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A multi-disruption risk analysis system for sustainable supply chain resilience

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A B S T R A C T

As global Supply Chains (SCs) face increasing complexities and risks, organizations must balance operational efficiency with preparedness for unforeseen disruptions. Recent events, including the devastating floods or wildfires and the impacts of the volatility of international relations, have underscored the vulnerability of SCs. The study explores the critical need for combining supply chain management, risk management, and sustainability for the systematic analysis of disruption risks from the unpredictability of natural disasters, man-made events, and rapid technological advancements. We develop a decision support system integrating the fuzzy C-means clustering and integrated multi-criteria decision-making approach for risk categorization and prioritization, respectively. The developed framework considers the significance of multiple risk factors (e.g., urgency and vulnerability) in the risk disruption analysis process through the hybrid Bayesian best-worst method-combined compromise solution approach. This enables managers to identify critical disruption risks (e.g., communication network disruptions, production facility-related risk, and increased demand for certain goods) while observing their adverse effects on the resiliency of sustainable SCs. Compared to the traditional risk priority number, the proposed system includes the importance of risk factors and provides a more stable and separable ranking, empowering managers to deal with potential resource limitations. This study also suggests risk mitigation strategies to alleviate the negative consequences of disruptions within organizational constraints and improve sustainable SC responsiveness to future disasters.

1. Introduction

The principle of sustainability revolves around balancing current needs with preserving resources and opportunities for future generations [1,2]. This balance has become more important than ever because of the pressing need to respond to climate change and mitigate its far-reaching implications on society, as well as on the ecological systems [3,4]. Over the past several years, the importance of Sustainable Supply Chains (SSCs) has surged and been influenced by intense global competition, expansive globalization, the complexities of outsourcing, unpredictable markets, and fluctuating consumer needs. Thus, SSCs strive to minimize environmental footprints, promote fair labor practices, and engage in ethical governance, thereby securing the expectations of current and potential stakeholders [5,6]. Organizations ought to operate with a view to long-term sustainability, rather than solely pursuing short-term profits [7]. Without a plan in place, these disruptions can undo sustainability efforts and lead the company to revert to less sustainable practices just to survive. The efforts to maintain sustainability are concentrating on making operations more efficient and larger in

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scale, while also ensuring there are enough safety measures in place to protect against unexpected disruption risks [8].

Recently many cases have shown that sustainability in Supply Chain Risk Management (SCRM) has often fallen short [9–12]. Overlooking the magnitude of risk management in favor of efficiency alone could precipitate the Supply Chain (SC) downfall. SC risks generally fall into two main categories: uncertainties (e.g., demand-supply mismatches) and disruptions resulting from natural disasters or man-made events [13]. While operational risks pertain to routine supply-demand coordination and are more manageable, disruption risks stem from unforeseen events (e.g., wildfires, floods, economic crises, and wars) that could interrupt the supply chain and are harder to control [7,14]. These disruptions don't arrive in isolation; they have the power to halt entire operations. When a crisis hits, these operational risks can no longer be ignored and start to shape how the supply chain deals with the disruption. These events don't just pose new challenges, they magnify the very risks that were always there. The disruptive events have resulted in extensive infrastructure damage, logistics disruption, and significant supply and demand imbalances [15].

The unforeseen disruptive event can cascade a snowball effect throughout the entire SC network [16]. For example, the movement of goods across North America was slowed by transportation disruptions from the 2023 Canadian wildfires [17]. Over three thousand major floods worldwide in the past two decades caused an estimated USD 651 billion in damages [18]. Moreover, geopolitical turbulence such as the Russian invasion of Ukraine in early 2022 triggered a sharp rise in oil and gas prices and plunged Europe into an energy crisis [19]. It even affects the black sea trading route of food supplies in Africa, the Middle East, and Asia [20]. The COVID-19 pandemic in 2020 cost American and European businesses $4 trillion, while global trade fell by 32 % and the economy shrank by 12 % [21]. Without proper command of procurement, unanticipated supply disruptions can result in prolonged recovery times, cripple production, price and demand fluctuations, substantial financial losses, and a negative impact on customer trust [22,23]. As shown in Fig. 1, in addition to focusing on conventional approaches (e.g., information management) for improving SC coordination and handling operational risks, mitigating disruption risks is essential to reduce the vulnerability of SSC.

SCRM strategically addresses potential disruptions and maintains profitability and continuity. It involves proactive identification, evaluation, and monitoring of risks to minimize the impact on SC operations [13,24]. Risk management (RM) can include two main strategies. Preventive strategies are proactive measures taken to avert damage, though often at a significant cost, while reactive strategies involve measures taken post-disruption to recover and potentially improve from the previous state [25]. The current focus on SSC resilience and adaptability to unpredictable forces illustrates the need for approaches to bounce back and even restore strength from disruptions [26,27]. Therefore, maintaining a sustainable yet disruption-proof SC requires a comprehensive risk management approach. Accordingly, this research adopts a multidisciplinary approach, drawing from Supply Chain Management (SCM), risk management, and sustainability studies, to address the following research questions.

(i) What are the potential risks faced by SSCs during disruptions?
(ii) How can these disruption risks be systematically analyzed and prioritized within the SCRM context?
(iii) How can the impact of Vulnerability (V) and Non-Recoverability (NR) factors on the criticality degree of disruption risks be investigated?
(iv) What are the most critical disruption risks affecting SSC performance?

To answer these questions, this study aims to contribute valuable insights to empower organizations and brace their SCs against disruptions while advancing their sustainability ambitions. Thus, this study develops a decision support system to integrate Disruption Risk Management (DRM) into SSC practices. In the first phase of the proposed approach, a Bayesian Best-Worst Method (BBWM) is employed to derive aggregated weights of risk factors considering different perspectives. Since this study focuses on DRM, V and NR factors are considered in the risk assessment and prioritization process in addition to conventional risk factors (i.e., Occurrence (O),

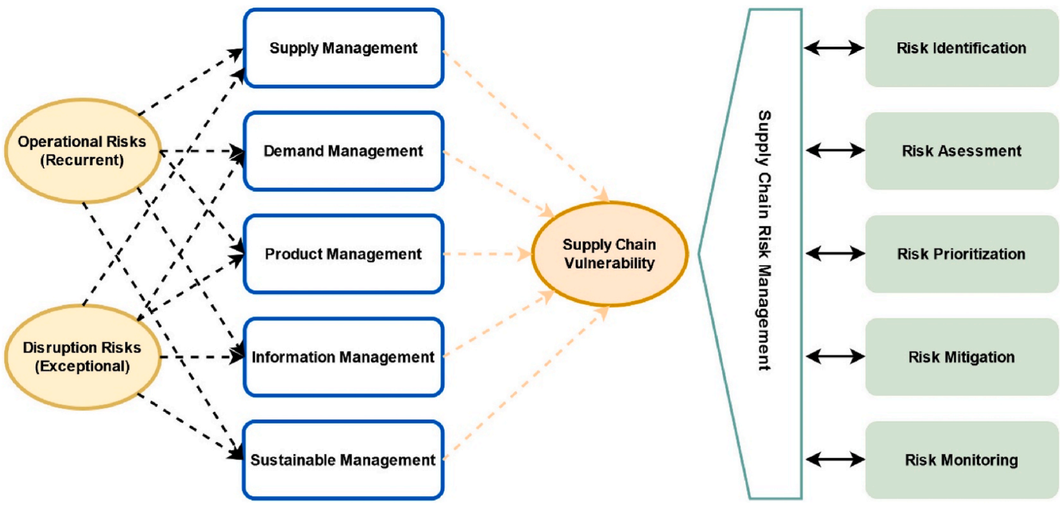

Fig. 1. The role of the SCRM framework for mitigating SSC vulnerability.

Detection (D), Urgency (U)). The BBWM technique optimizes probabilistic group decisions to provide Decision-Makers (DMs) with a set of more reliable weights [28]. Afterward, Fuzzy C-Means (FCM) clustering is implemented to identify critical clusters of disruption risks. It uses fuzzy logic to segregate overlapping data points [29]. This technique enables DMs to involve five risk factors and their importance in the clustering process to explore the critical risks. In the last phase, the identified critical risks are prioritized employing the Combined Compromise Solution (CoCoSo) method. It deals with the potential resource limitations during disruptions. Compared to traditional Multiple-Criteria Decision-Making (MCDM) methods, CoCoSo employs three aggregator strategies for the final ranking [30]. The proposed decision support system enhances the accuracy and reliability of risk prioritization to help managers develop more effective risk mitigation strategies while they face organizational constraints (e.g., financial, managerial, human resources, and time constraints). This approach also provides managers with insights to navigate DRM and advance towards SSCs.

The rest of this study is organized as follows: Section 2 represents a comprehensive review of recent studies concerning the dimensions of risk within SSCs, with an acute focus on the intricate field of disruption management. Section 3 describes the implementation phases of the BBWM, FCM clustering, and CoCoSo approaches. Subsequently, Section 4 proposes a decision support system for DRM within SSCs. Section 5 presents the results of the proposed approach and then sensitivity and comparative analyses of the obtained findings. Moving forward, Section 6 discusses the practical implications of the developed approach within the context of risk management for achieving SC sustainability. Lastly, Section 7 provides a summary of concluding remarks and recommends suggestions for potential research endeavours.

2. Literature review

A thorough understanding of SSC risks is essential for developing robust risk management strategies. Each industry presents unique challenges and requires diverse approaches due to its distinct operational, environmental, and market dynamics. By examining different industries, the identified disruption risk patterns and industry-specific strategies ensure a broader understanding of how sustainability can be integrated into SCs. As can be seen, research in Agri-food SSCs has centered attention on tackling challenges, such as food safety, distribution disruptions, and sustainable sourcing. Abadi and Darestani [22] determined with Best-Worst Method (BWM)-Weighted Aggregated Sum Product Assessment (WASPAS) that economic risks were ranked highest, and priority was assigned to credibility, working environments, human error, product perishability, supplier condition, and security. Raihan et al. [31] incorporated the fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation Method (FCEM) to categorize risks. They showed SC risk falls within the low-to-medium range, with demand risks being the highest and infrastructural risks the lowest. Alam et al. [32] addressed the socio-economic impacts of disruptions affecting global SCs and prioritized enablers to address sustainability and food security by utilizing Pareto analysis, Matrice d'Impacts Croisés Multiplication Appliquée à un Classement (MICMAC) and Total Interpretive Structural Modeling (TISM).

A variety of other industries have been the subject of several studies to delve into their unique risk management practices and the distinct challenges they face. For instance, Moktadir et al. [33] employed Pareto analysis and BWM to prioritize SSC risk factors in the leather industry. It found inefficient effluent treatment, improper solid waste disposal, changing consumer preferences and price and cost volatility are crucial SC risks. Kumar and Barua [34] employed the rough set theory and DEcision-MAking Trial and Evaluation Laboratory (DEMATEL) method to determine the prominent risks such as fluctuations in crude oil prices, product quality, and market variations within the petroleum industry. In the manufacturing industry, Alshehri et al. [35] utilized fuzzy AHP-WASPAS and observed primary risks are industrial emissions, management policy failures, and financial constraints. In Small and Medium Enterprises (SMEs), Sutrisno and Kumar [36] combined Failure Modes And Effects Analysis (FMEA) parameters with Shannon entropy and the Preference Selection Index and contributed to improved SC risk identification and mitigation planning with the five pillars of sustainability. Karmaker et al. [37] applied fuzzy theory, TISM, and MICMAC analysis to identify the primary factors hindering sustainable practices as an absence of passion in top management, a shortage of skilled workers, inadequate knowledge of political instabilities, modern technologies, and labor strikes in SMEs.

The decision-making methodologies have been underlined in the SC resilience and sustainability literature to enhance risk assessment and strategic planning. Abdel-Basset and Mohamed [12] determined the financial risk is primary and the supply risk has a relatively lower significance in SSC with integrated the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) and the Criteria Importance Through Inter-criteria Correlation (CRITIC) methods. Göçer [6] employed the combination of AHP, VIKOR, and Interval-Valued Picture-Fuzzy Sets (IVPFS) and the primary disruption risks identified are infectious disease outbreaks, political instability, and lack of training as areas requiring the most attention in SSCs. Anugerah et al. [38] employed FMEA and AHP to reveal that the primary risks in the palm oil SC are natural disasters, unsafe working conditions, and unreliable transportation systems. Reshad et al. [3] integrated TOPSIS and VIKOR to assess the dominance of information-related barriers where the lack of coordination and collaboration is the foremost barrier in SSC.

Considering the recent global disruptions, the concept of SC resilience has emerged as of critical importance. Researchers have concentrated on SC resiliency, specifically assessing the risks associated with disruptions. Yazdani et al. [30] utilized BWM-fuzzy Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS) to assess the resilience of significant entities against various risks. Findings revealed water system failures and natural disasters as the most critical risks. El Baz and Ruel [39] used the Partial Least Squares (PLS)-Structural Equation Modeling (SEM) to explore the contribution of SC resilience and robustness in improving the repercussions of disruptions. Soyer et al. [40] proposed a fuzzy cognitive mapping for analyzing the core structure of SSC risks and their effects on the resilience of SCs in the face of disruptive events. The results denoted that supplier-related risks are the most important, followed by operational and demand-side risks. Chowdhury et al. [8] utilized the Quality Function Deployment (QFD) method and a fuzzy set qualitative comparative analysis and exhibited that the sustainability of tourism SC performance at severe disruptions relies on the coactive impact of resilience strategies and risks.

Table 1 presents a comparative analysis of existing literature on DRM within SCs. As shown in this table, the current study seeks to understand the adaptive capabilities of SSCs when confronted with disruptions and develop strategic measures to improve their endurance. This has escalated due to the recent global disruptions, and the risks associated with SC sustainability should be prioritized. Since there is an inherent uncertainty accompanying the importance of risk factors, this study gathers perspectives on the weight of multiple risk factors from diverse situations rather than relying on a singular scenario to obtain a more reliable ranking. Compared to the previous studies applying the conventional BWM, this study employs the BBWM to consider varying perspectives on risk factors (i.e., different scenarios) by facilitating aggregated risk factor weighting [41]. Furthermore, to overcome the limitations commonly found using hard clustering algorithms in membership function, this study employs the FCM technique for identifying the critical disruption risks cluster [29]. This helps managers assign available resources more accurately to deal with the potential disruption risks because they are not able to mitigate all risks. Moreover, the CoCoSo method, a robust and advanced MCDM technique, is applied for the final prioritization of risks within critical clusters. This study evaluates the NR factor as the representative of the mitigation stage in the prioritization phase. Therefore, this facilitates the process of defining effective risk mitigation measures to deal with critical risks. The proposed framework also enhances the differentiation and reliability of the ranking compared to conventional FMEA and MCDM methods.

