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Multi-criteria Resilient and Sustainable Supply Chain Network Redesign Under Uncertainty: A Hybrid Fuzzy Bounded Confidence Approach

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Abstract
Redesigning supply chain networks is a complex decision-making process requiring the balance of multiple, often conflicting criteria such as cost, resilience, flexibility, and sustainability. In today's dynamic supply chains—facing fluctuating demand, geopolitical risks, and transportation disruptions—traditional methods often fail to integrate diverse expert perspectives and manage heterogeneous data, including crisp, interval, and fuzzy evaluations. To address these limitations, this study proposes a novel multi-criteria group decision-making (MCGDM) approach that uses the bounded confidence model (BCM) with experts trust levels to effectively capture and structure the inputs during the decision-making process. Additionally, the Choquet integral—enhanced to consider uncertainty in the input evaluations—is applied for robust aggregation. To ensure a balanced and consensus-driven ranking of redesign alternatives, the combined compromise for ideal solution (CoCoFISo) method is employed. The evaluation criteria are structured into core functional domains such as logistics, procurement, and operations, enabling subject-matter experts to contribute domain-specific insights and thereby enhancing decision reliability. Finally, a simple illustrative numerical example validates the effectiveness of the proposed approach, demonstrating its capacity to support collaborative and data-driven decision-making in dynamic supply chain environments. This research advances the field of MCGDM methodologies and offers practical guidance for strategic supply chain network redesign under uncertainty.

Keywords Multi-criteria · Group decision-making · Consensus · Bounded confidence model · Uncertainty · Supply chain

Context and Motivations

As efficiency becomes a primary focus in modern supply chains, redesigning supply chain networks has evolved into a complex, collaborative process. Key decisions including network redesign, facility relocation, distribution optimization, technology adoption, and logistics planning necessitate input from multiple stakeholders with diverse priorities. These challenges often lead to multi-criteria group decision-making (MCGDM) problems, requiring a careful balance between qualitative and quantitative factors. A well-executed redesign must optimize cost efficiency, enhance operational resilience, and incorporate environmental considerations while ensuring stakeholder alignment in an increasingly dynamic and uncertain supply chain environment. *However, existing studies often overlook the dynamic interplay between stakeholder preferences, sustainability concerns, and real-time adaptability in volatile markets. Further research is needed to develop holistic decision-making models that simultaneously integrate these factors while maintaining computational feasibility and practical applicability.*

The integration of supply chain network redesign into strategic decision-making is essential for improving operational performance, mitigating risks, and enhancing supply chain agility. This necessitates the use of advanced multi-criteria decision-making (MCDM) frameworks, which enable organizations to evaluate, rank, and refine supply chain configurations while accounting for logistical constraints and market dynamics. Effective redesign strategies contribute to risk management by diversifying suppliers,

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optimizing transportation flows, and streamlining inventory distribution (Tang 2006). A comprehensive decision support system is crucial for balancing trade-offs between cost-effectiveness, resilience, and service reliability, thereby allowing companies to develop adaptive and responsive supply chain structures (Ivanov 2018). Notably, Torkayesh et al. (2021) proposed a combined BWM-LBWA-CoCoSo framework for evaluating the European healthcare system, highlighting the increasing recognition of CoCoSo within the decision-making community. *Despite its effectiveness, the applicability of CoCoSo in complex, multi-tier supply chains remains underexplored. Future research should examine its robustness in real-time decision-making environments and its integration with predictive analytics to enhance forecasting accuracy and responsiveness.*

To address these complexities, researchers have developed various decision support methodologies, including multi-criteria decision analysis (MCDA), fuzzy logic, game theory, and multi-agent systems. These approaches are particularly valuable in MCGDM scenarios, where stakeholders with varying objectives and risk preferences must collaborate to reach a consensus under uncertainty. Among recent advancements, the combined compromise solution (CoCoSo) method has proven effective in synthesizing expert opinions and optimizing supply chain configurations by evaluating multiple performance criteria (Yazdani et al. 2019a, b). The essence of this method lies in its ability to integrate multiple compromise perspectives, enabling the final solution to balance conflicting criteria effectively. Despite being a relatively recent method, it has proven to be applicable in the areas such as supplier selection (Zolfani et al. 2019) and the evaluation of electric vehicles (Biswas et al. 2019). Additionally, several extensions of CoCoSo have been proposed to enhance its versatility. For instance, Yazdani et al. (2019b) used grey CoCoSo (CoCoSo-G) to solve the problem of supplier selection, and Peng et al. (2020) introduced a Pythagorean fuzzy MCDM model that integrates CoCoSo with the CRITIC method using a score function. Wen et al. (2020) proposed a hesitant fuzzy linguistic CoCoSo approach, enhancing its suitability for complex decision-making scenarios. Neutrosophic CoCoSo has been identified as an effective technique for selecting waste disposal sites (Karasan and Bolturk 2019). To optimize stock management costs, Erceg et al. (2019) introduced a model based on the Interval Rough CoCoSo method. Wen et al. (2019a) developed the probabilistic linguistic SWARA-CoCoSo model to support clinical decision-making. In the field of logistics, researchers have extended the CoCoSo method incorporating hesitant fuzzy linguistic numbers as a tool convenient for making proper decisions and choices (Wen et al. 2019b). Furthermore, the emergence of novel CoCoSo extensions, such as the combined compromise for ideal solution (CoCoFISo) method, has further enhanced decision-making capabilities by incorporating sophisticated ranking strategies. These innovations make CoCoSo-based approaches particularly suitable for allocating students (Rasoanaivo et al. 2024). *However, research remains limited on how these extensions perform under highly uncertain conditions, such as supply chain disruptions or rapid shifts in demand patterns. Further investigation is required to assess their stability, computational efficiency, and ability to support real-time adaptive decision-making.* By integrating these advanced methodologies, organizations can establish structured, consensus-oriented frameworks that enhance supply chain resilience, flexibility, and overall operational performance.

This research work addresses the complexities of MCGDM in supply chain network redesign, where decision-makers must evaluate multiple, often conflicting criteria to determine efficient and resilient network configurations. Modern supply chains operate in volatile environments affected by fluctuating demand, geopolitical risks, transportation disruptions, and supplier uncertainties. Traditional decision-making approaches often struggle to accommodate diverse stakeholder opinions and heterogeneous evaluation data, including crisp numerical values, interval judgments, and fuzzy assessments. To tackle these challenges, this study makes the following key contributions:

- It proposes a framework for supply chain network redesign that balances cost efficiency, resilience, and adaptability while effectively handling conflicting criteria.
- The approach integrates fuzzy assessments and expert trust levels using the bounded confidence model to accurately capture and structure diverse stakeholder opinions.
- It combines an enhanced Choquet integral with the CoCoFISo method to aggregate uncertain evaluations and rank alternatives, enabling balanced and well-informed decision-making.
- The methodology supports risk mitigation, improves supply chain flexibility, and facilitates data-driven strategic decisions in volatile and uncertain environments.

The rest of the paper is structured as follows: The "Related Works" section reviews some related works. The "Problem Description" section shows the problem under consideration. The "Theoretical Background" section outlines some theoretical backgrounds. The "Proposed Approach" section introduces and explains the proposed approach. The "Illustrative Numerical Example" section presents the experimental results through an illustrative numerical example involving resource efficiency program selection. Finally, the "Conclusion and Future Works" section concludes the paper with some future work directions.

Related Works

Effective supply chain redesign necessitates a balanced integration of consensus-based MCDM methodologies to address the growing complexity of modern supply chains. Redesign efforts must holistically evaluate cost efficiency, sustainability, resilience, and operational performance while simultaneously accommodating the diverse and sometimes conflicting interests of multiple stakeholders. Traditional MCDM techniques such as the analytic hierarchy process (AHP), technique for order preference by similarity to ideal solution (TOPSIS), and weighted sum model (WSM) play a critical role in structuring decision problems by systematically prioritizing economic, environmental, and logistical factors. However, as supply chains become more dynamic and data-driven, emerging aggregation operators, including combined compromise solution (CoCoSo), leverage advanced mathematical frameworks such as spherical fuzzy sets (SFS) and reliability measures to improve decision-making under uncertainty.

Consensus-based decision-making is particularly vital in supply chain redesign, ensuring that strategic decisions reflect collective stakeholder input and fostering collaboration through structured facilitation techniques or automated negotiation models. Despite recent advancements, several challenges persist, including the automation of consensus-reaching mechanisms, the empirical validation of novel aggregation techniques in real-world supply chain applications, and the seamless integration of circular economy principles into existing MCDM frameworks. Moreover, the need for robust sensitivity analysis methods to assess the stability of decision outcomes remains a crucial research gap. This review critically examines these developments, highlighting key methodologies, emerging trends, and unresolved challenges that warrant further investigation to enhance the effectiveness and adaptability of supply chain network redesign.

