_i, \zeta^+) + dis(O_i, \zeta^-)}. \tag{18}$$

Step 8: Decide the maximum degree, $RC(O_k)$, among the degrees $RC(O_i)$. This proves that O_k is the optimal alternative.

At present, the q-ROF-IS and q-ROF-AIS are estimated by Eqs. (14)–(15) as follows:

$\zeta^+ =$ **{**(0.756, 0.630, 0.682), (0.789, 0.610, 0.656), (0.881, 0.525, 0.556), (0.828, 0.579, 0.620), (0.723, 0.659, 0.696), (0.842, 0.570, 0.601), (0.741, 0.644, 0.689), (0.868, 0.540, 0.574), (0.789, 0.610, 0.656), (0.501, 0.756, 0.761), (0.731, 0.651, 0.693), (0.802, 0.600, 0.645), (0.532, 0.736, 0.767), (0.808, 0.606, 0.630), (0.812, 0.584, 0.642), (0.797, 0.610, 0.643), (0.661, 0.691, 0.725), (0.820, 0.572, 0.639), (0.820, 0.591, 0.623), (0.781, 0.620, 0.658), (0.722, 0.670, 0.686), (0.767, 0.634, 0.664), (0.729, 0.664, 0.683), (0.740, 0.646, 0.687)**},**

$\zeta^- =$**{**(0.514, 0.772, 0.739), (0.704, 0.673, 0.703), (0.634, 0.704, 0.735), (0.615, 0.717, 0.736), (0.661, 0.691, 0.725), (0.496, 0.781, 0.738), (0.379, 0.825, 0.726), (0.505, 0.704, 0.806), (0.632, 0.718, 0.723), (0.349, 0.857, 0.690), (0.448, 0.779, 0.578), (0.478, 0.763, 0.764), (0.410, 0.834, 0.705), (0.665, 0.686, 0.726), (0.660, 0.684, 0.732), (0.429, 0.808, 0.733), (0.420, 0.809, 0.735), (0.520, 0.765, 0.744), (0.624, 0.706, 0.739), (0.507, 0.770, 0.744), (0.519, 0.747, 0.763), (0.473, 0.791, 0.736), (0.615, 0.717, 0.736), (0.486, 0.767, 0.757)**}.**

The results of the q-ROF-TOPSIS model are obtained by Eqs. (16)–(18) and are illustrated in Table 7. Lastly, the prioritization order of organizations is obtained as $O_1 \succ O_3 \succ O_2 \succ O_4$. Therefore, the most company alternative is O_1.

4.2.2 q-ROF-WASPAS method

Steps 1–4: Analogous to the aforementioned model.

Table 4 Weights of challenges of supply chain 4.0 in LVs

Barriers	A_1	A_2	A_3	Aggregated q-ROFNs	Score values $\mathbb{S}^*\left(\breve{\xi}_{kj}\right)$
B_1	ML	MH	ML	(0.600, 0.722, 0.741)	0.4200
B_2	A	A	MH	(0.660, 0.684, 0.732)	0.4842
B_3	L	ML	L	(0.432, 0.786, 0.757)	0.2971
B_4	A	A	ML	(0.573, 0.715, 0.764)	0.4110
B_5	VL	L	ML	(0.410, 0.823, 0.720)	0.2554
B_6	MH	H	H	(0.781, 0.620, 0.658)	0.6187
B_7	ML	A	H	(0.665, 0.686, 0.726)	0.4853
B_8	MH	A	L	(0.646, 0.708, 0.721)	0.4573
B_9	ML	A	ML	(0.532, 0.736, 0.767)	0.3754
B_{10}	H	A	ML	(0.694, 0.671, 0.714)	0.5159
B_{11}	L	ML	MH	(0.595, 0.736, 0.731)	0.4058
B_{12}	ML	A	MH	(0.634, 0.704, 0.735)	0.4531
B_{13}	MH	ML	L	(0.628, 0.721, 0.722)	0.4365
B_{14}	H	ML	ML	(0.680, 0.683, 0.716)	0.4975
B_{15}	MH	MH	L	(0.689, 0.694, 0.697)	0.4960
B_{16}	ML	H	ML	(0.631, 0.707, 0.734)	0.4489
B_{17}	L	MH	ML	(0.579, 0.742, 0.736)	0.3930
B_{18}	ML	MH	MH	(0.679, 0.690, 0.711)	0.4921
B_{19}	A	ML	MH	(0.644, 0.696, 0.734)	0.4646
B_{20}	ML	A	VH	(0.745, 0.648, 0.680)	0.5711
B_{21}	MH	ML	MH	(0.708, 0.675, 0.696)	0.5233
B_{22}	ML	MH	H	(0.704, 0.673, 0.703)	0.5221
B_{23}	A	ML	L	(0.527, 0.744, 0.762)	0.3673
B_{24}	ML	A	MH	(0.634, 0.704, 0.735)	0.4531

Step 5: For each alternative, calculate the degrees of the weighted sum method (WSM) $\mathbb{C}_i^{(1)}$ with the use of Eq. (19):

$$\mathbb{C}_i^{(1)} = \sum_{j=1}^{n} w_j \, \breve{\xi}_{ij}. \tag{19}$$

Step 6: For each alternative, estimate the degrees of the weighted product method (WPM) $\mathbb{C}_i^{(2)}$ using Eq. (20) as follows:

$$\mathbb{C}_i^{(2)} = \prod_{j=1}^{n} w_j \, \breve{\xi}_{ij}. \tag{20}$$

Step 7: For each alternative, compute the aggregated measure of WASPAS with the use of Eq. (21):

$$\mathbb{C}_i = \lambda \, \mathbb{C}_i^{(1)} + (1 - \lambda) \, \mathbb{C}_i^{(2)}, \tag{21}$$

where λ stands for the coefficient of the decision mechanism. It was proposed with the aim of estimating the WASPAS accuracy level based on the initial attributes precision and when $\lambda \in [0, \ 1]$ (when $\lambda = 0$, and $\lambda = 1$, WASPAS is changed into WPM and WSM, respectively). It is already proved that the aggregating methods outperform the single models in terms of accuracy.