3. Preliminaries

This study proposes a decision support system for categorizing and prioritizing potential disruption risks in SSCs. This involves the integration of the BBWM for aggregated risk factors weighting, the FCM clustering method for critical disruption risks identification, and the CoCoSo method for final risk evaluation of potential critical risks and observing their adverse effects on the performance of SSCs.

3.1. Bayesian Best-Worst Method

This study employs BBWM, an evolution of the conventional BWM for group decisions, which sidesteps the drawbacks of traditional preference aggregation methods. It maintains the input structure of the original BWM while delivering outputs modeled probabilistically [28]. The conventional BWM, introduced by Rezaei [67], computes optimal criteria weights with inputs from a single DM with superior accuracy and reduced computational demand. Despite its strengths, the conventional BWM cannot effectively combine several perspectives in group decision-making scenarios. AHP, known for its simplicity, is another popular method for assigning criteria weights. However, AHP requires a large number of pairwise comparisons, which can cause DMs to become overwhelmed and lead to inconsistencies especially when dealing with complex criteria [41]. While traditional BWM improves on AHP by reducing the number of comparisons, BBWM simplifies the process even further. Unlike AHP, which requires DMs to provide fixed pairwise comparisons and does not explicitly account for uncertainty, BBWM incorporates uncertainty directly into the decision-making process through Bayesian inference [28]. The BBWM sets itself apart with its probabilistic approach and with its unique credal ranking function providing a refined measure of criteria dominance. This method employs the multinomial distribution for comparative pairwise analysis between criteria and utilizes the Dirichlet distribution to model and refine the aggregate weights for optimal outcomes [68]. The multinomial probability distributions are used to express all risk factors and show the range of possibilities with their probabilities. To account for the simultaneous occurrence of these risks, the dirichlet distribution is utilized as well. The BBWM methodology can be described in five main steps as follows.

Step 1 *Exploring a set of key decision criteria*: This step involves defining the set of criteria considering the problem under study. A set of criteria C signifies a group of criteria that have n attributes ($n = 1, 2, \ldots, N$) and are evaluated by k experts ($k = 1, 2, \ldots, K$) or within k scenarios.

Step 2 *Selecting the best (B) and the worst (W) decision criteria*: In the beginning, each scenario designated as k, is required to specify the 'best' and 'worst' criteria denoted as C_B^k and C_W^k, respectively. It ia a straightforward selection of the most and least significant criteria, labeled as 'best' (most crucial or most favorable) and 'worst' (least crucial or least favorable).

Step 3 *Conducting pairwise comparisons between the best criterion and the other criteria*: Here, the preferences for the best criterion C_B^k over the others in set C are evaluated. More precisely, values from 1 (equal importance) to 9 (absolutely more important than) provided in Table 2 can be employed to create a Best-to-Others (BO) vector (A_B^k). As shown in Eq. (1), A_B^k states to the preference of the 'best' criterion C_B^k over the criterion $C_j \epsilon C$.

Step 4 *Conducting pairwise comparison between others and the worst criterion*: In a similar manner, each scenario constructs a matrix for comparison between the 'worst' criterion C_W^k, with the remaining criteria in set C and leads to an Others-to-Worst (OW) vector, symbolized as A_W^k. The OW vector is mathematically represented as Eq. (2). Here, A_W^k states the preference of the criterion $C_j \epsilon C$ over the 'worst' criterion C_B^k.

Step 5 *Performing probabilistic computations for final aggregate weight:* The BBWM model utilizes the aggregation of criterion weights from multiple perspectives probabilistically. Here, $w^{agg} = w_1^{agg}, w_2^{agg}, \ldots, w_n^{agg}$ is the aggregated weight matrix. The w^{agg} differs with the individual optimal weights of each expert or scenario, labeled as w^k. The Bayesian hierarchy model employs an

Table 1
Comparative analysis of literature on DRM for SCs.

Author(s)	Methodology	SC Type	Resiliency	Sustainability	Risk Management Phases				Risk Factors					Weights of Risk Factors
					Identification	Clustering	Prioritization	Mitigation	Occurrence	Detection	Urgency	Vulnerability	Recovery	
Benabdallah et al. [42]	DEMATEL	Agro Food SC		✓	✓		✓		✓					
Abdel-Basset and Mohamed [12]	TOPSIS-CRITIC	General SC		✓	✓		✓		✓					
Shahed et al. [43]	Genetic algorithm and pattern search	Manufacturing SC			✓			✓						
Kumar and Sharma [44]	Chaos theory	Oil and gas SC			✓			✓						
Feitosa and Carpinetti [45]	Fuzzy TOPSIS	Textile SC			✓						✓			
Ivanov and Dolgui [46]	Conceptual Framework	Digital SC	✓		✓					✓				
El Baz and Ruel [39]	PLS-SEM	General SC	✓		✓						✓			
Bui et al. [11]	Fuzzy Delphi-DEMATEL	General SC	✓	✓	✓									✓
Göçer [6]	IVPFS-AHP-VIKOR	Manufacturing SC			✓		✓				✓			✓
Ali et al. [47]	Delphi-Fuzzy AHP	Textile SC	✓		✓		✓				✓			✓
Majumdar et al. [48]	Fuzzy TOPSIS	General SC	✓	✓	✓			✓					✓	
Moktadir et al. [33]	Pareto-BWM	Leather SC		✓	✓		✓				✓			✓
Bai et al. [49]	q-ROFSWARA-CoCoSo	Manufacturing SC		✓	✓		✓				✓			✓
Salehi et al. [50]	Fuzzy TOPSIS	Biomass SC	✓	✓	✓		✓				✓			
Akter et al. [51]	Grey theory and DEMATEL	Healthcare SC			✓		✓				✓			✓
Yazdani et al. [30]	BWM-Fuzzy MARCOS	Food SC	✓		✓		✓							
Alshehri et al. [35]	Fuzzy AHP- WASPAS	Manufacturing SC		✓	✓		✓	✓						
Kumar and Barua [34]	Rough set theory and DEMATEL	Oil SC		✓	✓		✓		✓					
Raihan et al. [31]	Fuzzy AHP-FCEM	Food SC		✓	✓		✓		✓		✓			
Anugerah et al. [38]	FMEA-AHP	Oil SC		✓	✓		✓	✓	✓	✓	✓			✓
Ahmed et al. [52]	Delphi-BBWM	Apparel SC	✓	✓			✓						✓	
Prakash et al. [25]	Grey-TOPSIS	Manufacturing SC									✓			

(*continued on next page*)

Table 1 (*continued*)

Author(s)	Methodology	SC Type	Resiliency	Sustainability	Risk Management Phases				Risk Factors					Weights of Risk Factors
					Identification	Clustering	Prioritization	Mitigation	Occurrence	Detection	Urgency	Vulnerability	Recovery	
Abadi and Darestani [22]	BWM-Fuzzy WASPAS	Food SC		✓	✓		✓				✓			✓
Bygballe et al. [53]	Conceptual Framework	General SC						✓						
Berger et al. [54]	SIS modeling	General SC									✓			
Hamidu et al. [55]	PLS-SEM	Manufacturing SC	✓											
Frederico [56]	Conceptual Framework	General SC	✓								✓			
Bø et al. [9]	Conceptual Framework	Pharmaceutical and Food SC	✓		✓									
Petratos and Faccia [57]	Conceptual Framework	General SC	✓						✓				✓	
Ngo et al. [58]	PLS-SEM	Digital SC			✓		✓		✓		✓			
Janjua et al. [59]	Bi-LSTM-CRF and FIS	General SC			✓	✓	✓		✓		✓			
Sun et al. [60]	PLS-SEM and ANN	SMEs	✓		✓		✓				✓		✓	
Soyer et al. [40]	Fuzzy cognitive map	General SC		✓	✓		✓				✓			
Karmaker et al. [37]	TISM-Fuzzy MICMAC	SMEs		✓	✓	✓	✓							
Sutrisno and Kumar [36]	FMEA, Preference selection index, and Shannon entropy	SMEs		✓	✓		✓		✓	✓	✓	✓	✓	✓
Ngo et al. [61]	PLS-SEM	SMEs			✓		✓							✓
Pandey et al. [62]	TOPSIS -DEMATEL	General SC			✓		✓				✓			
Zhang et al. [63]	Regret theory and VIKOR	Automotive SC			✓		✓	✓						✓
Azadnia et al. [64]	Delphi-BWM	Hydrogen SC		✓	✓		✓				✓			✓
Hashim et al. [5]	Fuzzy FMEA-AHP-TOPSIS	Textile SC		✓	✓		✓		✓	✓	✓			
Guntuka et al. [65]	Censored Data regression (Tobit)	Manufacturing SC			✓		✓						✓	
Krstić et al. [66]	BWM and COBRA	Food SC			✓		✓					✓		✓
Chowdhury et al. [8]	FsQCA-QFD	Tourism SC	✓		✓			✓						
Alam et al. [32]	Pareto analysis, TISM, and MICMAC	Food SC		✓		✓	✓	✓			✓			
Rafi-Ul-Shan et al. [24]	Fuzzy AHP and FMEA	Textile SC			✓		✓	✓	✓	✓	✓			✓
The current study	BBMW, FCM, and CoCoSo	SSC	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2
Numerical scale for pairwise comparison of the risk factors to generates the BO and OW vectors.

Scale	Linguistic Description	Scale	Linguistic Description
1	Equal importance	6	Between strong and very strong importance
2	Between equal and moderate importance	7	Very strongly important than
3	Moderately important than	8	Between very strong and absolute importance
4	Between moderate and strong importance	9	Absolutely important than
5	Strongly important than		

iterative approach for its calculations, suggesting that A_B^k and A_W^k vectors determine w^k. The vectors A_B^k and A_W^k are outlined as Eqs. (3) and (4), respectively.

$$A_B^k = A_{B1}^k, A_{B2}^k, \dots, A_{Bn}^k, \qquad \forall k, n \tag{1}$$

$$A_W^k = A_{W1}^k, A_{W2}^k, \dots, A_{Wn}^k, \qquad \forall k, n \tag{2}$$

$$A_B^k \mid w^k \sim multinomial\left(\frac{1}{w^k}\right), \qquad \forall k \tag{3}$$

$$A_W^k \mid w^k \sim multinomial\left(w^k\right), \qquad \forall k \tag{4}$$

Here, the multinomial distribution $A_B^k \mid w^k$ and $A_W^k \mid w^k$ is used to describe the probability of multiple outcomes of the vector A_B^k and A_W^k from a set of possible kth DM. Based on the following probabilistic model in Eq. (5) to Eq. (7), aggregate weight w^{agg} can be obtained. These equations combine the individual weights of various risk factors into a probabilistic model with Dirichlet distribution and produce a final aggregate weight that reflects the overall importance of each factor. Thus, it provides a more robust and realistic set of aggregate weights.

$$w^k \mid w^{agg} \sim Dir\left(\gamma \times w^{agg}\right), \qquad \forall k \tag{5}$$

$$w^{agg} \sim Dir\,(1) \tag{6}$$

$$\gamma \sim Gamma(0.1, 0.1) \tag{7}$$

The terms *multinomial* and *Dir* represent two different types of probability distributions: multinomial distribution and the Dirichlet distribution. *Dir* (1) in Eq. (6) specifies a Dirichlet distribution with a particular parameter, while γ (0.1, 0.1) in Eq. (7) denotes a Gamma distribution both set at 0.1. Due to its probabilistic nature, Eq. (6) does not have a closed solution. Thus, the computation of aggregate weights probabilistically requires Markov-chain Monte Carlo samplings. Moreover, the creedal ranking approach is proposed by Mohammadi and Rezaei [28] for a probabilistic comparison of criteria. It allocates confidence levels to reflect the preference intensity of a group of DMs for certain criteria over others and can be visualized using directed graphs [68,69].

3.2. Fuzzy C-means clustering algorithm

The FCM is a technique for clustering data allowing data points to associate with multiple clusters based on likelihood, unlike K-means and other traditional algorithms which restrict data points to a single cluster [70,71]. Data points within the same cluster exhibit greater similarity to each other compared to those in different clusters. FCM clustering is a variation that allows each data point to have partial membership in multiple clusters, rather than being assigned to just one. This makes the FCM particularly effective for overlapping datasets and provides superior results compared to hard clustering methods. Algorithms like K-means and hierarchical clustering fall into the category of hard clustering methods, which operate on a binary principle and assign data points to a definitive classification of either 0 or 1. In contrast, the FCM is a soft clustering technique that works within the range of [0, 1] to allow for a more fluid categorization of data points [29]. The FCM clustering algorithm is carried out step-by-step as follows.

Step 1 *Defining data points*: The data point vector X is represents the sample data set, shown in Eq. (8). In this equation, n indicates the number of samples.

$$X = (x_1, x_2, \dots, x_n)^T \subseteq R \tag{8}$$

Step 2 *Minimizing the objective function with clustering algorithm*: FCM organizes the sample set into a defined number of clusters K, where the objective function measures how well each data point fits within a cluster. This is performed with the algorithm provided in Eq. (8). The algorithm modifies the clusters to minimize this function to provide more accurate groupings. To begin with, the cluster centers matrix V and the membership matrix U are calculated in Eqs. (9) and (10), respectively. Where u_{ij} represents the membership of x_j in the ith cluster ($i = 1, 2, \ldots, k$).

$$V = (v_1, v_2, \ldots, v_k)^T \tag{9}$$

$$U = [u_{ij}]_{K\times n} \tag{10}$$

The cluster center matrix V consists of the center points for each cluster, which are denoted as $v_1, v_2, \ldots, v_k$. The membership of data indicates a fuzzy (uncertain) nature and is a criterion ranging between 0 and 1. The goal of FCM algorithm is to minimize an objective function (Eq. (11)) which measures how well the data points fit into their assigned clusters.

$$min\ J_m(u, v;\ x) = \sum_{i=1}^{k} \sum_{j=1}^{n} u_{ij}^m \|x_j - v\|^2 \tag{11}$$

In this equation, Euclidean distance $\|x_j - v\|$ is the distance between sample of x_j and the center of the cluster v. The FCM algorithm tries to minimize this distance by adjusting the clusters to ensure that data points are as close as possible to the center of their assigned clusters. Eq. (11) involves complex relationships between the membership values and distances. Because the memberships must add up to 1 for each data point, this constraint makes it difficult to minimize the objective function directly.