Supply Chain Network Redesign

The redesign of supply chain networks (SCNs) is essential for enhancing resilience, efficiency, and sustainability, particularly in response to disruptions such as pandemics, geopolitical instability, and climate-related crises. To effectively navigate these challenges, modern supply chains must adopt flexible and adaptive strategies that mitigate risks while optimizing costs, service levels, and environmental impact. Multi-criteria decision-making frameworks offer a systematic approach to evaluating redesign alternatives, ensuring a balanced consideration of key objectives, including operational robustness, cost efficiency, and sustainability (Mohammed et al. 2023).

A range of MCDM methodologies, such as the AHP, the TOPSIS, and the WSM, facilitate structured decision-making in SCN transformation. These techniques assist decision-makers in assessing trade-offs among various redesign strategies, including supplier diversification, facility relocation, and the adoption of digitalization initiatives (Ivanov and Dolgui 2020). The integration of artificial intelligence (AI) and data-driven decision support systems further enhances SCN redesign by providing predictive insights into potential disruptions and enabling real-time operational optimization (Moadab et al. 2023).

Key SCN redesign strategies involve relocating production closer to demand centers to reduce dependency on geographically distant suppliers, leveraging digital supply chain twins for predictive scenario analysis, and embedding circular economy principles to enhance sustainability (Shekarabi et al. 2024). AI-driven predictive analytics can proactively identify potential bottlenecks and dynamically adjust sourcing strategies in response to evolving risks. Additionally, blockchain technology is emerging as a transformative tool for improving supply chain transparency and traceability, ensuring compliance with sustainability standards and ethical sourcing regulations (Saberi et al. 2019). Moreover, to achieve a resilient and adaptive SCN, redesign strategies should integrate both quantitative and qualitative assessments, aligning resilience measures with long-term business objectives. Future research should prioritize the development of dynamic, real-time decision-making models capable of adapting to changing market conditions, regulatory frameworks, and emerging risks. The ongoing advancements in digitalization, automation, and advanced analytics will play a crucial role in shaping the next generation of resilient, agile, and sustainable supply chains (Dolgui and Ivanov 2020).

Consensus-Based Multi-criteria Group Decision-making

In group decision-making (GDM) scenarios, decision-makers (DMs) often hold divergent perspectives due to differences in expertise, priorities, and subjective judgments. Achieving a collective agreement on alternatives requires a structured consensus process that systematically aligns varying opinions toward a mutually acceptable decision. Traditionally, this iterative process is moderated by a facilitator who assesses consensus levels among DMs using predefined consensus measures, which quantify the degree of alignment. When consensus levels are insufficient, the facilitator encourages further discussion and negotiation to bridge opinion gaps. Conversely, once consensus reaches an acceptable threshold, the process transitions to the decision-selection phase, finalizing the agreed-upon solution within a multi-criteria decision-making framework.

A key challenge in GDM is automating the consensus-building process to reduce dependency on human facilitation while ensuring effective alignment among decision-makers. To address this, various automated consensus models have been developed, broadly classified into three categories: fuzzy preference models, linguistic preference models, and multiplicative priority models. These models structure diverse opinions, establish consensus thresholds, and facilitate automated decision support in uncertain environments. Several methodologies have been proposed to quantify and enhance consensus efficiency, each offering distinct advantages. For instance, Morente-Molinera et al. (2018) introduced a multi-granular linguistic approach that adapts to different levels of granularity in decision-making, minimizing the number of consensus iterations and improving overall efficiency. Similarly, Herrera-Viedma et al. (2014) developed a consensus model based on a 2-tuple fuzzy linguistic representation, enabling precise processing of linguistic assessments to evaluate agreement levels. In the context of large-scale decision-making, Meng et al. (2022) explored the role of trust in clustering and consensus-reaching processes, proposing a trust-constrained model that enhances decision quality by incorporating reliability measures. Furthermore, Wang et al. (2022) proposed an adaptive reinforcement learning-based algorithm to improve consensus efficiency in dynamic decision environments, ensuring greater flexibility and consistency in evolving decision contexts. Additionally, Lu et al. (2021) conducted a comparative study on consensus optimization, introducing a multi-stage framework that significantly enhances efficiency across diverse GDM applications.

The continuous advancement of these models is driving the automation of GDM processes, enabling the efficient management of complex decision scenarios characterized by uncertainty and diverse stakeholder inputs. These developments contribute to the evolution of more robust, scalable, and automated decision-making frameworks, enhancing not only supply chain network redesign but also a wide range of complex MCDM applications. Future research should focus on refining adaptive learning-based models, incorporating real-time feedback mechanisms, and developing hybrid approaches that integrate multiple preference modeling techniques to further improve consensus efficiency in dynamic decision-making environments.

Consensus-Based Multi-criteria Decision-making for Supply Chain Network Redesign

Multi-criteria decision-making methods play a pivotal role in optimizing supply chain network redesign by balancing cost efficiency, operational resilience, and adaptability. The redesign process involves strategic decisions such as facility location selection, transportation network redesign, supplier evaluation, and distribution optimization. Given the growing complexity and uncertainty of global supply chains, effective decision-making necessitates the integration of both quantitative and qualitative factors while accounting for the perspectives of multiple stakeholders. Consensus-building in such scenarios is crucial to ensure that redesign solutions align with business objectives, regulatory requirements, and market demands.

To address the inherent uncertainty in supply chain decisions, Zadeh (1965) introduced fuzzy sets (FSs), which have since become foundational in modeling imprecise and vague information in decision-making. Recent studies have demonstrated the effectiveness of the combined compromise solution (CoCoSo) method in optimizing supply chain structures. CoCoSo has received notable attention among the decision-making community. It obtained considerable citations among the research community, and it is implemented in many applications such as transport and logistics to circular economy and finance etc. Khan and Haleem (2021). Yazdani et al. (2019b) developed a grey interval extension of CoCoSo to evaluate the performance of construction suppliers. For instance, Yan et al. (2024) applied a spherical fuzzy CoCoSo method combined with the CRITIC weighting approach to enhance decision accuracy in electric vehicle charging station selection, illustrating its ability to manage complex multi-criteria evaluations. Similarly, Torkayesh et al. (2021) utilized CoCoSo to optimize logistics network efficiency by ranking potential distribution centers based on economic and environmental criteria, highlighting its capability to balance multiple conflicting objectives. Furthermore, Han et al. (2022) proposed a hybrid approach integrating CoCoSo with entropy weighting for supplier evaluation, demonstrating its robustness in assessing cost, sustainability, and reliability factors.

These applications underscore the increasing importance of advanced MCDM techniques in supply chain redesign, emphasizing the need for further research into integrating CoCoSo with AI-driven consensus mechanisms and real-time data analytics to enhance decision-making in dynamic supply chain environments. Recently, an extended version of the CoCoSo algorithm has been introduced to refine the weighting and ranking mechanisms, further improving decision-making accuracy in multi-criteria decision problems. Rasoanaivo et al. (2024) applied this enhanced model to a real-world case study, demonstrating its effectiveness in optimizing complex decision scenarios and benchmarking its performance against other MCDM approaches. Future research should explore the potential of hybrid MCDM models that incorporate machine learning and predictive analytics, enabling more adaptive and data-driven supply chain redesign strategies.

Research Gaps

Despite significant advancements in MCGDM scenarios, several critical research gaps remain. One major limitation is the reliance on human facilitators in consensus-building frameworks, particularly in complex and uncertain decision environments. While automated models have emerged, fully autonomous consensus mechanisms that can adapt in real-time to evolving decision dynamics remain underdeveloped. The absence of adaptive mechanisms that enable dynamic adjustments to sustainability challenges further restricts the responsiveness of existing MCGDM approaches. Additionally, although circular economy principles are widely acknowledged as essential for sustainable development, their integration with advanced MCDM techniques remains insufficient. This gap hinders the development of decision support systems that effectively balance economic, environmental, and social objectives by incorporating resource efficiency, waste minimization, and environmental impact reduction into the decision-making process.

