Sustainable Operations and Computers 2 (2021) 149–169

Contents lists available at ScienceDirect

Sustainable Operations and Computers

journal homepage: www.elsevier.com/locate/susoc

An integrated and comprehensive fuzzy multicriteria model for supplier selection in digital supply chains

Madjid Tavana[a,b,*], Akram Shaabani[c], Debora Di Caprio[d], Maghsoud Amiri[e]

[a] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, USA
[b] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany
[c] Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran
[d] Department of Economics and Management, University of Trento, Italy
[e] Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran

ARTICLE INFO

Keywords:
Digital supply chain
Supplier selection
Fuzzy set
Best-worst method
Consensus ranking

ABSTRACT

Digital supply chains (DSCs) are collaborative digital systems designed to quickly and efficiently move information, products, and services through global supply chains. The physical flow of products in traditional supply chains is replaced by the digital flow of information in DSCs. This digitalization has changed the conventional supplier selection processes. We propose an integrated and comprehensive fuzzy multicriteria model for supplier selection in DSCs. The proposed model integrates the fuzzy best-worst method (BWM) with the fuzzy multi-objective optimization based on ratio analysis plus full multiplicative form (MULTIMOORA), fuzzy complex proportional assessment of alternatives (COPRAS), and fuzzy technique for order preference by similarity to ideal solution (TOPSIS). The fuzzy BWM approach is used to measure the importance weights of the digital criteria. The fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS methods are used as prioritization methods to rank the suppliers. The maximize agreement heuristic (MAH) is used to aggregate the supplier rankings obtained from the prioritization methods into a consensus ranking. We present a real-world case study in a manufacturing company to demonstrate the applicability of the proposed method.

1. Introduction

Manufacturing companies are facing many challenges, including satisfying global competitiveness requirements, compensating for the potential lack of adaptability, and designing efficient go-to-market strategies due to the rapid technological and digital advances in supply chains (SCs) [124]. These challenges are compounded by dynamic customer demands and a wide variety of external frictions. Therefore, more flexibility and agility are needed to accelerate order processing and improve traceability and transparency of order tracking systems [142]. In this sense, emerging new technologies and digitalization are already generating important changes in SCs in terms of transparency, security, and reliability. ([34,142]a; Wang et al., 2019).

A digital supply chain (DSC) delivers products from origin to destination by electronic means [61]. It combines digital tools, strategies, and methods to support communication among employees, customers, and suppliers [134,172]. DSCs have many benefits, such as, for instance, the cost-effectiveness of services and the development of value-creating activities useful to many actors in the ecosystem, including the companies and their employees, customers, and suppliers [105]. The key role played by suppliers in improving the performance of DSC companies and maintaining their strategic competitiveness is undeniable. Thus, supplier evaluation can be considered one of the most important decision-making activities faced by a company.

The assessment and selection of suppliers are performed by a team of decision-makers (DMs) who deliver evaluations/judgments based on their expertise and personal experience. In doing so, DMs usually consider contradictory criteria [72]. As a consequence, they may make the wrong decisions and perform an inappropriate selection of suppliers. In this sense, Multiple Criteria Decision-Making (MCDM) techniques can be applied to help to obtain reasonably good solutions.

Given that DSCs represent a competitive advantage for organizations and selecting the most suitable suppliers has a significant effect on the performance of DSCs, the questions to address are the following.

* Corresponding author at: Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, United States.

E-mail addresses: tavana@lasalle.edu (M. Tavana), Shaabani_akram@atu.ac.ir (A. Shaabani), debora.dicaprio@unitn.it (D. Di Caprio), amiri@atu.ac.ir (M. Amiri).

https://doi.org/10.1016/j.susoc.2021.07.008
Received 16 May 2021; Received in revised form 10 July 2021; Accepted 15 July 2021
Available online 24 July 2021
2666-4127/

- How can the suppliers in a DSC be evaluated and the best one selected?
- How can we define an MCDM model able to provide a practical and efficient solution? What are the MCDM techniques that allow for ranking the suppliers in a DSC through a methodical but easy-to-implement procedure?
- What are the evaluation criteria to use for supplier selection in DSC?
- How can the uncertainty inherent to the DMs' evaluations be interpreted and formally incorporated in a ranking procedure?

To best address these questions, the proposed model integrates the fuzzy Best-Worst Method (BWM) with the fuzzy Multi-Objective Optimization based on Ratio Analysis plus full multiplicative form (MULTIMOORA), the fuzzy COmplex PRoportional ASsessment (COPRAS) method, and the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The Maximize Agreement Heuristic (MAH) [25] is applied to integrate the supplier rankings obtained by the different methods in a final consensus ranking.

All the MCDM chosen to create the integrated model are well-founded and widely used approaches to assess alternatives. COPRAS, MULTIMOORA, and TOPSIS have been effectively used in integrated frameworks and within both crisp and fuzzy environments to analyze a large number of real-life case studies. They all share the same initial step of creating a fuzzy decision matrix, but from the definition of the weighted normalized decision matrix, they involve different comparison rules and reference points. The variety of technical tools employed through these ranking methods allows an integrated setting to yield robust and sound results.

As for the MAH method, the agreement maximizing strategy behind this method makes it one of the most valid consensus ranking methods. The simplicity, flexibility, and general performance of MAH add to the reasons for preferring it to other consensus ranking methods in many practical implementations [185].

Overall, the main contributions of this research can be summarized as follows.

- It proposes a systematic and efficient approach to the supplier selection problem in a DSC.
- It develops an integrated and comprehensive fuzzy multicriteria model to evaluate and select the alternatives allowing for direct comparisons between approaches and more robust results.
- It uses triangular fuzzy numbers (TFNs) to account for the ambiguity and uncertainty deriving from the vagueness and imprecision associated with DMs' subjective evaluations.
- It includes a real-world case study whose results show the applicability of the integrated fuzzy-based methodology.
- The proposed approach can be realistically implemented to rank suppliers in a DSC setting but also naturally adapted to solve other real-life selection problems characterized by ambiguous and uncertain data.

The remainder of the paper is organized as follows. In Section 2, we provide a review of the recent literature on MCDM, DSCs, and supplier evaluation and selection. The supplier evaluation criteria used in the proposed model are extracted from the literature review. In Section 3, we introduce the proposed integrated framework. In Section 4, we present a case study to demonstrate the applicability of the proposed framework. A sensitivity analysis is included to validate the results obtained. Managerial implications are outlined in Section 5, while in Section 6 we present our conclusions and some future research directions.

2. Literature review

The following subsections provide a review of the recent works published on MCDM and fuzzy MCDM, BWM, MULTIMOORA, and fuzzy MULTIMOORA, COPRAS, and fuzzy COPRAS, TOPSIS and fuzzy TOPSIS, SC and DSC, supplier selection, and fuzzy supplier selection models.

2.1. MCDM and fuzzy MCDM

Multi-criteria decision-making (MCDM) can be defined as a formal and structured decision-making approach for solving intricate problems with contradictory criteria [132]. MCDM provides a systematic methodology that helps DMs to rank alternatives [125] and make decisions also when subject to very complex conditions [69,219]. More precisely, the optimal alternative is selected after analyzing a set of alternatives on multiple, often conflicting, criteria [91,147].

Several MCDM techniques have been applied to supplier selection over the last two decades: Analytical Hierarchy Process (AHP) [200]; Analytic Network Process (ANP) [83]; VIKOR (Jun [217,222]); Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [16]; simulation–optimization [46,47]; particle swarm optimization [108]; Decision Making Trial and Evaluation Laboratory (DEMATEL) [45,84]; Elimination and Choice Translating Reality (ELECTRE) [210]; Preference Ranking Organization Method (PROMETHEE) [22,63]; Simple Additive Weighting (SAW) [196]; Additive Ratio Assessment (ARAS) and SAW [36]; Stepwise Weight Assessment Ratio Analysis (SWARA) [11,79]; Weighted Aggregated Sum Product Assessment (WASPAS) [126]; Complex Proportional Assessment (COPRAS) [150]; Best-Worst Method (BWM) [148], MULTIMOORA [214].

DMs' knowledge and time are limited, and their opinions are often affected by vague and/or uncertain judgments. Due to this fact, MCDM models have been expanded using a fuzzy set theory (R. L. J. W. H. [219]). Nowadays, fuzzy sets [211] are considered the most effective tool to formalize and solve MCDM problems [188], where it is necessary to account for fuzzy decisions and fuzzy environments.

Popular fuzzy techniques for MCDM that have been used over the last two decades to formalize and solve supplier selection problems include fuzzy AHP [39], fuzzy ANP [194], fuzzy COPRAS [60], fuzzy DEMATEL [41], fuzzy goal programming [106], fuzzy MULTIMOORA [170], fuzzy SWARA [129,164], fuzzy TOPSIS [95], fuzzy VIKOR [160], and fuzzy WASPAS [9,102].

2.1.1. A review of BWM

The BWM is an effective MCDM for assigning importance weights to evaluation criteria through pairwise comparisons between (1) the best alternative and all other alternatives; and (2) the worst alternative and all other alternatives [8,27,55,89]. BWM has been used in combination with a variety of MCDM approaches to suggest solution patterns to diverse assessment problems. Bahrami et al. [18] used BWM for weighting criteria and sub-criteria and combined it with the ARAS method, Kumar et al. [107] used BWM in combination with the VIKOR method, Gupta [68] used BWM and Fuzzy TOPSIS to assess the performance of organizations, Rezaei et al. [149] used BWM and SERVQUAL for an analysis of the perceived service quality of a baggage handling system, Gupta and Barua [70] identified barriers to green innovation for SMEs and used BWM together with fuzzy TOPSIS, Ijadi Maghsoodi et al. [90] used BWM and Combinative Distance-Based Assessment (CODAS) for a hybrid approach for site selection, Tavana et al. [187] proposed a new hierarchical fuzzy BWM and used it for sustainable supplier evaluation and selection.

2.1.2. A review of MULTIMOORA and fuzzy MULTIMOORA

The MOORA and MULTIMOORA methods were proposed by Brauers and Zavadskas in 2006 and in 2010, respectively ([29]; 2010). MOORA has been used to solve a wide range of management-related optimation problems characterized by the presence of conflicting objectives, such as, for example, product design and production process structuring problems [6,38,59].

MULTIMOORA consists of three main phases, with MOORA being one of them. Indeed, MULTIMOORA includes a ratio system (RS) approach (i.e., MOORA method), a reference point (RP) approach, and a Full Multiplicative Form (FMF) approach (Ceballos et al., 2016; [49,73]a; [74]).

MULTIMOORA is more effective than MOORA, and it is considered one of the most robust multi-objective optimization tools [30,43] since it satisfies all the six conditions of robustness through the integration of three or more methods.

A comprehensive review of the MULTIMOORA method is presented by Hafezalkotob et al. [74]. However, we would like to mention a few of the recent applications of this technique. MULTIMOORA has been used to rank supplier performance evaluation [97,114,171,186] to evaluate risk [54,116,197,221], to evaluate and select product designs [168], to approach material selection problems ([73]a; [214]), to optimize the choice of agricultural machines and tools [77], to optimally decide mining methods [111], to evaluate science and technology projects [195], to choose logistics partners [17], to rank recycling modes of electric vehicle power batteries [48], to identify prioritization of failure modes [42].

The fuzzy version of the MULTIMOORA method was first proposed by Brauers et al. [28]. Since then, several researchers have been expressing their interest in the study of applications and extensions of fuzzy MULTIMOORA [20,21,64,75,169].

The most recent applications of fuzzy MULTIMOORA in the literature include personnel selection [20], risk evaluation [54], site selection [113,145].

2.1.3. A review of COPRAS and fuzzy COPRAS

COPRAS is a multiple attribute decision-making method developed by Zavadskas et al. [215]. This method calculates the solution by considering the best solution ratio. It exploits the proportionate and direct association between the importance-efficiency measures of previously checked versions and a system of criteria and weights according to which the values of the alternatives are estimated. [202].

In recent research papers, the COPRAS method has been applied to relative performance measurement problems [44], supplier selection problems [101], rapid prototyping system selection [123], alternative evaluation problems [146], COVID-19 regional safety assessment [81].

The fuzzy variant of the COPRAS approach was developed by Zavadskas and Antucheviciene [213], whose work opened the way to a wide realm of research opportunities. Just to mention a few examples, the fuzzy COPRAS method has been used to carry out risk analyses of critical infrastructures [201], to green supplier selection [119], to select the best maintenance strategy [56], to solve supplier selection problems [135], to provide performance measures in total productive maintenance [191], to rank renewable energy sources [10].

2.1.4. A review of TOPSIS and fuzzy TOPSIS

The TOPSIS technique was initially introduced by Hwang and Yoon [86]. This method is mainly used for ranking alternatives ([161]; Madjid [181]) and provides a convenient approach to untangle MCDM problems since the proposed solutions are extracted from a reduced set of variables [78]. TOPSIS is built on the fundamental concepts of positive ideal solutions (PIS) and negative ideal solutions (NIS) and requires the best alternative to be the one situated both at the smallest distance from the PIS and at the greatest distance from the NIS [103,109].

Through the years, TOPSIS has been applied to solve a large variety of problems, often combined or integrated with other MCDM techniques. Some recent applications include the selection of computer-integrated manufacturing technologies [87], risk assessment in FMEA [7], supplier selection [26], ranking potential links in multiplex networks [19].

The fuzzy TOPSIS technique was initially used by Chen [40] to analyze MCDM scenarios where it is necessary to address the indeterminacy characterizing DMs' judgments and assessments ([156]; Madjid [183]). It was immediately shown to outperform the traditional TOPSIS approach when considering MCDM problems whose variables and solutions are affected by uncertainties intrinsic to DMs' assessments ([165,166]; Madjid [184]).