Step 3 *Employing alternative optimization for final center of cluster*: To solve the issue regarding minimizing the objective function directly $\sum_{i=1}^{k} u_{ij} = 1$, an alternating optimization can be used. The optimal solution to minimize $J_m(u, v; x)$ is accomplished by utilizing this improvised iterative. Moreover, fuzzy membership function u_{ij} in each iteration and the center of ith cluster (v_i) can be calculated from Eqs. (12) and (13), respectively. In these equations, m is the fuzzy weighting parameter that can be any real number and varies over the range 1 to infinity [72]. A smaller value of m makes the clustering more certain (closer to hard clustering), while a larger value makes it fuzzier, meaning data points can more easily belong to multiple clusters.

$$u_{ij} = \frac{1}{\sum_{p=1}^{k} \left(\frac{\|x_j - v_i\|}{\|x_j - v_p\|} \right)^{2/(m-1)}}, \qquad 1 \le i \le k \quad ; \quad 1 \le j \le n \tag{12}$$

$$v_i = \frac{\sum_{j=1}^{n} (u_{ij})^m x_j}{\sum_{j=1}^{n} (u_{ij})} \tag{13}$$

3.3. Combined compromise solution technique

The MCDM problems with employing general compromise methods is the variations in the weight distributions of criteria can substantially influence the outcome of the rankings [72]. Given this limitation, there is a pressing need for more reliable and stable results. Unlike other MCDM methods, which may emphasize only the highest weighted criteria, general compromise methods consider the trade-offs between all criteria. This makes them more balanced and realistic in handling complex problems where multiple factors must be considered together [73]. Another potential compromise solution, namely CoCoSo, aims to improve final decisions. Yazdani et al. [30] proposed an innovative MCDM method that calculates the sum and product-weighted values for each alternative and utilizes three different strategies to assess the priority rankings. More precisely, three different compromise aggregation functions are used by the CoCoSo method to calculate the final score. The first strategy involves computing the arithmetic mean of the scores for each alternative, while in the second strategy, alternatives are ranked following each score to the top score. A combination of these two forms the third strategy. The final priority of each alternative in the ranking is calculated by averaging its arithmetic and geometric means from the three strategies. In other words, the CoCoSo technique combines simple additive weighting with exponentially weighted product models to identify the optimal alternative and thus exceeds other compromise solution ranking methods such as TOPSIS and VIKOR [73,74]. The CoCoSo method provides unmatched flexibility and a complete solution for ranking needs. The CoCoSo method is implemented in five main steps detailed below.

Step 1 *Determining the decision matrix with rough form*: First, it is essential to outline alternatives (e.g., disruption risks) and associated criteria (e.g., risk factors). Considering that x_{ij} exhibits the criterion j ($j = 1, 2, \ldots, n$) for the alternative i ($i = 1, 2, \ldots, m$), the decision matrix can be shown as Eq. (14).

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \tag{14}$$

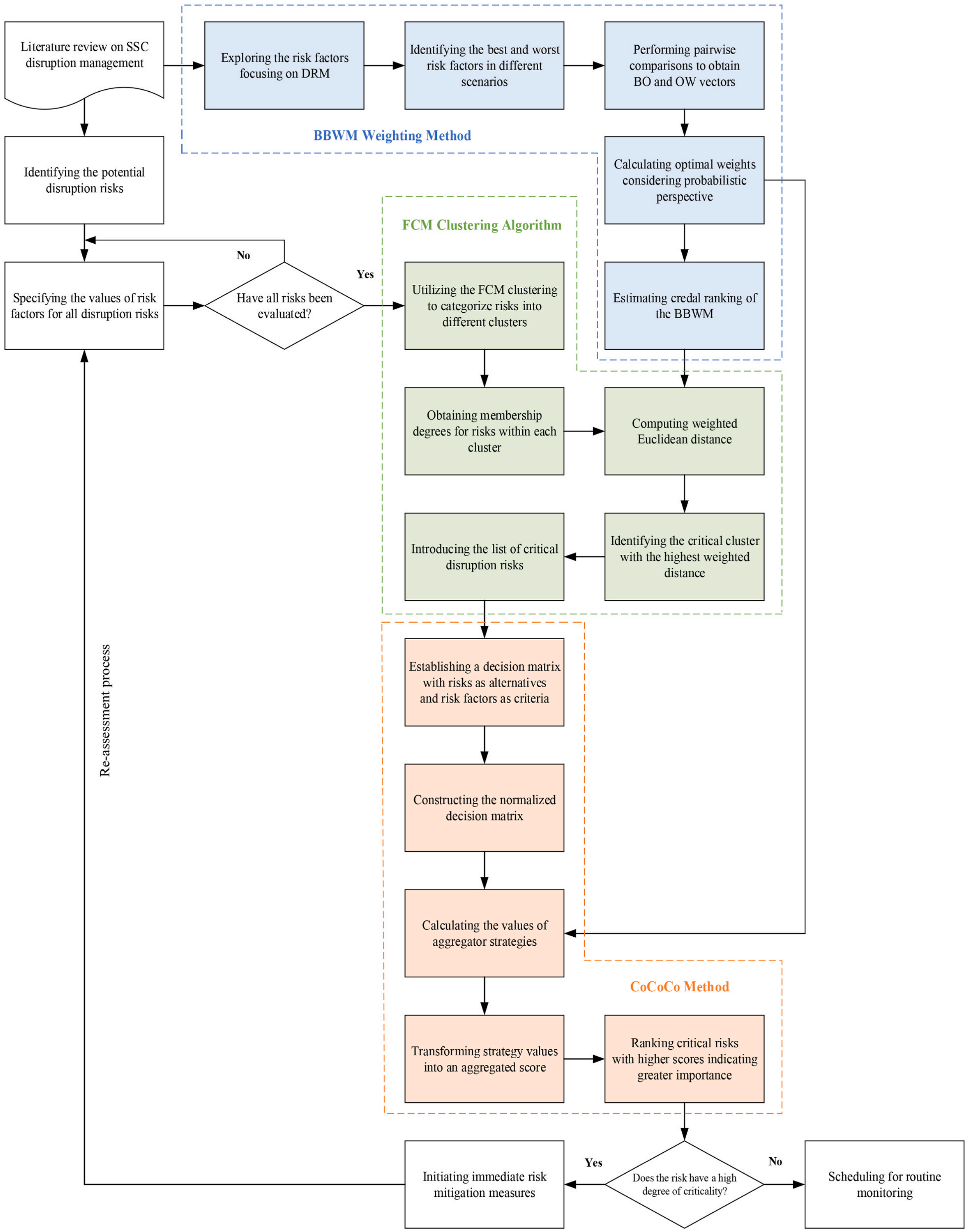

Fig. 2. The flowchart of the proposed decision support system for DRM in SSCs.

Step 2 *Utilizing the compromise normalization procedure for decision matrix normalization*: The initial decision matrix is normalized with the defined compromise normalization calculations. Equations (15) and (16) are respectively used for normalizing the benefit and cost criteria.

$$r_{ij} = \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}, \qquad \forall i, j \tag{15}$$

$$r_{ij} = \frac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}, \qquad \forall i, j \tag{16}$$

Step 3: *Calculating the sum of the weighted comparability sequence and power-weighted comparability sequence*: Once the matrix is normalized, the weights (w_j) can be assigned to each criterion. Then, the calculations for the weighted comparability sequences S_i and exponential weight of comparability sequences P_i are carried out for every alternative. To do this, Eqs. (17) and (18) are used to calculate S_i *and* P_i, which are defined as the aggregated Simple Additive Weighting (SAW) and Exponentially Weighted Product (EWP) methods, respectively.

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij}\right), \qquad \forall i \tag{17}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij}\right)^{w_j}, \qquad \forall i \tag{18}$$

Step 4 *Computing relative ranking of each alternative*: In this step, three distinct aggregator strategies (k_{ia}, k_{ib}, k_{ic}) are implemented to calculate the relative ranking of each alternative using Eqs. (19)–(21), where the value of k can be set by DMs and is typically 0.5. k_{ia} gives a score for each alternatives and shows how well it compares to the others. k_{ib} helps to see how close each alternatives is to the best possible outcome. k_{ic} considers both the overall score and the relative differences between alternatives.

$$k_{ia} = \frac{P_i + S_i}{\sum\limits_{i=1}^{m} (P_i + S_i)}, \qquad \forall i \tag{19}$$

$$k_{ib} = \frac{S_i}{\min\limits_i S_i} + \frac{P_i}{\min\limits_i P_i}, \qquad \forall i \tag{20}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)P_i}{\lambda \max\limits_i (S_i) + (1-\lambda) \max\limits_i P_i}, \qquad 0 \le \lambda \le 1 \quad ; \quad \forall i \tag{21}$$

Step 5 *Transforming to crisp number to get the final ranking of alternatives*: Ranking is finalized as stated by Eq. (22) by calculating scores for each option and sorting them from highest to lowest, with the principle that higher scores represent more significant choices [80,86].

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}), \qquad \forall i \tag{22}$$

4. Proposed approach

This section outlines the implementation process of the proposed decision support system for prioritizing critical disruption risks. As illustrated in Fig. 2, the proposed framework is executed in three incorporated phases. The first phase is dedicated to disruption risk identification through a comprehensive literature review within the SSCs and determining the weight of risk factors. This study extends beyond traditional risk factors (e.g., occurrence and detection). It includes two additional factors (V and NR factors) to acknowledge their critical roles through the risk assessment process. A list of potential disruption risks is identified at first. Following that, the values of risk factors are finalized by DMs or approximated from the literature review considering the standardized scoring mechanism.

In the following, the BBWM technique is utilized to determine the weight of the risk factors. This technique is chosen for its suitability in group settings with probability distribution outputs and offers a collective opinion of group preferences. All the risk factor inputs are formed as multinomial probability distributions to reflect the list of possibilities with their respective probabilities. In the later steps, the Dirichlet distribution is used to model the probabilities of multiple risk factors occurring at the same time. The first step of BBWM involves selecting the best and worst factors, and then conducting a comprehensive pairwise comparison of the risk factors against each other to generate the BO and OW vectors (refer to Eqs. (1) and (2)). This study evaluates a numerical scale ranging from 1 to 9 is employed (see Table 2). It computes the aggregated distribution and all the individual preferences at once with probabilistic modeling. The probability distribution of the BO and OW vectors is specified, and then the weight vector is generated using the Dirichlet distribution. These vectors serve as inputs to conduct a probabilistic analysis (Eq. (3) to (7)) in MATLAB and specify the final weights of risk factors. Ultimately, the weight distribution in individual scenarios is calculated, and a final aggregated distribution is determined based on the overall preferences in this group decision-making process. Additionally, the credal ranking approach is employed to investigate assigned confidence levels in directed graphs. It demonstrates how strong the preferences of DMs are while comparing them based on probabilistic criteria.

As clustering risks is essential for effectively focusing on the most critical ones, the FCM technique is implemented in the second phase. This technique is more reflective of real-world conditions in the clustering process since it acknowledges the inherent uncertainty of data and enables a more perceptive categorization. This technique utilizes fuzzy logic to segregate overlapping data points and thus it provides an improved approach to data categorization compared to the K-means algorithm [71,75]. Therefore, in the second phase, it appoints membership degrees to data points relative to their proximity to cluster centers and reduces uncertainty in group classification. After separating the data set into a defined number of clusters, the Euclidean distance should be measured between the origin of the coordinate system and the center point of each cluster. This study calculates the weighted Euclidean distance by employing the weights of risk factors from BBWM and here a higher value indicates greater criticality. Utilizing the obtained values, this research identifies the risk cluster with a high criticality degree and introduces the critical risks considering the minimum membership thresholds.

In the third phase, the risks within the critical cluster are prioritized because of existing constraints, such as time, budget, and manpower. Those constraints can limit the feasibility of addressing all risks simultaneously. Because of this, a cluster of the most critical risks only significantly aids in mitigating the adverse effects of handling the comprehensive dataset on the system. For this purpose, we employ the CoCoSo method which is noted for its robustness and precision [30] and outperforms other MCDM methods in accuracy and suitability for scenarios with numerous alternatives. This technique starts with determining the decision matrix by assigning the risks within the critical cluster risks as alternatives and the five risk factors as the criteria. After performing the normalization of the decision matrix, Eqs. (17) and (18) are used respectively to evaluate S_i to assess the overall performance of each disruption risk and P_i to amplify the differences between major risks and minor risks considering risk factor weights from BBWM. Then, the three aggregator strategies (k_{ia}, k_{ib}, and k_{ic}) are employed to get the relative ranking of each risk through Eqs. (19)–(21). The three aggregator strategies in the CoCoSo method prioritize the risks based on their overall performance, relative differences, or a combination of both respectively to evaluate critical risks. Ultimately, this results in the final score k_i which combines the results from the three aggregator strategies and prioritizes the most critical risks. Based on the distinct prioritization, DMs are allowed to allocate resources more effectively to tackle the critical risks first.

5. Results and discussion

This section explores the effectiveness of the proposed approach. After discussing the outcomes of this approach, its performance is compared to alternative MCDM techniques. The sensitivity analysis on the importance of risk factors is also done to demonstrate the practical implications of the outcomes of the study.

5.1. Outcomes of the proposed approach

The decision support system, as outlined in Section 4, begins with the identification of disruption risks. Subsequent sections provide detailed explanations of results obtained from implementing the proposed approach for deciding the weights of risk factors and clustering and prioritizing risks.