Step 8: Prioritize the candidates in accordance with the increasing degrees (i.e., score values) of $\mathbb{C}_i$.

To find out the ranking of the alternatives by q-ROF-WASPAS model, appraised the WSM $\left(\mathbb{C}_i^{(1)}\right)$ and its score values, WPM $\left(\mathbb{C}_i^{(2)}\right)$ and its score values, and measure of WASPAS $\left(\mathbb{C}_i\right)$ for each company candidate and depicted in Table 8. Therefore, the prioritization of the company is assessed as $O_1 \succ O_3 \succ O_4 \succ O_2$ and O_1, i.e., organization-I, is the most desirable option. Apparently, the outcomes are slightly different with introduced and extant methods. So far, the q-ROF-SWARA-COPRAS approach is more resilient and stable than the q-ROF-TOPSIS and q-ROF-WASPAS approaches and thus has wider applicability.

The comparative results confirmed that, in comparison with the above-discussed methods, q-ROF-SWARA-COPRAS is of higher robustness; therefore, it is applicable to a wider range of problems. Here, the most important benefits of the introduced model are presented (See Fig. 3):

Table 5 Significance degree of the challenges of supply chain 4.0 using SWARA method

Barriers	Crisp degrees	Comparative importance of attributes (s_j)	Coefficient (k_j)	Recalculated weight (ρ_j)	Final weight (w_j)
B_6	0.6187	-	1.000	1.0000	0.0489
B_{20}	0.5711	0.0476	1.0476	0.9546	0.0467
B_{21}	0.5233	0.0478	1.0478	0.9110	0.0446
B_{22}	0.5221	0.0012	1.0012	0.9099	0.0445
B_{10}	0.5159	0.0062	1.0062	0.9043	0.0443
B_{14}	0.4975	0.0184	1.0184	0.8880	0.0435
B_{15}	0.4960	0.0015	1.0015	0.8867	0.0434
B_{18}	0.4921	0.0039	1.0039	0.8833	0.0432
B_7	0.4853	0.0068	1.0068	0.8773	0.0429
B_2	0.4842	0.0011	1.0011	0.8763	0.0429
B_{19}	0.4646	0.0196	1.0196	0.8595	0.0421
B_8	0.4573	0.0073	1.0073	0.8533	0.0418
B_{12}	0.4531	0.0042	1.0042	0.8497	0.0416
B_{24}	0.4531	0.0000	1.0000	0.8497	0.0416
B_{16}	0.4489	0.0042	1.0042	0.8461	0.0414
B_{13}	0.4365	0.0124	1.0124	0.8357	0.0409
B_1	0.4200	0.0165	1.0165	0.8221	0.0402
B_4	0.4110	0.0090	1.0090	0.8148	0.0399
B_{11}	0.4058	0.0052	1.0052	0.8106	0.0397
B_{17}	0.3930	0.0128	1.0128	0.8004	0.0392
B_9	0.3754	0.0176	1.0176	0.7866	0.0385
B_{23}	0.3673	0.0081	1.0081	0.7803	0.0382
B_3	0.2971	0.0702	1.0702	0.7291	0.0357
B_5	0.2554	0.0417	1.0417	0.6999	0.0343

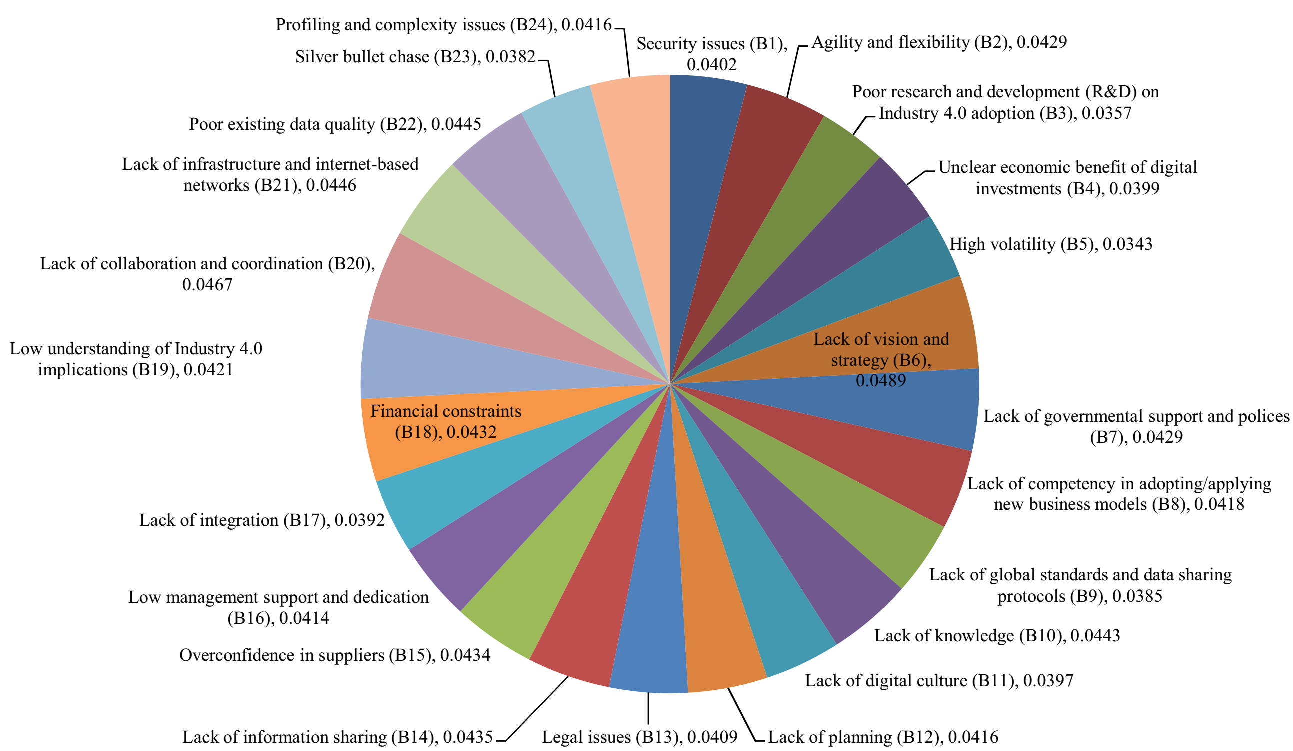

Fig. 2 Weight of different challenges of supply chain 4.0

Table 6 The computational outcome of the q-ROF-SWARA-COPRAS framework

Option	τ_i	γ_i	δ_i	Ranking
O_1	(0.707, 0.676, 0.696)	0.2609	100.00%	1
O_2	(0.684, 0.693, 0.703)	0.2469	94.63%	3
O_3	(0.680, 0.684, 0.716)	0.2486	95.29%	2
O_4	(0.674, 0.708, 0.697)	0.2377	91.11%	4