The recent literature on MCDM witnesses the vast range of application of fuzzy TOPSIS to real-life selection problems, such as service selection [117], virtual enterprise partner selection [207], risk assessment [50], business competition analysis [190], robot selection and rapid prototyping process selection [193], selection of warehouse locations [15], assessment of renewable energy goals [167].

2.2. Supply chains and digitalization

The concept of SC is known to researchers and managers since the early 1980s. An SC can be defined as "a network of organizations" interlinked, both upwards and downwards, through a series of activities and procedures that provide final users with finished products and active services [82,127,137]. The activities of an SC comprise the movement of natural and raw materials from suppliers to manufacturers, their transformation into finished products, and their delivery to customers [24,31,144]. An SC involves retailers, manufacturers, and suppliers, working together to obtain customer satisfaction. More generally, the different parties involved in an SC are interested in the movement of materials, money, and information/data across the supply chain [141,152].

Digitalization is a process integrating the cloud, real-time connectivity, and advanced analytics. This process is increasingly impacting several private and public dimensions of the socio-economical context. It is changing the structure of value chains and the dynamics of firm behavior, influencing investments and saving plans, affecting productivity and consumption, altering the way employment and work are perceived, conditioning individuals' skills and competition rules, redesigning business models and how business is conducted, guiding growth and industry [139]. Last but not least, digitalization is increasingly affecting SCs.

Introducing digitalization in SCs means using digital data and technologies in all the activities of an SC with consequent continuous incorporation of progressive changes in the managerial practices of all the companies [155]. DSCs allow to enhance processes, boost functions and activities, improve production, promote flexibility, increase revenue, and create new business opportunities [92]. Technology and digital processes support the interconnection among people. This yields more and more transparent information flows, which are immediately available to the organizations, their suppliers, and their potential customers [155]. Digital technology favors the introduction of smart factories and production, as well as the expansion of logistics networks [92].

Traditional SCs are linear and focus on the movement of products through silos. Indeed, in a traditional SC, the suppliers provide raw materials to the producers, the producers ship finished products to the distributors, the distributors pass on selected amounts of the products to the retailers who ultimately sell the products to the customers (see Figure 1). In contrast, in a DSC, digitalization brings down the silos while the entire SC becomes an integrated system visible to all the players, including the suppliers, producers, distributors, retailers, and customers (see Figure 2).

2.3. Supplier selection and fuzzy supplier selection models

Suppliers constitute one of the essential components of an SC since they provide all the necessary materials and services throughout the entire manufacturing process [205]. Manufacturing companies use supplier selection procedures to select suitable suppliers. The selection process requires the employment of a significant amount of human and financial resources, some of which may be wasted, leading to increased factories' costs. To avoid cost increases, it is then fundamental to use appropriate methods for selecting and evaluating suppliers [37]. In this sense, decision-making techniques provide an extensive and reliable realm of opportunities, allowing supplier selection problems to be approached in many different ways.

A large variety of models has been proposed over the last five years. Most of them are hybrid fuzzy models with the capability of considering uncertainties. Tables 1 and 2 show only some of the most recent

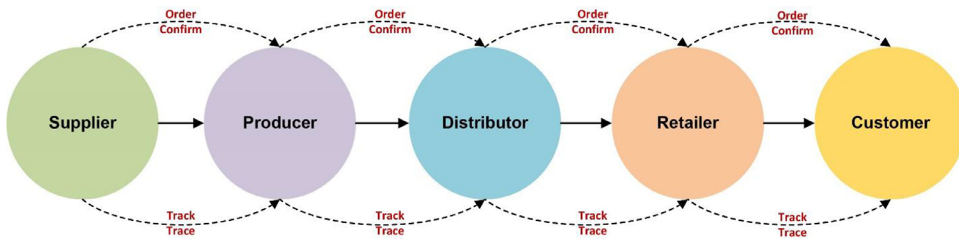

Fig. 1. Traditional supply chain.

Table 1
Recent supplier selection models.

Techniques	Methods	Type	Authors
MCDM	AHP and Delphi	Combined model	[23]
	AHP-Entropy-TOPSIS	Combined model	[57]
	AHP- ER	Combined model	[143]
	SWARA, QFD, and WASPAS	Combined model	[206]
	ELECTRE	Single model	[52]
	FMEA	Single model	[110]
	COPRAS, DEMATEL and QFD	Combined model	[205]
	AHP and VIKOR	Combined model	[121]
	PROMETHEE	Single model	[1]
	ANP-TOPSIS	Combined model	[99]
	TOPSIS	Single model	[174]
	Rough DEMATEL and FVIKOR	Combined model	[218]
	DEMATEL, FMEA, and EDAS	Combined model	[203]
	AHP-ARAS-MCGP	Combined model	[58]
	TOPSIS	Single model	[136]
	AHP and QFD	Combined model	[204]
Mathematical Programming (MP)	Goal programming	Single model	[93]
	Data Envelopment Analysis	Single model	[122]
	Linear programming	Single model	[66]
Artificial Intelligence (AI) techniques	Genetic Algorithm	Single model	[163]
	Bayesian Networks	Single model	[51]
	Rough Set Theory	Single model	[85]
	Neural Networks	Single model	[157]
	Colony Algorithm	Single model	[120]
	Clustering Algorithm	Single model	[220]

Table 2
Recent fuzzy supplier selection models

Techniques	Methods	Type	Authors
Fuzzy MCDM	Fuzzy TOPSIS, Goal programming	Combined model	[88]
	FVIKOR	Single model	[208]
	FVIKOR	Single model	[151]
	FMLMCDM, FTOPSIS, and FMOORA	Combined model	[128]
	FAHP, ARASF, and MSGP	Combined model	[112]
	IT2 FSs-based TODIM	Combined model	[153]
	BWM and fuzzy TOPSIS	Combined model	[69]
	Fuzzy set, TODIM, PROMETHEE, Fuzzy-TOPSIS, Fuzzy-VIKOR	Combined model	[154]
	Fuzzy AHP and Fuzzy MOORA	Combined model	[14]
	BWM, Fuzzy TOPSIS, and FMOLP	Combined model	[118]
	Fuzzy AHP-TOPSIS	Combined model	[94]
	Fuzzy MOORA and FMEA	Combined model	[13]
	Fuzzy MADM, TBL, QFD, and Fuzzy VIKOR	Combined model	[115]
	ANN, FAHP, and FTOPSIS	Combined model	[209]
	AHP Sort II, Interval type-2 fuzzy sets	Combined model	[199]
	Fuzzy VIKOR	Single model	[198]
	Rough-fuzzy DEMATEL-TOPSIS	Combined model	[41]
	Spherical fuzzy AHP	Single model	[158]
	Fuzzy SWARA and Fuzzy ARAS	Combined model	[192]
Fuzzy Mathematical Programming (MP)	Fuzzy multi-objective optimization	Combined model	[131]
	Fuzzy goal programming		
	Fuzzy Linear programming	Single model	[4]
	Fuzzy Data Envelopment Analysis	Single model	[53]
Fuzzy Artificial Intelligence (AI) techniques	Fuzzy Neural Networks	Single model	[96,133]
	Clustering Method (type-2 fuzzy set)	Single model	[80]

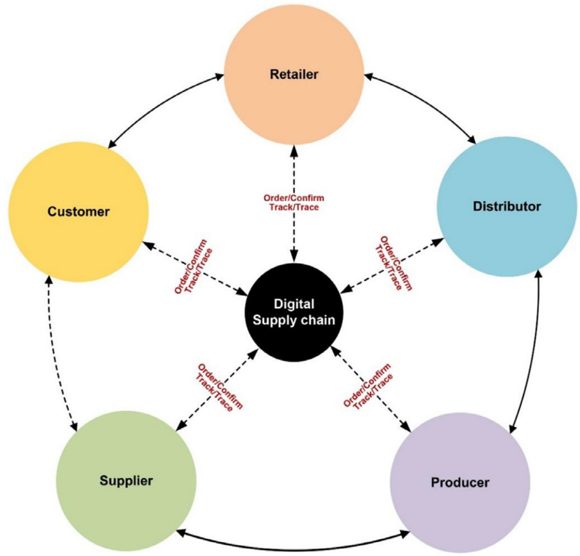

Fig. 2. Digital supply chain.

models (since 2015) that have been proposed to support supplier selection and fuzzy supplier selection, respectively. The models have been grouped into three categories in both tables: MCDM methods, mathematical programming (MP) formulations, and artificial intelligence (AI) techniques.

2.4. Supplier selection in DSC

Being able to assemble an efficient and competitive chain relies on the implementation of an appropriate supplier evaluation and selection method [57,176]. In particular, the increasing employment of outsourcing activities has strengthened companies' dependence on suppliers putting in the spotlight the need for reliable supplier selection procedures.

Supplier evaluation and selection procedures usually contemplate diverse objectives ([65]b), with suppliers having a significant impact on supply chain profitability [216]. In a DSC, all partners, including the suppliers, need to use technologies and innovations, that is, to be digital. As shown in Figure 2, digital suppliers play an essential role in DSC [5,139].

3. Methodology

3.1. Proposed method

We propose an integrated method for performing supplier evaluation and selection in DSCs, with the final ranking being achieved by employing fuzzy BWM, fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS through a four-step procedure. First, several selection criteria are reviewed, and the key ones for supplier selection within a DSC environment are identified (Phase 1). Second, experts' opinions are collected, and the importance weights of the criteria are calculated by fuzzy BWM (Phase 2). Third, fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS are used in three distinct and parallel phases (Phase 3, Phase 4, and Phase 5, respectively) to rank the suppliers. Fourth, the rankings obtained by applying fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS are integrated with MAH [25] to achieve a consensus ranking (Phase 6). A sensitivity analysis can be performed to validate the rankings obtained and further endorse the choice of employing MAH as a consensus ranking method.

Through all the phases of the proposed method (Phases 1 to 6), we make the following key assumptions regarding the experts' evaluations.

- All the experts' evaluations are affected by ambiguity and uncertainty that derive from the vagueness and imprecision inherent to any subjective evaluation process.
- All the experts' evaluations are formalized using TFNs. That is, all the pairwise comparisons and weights involved in the different phases are initially expressed in terms of TFNs.
- All the experts are confident in their evaluations and there are no external conditions creating further uncertainty. That is, there is no need to use more complex fuzzy tools such as intuitionistic, neutrosophic, and type-2 fuzzy numbers/sets.

Fig. 3 provides a schematic representation of the proposed four-step procedure. Next, we describe the fuzzy BWM, fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS methods used in this study.

3.2. Fuzzy BWM

BWM was proposed by Rezaei [148] and is used to assign the weights of the criteria in a flexible manner [18,62,175]. In particular, this method compensates for shortcomings such as inconsistency [162]. In contrast with other approaches such as AHP and ANP [2] allows it decreases the number of pairwise comparisons to be performed. The weights of the criteria are assigned based on preference comparisons of the best criterion over all the other criteria and of all the criteria on the worst criterion. Preferences are evaluated on a scale between 1 and 9 [138]. Moreover, secondary comparisons are not considered, which makes this approach more efficient and easy to use when assigning weights in an MCDM problem [104,162].

The fuzzy BWM method was proposed by Guo and Zhao [67] to account for the ambiguity and uncertainty intrinsic to human judgments. Indeed, fuzzy BWM enables DMs to incorporate linguistic judgments into the decision-making process (Ashkan [76]). The steps of fuzzy BWM are described below [67]:

Step 1. Fix the set of criteria: $\{C_1, C_2, ..., C_n\}$

Step 2. Decide the best (most important) criterion, B, and the worst (least important) criterion, W, by an expert or an expert team.

Step 3. Perform the fuzzy preference comparisons for the best criterion, B. The fuzzy preferences of B over all the criteria are expressed in linguistic terms corresponding to a fuzzy preference scale. See Table 3. The fuzzy best-to-others vector is as follow:

$$\tilde{A}_B = \left(\tilde{a}_{B1}, \tilde{a}_{B2}, ..., \tilde{a}_{Bn}\right) \tag{1}$$

where $\underset{Bj}{\tilde{a}}$ denotes the fuzzy preference of B over C_j $(j = 1, 2, ..., n)$. Note that $\underset{BB}{\tilde{a}} = (1, 1, 1)$.

Step 4. Perform the fuzzy preference comparisons for the worst criterion, W. The fuzzy preferences of all criteria over W are expressed in linguistic terms corresponding to a fuzzy preference scale. See Table 3. The fuzzy others-to-worst vector is as follows:

$$\tilde{A}_W = \left(\tilde{a}_{1W}, \tilde{a}_{2W}, ..., \tilde{a}_{nW}\right) \tag{2}$$

where $\tilde{a}_{jW}$ denotes the fuzzy preference of C_j $(j = 1, 2, ..., n)$ over W. Note that $\underset{WW}{\tilde{a}} = (1, 1, 1)$.

Step 5. Find the optimal fuzzy weight vector $(\bar{\omega}_1, \bar{\omega}_2, ..., \bar{\omega}_n)$.