5.1.1. Risk identification

The initial phase focuses on identifying and categorizing a variety of SC disruption risks within the domain of sustainable SCM. The identified 84 risks are categorized into six principal dimensions. These dimensions encompass economic risks, technical or operational risks, environmental risks, social risks, man-made risks and natural disasters, each with its distinct characteristics and consequences (see Table 3). The economic dimension highlights how market competition, financial vulnerabilities, and packaging issues are integral to managing economic aspects in SCs. In the technical or operational realm, the research considers the unpredictability of supply and demand, alongside challenges in quality control and workforce management. Furthermore, environmental concerns emphasizing the significance of pollution hazards, and waste disposal are investigated in the risk analysis. In exploring social aspects, the study intricately connects working conditions and labor compliance with the overarching need for regulatory adherence. The studied man-made risks refer to dangers and disruptions caused directly by human actions. Finally, we broaden the scope to include the impacts of natural disasters on SSCs. This, in turn, outlines the consequences of such disasters, ranging from demand fluctuations and supplier inaccessibility to workforce challenges and logistical disruptions.

After exploring the potential risks, these risks are assessed using the standard scoring table (see Table 4). In this study, the basis for calculating the risk prioritization score considers the scale of risk occurrence, challenges in risk detection, the severity of impacts on SCs, organizational vulnerability, and the lack of recoverability as non-beneficial attributes in the risk assessment process. Occurrence probability identifies the likelihood of each risk event and directing focus toward the most probable threats [34,42]. The detection factor underscores the importance of early identification of risks that essentially serve as a proactive shield against potential disruptions [33,76]. Seriousness or urgency ranks risks based on their potential severity and the immediacy of their impact whcich guides swift action against the most threatening issues [5,22,50]. The risk vulnerability examines the susceptibility of the organization to

Table 3
Overview of sustainability and disruption risk dimensions.

Dimensions	Divisions	Sym. Risks (Sources)	Risk Factors				
			O	D	U	V	NR
Economical	Market Rivalry Risk	R1 Influx of New Industry Players ([36,45])	4	2	3	5	1
		R2 Shifts in Consumer Choice ([15,34])	3	1	3	3	2
		R3 Competition Risk Due to Regulatory Revisions ([35,76])	4	2	5	5	1
		R4 Brand Reputation Threats ([6,12])	1	1	5	5	1
		R5 Political Instability ([13,30])	4	3	3	4	2
	Monetary Vulnerability	R6 Tax Evasion ([6,42])	5	2	4	2	3
		R7 Financial Strain ([33,45])	3	1	5	4	3
		R8 Financial Exposure to Price Fixing Schemes ([36,42])	5	2	4	4	2
		R9 Raw Material Price Volatility ([15,36])	3	2	3	3	2
		R10 Monetary Impact of Sudden Cancellations ([6,36])	1	1	5	5	2
		R11 Industrial Espionage Threat ([6,42])	4	4	4	4	2
		R12 Legal and Contractual Disputes ([15,76])	1	4	3	4	2
	Packaging Predicaments	R13 Unattractive packaging ([36])	1	5	1	2	2
		R14 Packaging Regulations Violations ([36])	1	4	2	4	1
		R15 Packaging Design Inconsistencies ([35,36])	1	3	4	5	1
		R16 Product Authentication Challenges ([36])	1	2	2	3	2
		R17 Packaging Contamination ([45,77])	3	3	4	4	3
Technical or Operational	Industrial Technology and Operational Exposures	R18 Production Facility Related Risk ([6,33])	5	3	4	4	2
		R19 Aging Infrastructure ([30,76])	2	2	2	3	4
		R20 Malfunctions or Breakdowns in Production Equipment ([15,30])	3	2	2	2	2
		R21 Outdated Technology and Innovation Competency Gaps ([33,35])	3	1	3	3	2
		R22 Failure of Information Sharing ([33,42])	3	2	4	4	3
		R23 Susceptible to Breaches and Data Theft ([30,33])	2	2	5	4	3
		R24 Difficulties in Managing Product Returns ([34,36])	1	1	4	4	3
		R25 Freight Capacity Shortages ([6,35])	2	1	2	2	2
		R26 Challenges in Integrating with External Systems ([30,33])	2	2	2	3	1
	Supply Uncertainty	R27 Single Sourcing Risks ([12,42])	4	2	3	3	1
		R28 Raw Material Scarcity ([13,15])	3	2	4	3	2
		R29 Supplier Certification Failures ([12,35])	4	1	4	2	2
		R30 Supplier Bankruptcy ([76,78])	2	1	3	2	2
	Demand Uncertainty	R31 Warehouse Capacity Limitations ([6,15])	2	2	3	3	4
		R32 Overstock-Related Problems (e.g. obsolescence) ([30,45])	3	2	2	3	3
		R33 Limited Understanding of Market Trends ([12,15])	3	4	5	3	4
	Quality management Challenge	R34 Incorporating Low-Quality Raw Resources ([6,37,42])	1	3	2	3	2
		R35 Inadequate Quality Assurance and Control ([13,76])	2	1	3	3	3
		R36 Labor Shortages ([12,34])	3	3	2	2	2
		R37 Unpreparedness for Remote Work Arrangements ([15,35])	2	2	2	1	2
		R38 Labor Unionization Challenges and Labor Strikes ([12,33])	1	1	2	3	3
		R39 Talent Shortage in Specialized Roles/ High Dependence on Key Employees ([12,15])	4	3	4	2	2
Environmental	Pollution-Related Hazard	R40 Excessive Noise Impact ([34,36])	1	4	1	2	4

(*continued on next page*)

Table 3 (*continued*)

Dimensions	Divisions	Sym. Risks (Sources)	Risk Factors				
			O	D	U	V	NR
		R41 Soil Erosion and Sedimentation ([33,36])	1	2	4	4	3
		R42 Thermal Pollution: Discharge of Heat ([6,34])	2	2	2	2	3
		R43 Excessive Use of Non-Biodegradable Plastics ([79])	2	2	3	3	3
		R44 Aerosol Pollution ([15,33])	3	2	2	2	4
	Waste Disposal Concerns	R45 Waste By-Product ([36])	2	3	5	5	3
		R46 Raw Material Waste ([6,35])	2	2	3	4	3
		R47 Wastewater Discharge ([13,42])	2	3	5	3	4
		R48 Obsolete Technology Disposal ([13])	1	2	4	3	2
		R49 Chemical Spills/Chemical Runoff ([15])	4	3	3	2	3
		R50 Biodegradable Waste Material ([35,36])	3	3	4	3	3
Social	Working Conditions and Labor Compliance Obligations	R51 Poor Occupational Health and Safety ([12,15])	5	5	3	3	2
		R52 Labor Exploitation ([15,42])	5	2	3	2	2
		R53 Wage Discrimination and Inequality ([36,42])	4	2	4	3	2
		R54 Compromised Employee Welfare ([6,12])	4	5	2	2	3
		R55 Unregulated Labor Practices ([12,42])	1	4	3	2	2
		R56 Inhumane Working Hours ([15,42])	3	3	2	2	2
		R57 Inadequate Accommodations for Disabled Workers ([45,80])	1	2	3	2	2
		R58 Inadequate Investment in Training and Skill Development ([6,45])	5	3	2	1	5
		R59 Inadequate Employee Feedback ([15])	4	1	1	2	2
	Regulatory Compliance Obligations	R60 Bank Credit Accessibility Barriers ([15,36])	1	3	1	2	2
		R61 Excessive Governmental Interference ([15,76])	1	2	4	2	3
		R62 Governmental Support Shortcomings ([35,36])	3	4	3	4	2
		R63 Intellectual Property Oversight ([6,76])	4	2	4	3	2
Man-Made Threats		R64 Cyberattacks ([33,76])	1	2	1	3	3
		R65 Transportation Blockades ([6])	3	1	4	2	3
		R66 Wars or Civil Unrest ([6,34])	1	1	3	3	4
		R67 Acts of Terrorism ([42,76])	3	5	5	5	1
		R68 Natural Resource Exploitation ([33])	4	2	4	3	4
		R69 Resource Hoarding ([6])	2	3	3	2	3
		R70 Black Market Trade ([12,76])	3	2	1	5	1
		R71 Geopolitical Trade Disruptions ([6,76])	3	3	4	4	4
		R72 Pathogenic Crisis ([6,34])	1	2	5	4	2
Natural Disaster		R73 Increased Demand for Certain Goods (e.g., building materials, medical supplies, or food) ([13])	5	3	4	5	1
		R74 Supplier Inaccessibility and Production Halts ([13])	4	3	3	5	2
		R75 Inventory Imbalances ([33,45])	4	2	4	4	3
		R76 The Temporary Lack of an Adequate Workforce ([33,76])	4	3	4	2	2
		R77 Disrupted Transportation/Logistical Overload ([30,33])	3	2	3	4	3
		R78 Communication Networks Disruptions ([13])	5	3	4	5	3
		R79 Damage to Production Facilities ([35,36])	3	3	3	5	4
		R80 Disruptions to IT Systems ([30,33])	5	2	3	5	3
		R81 Utility Outages ([6,30])	3	1	2	3	2
		R82 Market Instability ([6])	2	2	3	4	2
		R83 New Legal Requirements Challenges ([36])	2	1	3	3	2
		R84 Long-term SC Disruption ([42])	1	2	5	5	4

Table 4
Risk prioritization scoring scale in DRM.

Scale	O	D	U	V	NR
1	Rare occurrences	Negligible detection challenges	Minimal impact on SC performance	Low organizational vulnerability	Excellent recoverability
2	Occasional occurrences	Manageable detection challenges	Moderately low impact on SC performance	Moderate organizational vulnerability	Reasonable recoverability
3	Common occurrences	Significant detection challenges	Medium impact on SC performance	Notable organizational vulnerability	Moderate recoverability
4	Frequent occurrences	Major detection challenges.	High impact on SC performance	High organizational vulnerability	Limited recoverability
5	Constant occurrences	Extreme detection challenges	Severe impact on SC performance	Critical organizational vulnerability	Virtually no recoverability

various risks. It highlights the importance of understanding and fortifying weaknesses in the system [38,68]. Lastly, non-recoverability refers to the long-term consequences of risks, prioritizing those that pose enduring or irreversible damage, and ensuring a strategic focus on sustaining organizational integrity and continuity [52,60]. In this study, the values of risk factors for various SC risks are approximated from comprehensive study of relevant literature, such as Sutrisno and Kumar [36], Azadnia et al. [64], Abadi and Darestani [22], Anugerah et al. [38], Kumar and Barua [34], Alshehri et al. [35], Raihan et al. [31], Zhu et al. [77], Moktadir et al. [33], Abdel-Basset and Mohamed [12], and Benabdallah et al. [42]. To rescale the risk factor values outlined for each risk in the literature, they are adjusted according to the defined scales in Table 4.

5.1.2. Risk factor weighting process

To evaluate the importance of multiple risk factors in the risk analysis process, the BBWM methodology is employed. Considering five scenarios, the best criterion (the most significant) and the worst criterion (the least important) are identified, as shown in Table 5. For three out of the five defined scenarios, the U factor is recognized as the best criterion, while V and NR factors are each considered most significant in the remaining scenarios. However, the D factor frequently emerges as the least important criterion across several scenarios. Following this, BO and OW vectors are formulated based on the defined scenarios in Table 5. Utilizing these vectors, weights are then calculated by incorporating a probabilistic perspective.

As indicated in Table 6, based on their potential impact, the U factor is identified as the most significant risk factor valued at 0.3442. In MCDM methodologies, assigned higher weights are of greater importance. Consequently, the V factor is positioned as the second significant risk factor with a weight of 0.2545. The third position is held by the NR factor, followed by the O factor. D is being identified as the least important, carrying a weight of only 0.0956. This features the fundamental role of the U in driving swift responses to the most extreme issues during disruptions, as well as the significant positions of V and NR factors in the risk prioritization framework. In the traditional BWM approach, evaluation is limited to just a single scenario. This, in turn, poses a challenge as every scenario presents unique best and worst criteria. Under these circumstances, accurately assigning factor weights would become problematic, ultimately impacting the reliability of the risk assessment and prioritization processes [69].

The marginal differences in weight among criteria can sometimes pose a challenge in their ranking. This is particularly true in collective decision-making scenarios. In these situations, credal ranking helps clarify and explain which criterion is preferred over another [30]. The credal ranking of the five risk factors is illustrated in Fig. 3. The annotations beside the arrows, for instance, X→rY, illustrate the preferential dominance of factor X over factor Y, with 'r' denoting the reliability or probability value ranging from [0, 1]. In Fig. 3, node 1 represents D, which is potentially considered the least important based on the incoming edges and indicates a lower preference relative to other criteria. Specifically, Node 0 → 0.97Node 1 indicates that O (Node 0) is definitely more important than D (Node 1), with a high-reliability value of 0.97. Conversely, Node 2 (U factor) emerges as potentially the most significant criterion, evidenced by all outgoing edges marked with values of 1.0 and 0.91. It signifies a robust preference or a superior rank relative to the rest. Edges marked with values below 1.0 indicate cases where the dominance of one criterion over another is not definitive.

5.1.3. Risk clustering

Upon identifying the weights assigned to each risk factor, the FCM clustering algorithm is employed for its versatility in managing data points. It assigns the potential risks with varying degrees of membership to multiple clusters. The main intention of this phase is to mitigate the financial burden of corrective and preventive actions through an improved risk prioritization approach. The FCM application begins with setting the cluster count (four clusters in this study) and then feeding the algorithm with risk factor data for

Table 5
Analysis of best and worst criteria with BO and OW vectors for different scenarios.

Scenario	Best Criterion	O	D	U	V	NR	Worst Criterion	O	D	U	V	NR
1	U	5	8	1	3	3	D	3	1	8	5	5
2	U	5	6	1	2	7	NR	2	2	7	4	1
3	V	5	7	2	1	4	D	2	1	6	7	5
4	U	7	6	1	3	4	O	1	2	7	5	4
5	NR	4	5	2	2	1	D	4	1	3	3	5

Table 6
The obtained weights for risk factors using the BBWM method.