Table 7 Prioritization of alternative with q-ROF- TOPSIS model

Options	$dis(O_i, \zeta^+)$	$dis(O_i, \zeta^-)$	$RC(O_i)$	Ranking
O_1	0.134	0.178	0.5703	1
O_2	0.168	0.151	0.4724	3
O_3	0.156	0.150	0.4890	2
O_4	0.165	0.139	0.4575	4

- The q-ROFSs are capable of reflecting the DE's hesitancy with higher objectivity compared to other classic extensions of FS. For that reason, the q-ROF-SWARA-COPRAS method makes available higher flexibility in expressing the uncertainty when evaluating the challenges of supply chain 4.0.
- SWARA is used for the purpose of assessing the criteria weights in the process of evaluating the challenges of the supply chain 4.0 process; it has the capacity to add efficiency, reliability, and sensibility to the q-ROF-SWARA-COPRAS method.
- The q-ROF-SWARA-COPRAS method can appropriately process the available information from various points of view, e.g., the cost-type and benefit-type criteria.

4.3 Sensitivity analysis

In this part of the study, we discuss a sensitivity analysis based on diverse values of the parameter (φ). For this

Table 8 Results of q-ROF-WASPAS model

Options	WSM		WPM		WASPAS $\mathbb{C}_i(\lambda)$	Ranking
	$\mathbb{C}_i^{(1)}$	$\mathbb{S}^*\left(\mathbb{C}_i^{(1)}\right)$	$\mathbb{C}_i^{(2)}$	$\mathbb{S}^*\left(\mathbb{C}_i^{(2)}\right)$		
O_1	(0.707, 0.676, 0.696)	0.5218	(0.649, 0.698, 0.728)	0.467	0.494	1
O_2	(0.684, 0.693, 0.703)	0.4939	(0.612, 0.717, 0.482)	0.431	0.462	4
O_3	(0.680, 0.684, 0.716)	0.4972	(0.642, 0.693, 0.738)	0.466	0.482	2
O_4	(0.674, 0.708, 0.697)	0.4753	(0.635, 0.703, 0.735)	0.454	0.465	3

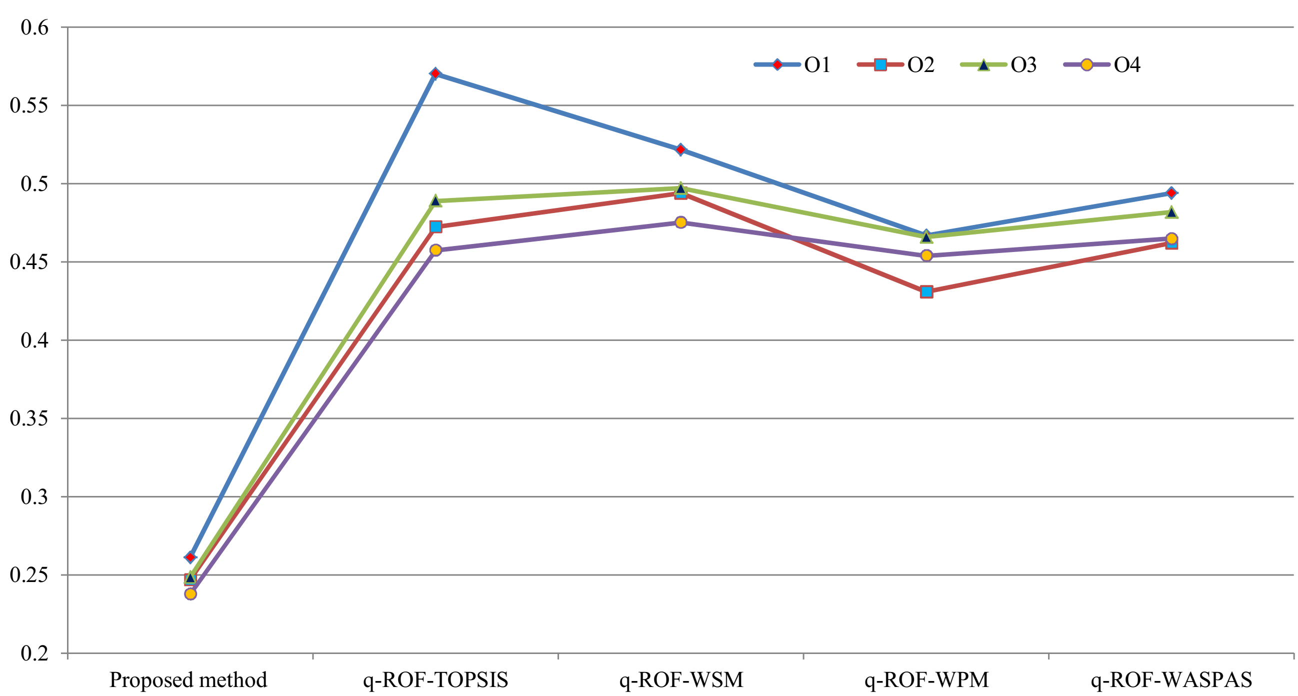

Fig. 3 Comparison of utility degree of each organization over different challenges of supply chain 4.0 with extant methods