Given the fuzzy preferences $\underset{Bj}{\tilde{a}}$ and $\underset{jW}{\tilde{a}}$, with $j = 1, 2, ..., n$, the optimal weights are those minimizing the maximum between the absolute differences $|{}^{\bar{\omega}_B}/_{\bar{\omega}_j} - \tilde{a}_{Bj}|$ and $|{}^{\bar{\omega}_j}/_{\bar{\omega}_W} - \tilde{a}_{jW}|$. Interpreting all the weights as TFNs, we let $\bar{\omega}_j = (l_j^w, m_j^w, u_j^w)$, $\bar{\omega}_B = (l_B^w, m_B^w, u_B^w)$ and $\bar{\omega}_W = (l_W^w, m_W^w, u_W^w)$ represent the fuzzy weight of C_j, B and W, respectively. Thus, assuming that the weights sum up to one and the non-negativity constraints are satisfied, the fuzzy BWM model can be formulated as

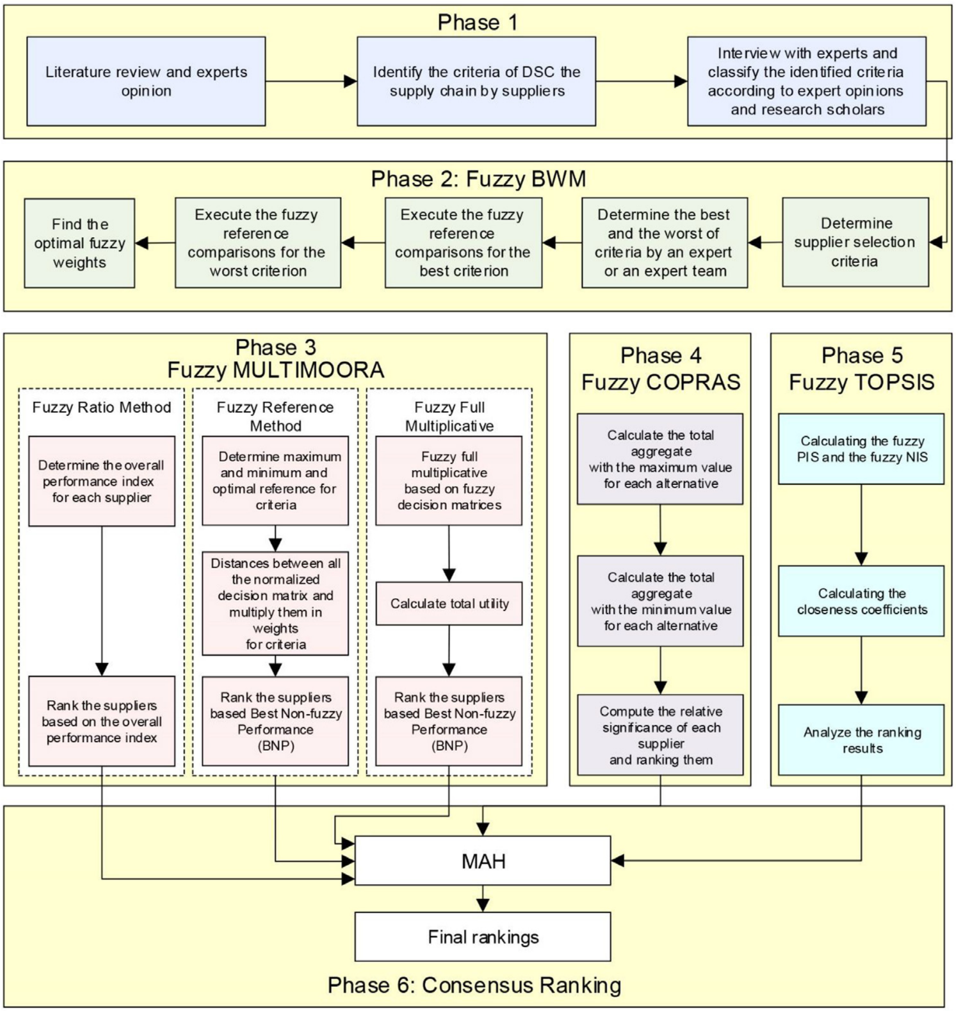

Fig. 3. Schematic diagram of the proposed methodology..

Table 3
Linguistic variables.

Linguistic variables for the fuzzy BWM [67]		Linguistic variables for the fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS [12]	
Linguistic variables	Fuzzy Scale	Linguistic variables	Fuzzy Scale
Equally importance (EI)	(1,1,1)	Very low (VL)	(0,0,0.2)
Weakly importance (WI)	(2/3,1,3/2)	Low (L)	(0,0.2,0.4)
Fairly importance (FI)	(3/2,2,5/2)	Medium (M)	(0.2,0.4,0.6)
Very importance (VI)	(5/2,3,7/2)	High (H)	(0.4,0.6,0.8)
Absolutely importance (AI)	(7/2,4,9/2)	Very High (VH)	(0.6,0.8,1)

follows [67]:

$$\begin{aligned}
&\min \max_{j} \left\{ \left| \tilde{w}_B / \tilde{w}_j - \tilde{a}_{Bj} \right|, \left| \tilde{w}_j / \tilde{w}_W - \tilde{a}_{jW} \right| \right\} \\
&s.t \ : \\
&\sum_{j=1}^{n} R\left(\tilde{w}_j\right) = 1\,, \\
&l_j^w \le m_j^w \le u_j^w, \quad \forall j = 1, \dots, n \\
&l_j^w \ge 0, \qquad \forall j = 1, \dots, n
\end{aligned} \tag{3}$$

Model (3) can be re-written as follows:

$$\begin{aligned}
&\min \tilde{\xi} \\
&s.t \ : \\
&\left| \tilde{w}_B / \tilde{w}_j - \tilde{a}_{Bj} \right| \le \tilde{\xi}, \quad \forall j = 1, \dots, n \\
&\left| \tilde{w}_j / \tilde{w}_W - \tilde{a}_{jW} \right| \le \tilde{\xi}, \quad \forall j = 1, \dots, n \\
&\sum_{j=1}^{n} R\left(\tilde{w}_j\right) = 1, \\
&l_j^w \le m_j^w \le u_j^w, \quad \forall j = 1, \dots, n \\
&l_j^w \ge 0, \qquad \forall j = 1, \dots, n
\end{aligned} \tag{4}$$

Table 4
Consistency index values for pairwise comparisons in fuzzy BWM.

Linguistic terms	Equally important (EI)	Weakly important (WI)	Fairly important (FI)	Very important (VI)	Absolutely important (AI)
$\tilde{a}_{BW}$	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(7/2, 4, 9/2)
CI	3.00	3.80	5.29	6.69	8.04

where $\tilde{\xi} = (l^{\xi}, m^{\xi}, u^{\xi})$. By considering $l^{\xi} \le m^{\xi} \le u^{\xi}$and supposing$\tilde{\xi}^* = (k^*, k^*, k^*)$, with $k^* \le l^{\xi}$, the Model (4) is transformed as follows:

$$
\begin{aligned}
&\min \tilde{\xi} \\
&s.t \\
&\left| \frac{\left(l_B^w, m_B^w, u_B^w\right)}{\left(l_j^w, m_j^w, u_j^w\right)} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \right| \le (k^*, k^*, k^*) \\
&\left| \frac{\left(l_j^w, m_j^w, u_j^w\right)}{\left(l_W^w, m_W^w, u_W^w\right)} - \left(l_{jW}, m_{jW}, u_{jW}\right) \right| \le (k^*, k^*, k^*) \\
&\sum_{j=1}^{n} R\left(\tilde{w}_j\right) = 1, \\
&l_j^w \le m_j^w \le u_j^w, \quad \forall j = 1, \ldots, n \\
&l_j^w \ge 0, \qquad \forall j = 1, \ldots, n
\end{aligned}
\tag{5}
$$

$$R\left(\tilde{w}_j\right) = \frac{l_j^w + 4m_j^w + u_j^w}{6} \tag{6}$$

In Models (3), (4) and (5), $R(\tilde{w}_j)$ stands for the graded mean integration representation (GMIR) of the fuzzy weight $\tilde{w}_j$, that is:

The solution to Model (5) provides the optimal fuzzy weights that are, in turn, transformed into crisp weights using the GMIR formula in Eq. (6).

Finally, the consistency ratio (CR) relative to the fuzzy comparisons must be calculated. By letting the fuzzy preferences of Eqs. (1) and (2) be represented by TFNs, a fuzzy pairwise comparison vector is fully consistent provided that $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$. If $\tilde{a}_{Bj} \times \tilde{a}_{jW} \ne \tilde{a}_{BW}$, then inconsistency occurs and attains its maximum value $\tilde{\xi}$ when both $\tilde{a}_{Bj}$ and $\tilde{a}_{jW}$ are equal to $\tilde{a}_{BW}$. Thus, based on the equality relation ${}^{\tilde{w}_B}/_{\tilde{w}_j} \times {}^{\tilde{w}_j}/_{\tilde{w}_W} = {}^{\tilde{w}_B}/_{\tilde{w}_W}$, in the case of occurrence of the greatest inequality, the following Eq. (7) can be formulated [67]:

$$\left(\tilde{a}_{BW} - \tilde{\xi}\right) \times \left(\tilde{a}_{BW} - \tilde{\xi}\right) = \left(\tilde{a}_{BW} + \tilde{\xi}\right) \tag{7}$$

where $\tilde{\xi} = (l^{\xi}, m^{\xi}, u^{\xi})$ and $\tilde{a}_{BW} = (l_{BW}, m_{BW}, u_{BW})$. Eq. (7) can also be rewritten as follows:

$$\tilde{\xi}^2 - \left(1 + 2\tilde{a}_{BW}\right)\tilde{\xi} + \left(\tilde{a}_{BW}^2 - \tilde{a}_{BW}\right) = 0 \tag{8}$$

For $\tilde{a}_{BW} = (l_{BW}, m_{BW}, u_{BW})$ the maximum fuzzy value cannot exceed 9/2. That is, u_{BW} can be used as the upper bound of an inconsistency index calculation. Furthermore, a crisp value ξ can be chosen to represent $\tilde{\xi}$. Hence, the CR can be calculated for fuzzy BWM as the quotient $CR = \xi^*/CI$ where ξ^* is the optimal value of ξ obtained by solving the nonlinear constrained optimization problem in Eq. (5), and CI is the consistency index, which is computed by solving the following Eq. (9) with $u_{BW} = 1,\ 3/2,\ 5/2, 7/2\ and\ 9/2$.

$$\xi^2 - \left(1 + 2u_{BW}\right)\xi + \left(u^2 - u_{BW}\right) = 0 \tag{9}$$

The CI values associated with the possible values taken by $\tilde{a}_{BW}$ are shown in Table 4. For further details, the reader may refer to [67].

3.3. Fuzzy MULTIMOORA

MULTIMOORA consists of three phases: the ratio system approach (i.e., MOORA method), the reference point approach, and the full multiplicative form approach.

3.3.1. Fuzzy ratio system method (Fuzzy MOORA)

The fuzzy variant of MOORA applied in this study follows the fuzzy ratio method of Akkaya et al. [6]. Thus, for its implementation, we will follow a series of steps that are similar to those outlined by Akkaya et al. [6], Gupta et al. [71], and Karande and Chakraborty [98].

Step 0. Fix the set of alternatives $\{\alpha_1, \ldots, \alpha_m\}$ and the set of criteria $\{C_1, C_2, \ldots, C_n\}$.

Step 1. Construct the fuzzy decision matrix. The elements of this matrix are TFNs.

$$X = \left[\tilde{x}_{ij}\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} = \left[\left(x_{ij}^l, x_{ij}^m, x_{ij}^u\right)\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} \tag{10}$$

Step 2. Normalize the fuzzy decision matrix.

$$X^* = \left[\tilde{x}_{ij}^*\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} = \left[(x_{ij}^{l*}, x_{ij}^{m*}, x_{ij}^{u*})\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} \tag{11}$$

where

$$x_{ij}^{l*} = x_{ij}^l \Big/ \sqrt{\sum\nolimits_{i=1}^{m} \left\|\tilde{x}_{ij}\right\|}, j = 1, \ldots, n \tag{12}$$

$$x_{ij}^{m*} = x_{ij}^m \Big/ \sqrt{\sum\nolimits_{i=1}^{m} \left\|\tilde{x}_{ij}\right\|}, j = 1, \ldots, n \tag{13}$$

$$x_{ij}^{u*} = x_{ij}^u \Big/ \sqrt{\sum\nolimits_{i=1}^{m} \left\|\tilde{x}_{ij}\right\|}, j = 1, \ldots, n \tag{14}$$

where $\|\tilde{x}_{ij}\| = (x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^u)^2$.

Step 3. Construct the weighted normalized fuzzy decision matrix.

$$X^{**} = \left[\tilde{x}_{ij}^{**}\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} = \left[\left(x_{ij}^{l**}, x_{ij}^{m**}, x_{ij}^{u**}\right)\right]_{\substack{i=1,\ldots,m \\ j=1,\ldots,n}} \tag{15}$$

where

$$x_{ij}^{l**} = w_j x_{ij}^{l*}, j = 1, \ldots, n, \tag{16}$$

$$x_{ij}^{m**} = w_j x_{ij}^{m*}, j = 1, \ldots, n \tag{17}$$

$$x_{ij}^{u**} = w_j x_{ij}^{u*}, j = 1, \ldots, n \tag{18}$$

The weights w_j, $j = 1, \ldots, n$, used to weight the elements of the normalized fuzzy decision matrix, are those obtained solving the fuzzy BWM model (see Model (5)).

Step 4. Compute the normalized performance value of each alternative. This is done by subtracting the performance value of an alternative on the total of cost criteria from the performance value on the total of benefit criteria. Thus, the normalized performance value of an alternative is computed as follows:

$$y_i = \sum_{j=1}^{\beta} \tilde{x}_{ij}^{**} - \sum_{j=\beta+1}^{n} \tilde{x}_{ij} \tag{19}$$

where $\tilde{x}_{ij}^{**}$ is the ij-th element of the weighted normalized fuzzy decision matrix X^{**}, $\sum_{j=1}^{\beta} \tilde{x}_{ij}^{**}$ is the performance value on the benefit criteria (for $j = 1, \ldots, \beta$), $\sum_{j=\beta+1}^{n} \tilde{x}_{ij}^{**}$ is the performance value on the cost criteria (for $j = \beta + 1, \ldots, n$), β is the maximum number of benefit criteria, and $(n - \beta)$ is the minimum number of cost criteria.