Criterion Type	O	D	U	V	NR
Weight	0.1204	0.0956	0.3442	0.2545	0.1852
Priority	4th	5th	1st	2nd	3rd

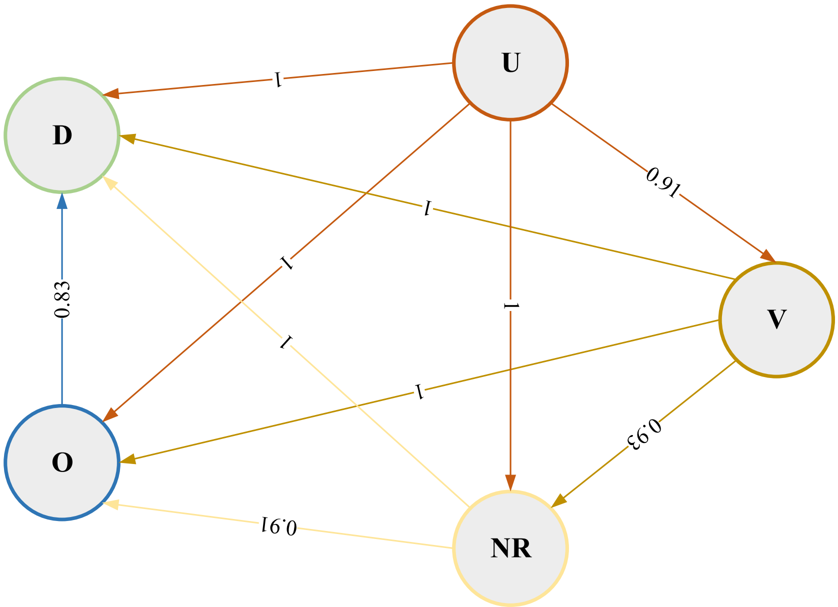

Fig. 3. Credal ranking graph for determining risk factor weights.

each risk. After implementing the FCM clustering algorithm, the identified risks are clustered based on the value of the five risk factors. The resulting outputs, illustrated in Table 7, show the degree of membership of each risk per cluster.

Next, the study calculates the center point of each cluster by computing the Euclidean distance from the center to the origin of each cluster. Here the proposed clustering method aligns with real-world issues. Therefore, the weights of the risk factors, derived from the BBWM, are employed to establish the weighted Euclidean distance. Clusters are grouped into four categories, including Intolerable, Major, Tolerable, and Minor, through this calculation. The significance of this distance directly correlates with the criticality of the risks within that cluster. Notably, the Intolerable and Minor clusters are on opposite ends of the spectrum in terms of weighted Euclidean distance. The analysis revealed that cluster 4 is categorized as critical, with a weighted Euclidean distance of 3.4481, and contains risks considered intolerable. Subsequently, it becomes necessary to pinpoint which risks within this critical cluster require prioritization. This metric allows DMs to tag clusters with the findings presented in Table 8.

A crucial step involves setting a minimum membership threshold, and clarifying which risks are considered part of the focused cluster. Setting the minimum membership threshold to 0.4, the study identifies 15 critical risks from this cluster (i.e., R5, R7, R17, R18, R22, R27, R68, R71, R73, R74, R75, R77, R78, R79, and R80) for the prioritization process. A comparative analysis between the FCM analysis results using conventional equally weighted factors (O, D, and U) and BBWM weighted factors (O, D, U, V, and NR) (shown in Table 9) can showcase how different weighting approaches can influence the clustering and prioritization of critical disruption risks. The analysis implies that using equally weighted factors, cluster 3 is identified as critical, while cluster 4 is ranked as major, indicating the second-highest priority level. In contrast, when additional factors (i.e., V and NR) are considered, the proposed approach identifies cluster 4 as the critical cluster, demoting cluster 3 to major status. The weighted risk factors show a distinctive shift in the Euclidean distance values and subsequent risk labeling. Moreover, both minor and tolerable categories display consistent results and identify cluster 1 as minor and cluster 2 as tolerable. It demonstrates their alignment in the lower-tier risk classifications.

This analysis details the numerical changes in critical risk priorities across various minimum thresholds in response to weight adjustments of risk factors. As mentioned before, a minimum threshold of 0.4 identified 15 critical risks for further scrutiny. This contrasts with the outcome from the conventional approach at the same minimum threshold, which yielded a higher number of critical risks (i.e., 23 risks). This inconsistency suggests a potential decision-making confusion due to an increased number of risks requiring attention. However, a more manageable threshold of 0.50 narrowed the critical risks down to 18 for the equally weighted criteria. Additionally, both methods exhibit a uniform shift in risk priority at a 0.75 threshold, ultimately dropping to zero (see Fig. 4 and Table 10). It indicates a convergence in risk assessment outcomes beyond this point. Therefore, this investigation highlights the sensitivity and adaptability of the proposed approach to varying risk factor weights and provides valuable insights for DMs in

Table 7
Membership degree of the specified risk clusters using the FCM analysis.

Risks	Membership Degree				Risks	Membership Degree			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4		Cluster 1	Cluster 2	Cluster 3	Cluster 4
R1	0.1786	0.2227	0.2935	0.3052	**R43**	0.2269	0.4965	0.2132	0.0635
R2	0.1988	0.2946	0.3472	0.1594	**R44**	0.3455	0.2519	0.2359	0.1667
R3	0.1499	0.2067	0.2555	0.3879	**R45**	0.1439	0.2274	0.2511	0.3775
R4	0.1941	0.2732	0.2717	0.2609	**R46**	0.1693	0.3502	0.2774	0.2030
R5	0.1091	0.1943	0.2556	0.4409	**R47**	0.1855	0.2495	0.2581	0.3070
R6	0.1930	0.2262	0.2964	0.2844	**R48**	0.2253	0.3636	0.2737	0.1374
R7	0.1284	0.2119	0.2536	0.4061	**R49**	0.3355	0.2429	0.2660	0.1556
R8	0.1920	0.2106	0.2797	0.3177	**R50**	0.1028	0.2051	0.3320	0.3601
R9	0.1083	0.2217	0.4374	0.2327	**R51**	0.1558	0.2505	0.4884	0.1053
R10	0.1836	0.2729	0.2675	0.2759	**R52**	0.3243	0.2629	0.3046	0.1082
R11	0.1440	0.2175	0.3491	0.2894	**R53**	0.2044	0.5327	0.2233	0.0396
R12	0.2686	0.2812	0.2507	0.1995	**R54**	0.5479	0.2194	0.1595	0.0732
R13	0.3495	0.2531	0.2285	0.1689	**R55**	0.4508	0.2518	0.2127	0.0846
R14	0.3004	0.2713	0.2454	0.1829	**R56**	0.4369	0.2222	0.2233	0.1176
R15	0.2543	0.3028	0.2745	0.1685	**R57**	0.3984	0.3067	0.2072	0.0876
R16	0.4224	0.2943	0.1929	0.0905	**R58**	0.3972	0.2356	0.2311	0.1362
R17	0.0669	0.1093	0.1504	0.6734	**R59**	0.3147	0.2500	0.2550	0.1803
R18	0.1378	0.1693	0.2215	0.4714	**R60**	0.4675	0.2485	0.1876	0.0963
R19	0.3449	0.2811	0.2217	0.1523	**R61**	0.4302	0.2917	0.2018	0.0763
R20	0.2084	0.2686	0.3513	0.1717	**R62**	0.2040	0.2244	0.2651	0.3065
R21	0.1988	0.2946	0.3472	0.1594	**R63**	0.1412	0.3645	0.3692	0.1251
R22	0.0398	0.0797	0.1160	0.7645	**R64**	0.3986	0.2705	0.2044	0.1265
R23	0.1793	0.2836	0.2669	0.2702	**R65**	0.1473	0.2575	0.3168	0.2784
R24	0.2234	0.3415	0.2664	0.1687	**R66**	0.2727	0.3161	0.2421	0.1691
R25	0.2959	0.2811	0.2765	0.1466	**R67**	0.2278	0.2482	0.2625	0.2615
R26	0.3657	0.2821	0.2404	0.1118	**R68**	0.1508	0.1946	0.2443	0.4103
R27	0.1374	0.1867	0.2718	0.4041	**R69**	0.4343	0.2575	0.2086	0.0997
R28	0.1083	0.2217	0.4374	0.2327	**R70**	0.3391	0.2547	0.2488	0.1574
R29	0.2392	0.3208	0.2966	0.1434	**R71**	0.1262	0.1764	0.2064	0.4911
R30	0.3242	0.3186	0.2547	0.1025	**R72**	0.1793	0.2836	0.2669	0.2702
R31	0.2620	0.3116	0.2484	0.1780	**R73**	0.1475	0.1838	0.2324	0.4363
R32	0.3503	0.2581	0.2498	0.1418	**R74**	0.1505	0.1883	0.2367	0.4244
R33	0.1993	0.2218	0.2471	0.3319	**R75**	0.0742	0.1132	0.1633	0.6493
R34	0.4256	0.2724	0.1977	0.1043	**R76**	0.2090	0.2245	0.2998	0.2667
R35	0.2357	0.3722	0.2669	0.1252	**R77**	0.0398	0.0797	0.1160	0.7645
R36	0.3715	0.2360	0.2514	0.1410	**R78**	0.1407	0.1754	0.2185	0.4654
R37	0.4456	0.2443	0.2064	0.1037	**R79**	0.1629	0.2045	0.2217	0.4109
R38	0.3444	0.3123	0.2193	0.1240	**R80**	0.1555	0.1897	0.2319	0.4230
R39	0.3443	0.2419	0.2811	0.1326	**R81**	0.2959	0.2811	0.2765	0.1466
R40	0.4263	0.2498	0.1994	0.1246	**R82**	0.1697	0.3649	0.3119	0.1534
R41	0.2243	0.3582	0.2617	0.1558	**R83**	0.2349	0.3770	0.2834	0.1048
R42	0.5479	0.2194	0.1595	0.0732	**R84**	0.1826	0.2566	0.2485	0.3123

Table 8
Categorization of risk clusters based on center points and weighted Euclidean distance.

Risk Cluster	Central point of each cluster for each risk factors					Prioritization of clusters by considering risk factors weights			
	O	D	U	V	NR	Euclidean Distance	Euclidean weighted distance	Risk Category Name	Priority
1	2.122	2.321	2.548	2.592	2.428	5.38469	2.4685	Minor	4
2	2.185	2.092	3.130	3.050	2.442	5.84944	2.7997	Tolerable	3
3	2.579	2.151	3.315	3.131	2.374	6.14096	2.9267	Major	2
4	3.178	2.357	3.782	3.859	2.779	7.25047	3.4481	Intolerable	1

managing SC disruption risks effectively.

5.1.4. *Critical risk prioritization*

This section seeks to prioritize the identified critical risks using the CoCoSo method. To enable DMs to define efficient risk mitigation measures and allocate the required resources effectively, the identified critical cluster with 15 risks is prioritized with the CoCoSo method. The ranking is established on the outputs of both the BBWM and the FCM clustering algorithm, where the 15 critical risks are treated as alternatives and the estimated weights for risk factors are considered. Then, the process starts with the construction of a normalized decision matrix. From this matrix, the weighted comparability sequence (S_i) and the exponential weight of the comparability sequence (P_i) are determined using Eqs. (17) and (18), respectively. Subsequent to these computations, three aggregator

Table 9
Comparative results from FCM analysis.

Conventional equally weighted factors O, D, and U					BBWM weighted factors O, D, U, V, and NR				
	Euclidean distance	Euclidean weighted distance	Assigned Label	Priority		Euclidean distance	Euclidean weighted distance	Assigned Label	Priority
Cluster 1	3.6190	2.0884	Minor	4	Cluster 1	5.3847	2.4686	Minor	4
Cluster 2	4.8498	2.7986	Tolerable	3	Cluster 2	5.8494	2.7998	Tolerable	3
Cluster 3	5.6537	3.2625	Intolerable	1	Cluster 3	6.1410	2.9267	Major	2
Cluster 4	4.9072	2.8318	Major	2	Cluster 4	7.2505	3.4482	Intolerable	1

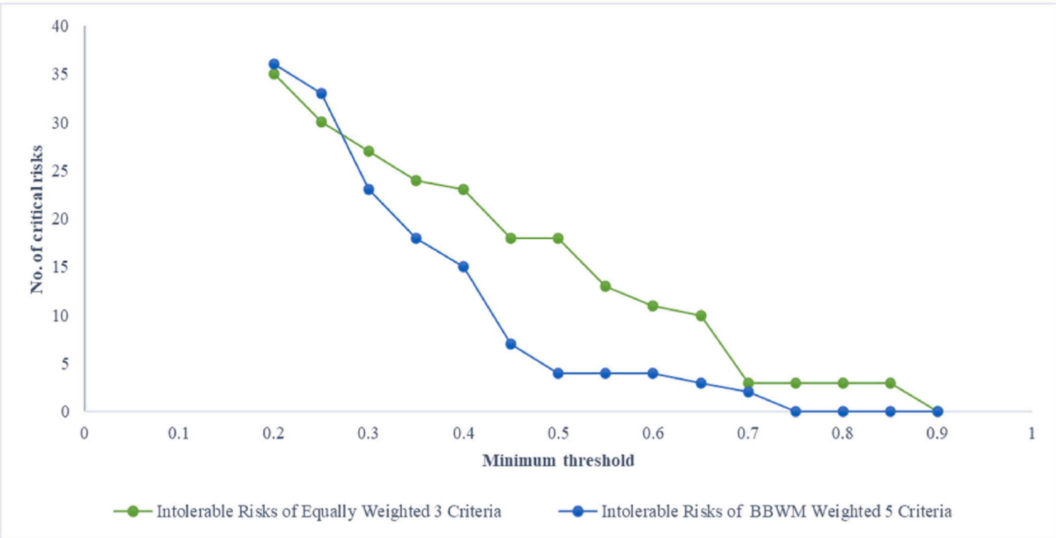

Fig. 4. Investigating intolerable risks at the minimum threshold using the conventional and proposed approaches.

Table 10
Comparative analysis of the number of intolerable risks at minimum threshold.

Minimum threshold	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
Equally weighted 3 criteria	35	30	27	24	23	18	18	13	11	10	3	3	3	3	0
BBWM weighted 5 criteria	36	33	23	18	15	7	4	4	4	3	2	0	0	0	0

Table 11
Results from implementing the proposed approach.