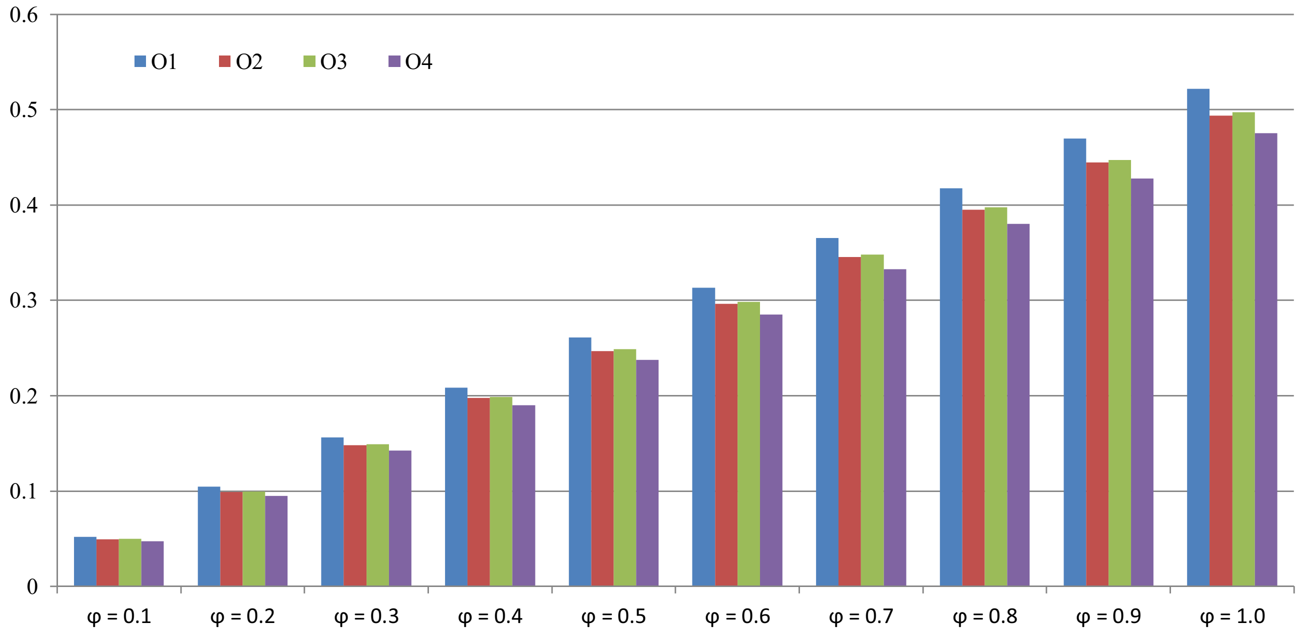

Fig. 4 Variation in the utility degree of alternatives over different parameter (ϕ) values

purpose, different values of φ are considered for the analyses performed, and the changeable values of φ are able to help the experts to assess the sensitivity of the proposed approach. Figure 4 displays the prioritizing orders of the organizations considering varied values of a parameter. As Fig. 4 clearly shows, option O_1 has the highest rank, when $\varphi = 0.0$ to 1.0. On the other hand, option O_4 has the worst rank when $\varphi = 0.0$ to 1.0. Therefore, it can be said that the present model has higher stability in the case of varied parameter values. In addition, the subjective attribute weights that were assessed using the SWARA technique increased the sensitivity of the developed framework. Accordingly, using diverse values of the parameter φ can enhance the strength of the q-ROF-SWARA-COPRAS method.

5 Conclusions

To accomplish the defined research objective, this paper first performed a comprehensive literature survey to recognize the most important supply chain 4.0 challenges in manufacturing companies under the circular economy concept. A unique set of 24 supply chain 4.0 challenges including security issues; agility, and flexibility; poor research and development (R&D) on Industry 4.0 adoption; the unclear economic benefit of digital investments; high volatility; lack of vision and strategy; lack of governmental support and polices; lack of competency in adopting/applying new business models; lack of global standards and data sharing protocols; lack of knowledge; lack of digital culture; lack of planning; legal issues; lack of information sharing; overconfidence in suppliers; low management support and dedication; lack of integration; financial constraints; low understanding of Industry 4.0 implications; lack of infrastructure and internet-based networks; poor existing data quality; silver bullet chase and profiling and complexity issues are obtained using a survey approach. To analyze and evaluate supply chain 4.0 challenges, this paper proposed an innovative integrated framework on the basis of the SWARA and the COPRAS methods on q-ROFSs for evaluating the challenges that may arise to supply chain 4.0. SWARA was employed for the purpose of eliciting the DEs' preferences during the process of criteria weights determination. Afterward, COPRAS was employed for assessing the challenges of supply chain 4.0.

The outcomes of the analysis found that lack of vision and strategy (0.0489) had the first rank followed by lack of collaboration and coordination (0.0467), lack of infrastructure and internet-based networks (0.0446), poor existing data quality (0.0445), lack of knowledge (0.0443), lack of information sharing (0.0435), etc. For the validation of the obtained results, sensitivity analysis and comparative studies were also carried out. The results of both confirmed the applicability of the developed method. Consequently, the final results revealed that the present method was of higher usefulness and feasibility in comparison with other approaches formerly proposed in this field. In the current study, we have focused on the supply chain 4.0 challenges in manufacturing companies; in this regard, future work can evaluate these challenges in different companies, such as services companies. In addition, further work can evaluate the important barriers and drivers of supply chain 4.0 in manufacturing firms during the circular economy era. The limitation of the present study is that only a small number of DEs were involved in this study, and the study did not take into account the interrelationships between the criteria, which to some extent confines the application scope of the developed framework. As a result, there is still a need for further research in the future, which considers a larger number of DEs and takes into account both inter and intra-relationships between the challenges of supply chain 4.0.

Acknowledgements The Ministry of Education of Humanities and Social Science Youth Project: A Study on the External Communication of Xi Jinping Thought on Socialism with Chinese Characteristics for a New Era (20YJC710069). General Project of Shandong Key Research and Development Plan (Soft science project): Research on the Construction and Development of Science and Technology Fund Supervision Subject Alliance from the Perspective of Collaborative Governance (2021RKY01014). Qingdao Social Science Planning and Research Project in 2021: A Study on the Multi-dimensional Path of building a Close-and-Clean Government and Business relationship (QDSKL2101144).

Declarations

Conflict of interest statement The authors have no competing interests to declare that are relevant to the content of this article.