Given the benefit criteria, we can compute the overall ratings of an alternative with respect to the extreme and middle values of the triangular membership functions characterizing the benefit related fuzzy evaluations $\tilde{x}_{ij}^{**}$. That is:

$$y_i^{+l} = \sum_{j=1}^{\beta} \tilde{x}_{ij}^{l**} \tag{20}$$

$$y_i^{+m} = \sum_{j=1}^{\beta} \tilde{x}_{ij}^{m**} \quad (21)$$

$$y_i^{+u} = \sum_{j=1}^{\beta} \tilde{x}_{ij}^{u**} \quad (22)$$

Similarly, the overall ratings of an alternative with respect to the extreme and middle values characterizing the cost related fuzzy evaluations $\tilde{x}_{ij}^{**}$ are calculated as follows:

$$y_i^{-l} = \sum_{j=\beta+1}^{n} \tilde{x}_{ij}^{l**} \quad (23)$$

$$y_i^{-m} = \sum_{j=\beta+1}^{n} \tilde{x}_{ij}^{m**} \quad (24)$$

$$y_i^{-u} = \sum_{j=\beta+1}^{n} \tilde{x}_{ij}^{u**} \quad (25)$$

Thus, the normalized performance value y_i of the i-th alternative is given by the following TFN:

$$y_i = (y_i^l, y_i^m, y_i^u) \quad (26)$$

where

$$y_i^l = y_i^{+l} - y_i^{-l}, \quad y_i^m = y_i^{+m} - y_i^{-m}, \quad y_i^u = y_i^{+u} - y_i^{-u} \ . \quad (27)$$

Step 5. Compute the overall performance index of each alternative. This is done by de-fuzzifying the values of the overall ratings of each alternative for the cost and benefit criteria using the vertex method. Thus, the overall performance index Y_i of the i-th alternative is computed as follows:

$$Y_i = \sqrt{\frac{1}{3}\left[\left(y_i^l\right)^2 + \left(y_i^m\right)^2 + \left(y_i^u\right)^2\right]} \quad (28)$$

Step 6. Rank the alternatives. The alternatives are ranked from the best to the worst, depending on the value of their overall performance indices. The most preferred alternative is the one with the highest overall performance index.

3.3.2. Fuzzy reference point method

The fuzzy reference point approach uses the normalized fuzzy decision matrix $X^* = [\tilde{x}_{ij}^*]_{\substack{i=1,\dots,m \\ j=1,\dots,n}}$ of Eq. (11). The ij-th element of this matrix, $(x_{ij}^{l*}, x_{ij}^{m*}, x_{ij}^{u*})$, is regarded as the normalized performance value of the i-th alternative on the j-th criterion. A reference point r_j needs to be identified that will account for both the benefit and the cost criteria in a realistic and non-subjective manner. Following Adalı & Işık [3] and Akkaya et al. [6], this reference point can be defined by a min-max formulation as in Eq. (29).

$$\begin{cases} \tilde{r}_j^+ = \left(\max_i x_{ij}{}^{l*}, \max_i x_{ij}{}^{m*}, \max_i x_{ij}{}^{u*}\right), j = 1, \dots, \beta (for\ criteria\ to\ be\ \max imized) \\ \tilde{r}_j^- = \left(\min_i x_{ij}{}^{l*}, \min_i x_{ij}{}^{m*}, \min_i x_{ij}{}^{u*}\right), j = 1+\beta, \dots, n (for\ criteria\ to\ be\ \min imized) \end{cases} \quad (29)$$

Given the reference point above and taking into account the weights of the criteria, $(w_j,\ j = 1, \dots, n)$, we can compute the overall rating s_i of the i-th alternative as follows:

$$s_i = \max_j w_j \times \left[\tilde{r}_j - \tilde{x}_{ij}^*\right] \quad (30)$$

As in Section 3.3.1, the overall rating s_i can be interpreted as a TFN, that is:

$$s_i = (s_i^l, s_i^m, s_i^u) \quad (31)$$

where:

$$s_i^l = \begin{cases} \max_j w_j \times \left|\left[\max_i x_{ij}{}^{l*}\right] - x_{ij}^{l*}\right|, & if\ j \le \beta \\ \max_j w_j \times \left|\left[\min_i x_{ij}{}^{l*}\right] - x_{ij}^{l*}\right|, & if\ j > \beta \end{cases} \quad (32)$$

$$s_i^m = \begin{cases} \max_j w_j \times \left|\left[\max_i x_{ij}{}^{m*}\right] - x_{ij}^{m*}\right|, & if\ j \le \beta \\ \max_j w_j \times \left|\left[\min_i x_{ij}{}^{m*}\right] - x_{ij}^{m*}\right|, & if\ j > \beta \end{cases} \quad (33)$$

$$s_i^u = \begin{cases} \max_j w_j \times \left|\left[\max_i x_{ij}{}^{u*}\right] - x_{ij}^{u*}\right|, & if\ j \le \beta \\ \max_j w_j \times \left|\left[\min_i x_{ij}{}^{u*}\right] - x_{ij}^{u*}\right|, & if\ j > \beta \end{cases} \quad (34)$$

Finally, the alternatives are ranked according to their normalized performances subject to defuzzification as defined in Eq. (35) [3]. The best alternative is the one deviating the less from the reference points.

$$BNP_i(s_i) = \frac{\left(s_i^u - s_i^l\right) + \left(s_i^m - s_i^l\right)}{3} + s_i^l \quad (35)$$

3.3.3. Fuzzy full multiplicative form

The Full Multiplicative Form was suggested by Miller and Starr [130]. This method simultaneously maximizes and minimizes a purely multiplicative utility function.

The utility function is characterized by non-linearity, non-additivity, and the absence of attribute weights [3] and is defined by the ratio of the product of the weighted normalized ratings of the alternatives on benefit criteria to that of the weighted normalized ratings of the alternatives on cost criteria [74]. Thus, we have the following fuzzy formulation for the utility value of the i-th alternative:

$$\tilde{U}_i = \frac{\tilde{\Phi}_i}{\tilde{\Psi}_i} \quad (36)$$

where

$$\tilde{\Phi}_i = \left(\Phi_{i1}, \Phi_{i2}, \Phi_{i3}\right) = \prod_{j=1}^{\beta} (x^*{}_{ij})^{w_j} \quad (37)$$

$$\tilde{\Psi}_i = \left(\Psi_{i1}, \Psi_{i2}, \Psi_{i3}\right) = \prod_{j=\beta+1}^{n} \left(x^*{}_{ij}\right)^{w_j} \quad (38)$$

$\tilde{\Phi}_i$ and $\tilde{\Psi}_i$ represent the products of the objectives of the i-th alternative to be maximized and minimized, respectively. The indices β and $n-\beta$ denote the number of these objectives (structural indicators) in the maximization and minimization cases, respectively.

Note that due to the form of the utility, multiplying the normalized ratings by the weights of the corresponding criteria does not affect the results. This is the reason for considering the weights as exponents in the utility equation [74].

The alternatives are ranked from the most to the least important. This ranking is based on the BNP values associated with the utility values of the alternatives and calculated as in Eq. (35). Higher positions in the ranking are occupied by alternatives corresponding to higher BNP values. Note that the overall utility $(\tilde{U}_i)$ of the i-th alternative is a fuzzy number. Thus, the fuzzy products $\tilde{\Phi}_i$ and $\tilde{\Psi}_i$ [6] need to be defuzzified before computing the BNP_i values.

3.3.4. Final ranking (dominance theory)

After applying the three methods illustrated above and obtaining three separate rankings for the same set of alternatives, an aggregation method is usually implemented to integrate the three rankings in a unique consensus ranking.

The aggregation method commonly used to complete the MULTIMOORA method is based on dominance theory [74]. Dominance theory assumes all the methods involved to be equally important and creates a final ranking through absolute dominance, general dominance in two of the three methods, and transitiveness principles [30].

Dominance theory actually represents the original approach to ranking aggregation in MULTIMOORA (see [30]). However, in this paper, it will be used in an extended form, that is, also considering the rankings produced by fuzzy COPRAS and fuzzy TOPSIS (see Section 3.6).

3.4. Fuzzy COPRAS

In this section, we describe the steps relative to the ranking process of fuzzy COPRAS. We follow the approach of Zarbakhshnia et al. [212].

Step 0. Fix the set of alternatives $\{\alpha_1, ..., \alpha_m\}$ and the set of criteria $\{C_1, C_2, ..., C_n\}$.

Step 1. Construct the fuzzy decision matrix. Use Eq. (10) for the matrix and Table 3 for the correspondence between linguistic terms and fuzzy membership functions [12,212].

Step 2. Normalize the fuzzy decision matrix. This is done by redefining the elements of the fuzzy decision matrix, according to Eqs. (12) to (14).

Step 3. Construct the weighted normalized decision matrix. This is done using Eq. (16) to (18).

Step 4. Compute the sums of the attribute values, whose larger values are more preferable.

$$\tilde{Z}_j = \sum_{i=1}^{k} \tilde{x}_{ij}^{**} \tag{39}$$

Step 5. Compute the sums of the attribute values, whose smaller values are more preferable.

$$\tilde{T}_j = \sum_{i=k+1}^{m} \tilde{x}_{ij}^{**} \tag{40}$$

Step 6. Compute the lower bound of $\tilde{T}_j$, where$j = 1, 2, ..., n$.

$$\underset{\min}{\tilde{T}} = \min_{j} \underset{j}{\tilde{T}} \tag{41}$$

Step 7. Compute the relative importance of each alternative.

$$\tilde{Q}_j = \tilde{Z}_j + \frac{\tilde{T}_{\min} \sum_{j=1}^{n} \tilde{T}_j}{\tilde{T}_j \sum_{j=1}^{n} \frac{\tilde{T}_{\min}}{\tilde{T}_j}}; j = 1, 2, ..., n \tag{42}$$

Step 8. Obtain crisp values for all the $\underset{j}{\tilde{Q}}$ fuzzy values. We can use the defuzzification rule of Eq. (35) to defuzzify the elements $\tilde{x}_{ij}^{**}$, that is:

$$x_{ij}^{**} = \frac{\left(x_{ij}^{u**} - x_{ij}^{l**}\right) + \left(x_{ij}^{m**} - x_{ij}^{l**}\right)}{3} + x_{ij}^{l**} \tag{43}$$

The non-fuzzy value of $\tilde{Q}_j$, denoted by Q_j, will follow from the defuzzified form of Eq. (42).

Step 9. Compute the upper weight limit of the alternatives.

$$Q_{\max} = \max_{j} Q_j \tag{44}$$

Step 10. Calculate the utility value of each alternative in percentage terms.

$$K_j = \frac{Q_j}{Q_{\max}} \times 100\%; \; j = 1, 2, ..., n \tag{45}$$

where Q_j is the non-fuzzy relative importance weight of the single alternative obtained in Step 8 and $Q_{\max}$ is the upper weight limit value obtained in Step 9. Using Eq. (45), the alternatives are ranked from the highest to the lowest one according to the their utility values.

3.5. Fuzzy TOPSIS

Regarding the fuzzy TOPSIS technique, this study follows Sun [173]. The steps of this ranking method are described below.

Step 0. Fix the set of alternatives $\{\alpha_1, ..., \alpha_m\}$ and the set of criteria $\{C_1, C_2, ..., C_n\}$.

Step 1. Construct the fuzzy decision matrix. This matrix consists of TFNs as in Eq. (10).

$$X = \left[\tilde{x}_{ij}\right]_{\substack{i=1,...,m \\ j=1,...,n}} = \left[\left(x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}\right)\right]_{\substack{i=1,...,m \\ j=1,...,n}} \tag{46}$$

Step 2. Normalize the fuzzy decision matrix. This is done by redefining the elements of the fuzzy decision matrix, according to Eqs. (48) and (49) below.

$$R = \left[\tilde{r}_{ij}\right]_{\substack{i=1,...,m \\ j=1,...,n}} \tag{47}$$

where:

$$\tilde{r}_{ij} = \left(\frac{x_{ij}^{l}}{x_{ij}^{+}}, \frac{x_{ij}^{m}}{x_{ij}^{+}}, \frac{x_{ij}^{u}}{x_{ij}^{+}}\right) and\ x_j^{+} = \max_{i} x_{ij}^{u} (benefit\ criteria) \tag{48}$$

$$\tilde{r}_{ij} = \left(\frac{x_j^{-}}{x_{ij}^{l}}, \frac{x_j^{-}}{x_{ij}^{m}}, \frac{x_j^{-}}{x_{ij}^{u}}\right) and\ x_j^{-} = \min_{i} x_{ij}^{l} (cost\ criteria) \tag{49}$$

Step 3. Construct the weighted normalized fuzzy decision matrix.

$$\mathrm{T} = \left[\tilde{\tau}_{ij}\right]_{\substack{i=1,...,m \\ j=1,...,n}}, \tilde{\tau}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j \tag{50}$$

Step 4. Calculate the fuzzy positive ideal solution and the fuzzy negative ideal solution. The elements $\tilde{\tau}_{ij}$ of the weighted normalized fuzzy decision matrix are positively normalized TFNs, whose membership functions take values in a range between 0 and 1. Hence, the fuzzy positive and negative ideal solutions, represented by Λ^{+} (aspiration levels) and Λ^{-} (worst levels), respectively, can be defined as follows:

$$\Lambda^{+} = \left(\tilde{\tau}_1^{+}, \tilde{\tau}_2^{+}, ..., \tilde{\tau}_n^{+}\right) \tag{51}$$

$$\Lambda^{-} = \left(\tilde{\tau}_1^{-}, \tilde{\tau}_2^{-}, ..., \tilde{\tau}_n^{-}\right) \tag{52}$$

where, for $j = 1, 2, ..., n$, we have $\tilde{\tau}_j^{+} = (1, 1, 1)$ and $\tilde{\tau}_j^{-} = (0, 0, 0)$.