Identified critical risks	S_i	P_i	k_{ia}	k_{ib}	k_{ic}	k_i	Priority
R5	0.2677	2.6537	0.0485	2.1376	0.5407	1.292	14
R7	0.5641	2.7178	0.0545	3.4216	0.6075	1.845	10
R17	0.4876	3.5055	0.0663	3.3934	0.7391	1.950	8
R18	0.6080	4.5055	0.0849	4.2821	0.9465	2.472	2
R22	0.4398	3.4414	0.0645	3.1660	0.7184	1.844	11
R27	0.2353	2.6940	0.0487	2.0152	0.5422	1.245	15
R68	0.4654	3.6435	0.0682	3.3508	0.7605	1.951	7
R71	0.5802	3.6260	0.0699	3.8324	0.7786	2.153	5
R73	0.6427	3.7877	0.0736	4.1589	0.8201	2.315	3
R74	0.4104	2.9199	0.0553	2.8444	0.6164	1.631	13
R75	0.5000	4.3613	0.0807	3.7686	0.8998	2.232	4
R77	0.4398	3.4414	0.0645	3.1660	0.7184	1.844	11
R78	0.7353	4.6673	0.0897	4.8839	1.0000	2.751	1
R79	0.5353	3.0000	0.0587	3.4058	0.6544	1.881	9
R80	0.5153	3.8154	0.0719	3.6281	0.8016	2.094	6

strategies k_{ia}, k_{ib} and k_{ic} are calculated following Eqs. (19)–(21), considering λ is set to 0.5. Finally, the final ranking score (k_i) for each risk is established using Eq. (22) and indexed from 1 to 15.

The obtained rankings are displayed in Table 11, where the risks R78 (i.e., communication networks disruptions), R18 (i.e., production facility-related risk), and R73 (i.e., increased demand for certain goods) have been assigned the top three rankings, respectively. Notably, two of the top three ranked risks are associated with natural disaster-related disruptions. Risk 18 experienced a decline in ranking due to its lower V score compared to R78. Although R73 had a higher V score than R18, its ranking was also lower because of its lesser NR value compared to both R18 and R78. Additionally, risks R22 (i.e., failure of information sharing) and R77 (i.e., disrupted transportation/logistical overload) are placed at an equal rank owing to their identical risk scores as listed in Table 4. Conversely, risk R27 (i.e., single sourcing risks) is positioned at rank 15, indicating it as the least critical during disruptions among the identified critical risks. This occurred because it received low scores for the U, NR, and D factors. Such definitive prioritization enables DMs to allocate both human and financial resources more strategically, while also considering the constraints of time.

5.2. Comparative analysis

This section measures the efficiency of the proposed approach by comparing its results with the traditional Risk Priority Number (RPN) and conventional MCDM techniques. More precisely, RPN scores are determined based on both the traditional criteria (O, D, and U) and five criteria introduced in this study (including V and NR). Then, the comparison of the proposed approach with several well-known FMEA-based MCDM techniques, including TOPSIS, Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), and MARCOS is presented. The findings of the above-mentioned techniques are offered in Table 12. To ensure a fair comparison, the weights of five risk factors derived from the BBWM are applied across all MCDM risk prioritizing techniques. Fig. 5 illustrates a side-by-side comparison between the proposed approach and other techniques, focusing on their ability to distinguish and align alternatives within decision-making processes.

The FMEA strives to identify as many potential hazards as possible within the current scope of evaluation and ranks them based on RPN score according to their severity, frequency, and detectability. The RPN value is extremely sensitive to minor changes of risk factors because it is derived from multiplying risk factors [37,38]. When focusing solely on the traditional RPN based on three criteria (O, D and U), where the RPN equals 60, risks R18, R73, and R78 were all assigned top priority as they have identical risk factor scores. Additionally, there are multiple instances where the same ranking is assigned to different risks. For example, the fourth rank has been assigned to R17, R71, and R74 and rank 11 to R22, R27, and R77. Despite R74 and R27 having unique risk factor values unlike the others, their overall score remained the same. Furthermore, risk R68 and R75 jointly received rank 7 although they have altered values for V and NR. This illustrates in Fig. 5a that the traditional RPN score does not account for the weight of the risk factors and simply multiplies these factors' values. It is inadequate for distinguishing between risk priorities. This score only identified eight distinct positions for the risks and must confuse DMs about which potential risks should be addressed with limited resources.

However, when the RPN calculation includes the five proposed risk factors (adding V and NR), the ranking dynamics change significantly. Only risk R78 being placed at the top. This modification to the factors immediately results in a more distinctive prioritization and moves from multiple risks sharing a single ranking to each risk having its own rank (see Fig. 5b). This represents an improvement over the traditional three-factor RPN score. Nevertheless, the RPN5 still neglects weights of risk factors and lacks precision in separation, as evidenced by ranks 8 and 11 being shared by risks R68 and R75 (with the same but altered values of V and NR) and R22 and R77 (with exactly the same factor score), respectively. This indicates the limitations of the five-factor RPN score in clearly differentiating risk priorities.

The TOPSIS method evaluates and ranks alternatives effectively by seeking to maximize the distance from the worst condition and minimize the distance from the best one. This approach is easy to understand and communicate, which makes it attractive for

Table 12
Comparative analysis of the proposed approach with conventional MCDM techniques.

Approaches	RPN3		RPN5		TOPSIS		MOORA		MARCOS		Proposed Approach	
Critical Risks	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	18	14	216	13	0.30	14	0.222	14	0.57	14	1.292	14
R7	15	15	180	15	0.61	2	0.259	6	0.66	6	1.845	10
R17	36	4	432	7	0.51	6	0.256	7	0.66	6	1.950	8
R18	60	1	720	2	0.56	4	0.272	2	0.70	2	2.472	2
R22	24	11	288	11	0.47	10	0.246	11	0.63	11	1.844	11
R27	24	11	192	14	0.25	15	0.215	15	0.55	15	1.245	15
R68	32	7	384	8	0.50	7	0.254	8	0.65	8	1.951	7
R71	36	4	576	4	0.59	3	0.271	4	0.69	4	2.153	5
R73	60	1	600	3	0.54	5	0.272	2	0.70	2	2.315	3
R74	36	4	360	10	0.40	13	0.240	13	0.62	13	1.631	13
R75	32	7	384	8	0.50	7	0.254	8	0.65	8	2.232	4
R77	24	11	288	11	0.47	10	0.246	11	0.63	11	1.844	11
R78	60	1	900	1	0.63	1	0.287	1	0.74	1	2.751	1
R79	27	10	540	5	0.49	9	0.263	5	0.68	5	1.881	9
R80	30	9	450	6	0.44	12	0.254	8	0.65	8	2.094	6
RBSCC	–		–		0.5607		0.8268		0.8250		0.8732	

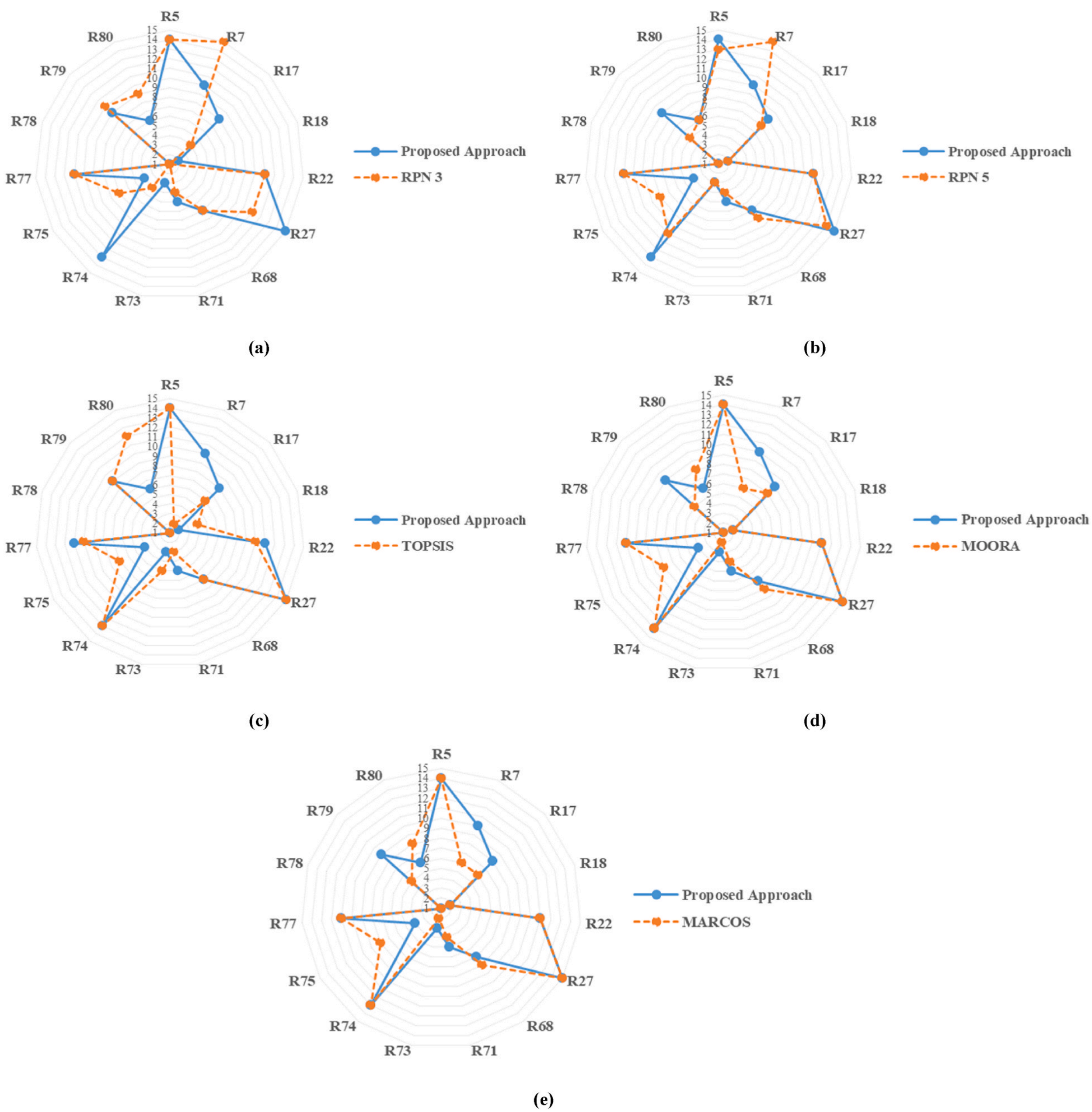

Fig. 5. Comparative analysis of separability of the proposed approach with (a) RPN3 (b) RPN5 (c) TOPSIS (d) MOORA (e) MARCOS.

organizations [12,25]. The TOPSIS method shown in Fig. 5c features two sets of tied rankings with the same factor values: R22 and R77 both ranked at the tenth position, and risk R68 and R75 ranked at the seventh. Furthermore, whereas risk R79 and R80 are ranked fifth and sixth, respectively, based on the traditional RPN5 method, they drop to ninth and twelfth place in the TOPSIS ranking both have low values of U. In contrast, risk R7 which ranked 15 according to RPN5, improved to second place attributed to possessing maximum U value in the ranking obtained through TOPSIS. To enhance risk prioritization clarity, researchers often have sought to refine and expand the FMEA methodology using MCDM techniques [81]. However, many of these attempts have struggled to maintain the practical applicability of the traditional FMEA approach. A method that maintains realistic changes and improves the differentiation between risk priorities would be considered effective. The RPN-Based Spearman Correlation Coefficient (RBSCC) can be used to assess this, with the rankings of the five MCDM methods presented in Table 12 indicating a higher level of distinction compared to the traditional FMEA technique. This table exhibits the lowest RBSCC value at 0.5607 when compared with the outcomes of other MCDM methods, indicating its comparatively lower performance.

In contrast, MOORA method sets itself apart by applying a ratio system to evaluate alternatives across multiple criteria [82]. It stands out as one of the most user-friendly, characterized by its simple and clear computational procedures [83]. Utilizing MOORA as shown in Fig. 5d, risks R68, R75, and R80 receive an equal ranking of eighth. Notably, R80 is distinguished by its lower U score compared to R68 and R75, yet it compensates with higher scores in the V and O factors. Furthermore, the MOORA method identifies two critical pairs of risks sharing the same priority: R22 and R77, mirroring RPN5 rankings, and a new pair, R18 and R73, at the second position. A notable change includes risk R7 ascending from the fifteenth to the sixth position and R80 descending to the eighth position attributed to the same underlying reason as in TOPSIS. The MOORA method achieves an RBSCC of 0.8268, which indicates superior stable performance sensitivity compared to TOPSIS.

Following that, the MARCOS method ranks alternatives by measuring their proximity to an ideal solution and considering both beneficial and non-beneficial criteria [30]. It is particularly effective and stable compared to other MCDM methods for analyzing large datasets. These include the use of reference points (such as ideal and anti-ideal values) and the ability to measure the utility degrees of each alternative in relation to both extremes [84]. MARCOS demonstrates a commendable RBSCC of 0.8250 and though identifies three sets of risks with equal priority rankings: R7 and R17 at sixth, R68 and R80 at eighth, and R22 and R77 at eleventh positions. It also indicates the priority shift of risk R7 to sixth and R80 to eighth from the RPN5 ranking for the same factor as MOORA and TOPSIS (see Fig. 5e).

The proposed approach is one of the least sensitive to change and offers an RBSCC of 0.87. This implies that its outcomes not only provide clearer differentiation among risk priorities but also enhance the reliability of the results. This improvement is attributed to its high consistency with the principles of the FMEA technique. Notably, risks R68 and R75, which were tied for eighth place according to traditional RPN5 scores, have been elevated to the seventh and fourth positions, respectively. R68 is adversely affected due to its lower value in factor V, its ranking fell due to the significant impact of the high weight of V. In contrast, R75, despite its lower NR value, advances to the fourth rank, as the impact of NR weighting is less pronounced. Additionally, risks R7 and R79 have been distinctly repositioned to the tenth (up from fifteenth) and ninth (down from fifth) positions, respectively, according to the high and low values of U. It is observed that across all provided rankings, risk R78 consistently maintains the highest priority ranking. Apart from TOPSIS, all methods demonstrate notably higher RBSCC values when compared to the risk priorities established by the FMEA method with the proposed five risk factors.