References

Alipour M, Hafezi R, Rani P, Hafezi M, Mardani A (2021) A new Pythagorean fuzzy-based decision-making method through entropy measure for fuel cell and hydrogen components supplier selection. Energy. https://doi.org/10.1016/j.energy.2021.121208

Atanassov KT (1986) Intuitionistic fuzzy sets. Fuzzy Sets Syst 20:87–96

Axelsson J, Fröberg J, Eriksson P (2018) Towards a system-of-systems for improved road construction efficiency using lean and industry 4.0. 2018 13th Annual Conference on System of Systems Engineering (SoSE), pp 576–582

Barbosa-Póvoa AP, da Silva C, Carvalho A (2018) Opportunities and challenges in sustainable supply chain: An operations research perspective. Eur J Oper Res 268:399–431

Bechtsis D, Tsolakis N, Vouzas M, Vlachos D (2017) Industry 4.0: Sustainable material handling processes in industrial environments, in: Espuña A, Graells M, Puigjaner L (eds), Computer Aided Chemical Engineering. Elsevier, pp 2281–2286

Bekar ET, Cakmakci M, Kahraman C (2016) Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis. J Bus Econ Manag 17:663–684

Belaud J-P, Prioux N, Vialle C, Sablayrolles C (2019) Big data for agri-food 4.0: Application to sustainability management for by-products supply chain. Comput Ind 111:41–50

Belhadi A, Kamble S, Jabbour CJC, Gunasekaran A, Ndubisi NO, Venkatesh M (2021) Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. Technol Forecast Soc Chang 163:120447

Bibaud-Alves J, El-Haouzi HB, Thomas P, Boucinha V (2019) Toward a sustainable new product development approach based on industry 4.0 assets. Springer International Publishing, Cham, pp 156–167

Birkel HS, Veile JW, Müller JM, Hartmann E, Voigt K-I (2019) Development of a risk framework for industry 4.0 in the context of sustainability for established manufacturers. Sustainability 11:384

Bonilla SH, Silva HRO, Terra da Silva M, Franco Gonçalves R, Sacomano JB (2018) Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. Sustainability 10:3740

Büyüközkan G, Göçer F (2019) A novel approach integrating AHP and COPRAS under Pythagorean fuzzy sets for digital supply chain partner selection. IEEE Trans Eng Manag 1–18

Buzys R, Maskeliunas R, Damaševičius R, Sidekerskiene T, Woźniak M, Wei W (2018) Cloudification of virtual reality gliding simulation game. Information (Switzerland) 9

Cai L, Qi Y, Wei W, Wu J, Li J (2019) mrMoulder: A recommendation-based adaptive parameter tuning approach for big data processing platform. Futur Gener Comput Syst 93:570–582

Campo GD, Calatrava S, Cañada G, Olloqui J, Martinez R, Santamaria A (2018) IoT Solution for Energy Optimization in Industry 4.0: Issues of a Real-life Implementation. 2018 Global Internet of Things Summit (GIoTS), pp 1–6

Chaim O, Muschard B, Cazarini E, Rozenfeld H (2018) Insertion of sustainability performance indicators in an industry 4.0 virtual learning environment. Procedia Manuf 21:446–453

Chen SW, Chiang DL, Liu CH, Chen TS, Lai F, Wang H, Wei W (2016a) Confidentiality protection of digital health records in cloud computing. J Med Syst 40

Chen TS, Chen TL, Chung YF, Huang YM, Chen TC, Wang H, Wei W (2016b) Implementation of online veterinary hospital on cloud platform. J Med Syst 40

Cui Y, Liu W, Rani P, Alrasheedi M (2021) Internet of Things (IoT) adoption barriers for the circular economy using Pythagorean fuzzy SWARA-CoCoSo decision-making approach in the manufacturing sector. Technol Forecast Soc Chang. https://doi.org/10.1016/j.techfore.2021.120951

Darko AP, Liang D (2020a) An extended COPRAS method for multi-attribute group decision making based on dual hesitant fuzzy Maclaurin symmetric mean. Int J Intell Syst 35:1021–1068

Darko AP, Liang D (2020b) Some q-rung orthopair fuzzy Hamacher aggregation operators and their application to multiple attribute group decision making with modified EDAS method. Eng Appl Artif Intell 87:103259

Daú G, Scavarda A, Scavarda LF, Portugal VJT (2019) The healthcare sustainable supply chain 4.0: The circular economy transition conceptual framework with the corporate social responsibility mirror. Sustainability 11:3259

de Sousa Jabbour ABL, Jabbour CJC, Foropon C, Godinho Filho M (2018) When titans meet – Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. Technol Forecast Soc Chang 132:18–25

Dehnavi A, Aghdam IN, Pradhan B, Morshed Varzandeh MH (2015) A new hybrid model using stepwise weight assessment ratio analysis (SWARA) technique and adaptive neuro-fuzzy inference system (ANFIS) for regional landslide hazard assessment in Iran. Catena 135:122–148

Dhiman HS, Deb D (2020) Fuzzy TOPSIS and fuzzy COPRAS based multi-criteria decision making for hybrid wind farms. Energy 202:117755

Ding B (2018) Pharma Industry 4.0: Literature review and research opportunities in sustainable pharmaceutical supply chains. Process Saf Environ Prot 119:115–130