Step 5. Calculate the distances δ_i^{+} and δ_i^{-} of each weighted alternative from the fuzzy positive ideal solution Λ^{+} and the fuzzy negative ideal solution Λ^{-}. That is:

$$\delta_i^{+} = \sum_{j=1}^{n} dist\left(\tilde{\tau}_{ij}, \tilde{\tau}_j^{+}\right), i = 1, 2, ..., m \tag{53}$$

$$\delta_i^{-} = \sum_{j=1}^{n} dist\left(\tilde{\tau}_{ij}, \tilde{\tau}_j^{-}\right), i = 1, 2, ..., m \tag{54}$$

The quantities $dist(\tilde{\tau}_{ij}, \tilde{\tau}_j^{+})$ and $dist(\tilde{\tau}_{ij}, \tilde{\tau}_j^{-})$ represent distances between TFNs calculated according to the following definition: for every pair of TFNs, $\tilde{\tau}_1 = (t_1^l, t_1^m, t_1^u)$ and $\tilde{\tau}_2 = (t_2^l, t_2^m, t_2^u)$, we have:

$$dist\left(\tilde{\tau}_1, \tilde{\tau}_2\right) = \sqrt{\frac{1}{3}\left[\left(t_1^l - t_2^l\right)^2 + \left(t_1^m - t_2^m\right)^2 + \left(t_1^u - t_2^u\right)^2\right]} \tag{55}$$

Step 6. Determine the values of the closeness coefficients. That is:

$$\gamma_i = \frac{\delta_i^{-}}{\delta_i^{-} + \delta_i^{+}} \tag{56}$$

3.6. Consensus ranking with maximize agreement heuristic

The term "consensus" is mathematically vague and subject to a variety of interpretations. Following Beck and Lin [25], "consensus" in a decision-making environment can be interpreted as the "maximization of rater agreement." In order to achieve this goal, Beck and Lin [25] proposed the maximize agreement heuristic (MAH) method, showing that the final consensus ranking produced by this method not only is significantly congruent with the preferences expressed by each rater but also yields the greatest number of agreements.

An agreement is reached if the following happens: object i is ranked above object j by some rater and, at the same time, the object i is ranked above object j in the final consensus ranking. That is, an agreement is reached if the ranking order of objects i and j by a single rater is the same as the one in final consensus ranking. Clearly, a disagreement prevails if this condition is not satisfied for objects i and j [25].

MAH turned out to be an effective consensus ranking method and has been applied to a wide range of multi-criteria decision-making problems [100,177–180,182]. In this study, we use the MAH method to aggregate in a final consensus ranking the rankings obtained by five different methods, namely, the fuzzy ratio method, the fuzzy reference point method, fuzzy full multiplicative method, fuzzy COPRAS, and fuzzy TOPSIS. The MAH method comprises the following steps.

Step 0. Fix the set of alternatives $\{\alpha_1, \ldots, \alpha_m\}$ and the set of the multi-criteria methods $\{M_1, \ldots, M_k\}$. The set of m alternatives is ranked by each method creating a set of k rankings.

Step 1. Construct the agreement matrix.

$$A = \left[a_{ij}\right]_{i,j=1,\ldots,m} \tag{57}$$

where the ij-th element a_{ij} represents the number of methods according to which the i-th alternative, α_i, is to be preferred to the j-th alternative, α_j. Clearly, the main diagonal consists of zero-entries.

Step 2. Define the positive and negative preference vectors of each alternative.

For every alternative α_i, we can consider the row vector $\vec{p}_i = \langle a_{i1}, a_{i2}, \ldots, a_{im}\rangle$ where each element represents the total number of times the i-th alternative, α_i, is preferred to the j-th alternative, α_j. This vector is called the positive preference vector of alternative α_i, and the sum of all its elements provides the total number of times that α_i is preferred to all the other alternatives. This sum is formally introduced below.

$$P_i = \sum_{j=1}^{m} a_{ij}, i = 1, 2, 3, \ldots, m. \tag{58}$$

Similarly, for every alternative α_i, we can consider the column vector $\vec{n}_i = \langle a_{1i}, a_{2i}, \ldots, a_{mi}\rangle^T$ where each element represents the total number of times the i-th alternative, α_i, is not preferred to the j-th alternative, α_j. This vector is called the negative preference vector of alternative α_i, and the sum of all its elements provides the total number of times that α_i is not preferred to all the other alternatives. This sum is formalized as follows.

$$N_i = \sum_{j=1}^{m} a_{ji}, i = 1, 2, 3, \ldots, m. \tag{59}$$

Step 3. Compute all the differences $|P_i - N_i|$, where $i = 1, 2, 3, \ldots, m$, and place an alternative in the final consensus ranking.

The final ranking is constructed through subsequent stages. At each stage, the absolute difference $|P_i - N_i|$ can be interpreted as an objective function whose maximum value $\max_i |P_i - N_i|$corresponds to the alternative that should be entered in the final ranking. Whether or not this alternative is ranked at this stage depends on the criterion highlighted below.

Fix an alternative α_i. Suppose that the negative preference vector $\vec{n}_i$ of alternative α_i has one or more zero-entries. Then, α_i has not been ranked below any of the alternatives corresponding to the zero-entries in any of the rankings provided by each method. Therefore, α_i has no negative impact on the objective function, and it can be entered in the next available position at the top of the final consensus ranking.

Suppose now that the positive preference vector $\vec{p}_i$ of α_i has one or more zero-entries. Then, alternative α_i has not been ranked above any of the alternatives corresponding to the zero-entries. Therefore, α_i has no positive impact on the objective function and should be placed at the bottom of the final consensus ranking.

Finally, if there are no zero-entries in either the positive or negative preference vectors of α_i, then two cases must be considered: (a) if $(P_i - N_i)$ is positive, α_i should be placed at the top of the final consensus ranking since its position in the ranking must account for the highest positive impact on the objective function; (b) if $(P_i - N_i)$is negative, α_i should be placed at the next available position at the bottom of the ranking since its position in the ranking represents the lowest negative impact on the objective function.

Thus, we can formulate the following ranking criterion.

Step 3.0. Compute $\max_i |P_i - N_i|$ and let α_i^* be the corresponding alternative.

Step 3.1. Check for zero-entries (other than those on the main diagonal) in either the positive or negative preference vectors.

1. If zero-entries occur in the positive preference vector of α_i^*, then enter α_i^* in the next available position at the bottom of the consensus ranking.
2. If zero-entries occur in the negative preference vector of α_i^*, then enter α_i^* in the next available position at the top of the consensus ranking.
3. If no zero-entry occurs, go to Step 3.2.

Step 3.2. Examine the difference $P_i^* - N_i^*$ corresponding to α_i^*

1. If $P_i^* - N_i^* > 0$, enter α_i^* in the next available position at the top of the consensus ranking.
2. If $P_i^* - N_i^* < 0$, enter α_i^* in the next available position at the bottom of the consensus ranking.
3. In case of a tie where more than one alternative is a candidate for the final consensus ranking, the tie is broken arbitrarily.

Step 3.3. Delete the column and row representing the negative and positive preference vectors of α_i^* from the agreement matrix A, and go to Step 4.

Step 4. Set $m = m - 1$

Step 5. If $m > 1$, return to Step 2. If $m = 1$, enter the last alternative in the next available position on the top of the ranking and stop.

It is worth mentioning that the MAH procedure is used to solve both complete and incomplete ranking problems. In a complete ranking problem, all methods ordinally or cardinally rank all the alternatives. On the other hand, in an incomplete ranking problem, each method manages ranking only a subset of alternatives [25].

4. Case study

The model proposed in this study was developed for a medium-sized manufacturing company in northern Pennsylvania. We invited six managers, including a purchasing manager, a supply chain manager, two production managers, and two industrial engineers to participate in the design, development, and implementation of the model. We provided the six managers with the selection criteria identified through a comprehensive literature review (see Table 5) and the linguistic terms/fuzzy preference conversion table (see Table 3). The mangers provided us with the fuzzy preference comparisons for the best and worst criteria as well as all fuzzy decision matrices resulting from aggregating the experts' estimates. Here is the process we followed in details:

4.1. Phase 1: deciding the selection criteria

The present research has built on the rigorous literature review conducted by Büyüközkan & Göçer [34] to explore the digital dimensions and determine the principal evaluation criteria. We identified twelve criteria for supplier selection in the DSC. These criteria are outlined in Table 5 and were used in the case study.

4.2. Phase 2: fuzzy BWM results

We used expert opinions to apply fuzzy BWM and compute the weights of the selection criteria. As already mentioned above, we identified twelve criteria (Table 5) for the supplier selection problem (Step 1). The 'agility and flexibility' (C6) and 'adopting advanced analytics' (C2) were considered, respectively, the best and the worst criterion based on the experts' opinions (Step 2). The fuzzy preference comparisons were performed (Steps 3 and 4). The linguistic terms used by the DMs to assign fuzzy preferences of the best criterion over all the criteria are listed in Table 6.

Table 5
Criteria for DSC supplier selection.

Criteria	Description
Real-Time Visibility (C1)	Dynamic, secure, and interactive visibility across the entire SC will facilitate the management of DSC [35].
Adopting Advanced Analytics (C2)	Advanced data analysis improves the decision-making process of an SC, allowing for a better understanding of known problems and to solve previously unsolvable or unknown problems. [35].
Technical Capability (C3)	To have technical capability means to be able to use technology for developing a product or providing a service. The use of technology by suppliers increases the competitive advantage of companies [32,33].
Continuous collaboration (C4)	Capabilities are harmonized within and beyond physical boundaries to increase collaboration among all the actors involved in the SC [35].
Alignment of the supplier (C5)	Aligning the interest of all the firms in the SC with one's own firm to create incentives for improving performance and developing trust (alignment) [35].
Agility and Flexibility (C6)	Lack of required flexible and agile SCM [35].
Lack of tools and technologies (C7)	Lack of tools and technologies makes problems in a DSC environment. DSC requires new tools and technologies that take into account the digitalization environment, such as the abundance of BD generated from ST and IoT. In addition, it affects maintenance, quality, inventory management, production planning, and procurement [35].
Lack of planning (C8)	Lack of proper demand planning and guidelines [35].
Lack of information sharing (C9)	DSC allows for an easier share of information on sale forecasts and production data. Companies' reluctance on information sharing is an important criterion in SS [35].
Lack of knowledge (C10)	Deficiency of SCM training and skills [35].
Lack of Digital Collaboration (C11)	Capabilities are harmonized within and beyond physical boundaries to increase collaboration among the actors involved in the DSC. A deficient collaboration with external associates and insufficient input from internal functions greatly affect supplier selection processes [35].
Lack of Technology Integration (C12)	Suppliers need to use their technological skills for learning and problem-solving in a DSC environment. [35].

Table 6
The linguistic terms for fuzzy preferences of the best criterion over all the criteria.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
VI	AI	FI	FI	VI	Best Criterion	FI	VI	VI	VI	FI	VI

Table 7
The linguistic terms for fuzzy preferences of all the criteria over the worst criterion.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
FI	Worst Criterion	VI	VI	FI	AI	VI	FI	FI	FI	VI	FI

The fuzzy Best-to-Others vector was obtained according to Table 3 and Eq. (1) as follows (Step 3):

$$\tilde{A}_B = \left[(5/2, 3, 7/2), (7/2, 4, 9/2), \ldots (3/2, 2, 5/2), (5/2, 3, 7/2)\right]$$

The fuzzy preference comparisons for the worst criterion were also performed. The linguistic terms used by the DMs for the fuzzy preferences of all the criteria over the worst criterion are listed in Table 7.

Hence, the fuzzy Others-to-Worst vector was obtained according to Table 3 and Eq. (2) as follows (Step 4):

$$\tilde{A}_W = \left[(3/2, 2, 5/2), (5/2, 3, 7/2), \ldots (5/2, 3, 7/2), (3/2, 2, 5/2)\right]$$

A nonlinear constrained optimization problem was built using Model (5) (Step 5) to obtain the optimal fuzzy weights of the criteria. The nonlinear constrained optimization problem resulting from implementing the above concrete vectors is presented in Appendix A. The optimal fuzzy weights are listed below:

$$\tilde{w}_1^* = (0.050022, 0.063556, 0.083345); \tilde{w}_2^* = (0.039828, 0.039879, 0.044635); \tilde{w}_3^* = (0.093403, 0.103464, 0.123173)$$
$$\tilde{w}_4^* = (0.093403, 0.103464, 0.012317); \tilde{w}_5^* = (0.050013, 0.063556, 0.083345); \tilde{w}_6^* = (0.174407, 0.174628, 0.195454)$$
$$\tilde{w}_7^* = (0.093403, 0.103464, 0.123173); \tilde{w}_8^* = (0.050022, 0.063556, 0.083345); \tilde{w}_9^* = (0.050022, 0.063556, 0.083345)$$
$$\tilde{w}_{10}^* = (0.050022, 0.063556, 0.083345); \tilde{w}_{11}^* = (0.093403, 0.10965, 0.123173); \tilde{w}_{12}^* = (0.050022, 0.063556, 0.083345)$$

Using the GMIR formula in Eq. (6), we calculated the crisp weights of the twelve criteria. The crisp weights are reported below:

$$w_1^* = 0.062918; w_2^* = 0.039624; w_3^* = 0.102339; w_4^* = 0.102339; w_5^* = 0.062918; w_6^* = 0.173512;$$
$$w_7^* = 0.102339; w_8^* = 0.062918; w_9^* = 0.062918; w_{10}^* = 0.062918; w_{11}^* = 0.102339; w_{12}^* = 0.062918.$$

Finally, the CR value obtained for the fuzzy comparisons performed by the experts according to the fuzzy BWM was CR = 0.474054/8.04 = 0.05896, corresponding to ξ^*= 0.474054 and CI = (Absolutely importance (AI)) = 8.04. Since the value obtained for CR is close to zero, we can assert that the implemented model has high consistency.