Recent advancements in aggregation operators, such as the stepwise maximum aggregation-ordered weighted averaging (SMA-OWA), the simplified linguistic fuzzy correlation-influenced weighted aggregation (SLFCIWA), and spherical fuzzy set-based methods, have demonstrated potential in managing uncertainty and accommodating diverse expert opinions. However, these techniques require extensive empirical validation across various industrial applications to assess their reliability and practical effectiveness. Another significant challenge is the limited incorporation of stakeholder diversity in decision-making models. Many existing approaches assume stakeholder homogeneity, failing to account for conflicting priorities, varying levels of influence, and asymmetric information access. Addressing this gap is crucial for enhancing the inclusivity and fairness of group decision-making processes.

Furthermore, the lack of comprehensive comparative studies evaluating the performance of emerging MCDM approaches such as the CoCoSo method and advanced fuzzy aggregation techniques against well-established methods like the AHP and the TOPSIS hinders a clear understanding of their advantages and suitability for specific decision contexts. Future research should prioritize the development of hybrid decision support models that integrate artificial intelligence (AI), fuzzy logic, and optimization techniques to enhance the robustness, efficiency, and adaptability of MCGDM frameworks. Expanding the application of these models to critical domains such as supply chain resilience, renewable energy planning, and smart city development could provide valuable insights into their real-world effectiveness. Additionally, the integration of real-time data analytics and reinforcement learning in MCDM frameworks may further improve decision adaptability in dynamic environments. Addressing these research gaps is essential for advancing decision-making methodologies that align with the increasing complexity and uncertainty of modern decision contexts.

Problem Description

Redesigning a supply chain network to enhance resilience against disruptions such as pandemics, natural disasters, or geopolitical instability is a critical challenge for organizations. Modern supply chains are inherently complex systems that must balance multiple, often conflicting, objectives, including cost efficiency, reliability, flexibility, and sustainability. These networks operate in dynamic and uncertain environments, necessitating adaptive decision-making strategies that can systematically evaluate and optimize alternative configurations (Ivanov and Dolgui 2020).

The redesign process involves a multi-criteria decision-making framework, wherein a panel of decision-makers/experts assesses various redesign alternatives based on a diverse set of evaluation criteria. Specifically, K experts, denoted as E_s $(s = 1, \ldots, K)$, evaluate a set of m potential alternatives (i.e., supply chain configurations) denoted as A_i $(i = 1, \ldots, m)$. To enhance the structure and domain-specific relevance of the evaluation process, the experts are classified into L distinct groups, denoted as G_l $(l = 1, \ldots, L)$, where each group corresponds to a specific functional domain within the organization. The alternatives are assessed against n criteria, represented as C_{11},..., $C_{j_1 1}$ of group G_1, C_{12},..., $C_{j_2 2}$ of group G_2, ..., C_{1L},..., $C_{j_L L}$ of group G_L, where $\sum_{l=1}^{L} j_l = n$. This categorization ensures that subject-matter experts conduct targeted assessments, thereby improving the reliability and consistency of the decision-making process (Singh and Benyoucef 2012).

Given the diverse nature of the evaluation data ranging from crisp numerical values and percentage-based metrics to fuzzy assessments and interval-based judgments, the decision-making process requires a structured approach. To achieve coherence and comparability, the assessments are systematically organized into a structured matrix format, aligning with the organization's strategic goals and facilitating robust decision analysis.

Conventional decision-making techniques often struggle to account for the diverse perspectives of experts and the complexity of evaluation data, which can include precise numerical values, interval assessments, and fuzzy judgments. To address these challenges, this paper proposes an approach that assists a group of decision-makers/experts in ranking and selecting the optimal alternative from a set of potential alternatives. To capture and structure the inputs during the decision-making process, the bounded confidence model (BCM) with experts' trust levels is used (Li et al. 2022).

Additionally, the Choquet integral operator is employed for input aggregation with accounting for their uncertainty. Furthermore, the CoCoFISo method is applied to rank alternatives using a compromise-driven approach, promoting balanced and well-informed decision-making (Rasoanaivo et al. 2024). Figure 1 provides a global overview of the problem under consideration.

To facilitate the reader's understanding of the problem under consideration, let us consider three groups of experts, namely G_1, G_2, and G_3, each associated with two evaluation criteria. Group G_1 is responsible for criteria C_{11} and C_{21}, group G_2 for criteria C_{12} and C_{22}, and group G_3 for criteria C_{13} and C_{23}. The experts are in charge of evaluating five potential supply chain structures $A_i, i = 1 \ldots 5$, and ultimately select the best one. A detailed explanation of these criteria is provided in the "Illustrative Numerical Example" section, where a numerical example and experimental results illustrate the applicability and effectiveness of the proposed approach.

- **Group 1: "Logistics and Distribution Department":** This department evaluates the efficiency and effectiveness of the supply chain's distribution network. It focuses on optimizing transportation and delivery performance to ensure **cost efficiency, reliability, and timely order fulfillment**.
  - C_{11} = **Transportation Cost (TC):** Assesses the total expenses incurred in transporting goods across the supply chain, including fuel costs, labor, warehousing, and logistics fees. Optimizing transportation costs is crucial for maintaining a competitive and cost-effective supply chain.
  - C_{21} = **Delivery Time (DT):** Measures the speed and reliability of order fulfillment, considering factors such as transit time, order processing speed, and potential delays. Efficient delivery time ensures high customer satisfaction and operational efficiency.
- **Group 2: "Procurement and Supplier Management Department":** This department is responsible for evaluating and managing supplier relationships to ensure a stable, cost-effective, and risk-minimized procurement process. It emphasizes supplier performance, reliability, and compliance with industry standards.
  - C_{12} = **Supplier Reliability (SR):** Evaluates the supplier's ability to consistently meet demand requirements by delivering the correct quantity of goods on time, in full, and in accordance with agreed specifications. Key indicators include on-time delivery rates, lead time consistency, and order accuracy.
  - C_{22} = **Quality and Compliance (QC):** Ensures that suppliers meet required quality standards, regulatory requirements, and industry certifications (e.g., ISO 9001). This criterion helps minimize defects, improve customer satisfaction, and maintain operational integrity while ensuring legal compliance.
- **Group 3: "Operations and Sustainability Department":** This department focuses on operational adaptability and sustainability, ensuring that supply chain activities remain resilient, efficient, and environmentally

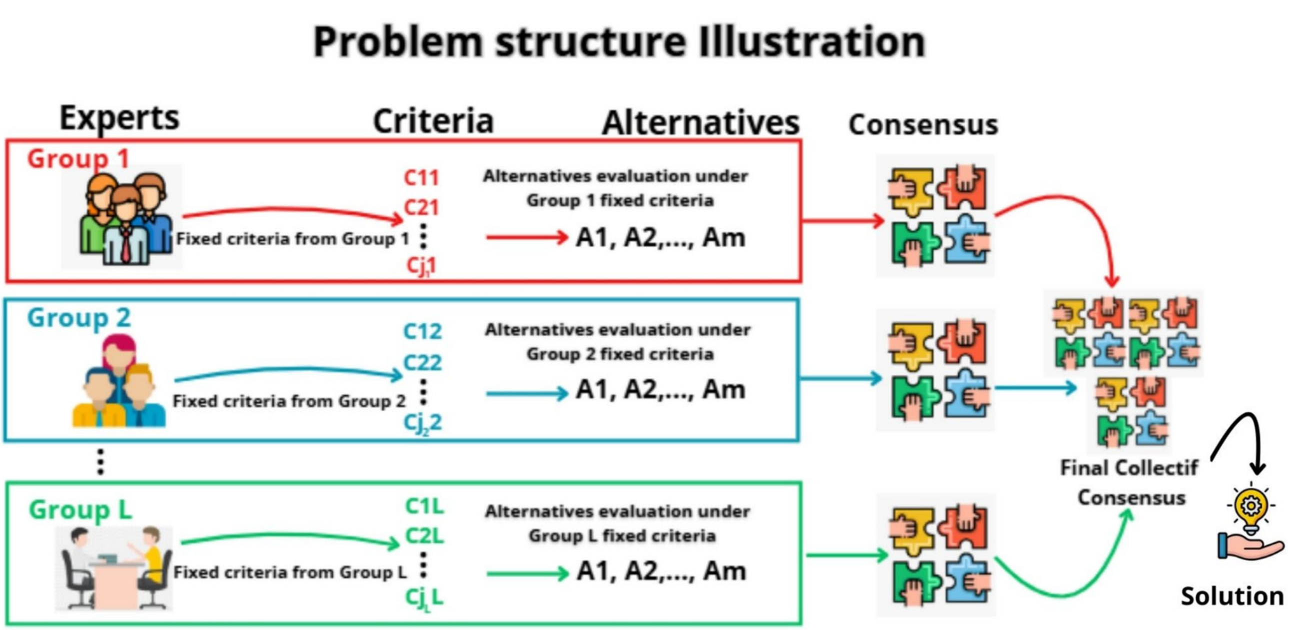

Fig. 1 Illustrative structure of the problem under consideration

responsible in the face of disruptions and evolving market demands.