Duarte S, Cruz-Machado V (2018) Exploring linkages between lean and green supply chain and the industry 4.0. Springer International Publishing, Cham, pp 1242–1252
Fitzsimmons J (1994) Information technology and the third industrial revolution. Electron Libr 12:295–297
Franciosi C, Iung B, Miranda S, Riemma S (2018) Maintenance for Sustainability in the Industry 4.0 context: a Scoping Literature Review. IFAC-PapersOnLine 51:903–908
Frederico GF, Garza-Reyes JA, Anosike A, Kumar V (2020) Supply Chain 4.0: concepts, maturity and research agenda. Supply Chain Manag 25(2):262–282. https://doi.org/10.1108/SCM-09-2018-0339
Fritzsche K, Niehoff S, Beier G (2018) Industry 4.0 and climate change—Exploring the science-policy gap. Sustainability 10:4511
Garg H, Chen S-M (2020) Multiattribute group decision making based on neutrality aggregation operators of q-rung orthopair fuzzy sets. Inf Sci 517:427–447
Ghadimi P, Wang C, Lim MK, Heavey C (2019) Intelligent sustainable supplier selection using multi-agent technology: Theory and application for Industry 4.0 supply chains. Comput Ind Eng 127:588–600
Ghobakhloo M (2018) The future of manufacturing industry: a strategic roadmap toward Industry 4.0. J Manuf Technol Manag 29:910–936
Ghoushchi SJ, Khazaeili M (2019) G-numbers: importance-necessity concept in uncertain environment. Int J Manag Fuzzy Syst 5(1):27–32
Gimenez C, Sierra V, Rodon J (2012) Sustainable operations: Their impact on the triple bottom line. Int J Prod Econ 140:149–159
Gray HJ (1984) The New Technologies: An Industrial Revolution. J Bus Strateg 5:83–85
Hamada T (2019) Determinants of decision-makers' attitudes toward industry 4.0 adaptation. Soc Sci 8:140
Han J, Lin N, Ruan J, Wang X, Wei W, Lu H (2020) A model for joint planning of production and distribution of fresh produce in agricultural internet of things. IEEE Internet Things J 1–1
He J, Huang Z, Mishra AR, Alrasheedi M (2021) Developing a new framework for conceptualizing the emerging sustainable community-based tourism using an extended interval-valued Pythagorean fuzzy SWARA-MULTIMOORA. Technol Forecast Soc Chang 171:120955. https://doi.org/10.1016/j.techfore.2021.120955
Hendiani S, Liao H, Jabbour CJC (2020) A new sustainability indicator for supply chains: theoretical and practical contribution towards sustainable operations. Int J Log Res Appl 1–26
Hermann M, Pentek T, Otto B (2016) Design principles for industrie 4.0 scenarios, 2016 49th Hawaii international conference on system sciences (HICSS). IEEE, pp 3928–3937
Hofmann E, Rüsch M (2017) Industry 4.0 and the current status as well as future prospects on logistics. Comput Ind 89:23–34
Huh J-H, Lee H-G (2018) Simulation and test bed of a low-power digital excitation system for industry 40. Processes 6:145
Kamble SS, Gunasekaran A, Gawankar SA (2018a) Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. Process Saf Environ Prot 117:408–425
Kamble SS, Gunasekaran A, Sharma R (2018b) Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry. Comput Ind 101:107–119
Karabasevic D, Paunkovic J, Stanujkic D (2015) Ranking of companies according to the indicators of corporate social responsibility based on SWARA and ARAS methods. Serb J Manag 11:43–53
Kersuliene V, Zavadskas EK, Turskis Z (2010) Selection of rational dispute resolution method by applying new stepwise weight assessment ratio analysis (SWARA). J Bus Econ Manag 11:243–258
Keshavarz Ghorabaee M, Amiri M, Sadaghiani JS, Goodarzi GH (2014) Multiple criteria group decision-making for supplier selection based on COPRAS method with interval type-2 fuzzy sets. Int J Adv Manuf Technol 75:1115–1130
Kiel D, Müller JM, Arnold C, Voigt K-I (2017) Sustainable industrial value creation: Benefits and challenges of industry 4.0. Int J Innov Manag 21:08. https://doi.org/10.1142/S1363919617400151
Kleindorfer PR, Singhal K, Van Wassenhove LN (2005) Sustainable. Oper Manag 14:482–492
Kovacs O (2019) Big IFs in productivity-enhancing industry 4.0. Soc Sci 8:37
Krishankumar R, Nimmagadda SS, Rani P, Mishra AR, Ravichandran KS, Gandomi AH (2021) Solving renewable energy source selection problems using a q-rung orthopair fuzzy-based integrated decision-making approach. J Clean Prod 279:123329
Kumar P, Singh RK, Kumar V (2021a) Managing supply chains for sustainable operations in the era of industry 4.0 and circular economy: Analysis of barriers. Resour Conserv Recycl 164:105215
Kumar R, Singh SP, Lamba K (2018) Sustainable robust layout using Big Data approach: A key towards industry 4.0. J Clean Prod 204:643–659
Kumar S, Raut RD, Nayal K, Kraus S, Yadav VS, Narkhede BE (2021b) To identify industry 4.0 and circular economy adoption barriers in the agriculture supply chain by using ISM-ANP. J Clean Prod 293:126023
Kumari R, Mishra AR (2020) Multi-criteria COPRAS method based on parametric measures for intuitionistic fuzzy sets: application of green supplier selection. Iran J Sci Technol Trans Electr Eng 1–18
Kurdve M, Bellgran M (2021) Green lean operationalisation of the circular economy concept on production shop floor level. J Clean Prod 278:123223
Li J, Feng G, Wei W, Luo C, Cheng L, Wang H, Song H, Ming Z (2018) PSOTrack: A RFID-based system for random moving objects tracking in unconstrained indoor environment. IEEE Internet Things J 5:4632–4641
Liao Y, Deschamps F, Loures EDFR, Ramos LFP (2017) Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. Int J Prod Res 55:3609–3629
Lin Y, Yang J, Lv Z, Wei W, Song H (2015) A self-assessment stereo capture model applicable to the internet of things. Sensors 15:20925–20944
Liu D, Chen X, Peng D (2019) Some cosine similarity measures and distance measures between q-rung orthopair fuzzy sets. Int J Intell Syst 34:1572–1587
Liu P, Liu W (2019) Multiple-attribute group decision-making based on power Bonferroni operators of linguistic q-rung orthopair fuzzy numbers. Int J Intell Syst 34:652–689
Liu P, Wang P (2018) Some q-rung orthopair fuzzy aggregation operators and their applications to multiple-attribute decision making. Int J Intell Syst 33:259–280
Luthra S, Mangla SK (2018) Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. Process Saf Environ Prot 117:168–179
Ma H (2019) An Industry 4.0 Technologies-Driven Warehouse Resource Management System. Springer Singapore, Singapore, pp 27–33
Majumdar A, Sinha SK (2019) Analyzing the barriers of green textile supply chain management in Southeast Asia using interpretive structural modeling. Sustain Prod Consumption 17:176–187
Manavalan E, Jayakrishna K (2019) A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. Comput Ind Eng 127:925–953
Massaro M, Secinaro S, Dal Mas F, Brescia V, Calandra D (2021) Industry 4.0 and circular economy: An exploratory analysis of

academic and practitioners' perspectives. Bus Strateg Environ 30:1213–1231

Medojevic M, Villar PD, Cosic I, Rikalovic A, Sremcev N, Lazarevic M (2018) Energy Management in Industry 4.0 Ecosystem: a Review on Possibilities and Concerns