4.3. Phase 3: fuzzy MULTIMOORA

We applied the proposed fuzzy MULTIMOORA method (Section 3.3) to evaluate the alternatives. Ten alternatives, that is, ten suppliers, denoted by S1, S2, S3, ..., S10, were considered in the evaluation process.

We started with the fuzzy ratio approach. After normalizing the fuzzy decision matrix using Eqs. (12) to (14), we constructed the weighted normalized fuzzy decision matrix as in Eqs. (16) to (18). For every supplier, we computed the overall ratings of the criteria as in Eq. (19). Hence, Eqs. (20) to (22) were applied in the benefit criteria case to compute the overall ratings of a supplier for the extreme and middle values of the triangular membership functions. Similarly, Eqs. (23) to (25) were applied in the cost criteria case to compute the overall score of a supplier for the extreme and middle values of the triangular membership

Table 8
Supplier ranking by the fuzzy ratio method.

Supplier	$y_i = \sum_{j=1}^{\beta} \tilde{x}_{ij}^{**} - \sum_{j=\beta+1}^{n} \tilde{x}_{ij}$						Y_i	Fuzzy ratio ranking
	Benefits			Cost				
	l	m	u	l	m	u		
S1	0.1446	0.2871	0.4297	0.1457	0.2491	0.3524	0.0586	10
S2	0.1963	0.3011	0.406	0.1184	0.2401	0.3619	0.1022	2
S3	0.1192	0.2801	0.441	0.1836	0.2565	0.3294	0.0941	3
S4	0.2186	0.3056	0.3926	0.1077	0.2378	0.368	0.1307	1
S5	0.1901	0.3	0.4099	0.1491	0.2496	0.3502	0.0736	7
S6	0.096	0.2263	0.4589	0.1289	0.2436	0.3583	0.069	9
S7	0.1268	0.2815	0.4362	0.0847	0.2292	0.3736	0.0762	6
S8	0.1087	0.2766	0.4446	0.1055	0.2085	0.3744	0.0793	5
S9	0.2045	0.3029	0.4013	0.1663	0.2533	0.3404	0.0718	8
S10	0.0379	0.2555	0.4731	0.0675	0.1973	0.39	0.0811	4

Table 9
Supplier ranking by the fuzzy reference point.

Supplier	$s_i = \max_j w_j \times \lvert \tilde{r}_j - \tilde{x}_{ij}^* \rvert$			BNP_i	Fuzzy reference point ranking
S1	0.0234	0.0351	0.0022	0.0202	3
S2	0.0168	0.0336	0.006	0.0188	1
S3	0.0434	0.0121	0.0108	0.0221	7
S4	0.0234	0.0351	0.0022	0.0202	2
S5	0.0267	0.0356	0	0.0208	4
S6	0.0434	0.0579	0	0.0338	10
S7	0.0736	0.0206	0	0.0314	8
S8	0.0434	0.0121	0.0108	0.0221	6
S9	0.0267	0.0356	0	0.0208	5
S10	0.0736	0.0206	0	0.0314	9

functions. We then used Eq. (28) to defuzzify the overall score of the criteria.

We obtained the ranking of suppliers presented in Table 8. The suppliers are ranked in decreasing order of importance as follows:

$$S4 > S2 > S3 > S10 > S8 > S7 > S5 > S9 > S6 > S1$$

Thus, after applying the fuzzy ratio method, the best supplier turned out to be Supplier 4.

Next, we applied the fuzzy reference point method. The overall performance values of the suppliers were computed according to Eqs. (29) and (30). Hence, Eq. (35) was used to calculate the fuzzy reference point ranking presented in Table 9. The suppliers are ranked in decreasing order of importance as follows:

$$S2 > S1 > S4 > S9 > S5 > S3 > S8 > S10 > S7 > S6$$

Thus, after applying the fuzzy reference point method, the best supplier turned out to be Supplier 2.

Finally, we analyzed the supplier selection problem implementing the fuzzy full multiplicative form presented in Eq. (36). The overall utility values relative to the single suppliers (i.e., $\tilde{U}'_i$, with $i = 1, \ldots, 10$) are presented in Table 10. These values are the final defuzzified values of the fuzzy overall utility and were obtained using the non-fuzzy values of the products $\tilde{\Phi}_i$ and $\tilde{\Psi}_i$ (where $i = 1, \ldots, 10$), also shown in Table 10. According to the full multiplicative form, the suppliers are ranked in decreasing order of importance as follows:

$$S8 > S10 > S4 > S2 > S7 > S5 > S9 > S1 > S3 > S6$$

with Supplier 8 ranked as the best supplier.

4.4. Phase 4: fuzzy COPRAS results

The proposed fuzzy COPRAS approach Section 3.4) was implemented to rank the suppliers. The weights assigned to the criteria in this phase were those obtained by fuzzy BWM. First, as in the fuzzy MULTIMOORA phase, we used Eqs. (12) to ((14) to normalize the fuzzy decision matrix and Eqs. (16) to (18) to obtain the weighted normalized fuzzy decision matrix. Eqs. (39) and (40) were used to calculate the sums of the attribute values for the maximum and minimum values, respectively. Next, we used Eq. (42) to calculate the relative importance of each alternative and Eq. (43) to defuzzify the obtained values. Finally, Eq. (45) was used to calculate the utility value of each alternative. The supplier ranking is presented in Table 11. The suppliers are ranked in decreasing order of importance as follows:

$$S2 > S9 > S4 > S5 > S8 > S7 > S3 > S10 > S1 > S6$$

with Supplier 2 representing the most preferred supplier.

4.5. Phase 5: fuzzy TOPSIS results

The proposed fuzzy TOPSIS approach Section 3.5) was implemented to rank the suppliers. The weights assigned to the criteria in this phase were those obtained by fuzzy BWM. We determined the weighted normalized fuzzy decision matrix (Eqs. (16) to ((18)) and calculated the values ofδ_i^+ , $\delta_i^-$and γ_i using Eqs. (51) to (56). All these values are displayed in Table 12. The suppliers are ranked on the basis of their closeness coefficients as follows:

$$S2 > S8 > S5 > S3 > S9 > S10 > S6 > S7 > S1 > S4$$

with Supplier 2 identified as the most preferred supplier.

4.6. Phase 6: consensus raking results

We implemented the MAH method to aggregate the supplier rankings obtained by fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS and create a final consensus ranking. The MAH allows for evaluating the alternative suppliers one at a time. Each alternative supplier is placed in the final consensus ranking by building an agreement matrix that does

Table 10
Supplier ranking by the fuzzy full multiplicative form.

Supplier	$\tilde{\Phi}_i$			$\tilde{\Psi}_i$			Non-fuzzy $\tilde{\Phi}_i$	Non-fuzzy $\tilde{\Psi}_i$	$\tilde{U}_i = \frac{\tilde{\Phi}_i}{\tilde{\Psi}_i}$	Fuzzy full multiplicative form ranking
S1	0	0.7055	0.8785	0.5903	0.7585	0.8885	0.528	0.7458	0.708	8
S2	0.57	0.7252	0.8527	0	0.7448	0.8985	0.716	0.5477	1.3071	4
S3	0	0.6957	0.8911	0.6594	0.7688	0.8617	0.5289	0.7633	0.6929	9
S4	0.6087	0.7311	0.8376	0	0.7416	0.9055	0.7258	0.5491	1.3219	3
S5	0.5603	0.7237	0.8572	0.5953	0.7592	0.8857	0.7138	0.7467	0.9558	6
S6	0	0	0.9087	0	0.75	0.8946	0.3029	0.5482	0.5525	10
S7	0	0.6974	0.8855	0	0.7283	0.9109	0.5276	0.5464	0.9657	5
S8	0	0.6908	0.895	0	0	0.9115	0.5286	0.3038	1.7398	1
S9	0.585	0.7276	0.8476	0.6285	0.7644	0.8746	0.7201	0.7559	0.9526	7
S10	0	0.6622	0.9267	0	0	0.929	0.5296	0.3097	1.7103	2

Table 11
Supplier ranking by fuzzy COPRAS.

Supplier	$\tilde{Z}_j$			$\tilde{T}_j$			$\tilde{Q}_j$			Non-fuzzy $\tilde{Q}_j$	K_j	Fuzzy COPRAS ranking
S1	0.0475	0.0821	0.1166	0.0505	0.0798	0.109	0.0758	0.1408	0.2081	0.1416	80.6536	9
S2	0.068	0.1011	0.1341	0.0354	0.0634	0.0914	0.1084	0.175	0.2433	0.1755	100	1
S3	0.042	0.0834	0.1247	0.0368	0.0641	0.0991	0.0808	0.1565	0.2254	0.1542	87.8476	7
S4	0.0677	0.0939	0.1201	0.0526	0.0748	0.097	0.0948	0.1565	0.2229	0.1581	90.0588	3
S5	0.0574	0.0878	0.1183	0.0423	0.0681	0.0939	0.0911	0.1566	0.2245	0.1574	89.6769	4
S6	0.0352	0.067	0.1062	0.0451	0.0783	0.1114	0.0669	0.1269	0.1957	0.1298	73.9685	10
S7	0.0439	0.0814	0.1189	0.032	0.0637	0.0954	0.0886	0.1549	0.2234	0.1556	88.6527	6
S8	0.0418	0.0862	0.1306	0.0325	0.0649	0.1025	0.0858	0.1584	0.2279	0.1574	89.6607	5
S9	0.0684	0.097	0.1256	0.0484	0.0726	0.0969	0.0979	0.1615	0.2285	0.1626	92.6414	2
S10	0.0141	0.068	0.122	0.0187	0.0582	0.1039	0.0903	0.1486	0.218	0.1523	86.7617	8

Table 12
Supplier ranking by fuzzy TOPSIS.

Supplier	δ_i^+	δ_i^-	$\gamma_i = \frac{\delta_i^-}{\delta_i^- + \delta_i^+}$	Fuzzy TOPSIS ranking
S1	11.249	0.805	0.0668	9
S2	11.1229	0.9786	0.0809	1
S3	11.2292	0.8982	0.0741	4
S4	11.2406	0.784	0.0652	10
S5	11.163	0.8962	0.0743	3
S6	11.2595	0.8286	0.0685	7
S7	11.2875	0.8171	0.0675	8
S8	11.2059	0.9466	0.0779	2
S9	11.1851	0.854	0.0709	5
S10	11.3535	0.8453	0.0693	6

not consider the alternative suppliers that have already been ranked. The process stops when all the alternative suppliers are ranked [185].

To simplify the comparisons between two rankings, we constructed a matrix whose rows display the position occupied by each supplier in each ranking. This matrix is given in Table 13.

Table 14 features all the agreement matrices used through the heuristic process. Matrix 13.1 shows the number of times each supplier was preferred to all the other suppliers by each method. For example, five methods preferred Supplier 2 to Supplier 3, three methods preferred Supplier 2 to Supplier 4, and so on. The entries of this matrix were obtained using the matrix of single method rankings provided in Table 13.

The elements of each row of Matrix 14.1 were summed to get the total number of methods agreeing on each supplier ($P_i, i = 1, \ldots, 10$). Similarly, the elements of each column were summed to get the total number of methods disagreeing on each supplier ($N_i, i = 1, \ldots, 10$). Finally, the differences $(P_i - N_i), i = 1, \ldots, 10$, were calculated. The highest value that was obtained for the absolute difference $|P_i - N_i|, i = 1, \ldots, 10$, is 37.

Matrix 14.1 shows zero-entries, other than those on the main diagonal, in the columns of suppliers S2, S3, S5, S8, and S9 and in the rows of suppliers S1, S3, S5, S6, S7, and S9. Since, S2 and S6 correspond to the $\max_i |P_i - N_i| = 37$, the heuristic focused on these two suppliers and placed S2 (whose negative preference vector has zero-entries) at the top of the final ranking. S6 should have gone at the bottom of the ranking since its positive preference vector has zero-entries. At this point, S2 was deleted, and a new matrix, Matrix 14.2, created.

In this new matrix, there were no zero-entries in the columns nor in the rows of the suppliers corresponding to the new highest positive difference $P_i - N_i = +20$, namely, suppliers S4 and S8. Thus, suppliers S4 and S8 were placed at the top of the final consensus ranking after S2. At this point, S4 and S8 were deleted, and a new matrix, Matrix 14.3, created.

Reasoning as for Matrix 14.2, suppliers S2, S4, and S8 were followed by suppliers S5, S9, S3, S10, S7, S1, and S6.

The final consensus ranking obtained for the suppliers is the following:

$$S2 > S4 > S8 > S5 > S9 > S3 > S10 > S7 > S1 > S6$$

4.7. Sensitivity analysis

A sensitivity analysis (SA) is used to validate the ranking results obtained in the case study and show the robustness of the proposed hybrid model against possible biases in experts' evaluations. Following [68], we performed a SA by allowing the criterion obtaining the highest weight to vary from 0.1 to 0.9. Table 15 shows the changes in weight values of all the criteria when the weight of C6 varies.

After determining the weights of criteria, the criteria were ranked using 9 different runs (see Table 15). The SA relative to the ranking of the criteria is shown in Figure 4.

The next step was to apply fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS analyses with the changing weights for the criteria and calculate the corresponding separated final rankings for the suppliers. Again, there were performed 9 different runs. Then, we computed the final ranking by the consensus ranking method (MAH). The SA results

Table 13
Initial supplier rankings by the single methods.