- C_{13} = **Production Flexibility (PF):** Assesses the ability of production systems to adapt efficiently to fluctuations in demand, supply chain disruptions, or shifts in product requirements. A flexible production process enhances responsiveness and reduces downtime.
- C_{23} = **Environmental Impact (EI):** Measures the sustainability and ecological footprint of supply chain operations, including carbon emissions, resource consumption, waste management, and adherence to environmental regulations. Prioritizing sustainability helps organizations meet corporate social responsibility (CSR) goals and regulatory expectations.

Theoretical Background

In this section, we discuss the fundamental concepts underlying the proposed approach, including data representations and aggregating decision-makers' evaluation opinions.

Trapezoidal Fuzzy Numbers and Choquet Integral

In this research, six linguistic values (LVs) and their corresponding trapezoidal fuzzy numbers are used to express certain criteria assessments, as presented in Table 1.

To aggregate the evaluations across multiple experts while capturing their interactions, we use the Choquet integral with respect to a fuzzy measure.

Definition The Choquet integral of a collection of inputs $X = \{x_1 \ldots x_n\}$ is an aggregation operator with respect to the fuzzy measure μ defined by Eq. 1 as follows: (Yager 2019):

$$\mathrm{Ch}_\mu(\{x_1, \ldots, x_n\}) = \sum_{j=1}^{n} \left(\mu(H_j) - \mu(H_{j-1})\right) x_{\rho(j)} \tag{1}$$

Table 1 Linguistic values and their corresponding TRFNs for experts' opinions

Linguistic values	Initialism	TRFNs (a, b, c, d)
Very low	VL	(0.1, 0.2, 0.2, 0.3)
Low	L	(0.2, 0.3, 0.4, 0.5)
Medium	M	(0.4, 0.5, 0.5, 0.6)
High	H	(0.5, 0.6, 0.7, 0.8)
Very high	VH	(0.7, 0.8, 0.8, 0.9)
Extremely high	EH	(0.8, 0.9, 1, 1)

where ρ is an index function of the j^{th} largest element among the values x_i, i.e., $x_{\rho(1)}$ is the largest, and $x_{\rho(2)}$ is the second-largest. Based on this, we define the set:

$$H_j = \{x_{\rho(k)} \mid k = 1, 2, \ldots, j\}$$

which contains the top j largest values from the set $\{x_1, x_2, \ldots, x_n\}$. Let us consider the case where p_{x_i} is the probability of the input x_i and $\sum_{i=1}^{n} p_{x_i} = 1$; $x_i \in A$ and A is a subset from X. Considering a measure μ_P such that $\mu_P(\{x_i\}) = p_i$ and $\mu_P(A) = \sum_{x_i \in A} p_i$. Here, μ_P is a probability measure. Consequently, the Choquet integral of $\{x_1, \ldots, x_n\}$ with respect to μ_P can be formulated as follows:

$$\mathrm{Ch}_\mu(\{x_1, \ldots, x_n\}) = \sum_{j=1}^{n} (\mu_P(H_j) - \mu_P(H_{j-1})) x_{\rho(j)}$$

Since $H_j = \{x_{\rho(k)}, k = 1 \text{ to } j\}$ then $\mu_P(H_j) = \mathrm{Prob}(H_j) = \sum_{k=1}^{j} p_{\rho(k)}$ and $\mu_P(H_{j-1}) = \mathrm{Prob}(H_{j-1}) = \sum_{k=1}^{j-1} p_{\rho(k)}$.

For $\mu_P(H_j) - \mu_P(H_{j-1}) = P_{\rho(j)}$, the Choquet integral of inputs $\{x_1 \ldots x_n\}$ can be expressed using Eq. 2:

$$\mathrm{Ch}_\mu(\{x_1, \ldots, x_n\}) = \sum_{j=1}^{n} p_{\rho(j)} x_{\rho(j)} = \sum_{i=1}^{n} p_i x_i \tag{2}$$

It corresponds to the expected value of $\{x_1, \ldots, x_n\}$ with the probability distribution P.

Bounded Confidence Model for Multiple Attributes

The bounded confidence model (BCM) provides a structured framework for iteratively refining expert opinions. It introduces a bounded confidence threshold, meaning experts adjust their opinions only when the differences between them fall within this threshold. If the difference is within the threshold, experts influence each other's opinions; otherwise, they disregard one another. This iterative process gradually refines their opinions based on those within their confidence bounds.

The detailed steps of the BCM model for multi-criteria groups are outlined below (Li et al. 2022):

Step 0: Compute the Manhattan distance d between expert's opinions evaluations matrices
Let be the decision-making matrices $Z_p^{l,(t)}$ and $Z_q^{l,(t)}$ at iteration t of experts E_p and E_q, respectively, $p, q = 1 \ldots k$ within group G_l. The bounded confidence value of expert E_p is denoted by ε_p. The Manhattan distance between $Z_p^{l,(t)}$ and $Z_q^{l,(t)}$ at iteration t can be computed using Eqs. 3 and 4:

$$Z_p^{l,(t)} = \left(z_{ij}^{p,l,t}\right)_{m \times n} \quad \text{and} \quad Z_q^{l,(t)} = \left(z_{ij}^{q,l,t}\right)_{m \times n} \tag{3}$$

$$d\left(Z_p^{l,(t)}, Z_q^{l,(t)}\right) = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left| Z_p^{l,(t)} - Z_q^{l,(t)} \right| = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left| z_{ij}^{p,l,(t)} - z_{ij}^{q,l,(t)} \right| \quad (4)$$

Step 1: Identify the bounded confidence set I_p of the expert E_p

$$I_p = \left\{ E_q(q \neq p) \in G_L \mid d\left(Z_p^{l,(t)}, Z_q^{l,(t)}\right) \leq \varepsilon_p \right\} \quad (5)$$

Step 2: Calculate the influence of weight w_{pq}

$$w_{pq}(t) = \begin{cases} \frac{1}{\#I_p}, E_q \in I_p & \text{where } p = 1 \dots k_l \\ 0, E_q \notin I_p \end{cases} \quad (6)$$

Such that, $w_{pq}(t) \geq 0$ and $\sum_{q=1}^{k_l} w_{pq}(t) = 1$

Step 3: Update the opinions evaluations matrix $Z_p^{l,(t+1)}$ at iteration $(t+1)$ of expert E_p

$$Z_p^{l,(t+1)} = \frac{\sum_{E_q \in I_p} Z_q^{l,(t)}}{\#I_p} = w_{p_1} Z_1^{l,(t)} + w_{p_2} Z_2^{l,(t)} + \dots + w_{p_{k_l}} Z_{k_l}^{l,(t)} \quad ; l = 1, 2, \dots, L \quad (7)$$

Step 4: STOP the procedure when $I_p = \emptyset$.

Proposed Approach

This section provides a detailed description of the developed approach aimed at addressing more complex and extended problems, as structured in the "Problem Description" section, within the MCGDM framework. The approach is organized into three main phases:

- Phase 0 "Convert heterogeneous evaluations values into homogeneous values": This phase aims to convert all the expert's opinions evaluations into normalized data and gather it in an n-tuples format to facilitate the computation process.
- Phase 1 "Consensus Reaching Process": Based on the bounded confidence model, this phase aims to achieve a high level of agreement among experts from diverse groups with varying knowledge and backgrounds.
- Phase 2 "Alternatives Ranking": This phase employs the CoCoFISo method to rank alternatives effectively.

Given the involvement of multiple experts, ensuring a reliable and equitable decision-making process is crucial. To achieve this, our approach integrates key elements that contribute to a robust resolution model:

- Expert's trust degree (expertise level)
- Expert's bounded confidence value
- Group importance based on organizational hierarchy (group weighting)
- Interdependencies between criteria

Motivated by Li et al. (2022) and Zegai et al. (2024), our approach enhances existing methods by incorporating both the trust degree (expertise level) of each expert and the relative importance of the group to which they belong to. More specifically:

- We compute the trust degree of each expert using a combined technique that integrates both subjective and objective assessments. This is done first for each criterion individually and then aggregated across the entire problem to obtain an overall trust degree (Zegai et al. 2024).
- We assign a customized bounded confidence value to each expert based on their computed trust degree, allowing the model to reflect individual expertise more accurately (Li et al. 2022).
- We propose a linear mapping (Eq. 11) between each expert's trust degree and their bounded confidence value. Unlike the standard bounded confidence model, which assigns the same confidence value to all experts, this approach provides a more realistic and individualized evaluation.
- We incorporate the relative importance of each group according to the company's hierarchy to guarantee a fair and balanced final solution.