Meng Y, Yang Y, Chung H, Lee P-H, Shao C (2018) Enhancing sustainability and energy efficiency in smart factories: A review. Sustainability 10:4779

Mishra AR, Rani P, Mardani A, Pardasani KR, Govindan K, Alrasheedi M (2020a) Healthcare evaluation in hazardous waste recycling using novel interval-valued intuitionistic fuzzy information based on complex proportional assessment method. Comput Ind Eng 139:106140

Mishra AR, Rani P, Pandey K, Mardani A, Streimikis J, Streimikiene D, Alrasheedi M (2020b) Novel multi-criteria intuitionistic fuzzy SWARA–COPRAS approach for sustainability evaluation of the bioenergy production process. Sustainability 12:4155

Mokyr J, Strotz RH (1998) The second industrial revolution, 1870–1914. Storia Dell'economia Mondiale 21945:1

Monteleone S, Moraes EAD, Maia RF (2019) Analysis of the variables that affect the intention to adopt Precision Agriculture for smart water management in Agriculture 4.0 context, 2019 Global IoT Summit (GIoTS), pp 1–6

Mostafa N, Hamdy W, Alawady H (2019) Impacts of internet of things on supply chains: a framework for warehousing. Soc Sci 8:84

Müller JM, Kiel D, Voigt K-I (2018) What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. Sustainability 10:247

Nascimento DLM, Alencastro V, Quelhas OLG, Caiado RGG, Garza-Reyes JA, Rocha-Lona L, Tortorella G (2019) Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context. J Manuf Technol Manag 30:607–627

Oks SJ, Fritzsche A, Möslein KM (2017) An application map for industrial cyber-physical systems. In: Jeschke S, Brecher C, Song H, Rawat DB (eds) Industrial internet of things: Cybermanufacturing systems. Springer International Publishing, Cham, pp 21–46

Oztemel E, Gursev S (2020) Literature review of Industry 4.0 and related technologies. J Intell Manuf 31:127–182

Pamucar D, Ecer F (2020) Prioritizing the weights of the evaluation criteria under fuzziness: The fuzzy full consistency method – FUCOM-F. Facta Univ Ser Mech Eng 18(3):419–437

Pamučar D, Stević Ž, Sremac S (2018) A new model for determining weight coefficients of criteria in MCDM models: Full consistency method (FUCOM). Symmetry 10:393

Pang Q, Wang H, Xu Z (2016) Probabilistic linguistic term sets in multi-attribute group decision making. Inf Sci 369(2016):128–143

Paravizo E, Chaim OC, Braatz D, Muschard B, Rozenfeld H (2018) Exploring gamification to support manufacturing education on industry 4.0 as an enabler for innovation and sustainability. Procedia Manuf 21:438–445

Peng X, Dai J (2017) Hesitant fuzzy soft decision making methods based on WASPAS, MABAC and COPRAS with combined weights. J Intell Fuzzy Syst 33:1313–1325

Peng X, Liu L (2019) Information measures for q-rung orthopair fuzzy sets. Int J Intell Syst 34:1795–1834

Pinar A, Boran FE (2020) A q-rung orthopair fuzzy multi-criteria group decision making method for supplier selection based on a novel distance measure. Int J Mach Learn Cybern 11:1749–1780

Rajesh R (2020) Sustainable supply chains in the Indian context: An integrative decision-making model. Technol Soc 61:101230

Rani P, Mishra AR (2020) Multi-criteria weighted aggregated sum product assessment framework for fuel technology selection using q-rung orthopair fuzzy sets. Sustain Prod Consum 24:90–104

Rani P, Mishra AR, Krishankumar R, Mardani A, Cavallaro F, Ravichandran KS, Balasubramanian K (2020a) Hesitant fuzzy SWARA-complex proportional assessment approach for sustainable supplier selection (HF-SWARA-COPRAS). Symmetry 12

Rani P, Mishra AR, Krishankumar R, Ravichandran KS, Gandomi AH (2020b) A new Pythagorean fuzzy based decision framework for assessing healthcare waste treatment. IEEE Trans Eng Manag 1–15

Rani P, Mishra AR, Mardani A (2020c) An extended Pythagorean fuzzy complex proportional assessment approach with new entropy and score function: application in pharmacological therapy selection for type 2 diabetes. Appl Soft Comput https://doi.org/10.1016/j.asoc.2020.106441

Ranta V, Aarikka-Stenroos L, Ritala P, Mäkinen SJ (2018) Exploring institutional drivers and barriers of the circular economy: A cross-regional comparison of China, the US, and Europe. Resour Conserv Recycl 135:70–82

Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega 53:49–57

Roda-Sanchez L, Garrido-Hidalgo C, Hortelano D, Olivares T, Ruiz MC (2018) OperaBLE: an IoT-based wearable to improve efficiency and smart worker care services in Industry 4.0. J Sensors 2018:6272793

Saaty TL (1977) The Analytical Hierarchy Process. McGraw-Hill Co., New York

Saaty TL (1999) Fundamentals of the analytic network process, Proceedings of the 5th international symposium on the analytic hierarchy process, pp 12–14

Saraji MK, Mardani A, Köppen M, Mishra AR, Rani P (2021) An extended hesitant fuzzy set using SWARA-MULTIMOORA approach to adapt online education for the control of the pandemic spread of COVID-19 in higher education institutions. Artif Intell Rev. https://doi.org/10.1007/s10462-021-10029-9

Schlüter F, Hetterscheid E (2017) Supply chain process oriented technology-framework for Industry 4.0, Digitalization in Supply Chain Management and Logistics: Smart and Digital Solutions for an Industry 4.0 Environment. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol 23. Berlin: epubli GmbH, pp 275–299