Method	Suppliers									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Fuzzy ratio method rankings (Table 7)	10	2	3	1	7	9	6	5	8	4
Fuzzy reference point rankings (Table 8)	3	1	7	2	4	10	8	6	5	9
Fuzzy full multiplicative rankings (Table 9)	8	4	9	3	6	10	5	1	7	2
Fuzzy COPRAS ranking (Table 10)	9	1	7	3	4	10	6	5	2	8
Fuzzy TOPSIS ranking (Table 11)	9	1	4	10	3	7	8	2	5	6

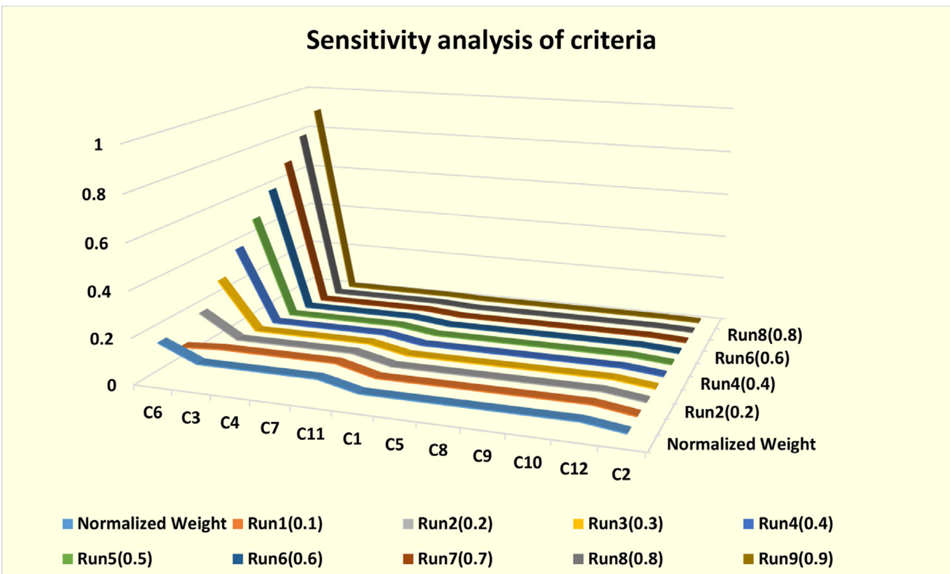

Fig. 4. Sensitivity analysis of the weights of the criteria.

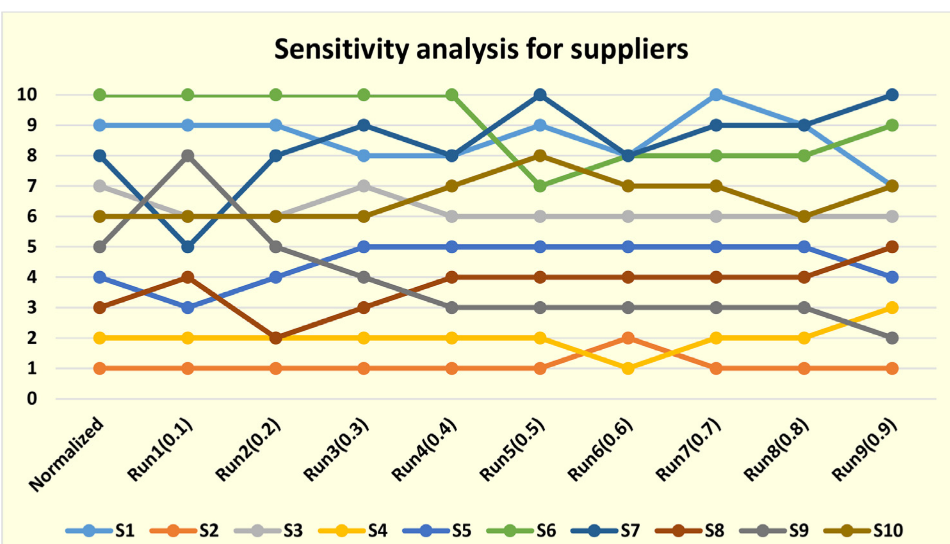

Fig. 5. Sensitivity analysis of the final supplier ranking by MAH.

for the ranking of the suppliers through 9 different runs are shown in Table 16.

Also, Figure 5 shows the SA results for the final ranking of the suppliers. Figures 4 and 5 clearly show that there is no much variation in the final ranking of the criteria or the final ranking of the suppliers. Therefore, the integrated model can be confirmed to be free from any bias and robust.

5. Managerial implications

From a managerial viewpoint, supplier selection is one of the most important issues that managers and decision-makers must deal with. This is particularly true within a DSC setting. The proposed integrated fuzzy BWM, fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS approach allows managers and experts to perform coherent

Table 14
Final consensus ranking using MAH.

Matrix 14.1													
Supplier	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	P_i	P_i - N_i	
S1	0	0	2	1	1	3	1	1	1	1	11	-23	
S2	5	0	5	3	5	5	5	4	5	4	41	37	Rank 1
S3	3	0	0	1	1	5	3	1	2	4	20	-5	
S4	4	2	4	0	4	4	4	3	4	3	32	19	
S5	4	0	4	1	0	5	4	2	4	3	26	7	
S6	2	0	0	1	0	0	1	0	0	0	4	-37	
S7	4	0	2	1	1	4	0	0	2	2	16	-13	
S8	4	1	4	2	3	5	5	0	3	4	31	17	
S9	4	0	3	1	1	5	3	2	0	3	22	-1	
S10	4	1	1	2	2	5	3	1	2	0	21	-3	
N_i	34	4	25	13	19	41	29	14	23	24			
Matrix 14.2													
Supplier	S1	S3	S4	S5	S6	S7	S8	S9	S10	P_i		P_i - N_i	
S1	0	2	1	1	3	1	1	1	1	11		-18	
S3	3	0	1	1	5	3	1	2	4	20		0	
S4	4	4	0	4	4	4	3	4	3	30		20	Rank 2
S5	4	4	1	0	5	4	2	4	3	26		12	
S6	2	0	1	0	0	1	0	0	0	4		-32	
S7	4	2	1	1	4	0	0	2	2	16		-8	
S8	4	4	2	3	5	5	0	3	4	30		20	Rank 3
S9	4	3	1	1	5	3	2	0	3	22		4	
S10	4	1	2	2	5	3	1	2	0	20		0	
N_i	29	20	10	14	36	24	10	18	20				
Matrix 14.3													
Supplier	S1	S3	S5	S6	S7	S9	S10	P_i				P_i - N_i	
S1	0	2	1	3	1	1	1	9				-12	
S3	3	0	1	5	3	2	4	19				6	
S5	4	4	0	5	4	4	3	23				16	Rank 4
S6	2	0	0	0	1	0	0	3				-24	
S7	4	2	1	4	0	2	2	15				0	
S9	4	3	1	5	3	0	3	19				8	
S10	4	1	2	5	3	2	0	17				4	
N_i	21	12	7	27	15	11	13						
Matrix 14.4													
Supplier	S1	S3	S6	S7	S9	S10	P_i					P_i - N_i	
S1	0	2	3	1	1	1	8					-9	
S3	3	0	5	3	2	4	17					9	
S6	2	0	0	1	0	0	3					-19	
S7	4	2	4	0	2	2	14					3	
S9	4	3	5	3	0	3	18					11	Rank 5
S10	4	1	5	3	2	0	15					5	
N_i	17	8	22	11	7	10							
Matrix 14.5													
Supplier	S1	S3	S6	S7	S10	P_i						P_i - N_i	
S1	0	2	3	1	1	7						-6	
S3	3	0	5	3	4	15						10	Rank 6
S6	2	0	0	1	0	3						-14	
S7	4	2	4	0	2	12						4	
S10	4	1	5	3	0	13						6	
N_i	13	5	17	8	7								
Matrix 14.6													
Supplier	S1	S6	S7	S10	P_i							P_i - N_i	
S1	0	3	1	1	5							-5	
S6	2	0	1	0	3							-9	
S7	4	4	0	2	10							5	
S10	4	5	3	0	12							9	Rank 7
N_i	10	12	5	3									
Matrix 14.7													
Supplier	S1	S6	S7	P_i								P_i - N_i	
S1	0	3	1	4								-2	
S6	2	0	1	3								-4	
S7	4	4	0	8								6	Rank 8
N_i	6	7	2										
Matrix 14.8													
Supplier	S1	S6	P_i									P_i - N_i	
S1	0	3	3									1	Rank 9
S6	2	0	2									-1	Rank 10
N_i	2	3											

Table 15
Changes in weight values for all criteria after varying the weight of C6.

Criterion	Normalized Weight	Run1(0.1)	Run2(0.2)	Run3(0.3)	Run4(0.4)	Run5(0.5)	Run6(0.6)	Run7(0.7)	Run8(0.8)	Run9(0.9)
C6	0.1735	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
C3	0.1023	0.1114	0.0991	0.0867	0.0743	0.0619	0.0495	0.0371	0.0248	0.0124
C4	0.1023	0.1114	0.0991	0.0867	0.0743	0.0619	0.0495	0.0371	0.0248	0.0124
C7	0.1023	0.1114	0.0991	0.0867	0.0743	0.0619	0.0495	0.0371	0.0248	0.0124
C11	0.1023	0.1114	0.0991	0.0867	0.0743	0.0619	0.0495	0.0371	0.0248	0.0124
C1	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C5	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C8	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C9	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C10	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C12	0.0629	0.0685	0.0609	0.0533	0.0457	0.0381	0.0305	0.0228	0.0152	0.0076
C2	0.0396	0.0431	0.0384	0.0336	0.0288	0.024	0.0192	0.0144	0.0096	0.0048

Table 16
Sensitivity analysis of MAH ranking results for suppliers.

Supplier	Normalized	Run1(0.1)	Run2(0.2)	Run3(0.3)	Run4(0.4)	Run5(0.5)	Run6(0.6)	Run7(0.7)	Run8(0.8)	Run9(0.9)
S1	9	9	9	8	8	9	8	10	9	7
S2	1	1	1	1	1	1	2	1	1	1
S3	7	6	6	7	6	6	6	6	6	6
S4	2	2	2	2	2	2	1	2	2	3
S5	4	3	4	5	5	5	5	5	5	4
S6	10	10	10	10	10	7	8	8	8	9
S7	8	5	8	9	8	10	8	9	9	10
S8	3	4	2	3	4	4	4	4	4	5
S9	5	8	5	4	3	3	3	3	3	2
S10	6	6	6	6	7	8	7	7	6	7

assessments and make sound decisions using an easy-to-implement methodology.

The proposed framework has been used to analyze a case study in a manufacturing company, but it can be naturally modified to be applied to other case studies of companies with similar features and interest in boosting their DSCs.

A limitation of a study like the one being proposed is the ability of the manager(s) to select a team of experts appropriately. The fuzzy approach proposed in this paper partially compensates for this shortcoming since it allows for incorporating the uncertainty and vagueness of the experts' judgments. Once the evaluation criteria have been defined in a comprehensive manner, how much are the TFNs effective to correctly interpret uncertain and/or vague evaluations depends on the experience and expertise of the expert team.

On the other hand, an operational advantage of the proposed methodology is its capability to rank multiple suppliers, a particularly relevant feature when considering supplier selection problems in DSCs since working with and considering a large number of suppliers is a common phenomenon in digital environments.

From a more academic perspective, despite supplier selection being one of the main determinants of DSC success, the number of studies involving MCDM combined approaches to this problem is still limited. Recently, Torkayesh et al. [189] have used an integrated BWM-WASPAS method to rank digital suppliers in an online retail shop in Iran, identifying "information sharing" and "digital engagement" as the important criteria to select suppliers in a DSC. Özbek & Yildiz [140] have used an interval type-2 fuzzy TOPSIS approach, while Sharma & Joshi [159] have identified the factors influencing the selection of digital suppliers using an integrated SWARA-WASPAS method. In particular, the last study shows that sustainable practices and digital innovation are among the key characteristics that the industries are currently aiming at for the development of their DSCs. Finally, Chen, et al. [41] have proposed a novel rough-fuzzy DEMATEL-TOPSIS approach to sustainable supplier selection in a smart supply chain.

Considering these studies, managerial implications of the proposed methodology can also be outlined regarding sustainability issues. The increasing interest of consumers and governmental policies in industries and companies showing an eco-friendly behavior plays in favor of the proposed research and the performed case study, opening the way to several applications to real-life situations.

6. Conclusion and future research directions

In this study, we proposed an integrated and comprehensive fuzzy multicriteria model for supplier selection in DSCs. The proposed framework consisted of a six-phase procedure to integrate fuzzy BWM with fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS. The supplier selection criteria were identified in Phase 1, while their importance weights are measured in Phase 2 by applying the fuzzy BWM method. In Phases 3 to 5, the suppliers were ranked using the fuzzy MULTIMOORA, fuzzy COPRAS, and fuzzy TOPSIS methods. Finally, in Phase 6, the supplier rankings obtained in the previous phases were aggregated using MAH. We presented a real-life case study to demonstrate the applicability of the proposed integrated procedure in a medium-sized enterprise.

The DSC selection criteria used in this study are extrapolated from a rigorous literature review. This is an advantage but also a limitation of this study. Indeed, managers could face situations where it is necessary to address a specific problem or account for particular requests coming from customers, retailers, distributors and/or producers. In those situations, the list of criteria will need to be modified according to the problem-specific requirements. The proposed model considers a holistic approach that encompasses all features of the singular methods employed in the proposed integrated framework. The final consensus ranking coherently integrates the single method rankings and builds confidence in the overall solution. Decision-makers and all DSC players, including producers, distributors, and retailers, can be confident that the problem has been formulated and evaluated from multiple angles using multiple methods.