For reliable opinion evaluations aggregation, we employ the Choquet integral as a non-linear aggregation tool to account for interdependencies between criteria, ensuring a more accurate representation of expert preferences.

In Phase 2, we use the CoCoFISo method, an enhanced version of the CoCoSo method proposed by Rasoanaivo et al. (2024), which integrates three ranking strategies to produce more robust ranking results. For better clarity, Fig. 2 illustrates our proposed approach.

PHASE 0: Conversion of Heterogeneous Evaluation Values Into Homogeneous Values

Step 1. Each E_s within each group l should provides his own heterogeneous preferences decision matrix.
Step 2. Convert the heterogeneous preferences decision matrix into homogeneous preference decision matrix following (a), (b), or (c):

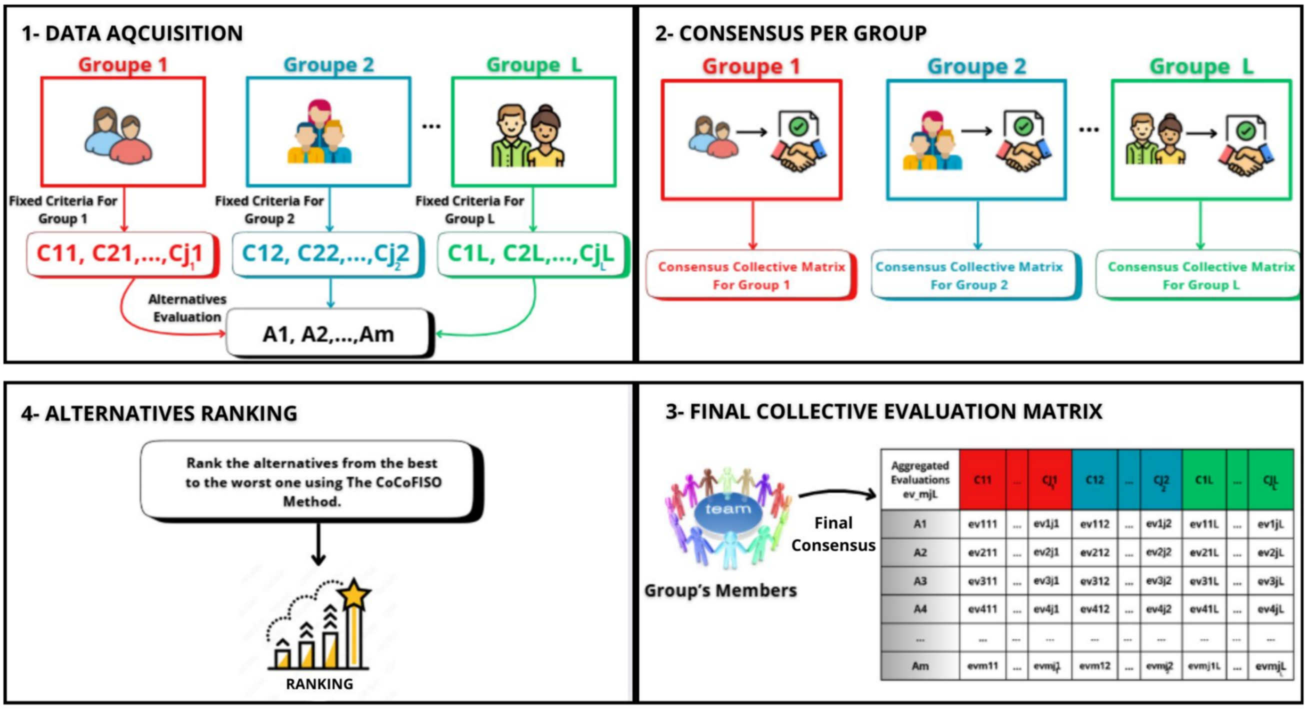

Fig. 2 Global overview of the proposed approach

a) For the crisp criteria values, normalize each crisp value in the interval of [0,1] using the following two equations:

$$\text{For cost criteria: } r_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad \text{For benefit criteria: } r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{8}$$

b) For the interval valued criteria, apply λ-function to get a crisp value from each interval valued using the equation below:

$$I_\lambda = (1-\lambda) \times \alpha_L + \lambda \times \alpha_U \quad \text{with} \quad \lambda \in [0, 1] \tag{9}$$

Then, normalize them using Eq. 8.

c) On each linguistic value criterion, apply the α-cut procedure to defuzzify each linguistic value (see Table 1), resulting in a normalized interval a^α. Subsequently, use the λ-function to get a crisp value from each interval.

$$\alpha\text{-cut procedure:} \quad a^\alpha = [a_L^\alpha, a_U^\alpha] = [(b-a)\times\alpha + a, (c-d)\times\alpha + d] \tag{10}$$

Step 3. For expert E_s within each group l, construct the normalized preferences decision matrix which elements are tuples based on sets as follows:

$$Z_l^s = \begin{array}{c|ccc} & C_{1l} & \dots & C_{jl} \\ \hline A_1 & \{z_{11l}^1, z_{11l}^2, \dots, z_{11l}^s\} & \dots & \{z_{1nl}^1, z_{1nl}^2, \dots, z_{1nl}^s\} \\ A_2 & \{z_{21l}^1, z_{21l}^2, \dots, z_{21l}^s\} & \dots & \{z_{2nl}^1, z_{2nl}^2, \dots, z_{2nl}^s\} \\ \vdots & \vdots & \ddots & \vdots \\ A_m & \{z_{m1l}^1, z_{m1l}^2, \dots, z_{m1l}^s\} & \dots & \{z_{mnl}^1, z_{mnl}^2, \dots, z_{mnl}^s\} \end{array}$$

PHASE 1: Consensus Reaching Process The consensus model proposed in this phase aims to achieve a higher level of agreement among the experts in each group L, where $l = 1, \dots, L$. It is based on the BCM described in the "Bounded Confidence Model for Multiple Attributes" section.

In our proposed approach, unlike the standard BCM, the bounded confidence value for each expert is computed based on their trust degree (expertise level). Specifically, an expert with a high level of expertise is more confident and less influenced by others, resulting in a lower bounded confidence value. Conversely, a less experienced expert is more open to influence, leading to a higher bounded confidence value. Mathematically, this relationship between the bounded confidence value and the trust degree of each expert is expressed by the following Eq. 11:

$$\epsilon_s = \epsilon^* \times \tilde{t_s} \text{ with } \quad \epsilon_s, \epsilon^*, \tilde{t_s} \in [0.1] \tag{11}$$

where ϵ_s is the bounded confidence value of expert E_s. ϵ^* is the basic bounded confidence value given as a data value, and $\tilde{t_s}$ is the normalized trust degree of expert E_s.

The main steps of our proposed consensus model are described in detail in the following nine steps:

Step 1. Compute the expert's trust degree using a combinative method explained in steps (a), (b), and (c), detailed below (Wan et al. 2022):

a) **Determine expert weights within each group l through self-evaluation using a subjective technique for each criterion, then aggregate across the problem:** The weight of expert E_s under each criterion C_j is computed through self-evaluation, represented by the self-evaluation coefficient $\beta_s^{'j}$. This coefficient reflects the degree of alignment between the expert's personal traits and the decision being made. The value of $\beta_s^{'j}$ ranges from 0 to 1, where 0 indicates complete inconsistency between the expert's traits and the criterion, and 1 indicates total consistency. To calculate the self-evaluation weight $\beta_s^{'j}$ for expert E_s under criterion C_j, we normalize the self-evaluation coefficients $\beta_s^{'j}$ provided by expert E_s for each criterion C_j using linear normalization, as shown in Eq. 12.

$$\beta_s^j = \frac{\beta_s^{\prime j}}{\sum_{s=1}^{k} \beta_s^{\prime j}} \quad s = 1, 2 \ldots k \quad \text{and } j = 1 \ldots n \tag{12}$$

Next, we compute the overall self-evaluation coefficient β_s for expert E_s using Eq. 13:

$$\beta_s = \frac{\sum_{j=1}^{n} \beta_s^j}{\sum_{s=1}^{k} \sum_{j=1}^{n} \beta_s^j} \quad s = 1, 2 \ldots k \tag{13}$$

b) **Determine expert weights within each group l through mutual evaluation using an objective technique for each criterion, then aggregate across the problem:** Expert weights E_s are determined through mutual evaluation. In this process, each expert assesses the other experts by assigning relative evaluation weights, also known as paired evaluations, based on the comparison of the alignment between the experts' personal qualities and the decision problem. This approach enables the calculation of each expert's relative weight. After aggregating all evaluations, the weights are normalized through linear normalization, resulting in the final weights for each expert. Equation 14 provides the calculation.