5.3. Sensitivity analysis

The following section conducts a sensitivity analysis to investigate the efficacy of the proposed approach when subjected to changes in the weights of risk factors. Each risk factor undergoes evaluation across five distinct scenarios with incremental weight adjustments of 0.1, 0.15, 0.20, 0.25, and 0.3, respectively, offset by corresponding decreases in other factors by 0.025, 0.0375, 0.05, 0.0625, and 0.075. Table 13 illustrates the configuration of the defined 25 scenarios.

Focusing on the most important risk factor (i.e., factor U), the analysis revealed a noticeable decline in the Spearman Correlation Coefficient (SCC) from 0.9429 to 0.7964, as shown in Table 14. This indicates a significant sensitivity to the risk factor U, particularly

Table 13
Analyzing sensitivity of the influence of weight change on risk priorities through defined scenarios.

Scenarios	Risk factor	Increment of weight	Decrement of weight in rest	Weights of risk factors				
				O	D	U	V	NR
Original	–	–	–	0.1204	0.0956	0.3442	0.2545	0.1852
Scenario 1	U	0.1	0.025	0.0954	0.0706	**0.4442**	0.2295	0.1602
Scenario 2		0.15	0.0375	0.0829	0.0581	**0.4942**	0.2170	0.1477
Scenario 3		0.2	0.05	0.0704	0.0456	**0.5442**	0.2045	0.1352
Scenario 4		0.25	0.0625	0.0579	0.0331	**0.5942**	0.1920	0.1227
Scenario 5		0.3	0.075	0.0454	0.0206	**0.6442**	0.1795	0.1102
Scenario 6	V	0.1	0.025	0.0954	0.0706	0.3192	**0.3545**	0.1602
Scenario 7		0.15	0.0375	0.0829	0.0581	0.3067	**0.4045**	0.1477
Scenario 8		0.2	0.05	0.0704	0.0456	0.2942	**0.4545**	0.1352
Scenario 9		0.25	0.0625	0.0579	0.0331	0.2817	**0.5045**	0.1227
Scenario 10		0.3	0.075	0.0454	0.0206	0.2692	**0.5545**	0.1102
Scenario 11	NR	0.1	0.025	0.0954	0.0706	0.3192	0.2295	**0.2852**
Scenario 12		0.15	0.0375	0.0829	0.0581	0.3067	0.2170	**0.3352**
Scenario 13		0.2	0.05	0.0704	0.0456	0.2942	0.2045	**0.3852**
Scenario 14		0.25	0.0625	0.0579	0.0331	0.2817	0.1920	**0.4352**
Scenario 15		0.3	0.075	0.0454	0.0206	0.2692	0.1795	**0.4852**
Scenario 16	O	0.1	0.025	**0.2204**	0.0706	0.3192	0.2295	0.1602
Scenario 17		0.15	0.0375	**0.2704**	0.0581	0.3067	0.2170	0.1477
Scenario 18		0.2	0.05	**0.3204**	0.0456	0.2942	0.2045	0.1352
Scenario 19		0.25	0.0625	**0.3704**	0.0331	0.2817	0.1920	0.1227
Scenario 20		0.3	0.075	**0.4204**	0.0206	0.2692	0.1795	0.1102
Scenario 21	D	0.1	0.025	0.0954	**0.1956**	0.3192	0.2295	0.1602
Scenario 22		0.15	0.0375	0.0829	**0.2456**	0.3067	0.2170	0.1477
Scenario 23		0.2	0.05	0.0704	**0.2956**	0.2942	0.2045	0.1352
Scenario 24		0.25	0.0625	0.0579	**0.3456**	0.2817	0.1920	0.1227
Scenario 25		0.3	0.075	0.0454	**0.3956**	0.2692	0.1795	0.1102

Table 14
Re-evaluating risk priorities with sensitivity analysis for risk factor U.

Critical Risks	Original		Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	1.2917	14	1.3085	14	1.3184	14	1.3267	14	1.3370	14	1.3505	14
R7	1.8451	10	2.1816	6	2.3977	5	2.6558	3	2.9779	2	3.3927	2
R17	1.9496	8	2.0926	8	2.1877	7	2.3010	7	2.4455	7	2.6352	7
R18	2.4720	2	2.5995	2	2.6852	2	2.7865	2	2.9168	3	3.0894	3
R22	1.8436	11	2.0035	10	2.1087	10	2.2335	9	2.3915	9	2.5976	9
R27	1.2447	15	1.2512	15	1.2545	15	1.2545	15	1.2544	15	1.2542	15
R68	1.9514	7	2.0886	9	2.1798	8	2.2883	8	2.4265	8	2.6083	8
R71	2.1532	5	2.2931	5	2.3871	6	2.4997	6	2.6442	6	2.8352	6
R73	2.3149	3	2.4430	3	2.5304	3	2.6352	4	2.7709	4	2.9516	5
R74	1.6315	13	1.6306	13	1.6310	13	1.6285	13	1.6271	13	1.6273	13
R75	2.2324	4	2.3897	4	2.4929	4	2.6143	5	2.7679	5	2.9684	4
R77	1.8436	11	2.0035	10	2.1087	10	2.2335	9	2.3915	9	2.5976	9
R78	2.7508	1	2.8860	1	2.9778	1	3.0868	1	3.2278	1	3.4154	1
R79	1.8807	9	1.8873	12	1.8935	12	1.8988	12	1.9082	12	1.9236	12
R80	2.0942	6	2.1039	7	2.1109	9	2.1151	11	2.1221	11	2.1334	11
SCC	–		0.9429		0.9143		0.8000		0.7964		0.7964	

in Scenario 5 (see Fig. 6a). U originally has the highest weight and its increment notably diminished the impact of the rest of the risk factors in the risk prioritization process. Further examination highlighted that risk R80 (i.e., disruptions to IT systems) dropped from sixth to the eleventh priority due to having a low value of U. Despite the risk of single sourcing (R27) possessing decent values in risk factors O and V, an increase in weight of U caused its priority to drop to the eleventh position for its low values of U as well. Conversely, risk R7 (i.e., financial strain) ascended to the second priority in Scenario 5 attributed to its high value of U and marked a significant shift from its tenth position in the original ranking.

When examining risk factor V, as the second most weighted factor, in Scenarios 6 to 10, the SCC index exhibited a minor decline from 0.9393 to 0.8286, demonstrating a less sensitivity of risk prioritization on factor V compared to the factor U (see Table 15 and Fig. 6b). This observation was further demonstrated by risk R68 (i.e., natural resource exploitation) with a low value of V. It demoted from seventh to the thirteenth priority despite its strong values in factors O, U, and NR. The risk of supplier inaccessibility and production halts (R74), however, climbed to the thirteenth priority in Scenario 5. It benefited from its highest value in factor V, contrary to its initial eighth-ranking position.

Focusing on risk factor NR in scenarios 11 to 15, the SCC index dropped to 0.6964, marking the most drastic reduction across all factors (see Table A1). This dramatic alteration in SSC underscores the sensitivity of factor NR. Scenario 14 particularly showcased a significant shift in the SCC. With risk R78 maintains its top rank across all scenarios except for Scenario 15 (see Fig. 6c). However, it shifted to R71 (i.e., geopolitical trade disruptions) because it has a higher NR value. Another notable change was observed in risk R73 (i.e., increased demand for certain goods) because of an insignificant value of NR, which moved from the third to the twelfth position.

The analysis of the increase in weight of risk factor O through scenarios 16 to 20 indicated relative stability in the SCC index. It has only minor shifts in risk priorities observed in Table A2. Here, the highest reduction in the SCC to 0.9071 suggests O has the best overall stability amongst risk factors. In Scenario 20 shown in Fig. 6d, risk R74 improved from the thirteenth to the ninth position due to the high value of O. While risk R79 (i.e., damage to production facilities) experienced a decline from the ninth to the thirteenth attributed to its lower score.

Lastly, Scenarios 21 to 25 addressing the change in weight of factor D (see Table A3) displayed the favorable constancy in the SCC after factor O. Moreover, Scenarios 22 and 23 show no change in the SCC index despite a 0.05 increase in the weight of factor D. However, one notable shift involves risk R74 climbing from rank 12 to 9 between Scenarios 23 and 25 (see Fig. 6e) for an insignificant value of D. This pattern underscores a subtle response to the increase of weight of factor D. As it is the least impactful, its adjustment shows minimal sensitivity significance compared to other factors.

6. Practical and managerial implications

This research introduces a decision support system to help managers prioritize and mitigate disruption risks and enhance SC resilience against unexpected disruptions. The proposed systematic framework shown in Fig. 7 ensures a thorough assessment and prioritization of potential risks. It also guides managers in taking strategic, data-driven steps to mitigate the most critical risks. The developed system integrates BBWM, FCM clustering, the CoCoSo approaches to redefine risk management and navigate the complexities of modern SCs. These approaches are employed to cover different dimensions of a disruption risk management problem, including identifying, assessing, prioritizing, and mitigating risks. Since the risk factors have their inherent effects on the criticality degree of disruption risks. This study employs BBWM to enable partitioners to apply the weight of multiple risk factors considering different scenarios, which enhances the separability of the ranking process. The multinomial distribution and Dirichlet distribution embedded in this technique provide a consolidated final distribution that reflects the collective preferences of all DMs involved or situations that happened. Additionally, the confidence measure of criteria dominance with the credal ranking system indicates the certainty of the relationships between risk factor pairs. Thereby, this would significantly improve the accuracy the weights of risk

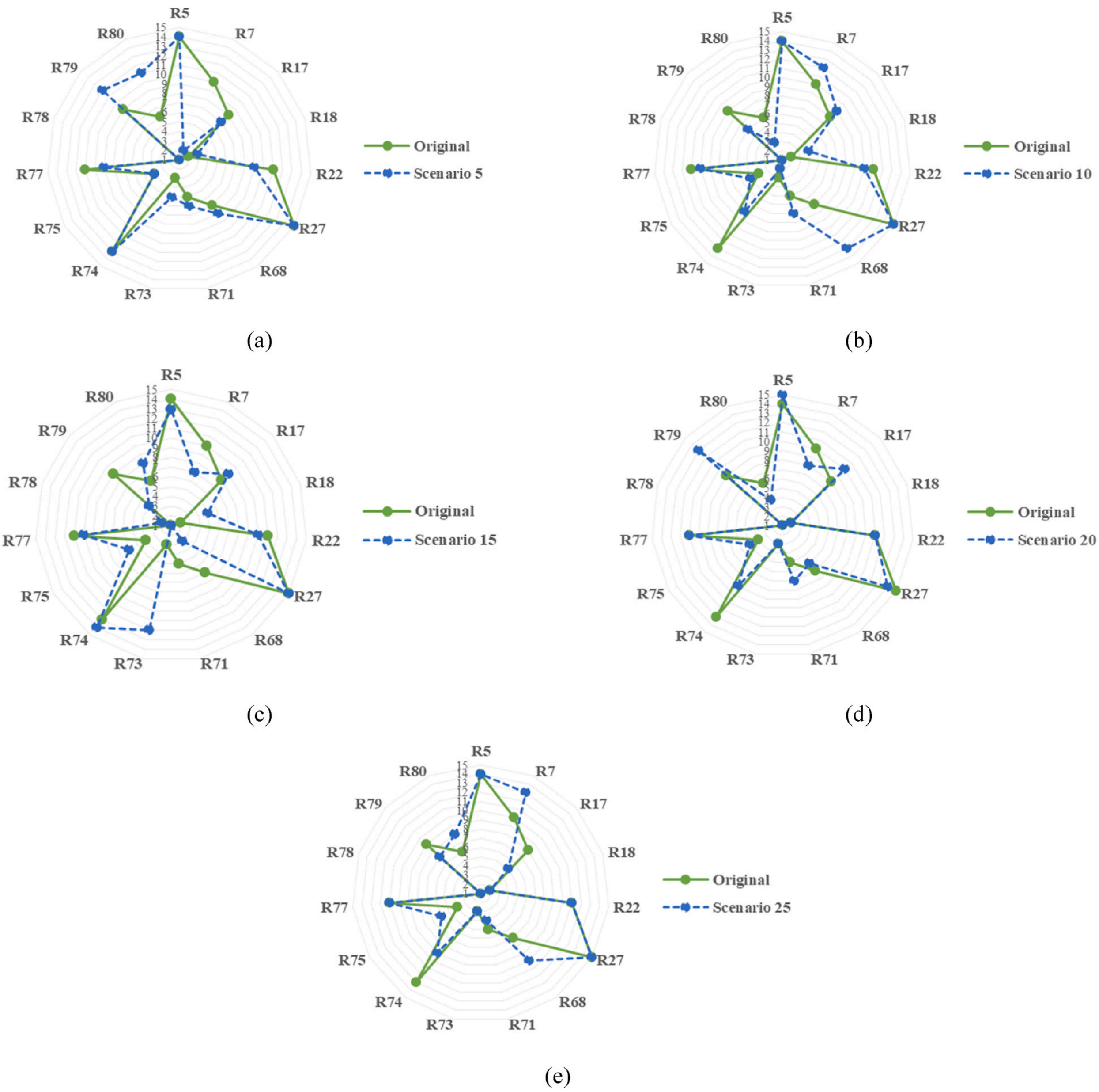

Fig. 6. Changes in risk ranking from original in considered maximum increase in weight of the risk factors: (a) U (b) V (c) NR (d) O (e) D.

factors by integrating the probabilistic sense of managers. By systematically weighing risk factors, the framework also allows managers to recognize the most significant risks based on their potential impact.

Dealing with multiple disruption risks simultaneously is not efficient due to resource limitations. Therefore, this study adopts the FCM clustering algorithm to find a list of risks with a high criticality degree before starting the prioritization stage. This technique assigns data points to multiple clusters and thus improves managers' ability to handle overlapping datasets. SC managers can more accurately model real-world complexities where relationships and characteristics often overlap and are not distinctly separable. Following the weighting process, the FCM clustering identifies critical clusters of risks, focusing on weighted risk factors most significantly. The risk clustering stage embedded in the risk assessment process helps managers prioritize the identified risks reliably in the next stage. This clustering not only clarifies which risks are connected but also highlights critical areas that might need immediate attention.

The proposed decision support system empowers DMs to effectively manage uncertainty by shifting organizational priorities through the CoCoSo technique in the prioritization stage. The CoCoSo prioritization helps in focusing resources and efforts on areas that pose the greatest threat to SC stability. More precisely, managers can proactively plan and respond to potential disruptions. It ensures investment in mitigation efforts is directed towards areas with the highest return on operational continuity. As shown in Fig. 7,

Table 15
Re-evaluating risk priorities with sensitivity analysis for risk factor V.