Seiti H, Hafezalkotob A, Martínez L (2019) R-numbers, a new risk modeling associated with fuzzy numbers and its application to decision making. Inf Sci 483:206–231. https://doi.org/10.1016/j.ins.2019.01.006

Sherazi HHR, Imran MA, Boggia G, Grieco LA (2018) Energy Harvesting in LoRaWAN: A Cost Analysis for the Industry 4.0. IEEE Commun Lett 22:2358–2361

Shi Z, Wang H, Wei W, Zheng X, Zhao M, Zhao J (2016a) A novel individual location recommendation system based on mobile augmented reality. Proceedings - 2015 International Conference on Identification, Information, and Knowledge in the Internet of Things, IIKI 2015, pp 215–218

Shi Z, Wang H, Wei W, Zheng X, Zhao M, Zhao J, Wang Y (2016b) Novel individual location recommendation with mobile based on augmented reality. Int J Distrib Sens Netw 12

Stefanou C (1999) Supply Chain Management (SCM) and Organizational Key Factors for Successful Implementation of Enterprise Resource Planning (ERP) Systems. AMCIS 1999 Proceedings. 276. https://aisel.aisnet.org/amcis1999/276

Stock T, Obenaus M, Kunz S, Kohl H (2018) Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. Process Saf Environ Prot 118:254–267

Tang G, Chiclana F, Liu P (2020) A decision-theoretic rough set model with q-rung orthopair fuzzy information and its application in stock investment evaluation. Appl Soft Comput 91:106212

Tsai W-H (2018) Green production planning and control for the textile industry by using mathematical programming and industry 4.0 techniques. Energies 11:2072

Tsai W-H, Chu P-Y, Lee H-L (2019) Green activity-based costing production planning and scenario analysis for the aluminum-alloy wheel industry under industry 4.0. Sustainability 11:756

Tsai W-H, Lu Y-H (2018) A framework of production planning and control with carbon tax under industry 4.0. Sustainability 10:3221

Tseng M-L, Tan RR, Chiu ASF, Chien C-F, Kuo TC (2018a) Circular economy meets industry 4.0: Can big data drive industrial symbiosis? Resour Conserv Recycl 131:146–147

Tseng M-L, Zhu Q, Sarkis J, Chiu ASF (2018b) Responsible consumption and production (RCP) in corporate decision-making models using soft computation. Ind Manag Data Syst 118:322–329

Velenturf APM, Purnell P (2021) Principles for a sustainable circular economy. Sustain Prod Consum 27:1437–1457

Waibel MW, Steenkamp LP, Moloko N, Oosthuizen GA (2017) Investigating the effects of smart production systems on sustainability elements. Procedia Manuf 8:731–737

Wang C, Ghadimi P, Lim MK, Tseng M-L (2019) A literature review of sustainable consumption and production: A comparative analysis in developed and developing economies. J Clean Prod 206:741–754

Wang C, Huang H, Chen J, Wei W, Wang T (2020) An online and real-time adaptive operational modal parameter identification method based on fog computing in Internet of Things. Int J Distrib Sens Netw 16

Wang J, Wei W, Wang W, Li R (2018) RFID hybrid positioning method of phased array antenna based on neural network. Ieee Access 6:74953–74960

Wang XV, Wang L (2019) Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0. Int J Prod Res 57:3892–3902

Wei-Gang MA, Yuan CAO, Wei W, Wei L, Jian-Feng MA, Xin-Hong HEI (2013) Research on the security of computer platforms HMM-based fault diagnosis. Inf Technol J 12:8686–8695

Wei W, Song H, Wang H, Fan X (2017) Research and simulation of queue management algorithms in ad hoc networks under DDoS attack. Ieee Access 5:27810–27817

Wu C, Li H, Wei W (2013) Research on classified protection-based security construction for university information systems. Inf Technol J 12:7930–7937

Yadav G, Luthra S, Jakhar SK, Mangla SK, Rai DP (2020) A framework to overcome sustainable supply chain challenges through solution measures of industry 4.0 and circular economy: An automotive case. J Clean Prod 254:120112

Yager RR (2013) Pythagorean fuzzy subsets, 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), pp 57–61

Yager RR (2014) Pythagorean membership grades in multicriteria decision making. IEEE Trans Fuzzy Syst 22:958–965

Yager RR (2017) Generalized orthopair fuzzy sets. IEEE Trans Fuzzy Syst 25:1222–1230

Yager RR, Alajlan N (2017) Approximate reasoning with generalized orthopair fuzzy sets. Information Fusion 38:65–73

Yang F, Qiao Y, Wei W, Wang X, Wan D, Damaševičius R, Woźniak M (2020) DDTree: A hybrid deep learning model for real-timewaterway depth prediction and smart navigation. Appl Sci (Switzerland) 10

Yang K, Duan T, Feng J, Mishra AR (2021) Internet of things challenges of sustainable supply chain management in the manufacturing sector using an integrated q-Rung Orthopair Fuzzy-CRITIC-VIKOR method. J Enterp Inf Manag. https://doi.org/10.1108/JEIM-06-2021-0261

Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353

Zadeh LA (2011) A note on Z-numbers. Inf Sci 181(14):2923–2932. https://doi.org/10.1016/j.ins.2011.02.022

Zambon I, Cecchini M, Egidi G, Saporito MG, Colantoni A (2019) Revolution 4.0: Industry vs. agriculture in a future development for SMEs. Processes 7:36

Zavadskas E, Kaklauskas A, Sarka V (1994) The new method of multicriteria complex proportional assessment of projects. Technol Econ Dev Econ 1:131–139

Zhang L, Feng Y, Shen P, Zhu G, Wei W, Song J, Ali Shah SA, Bennamoun M (2018) Efficient finer-grained incremental processing with MapReduce for big data. Futur Gener Comput Syst 80:102–111

Zheng YH, Xu ZS, He Y, Liao HC (2018) Severity assessment of chronic obstructive pulmonary disease based on hesitant fuzzy linguistic COPRAS method. Appl Soft Comput 69:60–71

Žižović M, Pamucar D (2019) New model for determining criteria weights: Level Based Weight Assessment (LBWA) model. Decis Mak Appl Manag Eng 2:126–137