$$\gamma_s^j = \frac{\sum_{d=1}^{k} \sum_{b=1}^{k} C_{dab}^j}{\sum_{d=1}^{k} \sum_{a=1}^{k} \sum_{b=1}^{k} C_{dab}^j} \quad j = 1, 2 \ldots n \quad \text{and } s = 1, 2 \ldots k \tag{14}$$

Next, we compute the expert's objective weighting across the entire problem by summing the products of each γ_k^j and the weight W_j of criterion C_j. At this stage, we assume that all criteria have the same importance in the decision-making process, and thus, each criterion is assigned the same weight. Equation 15 shows how to compute the aggregated objective evaluations:

$$\gamma_s = \sum_{j=1}^{n} w_j * \gamma_s^j \quad s = 1, 2 \ldots k \tag{15}$$

c) **Determine the combinative weights of experts' opinions within each group l across the entire problem:** To provide a more accurate and balanced weighting for the experts' opinions, the geometric mean and normalization techniques are employed to aggregate the weights from both the subjective and objective weighting methods using Eqs. 16 and 17, respectively:

$$t_s = \frac{\sqrt{(\beta_s) \cdot (\gamma_s)}}{\sum_{s=1}^{k} \sqrt{\sqrt{(\beta_s) \cdot (\gamma_s)}}} \quad t_s \in [0, 1] \text{ and } \quad s = 1, 2 \ldots k \tag{16}$$

$$\tilde{t_s} = \frac{t_s}{\sum_{s=1}^{k} t_s} \quad \text{such that} \sum_{s=1}^{k} \tilde{t_s} = 1 \tag{17}$$

Step 2. Compute each expert's bounded confidence value ϵ_s using Eq. 11.
Step 3. Compute the Manhattan distance between experts opinions within each group $G_l, l = 1 \ldots L$, using Eq. 4.
Step 4. Identify the set of experts who influence each other's opinions using Eq. 5.
Step 5. Compute the influence weights of experts using Eq. 6.
Step 6. Experts update the expert's opinions using Eq. 7.
Step 7. Return to **Step 3.** until no necessary opinions evaluations updating is needed.
Step 8. The final collective evaluations matrix within each group G_l, $l = 1 \ldots L$ is obtained by aggregating experts opinions evaluations matrices within each group l using Choquet Inegral with uncertainty over the inputs operator using Eq. 2, such as, the probability of the input

(P_{input}) is selected based on the expert's number within the group G_l they belong to, meaning that $P^l_{input} = \frac{1}{k_l}$ for each opinion evaluation (input) within each group G_l.

Step 9. Assign weights w_{g_l} such that $w_{g_l} \in [0, 1]$ to each group according to the company's hierarchy and compute the final weighted collective opinions evaluations matrix for each group $G_l, l = 1 \ldots L$ with $\sum_{g=1}^{L} w_{g_l} = 1$.

PHASE 2: Alternatives Ranking Process Using CoCoFISo The combined compromise solution (CoCoSo) method was first proposed by Yazdani et al. (2019b) as a novel approach to multi-criteria decision-making. CoCoSo offers several advantages over traditional ranking methods, making it a robust choice for complex decision-making problems. By integrating multiple criteria aggregation strategies, it enhances the flexibility and reliability of the ranking process. This multi-perspective fusion mitigates sensitivity to extreme values, a common limitation of TOPSIS, where significant variations in criteria weights or values can distort rankings. Furthermore, CoCoSo effectively incorporates decision-maker preferences through its adaptable weighting and aggregation mechanisms, making it particularly well-suited for uncertain and multi-criteria group decision-making environments.

Building on the strengths of CoCoSo, the combined compromise for the ideal solution (CoCoFISo) method has been introduced, inspired by Rasoanaivo et al. (2024), as an extended framework to further enhance decision-making clarity. CoCoFISo refines the original approach by incorporating a more sophisticated compromise-driven ranking strategy, ensuring a balanced and reliable evaluation of alternatives even in highly uncertain and dynamic contexts. By leveraging its improved aggregation mechanisms, CoCoFISo enables organizations to make more effective decisions in applications such as supply chain network redesign, resource allocation, and project and risk management. The detailed methodological steps are outlined below.

Adapted CoCoFISo Steps

Step 1. Reacquire the final weighted collective opinions evaluations matrix from Step 9 of PHASE 1

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} i = 1, 2, \ldots m, \text{ and } j = 1, 2, \ldots, n \tag{18}$$

Step 2. Weighted comparability sequence

The total weighted comparability sequence and the sum of the power weights of the comparability sequences for each alternative are denoted as S_i and P_i, respectively. S_i is obtained using the grey relational generation approach, as defined in Eq. 19. Similarly, the value of P_i is determined based on the WSAPAS multiplicative attitude and is computed using Eq. 20.

$$S_i = \sum_{j=1}^{n} \left(w_j x_{ij}\right) \tag{19}$$

$$P_i = \sum_{j=1}^{n} \left(x_{ij}\right)^{w_j} \tag{20}$$

Step 3. Aggregation alternatives evaluations strategies

Compute relative weights of the alternatives using the following aggregation strategies. In this step, three appraisal score strategies to generate relative weights of other alternatives, which are derived by Eqs. 21, 22, 23, and 24, are proposed.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{21}$$

$$k_{ib} = \left(\frac{S_i + P_i}{1 + \frac{S_i}{1+S_i} + \frac{P_i}{1+P_i}} \right) \tag{22}$$

$$k_{ic} = \frac{\lambda (S_i) + (1 - \lambda) (P_i)}{(\lambda \max_i S_i + (1 - \lambda) \max_i P_i)}; 0 \leq \lambda \leq 1 \tag{23}$$

In Eq. 23, λ is generally fixed as $\lambda = 0.5$.

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3} (k_{ia} + k_{ib} + k_{ic}) \tag{24}$$

Step 4. Alternatives ranking and selection

The final ranking of the alternatives is determined based on k_i, where $i = 1, 2, \ldots, m$ values. The highest k_i value indicates the best alternative i.

Illustrative Numerical Example

A company employs three specialized decision-making groups, each responsible for evaluating critical aspects of its supply chain operations. **Group 1: The Logistics and Distribution Department**, composed by two experts, focuses on optimizing transportation and delivery performance to ensure cost efficiency, reliability, and timely order fulfillment by evaluating **Transportation Cost** (C_{11}) evaluated with crisp values and **Delivery Time** (C_{21}) estimated by interval values to enhance distribution efficiency. **Group 2: The Procurement and Supplier Management Department**, composed by three experts, manages supplier relationships and ensures a stable and cost-effective procurement process by assessing **Supplier Reliability** (C_{12}) presented with percentages (%) and **Quality and Compliance** (C_{22}) described with linguistic values (LV) to maintain operational integrity and minimize risks. **Group 3: The Operations and Sustainability Department**, composed by two experts, prioritizes operational adaptability and environmental responsibility, evaluating **Production Flexibility** (C_{13}) assessed with linguistic values (LV) and **Environmental Impact** (C_{23}) measured with crisp data to ensure resilience and sustainability in supply chain activities. The set of the above six criteria will serve to evaluate five potential alternatives A_i, $i = 1 \ldots 5$ and ultimately select the best one. It corresponds to the best supply chain redesign structure. By integrating the expertise of these groups, the organization establishes a comprehensive decision-making framework that enhances supply chain performance and strategic alignment (Sahoo and Goswami 2023).

The input data in this illustrative example were selected to represent typical supply chain decision-making scenarios, covering relevant criteria such as logistics, procurement, and operations. Values and ranges were chosen to reflect realistic variations and uncertainties commonly encountered in such contexts. While illustrative, the example demonstrates the applicability and functionality of the proposed methodology, including the handling of crisp, interval, and fuzzy evaluations, providing transparency regarding the data selection and underlying assumptions (Singh and Benyoucef 2012).

Conversion of Heterogeneous Evaluation Values into Homogeneous Evaluation Values

Initially, experts within each group (E_1, E_2 for G_1, E_3, E_4, E_5 for G_2, and E_6, E_7 for G_3) provide their individual heterogeneous opinion evaluation matrices. Table 2 presents the expert opinion evaluations within each group. Next, these evaluations are normalized to obtain homogeneous opinion evaluation values using Eqs. 8, 9, and 10, with the resulting normalized values displayed in Table 3. Upon completing this conversion process, we construct the opinion evaluation matrices within each group using a tuple-based representation. The results are summarized in Tables 4, 5, and 6, respectively.