Critical Risks	Original		Scenario 6		Scenario 7		Scenario 8		Scenario 9		Scenario 10	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	1.2917	14	1.2832	14	1.2796	14	1.2762	14	1.2732	14	1.3209	14
R7	1.8451	10	1.7647	12	1.7294	11	1.6968	12	1.6667	12	1.7253	12
R17	1.9496	8	1.8641	8	1.8267	8	1.7924	8	1.7606	8	1.8029	9
R18	2.4720	2	2.3260	2	2.2621	3	2.2032	3	2.1488	3	2.1770	4
R22	1.8436	11	1.7912	9	1.7686	9	1.7481	9	1.7294	9	1.7825	10
R27	1.2447	15	1.2417	15	1.2404	15	1.2392	15	1.2382	15	1.2833	15
R68	1.9514	7	1.7877	11	1.7167	12	1.6517	13	1.5919	13	1.5786	13
R71	2.1532	5	2.0281	6	1.9732	6	1.9224	6	1.8753	7	1.9109	7
R73	2.3149	3	2.2794	3	2.2644	2	2.2509	2	2.2385	2	2.3368	2
R74	1.6315	13	1.6743	13	1.6935	13	1.7115	11	1.7283	11	1.8306	8
R75	2.2324	4	2.1544	4	2.1209	4	2.0905	5	2.0628	5	2.1117	5
R77	1.8436	11	1.7912	9	1.7686	9	1.7481	9	1.7294	9	1.7825	10
R78	2.7508	1	2.6847	1	2.6566	1	2.6312	1	2.6080	1	2.7051	1
R79	1.8807	9	1.8783	7	1.8775	7	1.8769	7	1.8764	6	1.9746	6
R80	2.0942	6	2.1046	5	2.1100	5	2.1154	4	2.1209	4	2.2233	3
SCC	–		0.9393		0.9250		0.8857		0.8714		0.8286	

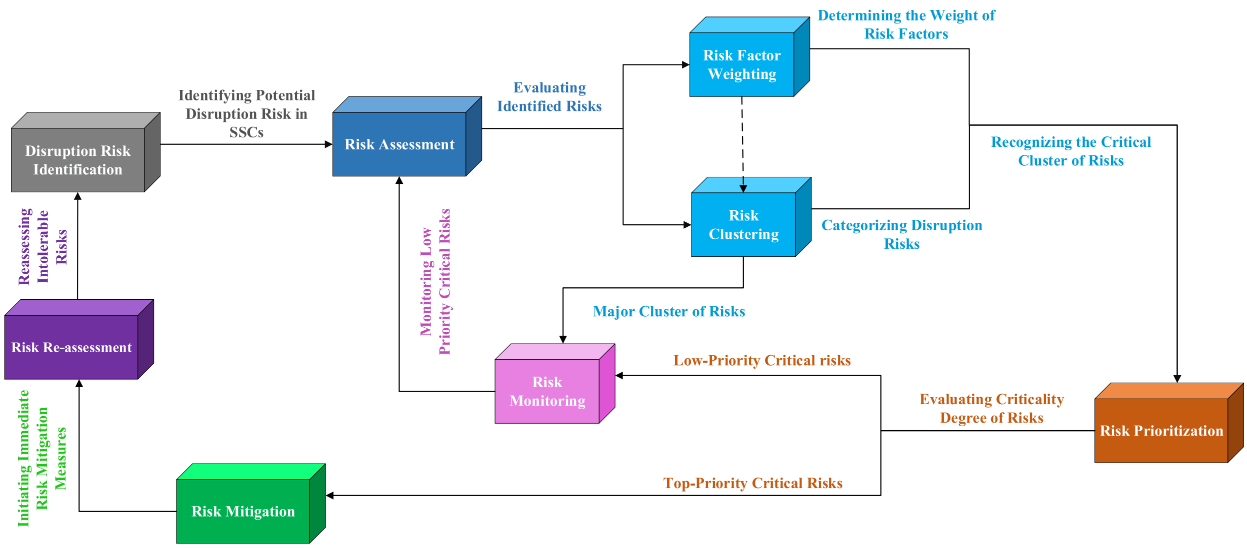

Fig. 7. The structured framework for managing disruption risk in SSCs.

the proposed framework is also adaptable to changing market and operational conditions, which allows managers to reassess risks and reprioritize actions as new information becomes available or as the business environment evolves.

Focusing on the risk mitigation phase, this study suggests actionable strategies to mitigate critical disruption risks by merging diverse disciplines and data-driven techniques. SC managers are encouraged to adopt advanced information systems (e.g., blockchain technology and IoT) and Industry 4.0 principles to streamline operations and mitigate the bullwhip effect through digitized systems. For instance, communication network disruptions could be mitigated by adopting blockchain technology. Since it enhances resilience and transparency and maintains visibility and prevents breakdowns [85]. Moreover, with comprehensive security policies and procedures for industrial control systems, managers can improve network integrity. It would maintain accurate asset inventories and preserve market share and brand value. More precisely, the integration of Internet of Things (IoT) devices can revolutionize inventory management by providing real-time visibility and control, which facilitates immediate responses to shifts within the SSC [57]. Furthermore, the system emphasizes the necessity for proactive financial planning to handle inflationary pressures. Therefore, companies actively manage cost variability and safeguard their competitive position. It encourages to endure economic shocks and sustain their market presence [86,87]. This can guide managers to view resource allocation not merely as a cost but as a long-term strategic investment.

Additionally, in response to increased demand for goods, it can improve production flexibility for accurate replenishment. Besides, partitioners are advised to refine procurement processes through standard operating procedures. It emphasizes speed, cost-efficiency, and quality, and adopts advanced logistics and traceability technologies [51]. Operational resilience requires a commitment to continual improvement and open communication across the SCs. With operational challenges like equipment failure, the system could recommend regular maintenance schedules and the adoption of agile methodologies [88]. Managers should advocate for strict adherence to environmental regulations and the implementation of emerging technologies that contribute to the longevity of the ecosystem. Therefore, the identified risk factors (e.g., V and NR) proposed in this approach enhance managerial understanding and preparedness. Hence, the insights provide valuable guidance for managers and shape policies in uncertain environments to create a sustainable, secure, and resilient SC.

7. Conclusions

SC networks should remain alert to potential disruption risks to maintain their operational continuity and sustainability. To manage the potential risks affecting the resilience and sustainability of SCs, this research has proposed a decision support system integrating BBWM, FCM, and CoCoSo methods to address the DRM within SSC networks. After identifying potential disruption risks, the proposed system uses the BBWM to determine the weight of conventional risk factors (O, D, and U), while also incorporating evaluations of V and NR factors within the risk assessment process. Following this, the FCM clustering algorithm has organized risks into multiple clusters, leveraging weighted Euclidean distances to determine the most critical cluster. Finally, the CoCoSo method has ranked the top critical risks to help managers develop more effective mitigation strategies. The findings have implied that communication network disruptions, failure in production facilities due to operational challenges, and increased demand for certain goods (e.g., building materials, medical supplies, or food) are the most critical risks. The outcomes have also shown that the proposed decision support system prioritizes risks more precisely compared to the traditional RPN scores and conventional MCDM methods. More precisely, this system would allow DMs to achieve better risk separability and more accurate prioritization. This would enable industries to promptly make informed decisions and implement targeted interventions to address the most critical challenges and minimize the impact of disruptions. This, in turn, yields insights that can assist SC managers and practitioners in evaluating their SCs' vulnerability and preparedness for present and upcoming disruptions.

The current study has primarily focused on assessing disruption risks, but it is equally important to emphasize the risk mitigation process. Future research should incorporate predictive analytics, such as Bayesian belief networks, to evaluate the effectiveness of mitigation strategies for minimizing risk and facilitating quick adaptation and recovery during disruptions. Additionally, the generalizability of the results can be influenced by uncertainty and interactions among risks. To address probabilistic scenarios and provide an understanding of risks' behaviors, Z-number theory could be integrated with systems modeling techniques to assess and prioritize the potential risks.

CRediT authorship contribution statement

Oishwarjya Ferdous: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Visualization. **Samuel Yousefi:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Babak Mohamadpour Tosarkani:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A

Table A1
Re-evaluating risk priorities with sensitivity analysis for risk factor NR

Critical Risks	Original		Scenario 11		Scenario 12		Scenario 13		Scenario 14		Scenario 15	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	1.2917	14	1.4299	14	1.5193	14	1.6271	14	1.7605	13	1.9330	13
R7	1.8451	10	2.0394	10	2.1663	10	2.3207	10	2.5135	8	2.7643	7
R17	1.9496	8	2.1042	9	2.2046	9	2.3257	9	2.4758	9	2.6708	9
R18	2.4720	2	2.6152	2	2.7081	2	2.8198	3	2.9577	3	3.1376	5
R22	1.8436	11	2.0150	11	2.1254	11	2.2579	11	2.4216	10	2.6330	10
R27	1.2447	15	1.2626	15	1.2714	15	1.2789	15	1.2848	15	1.2906	15

(continued on next page)

Table A1 (*continued*)

Critical Risks	Original		Scenario 11		Scenario 12		Scenario 13		Scenario 14		Scenario 15	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R68	1.9514	7	2.2555	6	2.4476	5	2.6767	4	2.9574	4	3.3162	3
R71	2.1532	5	2.4589	3	2.6533	3	2.8860	2	3.1723	2	3.5395	1
R73	2.3149	3	2.3476	5	2.3680	6	2.3905	8	2.4166	12	2.4513	12
R74	1.6315	13	1.6425	13	1.6486	13	1.6539	13	1.6585	14	1.6647	14
R75	2.2324	4	2.4051	4	2.5155	4	2.6470	5	2.8083	6	3.0162	6
R77	1.8436	11	2.0150	11	2.1254	11	2.2579	11	2.4216	10	2.6330	10
R78	2.7508	1	2.9022	1	3.0013	1	3.1211	1	3.2699	1	3.4649	2
R79	1.8807	9	2.1603	8	2.3392	7	2.5544	6	2.8204	5	3.1627	4
R80	2.0942	6	2.2286	7	2.3165	8	2.4227	7	2.5546	7	2.7269	8
SCC	–		0.9786		0.9536		0.9000		0.7679		0.6964	

Table A2
Re-evaluating risk priorities with sensitivity analysis for factor O

Critical Risks	Original		Scenario 16		Scenario 17		Scenario 18		Scenario 19		Scenario 20	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	1.2917	14	1.2411	15	1.2458	15	1.2504	15	1.2550	15	1.2594	15
R7	1.8451	10	1.7785	11	1.8097	9	1.8465	9	1.8909	8	1.9456	8
R17	1.9496	8	1.8592	8	1.8677	8	1.8773	8	1.8884	9	1.9015	10
R18	2.4720	2	2.5685	2	2.7087	2	2.8729	2	3.0689	2	3.3081	2
R22	1.8436	11	1.7794	9	1.7977	10	1.8183	10	1.8419	10	1.8698	11
R27	1.2447	15	1.2863	14	1.3470	14	1.4193	14	1.5071	14	1.6156	14
R68	1.9514	7	1.9525	7	2.0181	7	2.0967	6	2.1927	6	2.3120	6
R71	2.1532	5	2.0387	6	2.0443	6	2.0509	7	2.0591	7	2.0695	7
R73	2.3149	3	2.4039	3	2.5430	3	2.7069	3	2.9035	3	3.1444	3
R74	1.6315	13	1.6225	13	1.6748	13	1.7385	13	1.8174	12	1.9166	9
R75	2.2324	4	2.2428	4	2.3187	5	2.4088	5	2.5176	5	2.6516	5
R77	1.8436	11	1.7794	9	1.7977	10	1.8183	10	1.8419	10	1.8698	11
R78	2.7508	1	2.8237	1	2.9654	1	3.1321	1	3.3319	1	3.5765	1
R79	1.8807	9	1.7573	12	1.7516	12	1.7458	12	1.7397	13	1.7335	13
R80	2.0942	6	2.2078	5	2.3462	4	2.5085	4	2.7024	4	2.9389	4
SCC	–		0.9607		0.9643		0.9571		0.9357		0.9071	

Table A3
Re-evaluating risk priorities with sensitivity analysis for factor D

Critical Risks	Original		Scenario 21		Scenario 22		Scenario 23		Scenario 24		Scenario 25	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
R5	1.2917	14	1.2815	14	1.2770	14	1.2728	14	1.2690	14	1.2655	14
R7	1.8451	10	1.6850	12	1.6156	13	1.5519	13	1.4934	13	1.4393	13
R17	1.9496	8	1.9896	6	2.0083	6	2.0261	6	2.0432	6	2.0597	5
R18	2.4720	2	2.4521	2	2.4445	2	2.4382	2	2.4329	2	2.4286	2
R22	1.8436	11	1.7896	10	1.7663	10	1.7451	10	1.7258	11	1.7080	11
R27	1.2447	15	1.2400	15	1.2378	15	1.2359	15	1.2341	15	1.2324	15
R68	1.9514	7	1.8685	9	1.8322	9	1.7989	9	1.7681	9	1.7396	10
R71	2.1532	5	2.1534	4	2.1543	4	2.1557	4	2.1574	4	2.1594	4
R73	2.3149	3	2.2804	3	2.2658	3	2.2528	3	2.2409	3	2.2302	3
R74	1.6315	13	1.6751	13	1.6947	12	1.7130	12	1.7301	10	1.7463	9
R75	2.2324	4	2.1531	5	2.1191	5	2.0882	5	2.0600	5	2.0342	6
R77	1.8436	11	1.7896	10	1.7663	10	1.7451	10	1.7258	11	1.7080	11
R78	2.7508	1	2.6859	1	2.6584	1	2.6336	1	2.6111	1	2.5906	1
R79	1.8807	9	1.8790	8	1.8786	8	1.8783	8	1.8781	7	1.8781	7
R80	2.0942	6	1.9784	7	1.9275	7	1.8804	7	1.836722	8	1.7960	8
SCC	–		0.9679		0.9571		0.9571		0.9357		0.9000	

Data availability

Data will be made available on request.

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