Consensus Reaching Process

At the beginning of the consensus-reaching process, the subjective, objective, and combined expert weights within each group are computed using Eqs. 12–15, respectively, while assuming equal criteria weights of $w_j = 0.166$. Next, the expert's weights are computed using Eqs. 16 and 17; after that, the bounded confidence value for each expert is determined using Eq. 11. The obtained values within each group are presented in Tables 7, 8, and 9, respectively.

For opinion evaluations, studying, and updating, we apply the steps of the BCM model (from **Step 3** to **Step 7**), as outlined in **Phase 1** of the "Proposed Approach" section

Table 2 Heterogeneous opinions evaluations matrices of experts from Group 1, Group 2, and Group 3

Experts /criteria	Alternatives	A_1	A_2	A_3	A_4	A_5
(a) Group 1						
E_1	$C_{11}(Crisp)$	5000	3550	4200	2900	5200
	$C_{21}(Interval)$	2–3	3–4	2–3	3–4	1–3
E_2	$C_{11}(Crisp)$	5500	4000	3900	3000	5000
	$C_{21}(Interval)$	2–3	3–5	4–6	3–7	2–4
(b) Group 2						
E_3	$C_{12}(\%)$	90–95	85–90	80–95	75–82	90–93
	$C_{22}(LV)$	EH	H	M	VL	M
E_4	$C_{12}(\%)$	88–94	87–90	90–95	80–85	90–93
	$C_{22}(LV)$	VH	H	L	L	H
E_5	$C_{12}(\%)$	90–93	85–90	93–96	85–90	94–95
	$C_{22}(LV)$	H	H	H	L	M
(c) Group 3						
	$C_{22}(LV)$	H	H	H	L	M
E_6	$C_{13}(LV)$	H	M	EH	VL	H
	$C_{23}(Crisp)$	30	50	35	65	50
E_7	$C_{13}(LV)$	EH	M	H	L	M
	$C_{23}(Crisp)$	35	55	40	60	60

Table 3 Normalized opinions evaluations matrices of experts from Group 1, Group 2 and Group 3

Experts/criteria \ Alternatives		A_1	A_2	A_3	A_4	A_5
(a) Group 1						
E_1	C_{11}	0.47	0.63	0.56	0.70	0.45
	C_{21}	0.61	0.46	0.61	0.46	0.65
E_2	C_{11}	0.44	0.59	0.60	0.69	0.49
	C_{21}	0.61	0.36	0.22	0.16	0.50
(b) Group 2						
E_3	C_{12}	0.47	0.44	0.45	0.40	0.46
	C_{22}	0.94	0.65	0.50	0.20	0.50
E_4	C_{12}	0.46	0.44	0.46	0.41	0.46
	C_{22}	0.80	0.65	0.35	0.35	0.50
E_5	C_{12}	0.45	0.43	0.46	0.43	0.46
	C_{22}	0.65	0.65	0.65	0.35	0.50
(c) Group 3						
E_6	C_{13}	0.65	0.50	0.94	0.20	0.65
	C_{23}	0.72	0.53	0.67	0.39	0.53
E_7	C_{13}	0.94	0.50	0.65	0.35	0.50
	C_{23}	0.69	0.52	0.65	0.47	0.47

Table 4 Opinions evaluations matrix with 2-tuples representation for Group 1

	Criteria	Alternatives A_1		A_2		A_3		A_4		A_5	
Group 1	C_{11}	0.47	0.44	0.63	0.59	0.56	0.60	0.70	0.69	0.45	0.49
	C_{21}	0.61	0.61	0.46	0.36	0.61	0.22	0.46	0.16	0.65	0.50

Table 5 Opinions evaluations matrix with 3-tuples representation for Group 2

	Criteria	Alternatives A_1			A_2			A_3			A_4			A_5		
Group 2	C_{12}	0.47	0.46	0.45	0.44	0.44	0.43	0.45	0.46	0.46	0.40	0.41	0.43	0.46	0.46	0.46
	C_{22}	0.94	0.80	0.65	0.65	0.65	0.65	0.50	0.35	0.65	0.20	0.35	0.35	0.50	0.50	0.50

Table 6 Opinions evaluations matrix with 2-tuples representation for Group 3

	Criteria	Alternatives A_1		A_2		A_3		A_4		A_5	
Group 3	C_{13}	0.65	0.94	0.50	0.50	0.94	0.65	0.20	0.35	0.65	0.50
	C_{23}	0.72	0.69	0.53	0.52	0.67	0.65	0.39	0.47	0.53	0.47

Table 7 Subjective, objective, and combinative expert's weights for Group 1 and their bounded confidence values

Group 1	E_1	E_2
β_s	0.44	0.51
γ_s	0.33	0.32
t_s	0.70	0.74
$\tilde{t}_s$	0.48	0.51
ϵ_s	0.09	0.1

Table 9 Subjective, objective, and combinative expert's weights for Group 3 and their bounded confidence values

Group 3	E_6	E_7
β_s	0.45	0.45
γ_s	0.52	0.52
t_s	0.67	0.67
$\tilde{t}_s$	0.5	0.5
ϵ_s	0.1	0.1

to the normalized expert opinion evaluation matrices from the "Conversion of Heterogeneous Evaluation Values into Homogeneous Evaluation Values" section within each group. The results for each group are presented as follows:

For Group 1: We compute the Manhattan distance value, which is $d(E_1, E_2) = 0.11$, since:

$$d(E_1, E_2) = 0.11 > \epsilon_1 = 0.09, \quad \text{meaning that} \quad E_1 \text{ doesn't trust } E_2.$$

$$d(E_1, E_2) = 0.11 > \epsilon_2 = 0.10, \quad \text{meaning that} \quad E_2 \text{ doesn't trust } E_1.$$

This implies that each expert will maintain their own opinion evaluations without any changes, and it is unnecessary to proceed to Steps 4, 5, 6, and 7 of PHASE 1 in this case. In the final Step 8 of this process within Group 1, we apply the Choquet integral with uncertainty over the opinion evaluations to aggregate the E_1 and E_2 matrices with the probability $p^1_{\text{input}} = \frac{1}{2}$ for the 2-tuples opinion evaluation matrix. This probability is based on the number of experts within the group. The resulting collective consensus opinion evaluation matrix is shown in Table 10:

For Group 2 We start with computing the Manhattan distances between E_3, E_4, and E_5: $d(E_3, E_4) = 0.047$; $d(E_3, E_5) = 0.066$; and $d(E_4, E_5) = 0.049$; next, we verify the distances values that are within the bounded confidence value ϵ_s of each expert E_s, and we find that:

$d(E_3, E_4) = 0.047 < \epsilon_3 = 0.07$, means that E_3 trust E_4.

$d(E_3, E_4) = 0.047 < \epsilon_4 = 0.07$, means that E_3 trust E_4.

$d(E_3, E_5) = 0.066 < \epsilon_3 = 0.07$, means that E_3 trust E_5.

$d(E_3, E_5) = 0.066 > \epsilon_5 = 0.06$, means that E_3 doesn't trust E_5.

$d(E_4, E_5) = 0.049 < \epsilon_4 = 0.07$, means that E_4 trust E_5.

$d(E_4, E_5) = 0.049 < \epsilon_5 = 0.06$, means that E_4 trust E_5.

In step 4, we identify the set of experts who influence each other's opinions for each expert; the sets are as follows:

$$I_{E_3} = \{E_3, E_4, E_5\}; \quad I_{E_4} = \{E_3, E_4, E_5\} \text{ and } I_{E_5} = \{E_4, E_5\}$$

In step 5, we compute each expert's influencing weight within each set. The results are displayed as follows:

$$Weights_{(E_3)} = \{w_{E_{3,3}} = 0.33, w_{E_{3,4}} = 0.33, w_{E_{3,5}} = 0.33\}$$

$$Weights_{(E_4)} = \{w_{E_{4,3}} = 0.33, w_{E_{4,4}} = 0.33, w_{E_{4,5}} = 0.33\}$$

$$Weights_{(E_5)} = \{w_{E_{5,4}} = 0.5, w_{E_{5,5}} = 0.5\}$$

Based on these weights, experts update their opinion evaluation matrices as mentioned in step 6 by multiplying each expert's matrix by the corresponding weights: $Weights_{(E_s)}$. Then, we sum the weighted matrices for each expert. The updated opinions evaluation matrices for each expert after the necessary number of iterations are presented in Table 11:

In Step 8, we apply the Choquet integral with uncertainty over the opinion evaluations to aggregate the updated opinion evaluation matrices of the experts, considering the probability $p^2_{\text{input}} = \frac{1}{3}$ for each evaluation in each tuple. This probability is derived from the fact that there are three experts in this group. The final collective consensus opinion evaluation matrix within this group is presented in Table 12:

Table 8 Subjective, objective, and combinative expert's weights for Group 2 and their bounded confidence values

Group 2	E_1	E_2	E_3
β_s	0.54	0.51	0.44
γ_s	0.33	0.31	0.35
t_s	0.57	0.54	0.53
$\tilde{t}_s$	0.34	0.32	0.32
ϵ_s	0.07	0.07	0.06

Table 10 Consensus collective opinions evaluations matrix for Group 1

Criteria \ Alternatives	A_1	A_2	A_3	A_4	A_5
C_{11}	0.54	0.52	0.55	0.48	0.59
C_{21}	0.41	0.58	0.43	0.55	0.49

Table 11 Updated opinions evaluations 3-tuple matrix of experts from Group 2

	Criteria	Alternatives														
		A_1			A_2			A_3			A_4			A_5		
Group 2	C_{12}	0.46	0.46	0.46	0.44	0.44	0.44	0.46	0.46	0.46	0.42	0.42	0.41	0.46	0.46	0.46
	C_{22}	0.76	0.76	0.80	0.65	0.65	0.65	0.50	0.50	0.50	0.32	0.32	0.30	0.50	0.50	0.50

For Group 3 The Manhattan distances between the experts E_6 and E_7 opinions evaluations matrices are displayed as follows:

$d(E_6, E_7) = 0.108 > \epsilon_6 = 0.1$, means that E_6 doesn't trust E_7. $d(E_6, E_7) = 0.108 > \epsilon_7 = 0.1$, means that E_6 doesn't trust E_7.

Indicating that each expert will only trust their own opinion. In this case, we do not need to proceed to steps 4, 5, 6, and 7, meaning that we do not need to update the expert's opinions within this group.

In the step 8 of this process, we apply the Choquet integral with uncertainty over the opinions evaluations to aggregate the updated resulted matrices of E_6 and E_7 with $p^3_{input} = \frac{1}{2}$ for each evaluation from the 2-tuples opinions evaluations matrix, and this probability value is due to the number of experts within this group. The resulting collective consensus opinion evaluation matrix is shown in Table 13.

At the end of this phase (Step 9), we assign a weight $w_{g_l} \in [0, 1]$ to each group based on the company's hierarchy. Then, we retrieve the collective consensus opinion evaluation matrices obtained from step 8 within each group. Next, we multiply each of these matrices by the corresponding weight w_{g_l}. In our example, the weights are assigned as follows:

$$w_{g_l} = \{w_{g_1} = 0.40; \quad w_{g_2} = 0.20; \quad w_{g_3} = 0.40\}$$

The final weighted collective opinions evaluation matrix is displayed in Table 14.

Alternatives Ranking Process

In this phase, the steps of the CoCoFISo method, outlined in PHASE 2, are applied to derive a robust ranking of the alternatives. In Step 1, the final weighted collective opinion evaluation matrix is reacquired. Then, in step 2, the total weighted comparability sequence S_i and the sum of the power weights of the comparability sequences are calculated using Eqs. 19–20. The corresponding results are presented in Table 15.

In Step 3, the different evaluation strategies k_{ia}, k_{ib}, k_{ic}, and k_i are calculated to generate the relative weights of alternatives i using Eqs. 21–24. The obtained values are displayed in Table 16.

Finally, the ranking of the five different alternatives is performed based on the obtained values of k_i as follows: $k_1 > k_3 > k_2 > k_5 > k_4$. The alternative A_1 has the highest value k_1; consequently, it is the best supply chain redesign structure to select from the five alternatives.

Conclusion and Future Works

This research work presented a novel multi-criteria group decision-making approach for supply chain network redesign, integrating the bounded confidence model with expert trust levels to effectively capture and structure inputs during the decision-making process. The Choquet integral, enhanced to account for uncertainty in the input evaluations, was applied for robust aggregation, and the CoCoFISo method enabled balanced, consensus-driven decision-making. By organizing evaluation criteria into core functional domains such as logistics, procurement, and operations, the approach enhances decision reliability and supports strategic planning in dynamic and uncertain environments. A numerical example validated its practical applicability, demonstrating effectiveness in facilitating collaborative, data-driven decision-making. The results highlight the approach's capability to

Table 12 Consensus collective opinions evaluations matrix for Group 2

Criteria \ Alternatives	A_1	A_2	A_3	A_4	A_5
C_{12}	0.45	0.43	0.45	0.41	0.45
C_{22}	0.76	0.64	0.49	0.31	0.49

Table 13 Consensus collective opinions evaluations matrix for Group 3

Criteria \ Alternatives	A_1	A_2	A_3	A_4	A_5
C_{13}	0.80	0.50	0.80	0.27	0.57
C_{23}	0.70	0.52	0.66	0.43	0.50

Table 14 Final weighted collective opinions evaluations matrix

Groups / Criteria / Alternatives	Group 1		Group 2		Group 3	
	C_{11}	C_{21}	C_{12}	C_{22}	C_{13}	C_{23}
A_1	0.21	0.16	0.09	0.15	0.32	0.28
A_2	0.20	0.23	0.08	0.12	0.20	0.20
A_3	0.22	0.17	0.09	0.09	0.32	0.26
A_4	0.19	0.22	0.08	0.06	0.10	0.17
A_5	0.23	0.19	0.09	0.09	0.22	0.20

Table 16 Strategies k_{ia}, k_{ib}, k_{ic}, and k_i resulted values for each alternative i

Strategies / Alternatives	k_{ia}	k_{ib}	k_{ic}	k_i
A_1	0.205	2.392	1.029	2.006
A_2	0.200	2.360	1.004	1.969
A_3	0.203	2.372	1.016	1.985
A_4	0.190	2.280	0.953	1.886
A_5	0.199	2.352	1.000	1.961

balance cost efficiency, resilience, flexibility, and sustainability while addressing diverse preferences and risk perceptions of multiple decision-makers. By leveraging structured non-linear aggregation mechanisms and consensus-oriented techniques, the approach mitigates biases and inconsistencies, fostering transparent and robust decision outcomes.

Despite these contributions, the study has some limitations. It relies on expert evaluations, which may be subjective, and the illustrative example does not fully capture the complexity of real-world supply chains. The approach also focuses on a specific set of criteria, leaving room to incorporate additional factors such as environmental or social sustainability metrics. Sensitivity to parameter variations, particularly the bounded confidence threshold and expert trust levels, is another important consideration; while our example suggests stable results under reasonable variations, a systematic sensitivity analysis was beyond the scope of this study. Additionally, the work does not include a formal comparison with existing MCDM approaches, such as TOPSIS, VIKOR, or fuzzy AHP, which could further clarify the added value of the proposed methodology.

Future research works could address these limitations by applying the approach to larger-scale, real-world supply chains, including more diverse expert panels, extending the framework to additional criteria, exploring alternative aggregation and ranking techniques, and incorporating dynamic, time-dependent uncertainties. Additional directions include integrating real-time data streams and predictive analytics, leveraging machine learning to refine preference aggregation, evaluating scalability in multi-tier supply chains, and exploring hybrid decision support systems that combine CoCoFISo with reinforcement learning or stochastic optimization. Advancing these directions will contribute to more intelligent, adaptive, and robust decision-making frameworks, ultimately enhancing the efficiency, resilience, and agility of modern supply chains.

Table 15 S_i and P_i resulted values for each alternative i

S_i and P_i	S_i	P_i
A_1	0.202	4.555
A_2	0.176	4.467
A_3	0.193	4.504
A_4	0.138	4.266
A_5	0.173	4.448

Author Contribution Ryma Zegai: conceptualization, methodology, validation, visualization, writing—original draft, review and editing. Imen Khettabi: methodology, writing—original draft, review and editing. Lyes Benyoucef: conceptualization, methodology, validation, visualization, writing—original draft, review and editing, supervision.

Data Availability The data that support the findings of this study are available from the corresponding author, upon reasonable request. Moreover, we can deliver the used codes to help potential users.

Declarations

Ethics Approval The paper is not currently being considered for publication elsewhere.

Consent for Publication With the consent, the authors give the publisher a license of the copyright which provides the publisher with the exclusive right to publish the research findings.

Conflict of Interest The authors declare no competing interests.

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