A case study has been conducted in a manufacturing company to demonstrate the applicability of the proposed method. The obtained results have been validated with a sensitivity analysis. Managerial implications and limitations, as well as the current interest in sustainability-related issues, have been highlighted.

Future researches could use the proposed integrated method for applications to different selection problems such as site selection, service selection, partner selection, and selection problems related to warehouse locations. In addition, future researchers could concentrate on developing and testing other integrated methods and combine them with the MAH method. Finally, it would be interesting to expand the current study on DSC to humanitarian supply chains focusing in particular on case studies related to the COVID-19 Vaccine supply chain.

Declaration of Competing Interest

The above 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.

Acknowledgment

Dr. Madjid Tavana is grateful for the partial support he received from the Czech Science Foundation (GAˇCR19-13946S) for this research.

Appendix A

The nonlinear constrained optimization problem

$$
\begin{array}{l}
\min \quad k^* \\
s.t. \\
l_6 - 2.5 * u_1 \le k * u_1; l_6 - 2.5 * u_1 \ge -k * u_1; \\
m_6 - 3 * m_1 \le k * m_1; m_6 - 3 * m_1 \ge -k * m_1; \\
u_6 - 3.5 * l_1 \le k * l_1; u_6 - 3.5 * l_1 \ge -k * l_1; \\
l_6 - 3.5 * u_2 \le k * u_2; l_6 - 3.5 * u_2 \ge -k * u_2; \\
m_6 - 4 * m_2 \le k * m_2; m_6 - 4 * m_2 \ge -k * m_2; \\
u_6 - 4.5 * l_2 \le k * l_2; u_6 - 4.5 * l_2 \ge -k * l_2; \\
\vdots \\
l_6 - 1.5 * u_{11} \le k * u_{11}; l_6 - 1.5 * u_{11} \ge -k * u_{11}; \\
m_6 - 2 * m_{11} \le k * m_{11}; m_6 - 2 * m_{11} \ge -k * m_{11}; \\
u_6 - 2.5 * l_{11} \le k * l_{11}; u_6 - 2.5 * l_{11} \ge -k * l_{11}; \\
l_6 - 2.5 * u_{12} \le k * u_{12}; l_6 - 2.5 * u_{12} \ge -k * u_{12}; \\
m_6 - 3 * m_{12} \le k * m_{12}; m_6 - 3 * m_{12} \ge -k * m_{12}; \\
u_6 - 3.5 * l_{12} \le k * l_{12}; u_6 - 3.5 * l_{12} \ge -k * l_{12}; \\
l_1 - 1.5 * u_2 \le k * u_2; l_1 - 1.5 * u_2 \ge -k * u_2; \\
m_1 - 2 * m_2 \le k * m_2; m_1 - 2 * m_2 \ge -k * m_2; \\
u_1 - 2.5 * l_2 \le k * l_2; u_1 - 2.5 * l_2 \ge -k * l_2; \\
l_3 - 2.5 * u_2 \le k * u_2; l_3 - 2.5 * u_2 \ge -k * u_2; \\
m_3 - 3 * m_2 \le k * m_2; m_3 - 3 * m_2 \ge -k * m_2; \\
u_3 - 3.5 * l_2 \le k * l_2; u_3 - 3.5 * l_2 \ge -k * l_2; \\
\vdots \\
l_{11} - 2.5 * u_2 \le k * u_2; l_{11} - 2.5 * u_2 \ge -k * u_2; \\
m_{11} - 3 * m_2 \le k * m_2; m_{11} - 3 * m_2 \ge -k * m_2; \\
u_{11} - 3.5 * l_2 \le k * l_2; u_{11} - 3.5 * l_2 \ge -k * l_2; \\
l_{12} - 1.5 * u_2 \le k * u_2; l_{12} - 1.5 * u_2 \ge -k * u_2; \\
m_{12} - 2 * m_2 \le k * m_2; m_{12} - 2 * m_2 \ge -k * m_2; \\
u_{12} - 2.5 * l_2 \le k * l_2; u_{12} - 2.5 * l_2 \ge -k * l_2; \\
l_1 + 4 * m_1 + u_1 + l_2 + 4 * m_2 + u_2 + \\
l_3 + 4 * m_3 + u_3 + \ldots + l_{11} + 4 * m_{11} + \\
u_{11} + l_{12} + 4 * m_{12} + u_{12} = 6; \\
l_1 \le m_1 \le u_1; l_2 \le m_2 \le u_2; l_3 \le m_3 \le u_3; l_4 \le m_4 \le u_4; l_5 \le m_5 \le u_5; l_6 \le m_6 \le u_6; \\
l_7 \le m_7 \le u_7; l_8 \le m_8 \le u_8; l_9 \le m_9 \le u_9; l_{10} \le m_{10} \le u_{10}; l_{11} \le m_{11} \le u_{11}; l_{12} \le m_{12} \le u_{12}; \\
l_1 \ge 0; l_2 \ge 0; l_3 \ge 0; l_4 \ge 0; l_5 \ge 0; l_6 \ge 0; l_7 \ge 0; l_8 \ge 0; l_9 \ge 0; l_{10} \ge 0; l_{11} \ge 0; l_{12} \ge 0; \\
k \ge 0
\end{array}
$$

References

[1] L. Abdullah, W. Chan, A. Afshari, Application of PROMETHEE method for green supplier selection: a comparative result based on preference functions, Journal of Industrial Engineering International (2018), doi:10.1007/s40092-018-0289-z.

[2] H. Aboutorab, M. Saberi, M. Rajabi, O. Hussain, E. Chang, ZBWM : The Z-number extension of Best Worst Method and its application for supplier development, Expert Syst. Appl. 107 (2018) 115–125, doi:10.1016/j.eswa.2018.04.015.

[3] E.A. Adalı, A.T. Işık, The multi-objective decision making methods based on MULTIMOORA and MOOSRA for the laptop selection problem, Journal of Industrial Engineering International 13 (2) (2017) 229–237.

[4] A. Afzali, M.K. Rafsanjani, A.B. Saeid, A fuzzy multi-objective linear programming model based on interval-valued intuitionistic fuzzy sets for supplier selection, Int. J. Fuzzy Syst. 18 (5) (2016) 864–874.

[5] P. Agrawal, R. Narain, Digital supply chain management: An Overview, in: IOP Conference Series: Materials Science and Engineering, 2018, p. 455, doi:10.1088/1757-899X/455/1/012074.

[6] G. Akkaya, B. Turanoğlu, S. Öztaş, An integrated fuzzy AHP and fuzzy MOORA approach to the problem of industrial engineering sector choosing, Expert Syst. Appl. 42 (24) (2015) 9565–9573.

[7] M. Akram, A. Luqman, J.C.R. Alcantud, Risk evaluation in failure modes and effects analysis: hybrid TOPSIS and ELECTRE I solutions with Pythagorean fuzzy information, Neural Computing and Applications 33 (11) (2021) 5675–5703, doi:10.1007/s00521-020-05350-3.

[8] M. Alimohammadlou, A. Bonyani, Fuzzy BWANP multi-criteria decision-making method, Decision Science Letters 8 (1) (2019) 85–94.

[9] M. Alimohammadlou, Z. Khoshsepehr, Investigating organizational sustainable development through an integrated method of interval-valued intuitionistic fuzzy AHP and WASPAS, Environment, Development and Sustainability, 2021, doi:10.1007/s10668-021-01525-7.

[10] Ö. Alkan, Ö.K. Albayrak, Ranking of renewable energy sources for regions in Turkey by fuzzy entropy based fuzzy COPRAS and fuzzy MULTIMOORA, Renewable Energy 162 (2020) 712–726, doi:10.1016/j.renene.2020.08.062.

[11] M. Alrasheedi, A. Mardani, A.R. Mishra, P. Rani, N. Loganathan, An extended framework to evaluate sustainable suppliers in manufacturing companies using a new Pythagorean fuzzy entropy-SWARA-WASPAS decision-making approach, Journal of Enterprise Information Management, ahead-of-p(ahead-of-print) (2021), doi:10.1108/JEIM-07-2020-0263.

[12] M.P. Amiri, Project selection for oil-fields development by using the AHP and fuzzy TOPSIS methods, Expert Syst. Appl. 37 (9) (2010) 6218–6224, doi:10.1016/j.eswa.2010.02.103.

[13] A. Arabsheybani, M.M. Paydar, A.S. Safaei, An integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection considering quantity discounts and supplier's risk, J. Cleaner Prod. 190 (2018) 577–591.

[14] S. Arslankaya, M.T. Çelik, Green Supplier Selection in Steel Door Industry Using Fuzzy AHP and Fuzzy MOORA Methods, Emerging Materials Research (2021) 1–11.

[15] Ashrafzadeh, M. (2012). Application of fuzzy TOPSIS method for the selection of Warehouse Location : A Case Study. 655–671.

[16] G.J. Avlonitis, N.G. Panagopoulos, Antecedents and consequences of CRM technology acceptance in the sales force, Industrial Marketing Management 34 (4) (2005) 355–368.

[17] A. Awasthi, T. Baležentis, A hybrid approach based on BOCR and fuzzy MULTIMOORA for logistics service provider selection, International Journal of Logistics Systems and Management 27 (3) (2017) 261–282.

[18] Y. Bahrami, H. Hassani, A. Maghsoudi, BWM-ARAS: A new hybrid MCDM method for Cu prospectivity mapping in the Abhar area, Spatial Statistics 33 (2019) 100382.

[19] S. Bai, Y. Zhang, L. Li, N. Shan, X. Chen, Effective link prediction in multiplex networks: A TOPSIS method, Expert Syst. Appl. 177 (2021) 114973, doi:10.1016/j.eswa.2021.114973.

[20] Baležentis, A., Baležentis, T., & Brauers, W. K. M. (2012 a). MULTIMOORA-FG : A Multi-Objective Decision Making Method for Linguistic Reasoning with an Application to Personnel Selection. 23(2), 173–190.

[21] T. Baležentis, S. Zeng, Group multi-criteria decision making based upon interval-valued fuzzy numbers: An extension of the MULTIMOORA method, Expert Syst. Appl. 40 (2) (2013) 543–550, doi:10.1016/j.eswa.2012.07.066.

[22] Balugani, E., Lolli, F., Butturi, M. A., Ishizaka, A., & Sellitto, M. A. (2020). Logistic Regression for Criteria Weight Elicitation in PROMETHEE-Based Ranking Methods BT - Intelligent Human Systems Integration 2020 (T. Ahram, W. Karwowski, A. Vergnano, F. Leali, & R. Taiar (eds.); pp. 474–479). Springer International Publishing.

[23] N. Banaeian, H. Mobli, I.E. Nielsen, M. Omid, Criteria definition and approaches in green supplier selection – a case study for raw material and packaging of food industry, Production & Manufacturing Research 3 (1) (2015) 149–168, doi:10.1080/21693277.2015.1016632.

[24] A.P. Barbosa-Povoa, J.M. Pinto, Process supply chains: Perspectives from academia and industry, Comput. Chem. Eng. 132 (2020) 106606, doi:10.1016/j.compchemeng.2019.106606.

[25] M.P. Beck, B.W. Lin, Some heuristics for the consensus ranking problem, Computers & Operations Research 10 (1) (1983) 1–7.

[26] Bhutia, P. W., & Phipon, R. (2012). Appication of ahp and topsis method for supplier selection problem. 2(10), 43–50.

[27] A. Bonyani, M. Alimohammadlou, A novel approach to solve the problems with network structure, Operational Research 21 (2) (2021) 1279–1297, doi:10.1007/s12351-019-00486-0.

[28] W.K. Brauers, A. Baležentis, T Baležentis., MULTIMOORA FOR THE EU MEMBER STATES UPDATED, Technological and Economic Development of Economy 17 (2) (2011) 259–290, doi:10.3846/20294913.2011.580566.

[29] W.K.M. Brauers, E.K. Zavadskas, The MOORA method and its application to privatization in a transition economy, Control and Cybernetics 35 (2) (2006) 445–469.

[30] W. Brauers, E.K. Zavadskas, MULTIMOORA optimization used to decide on a bank loan to buy property, Technological and Economic Development of Economy 17 (1) (2011) 174–188, doi:10.3846/13928619.2011.560632.

[31] A.C. Braz, A.M. De Mello, L.A. de Vasconcelos Gomes, P.T. de Souza Nascimento, The bullwhip effect in closed-loop supply chains: A systematic literature review, J. Cleaner Prod. 202 (2018) 376–389, doi:10.1016/j.jclepro.2018.08.042.

[32] G. Büyüközkan, G. Çifçi, A novel fuzzy multi-criteria decision framework for sustainable supplier selection with incomplete information, Comput. Ind. 62 (2) (2011) 164–174, doi:10.1016/j.compind.2010.10.009.

[33] G. Büyüközkan, G. Çifçi, A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers, Expert Syst. Appl. 39 (3) (2012) 3000–3011, doi:10.1016/j.eswa.2011.08.162.

[34] G. Büyüközkan, F. Göçer, An extension of ARAS methodology under Interval Valued Intuitionistic Fuzzy environment for Digital Supply Chain, Appl. Soft Comput. 69 (2018) 634–654, doi:10.1016/j.asoc.2018.04.040.
[35] G. Büyüközkan, F. Göçer, Digital Supply Chain: Literature review and a proposed framework for future research, Comput. Ind. 97 (2018) 157–177.
[36] Büyüközkan, G., & Güler, M. (2020). Smart watch evaluation with integrated hesitant fuzzy linguistic SAW-ARAS technique. 153, doi:10.1016/j.measurement.2019.107353.
[37] J. Chai, E.W.T. Ngai, Decision-making techniques in supplier selection: Recent accomplishments and what lies ahead, Expert Syst. Appl. 140 (2020) 112903, doi:10.1016/j.eswa.2019.112903.
[38] S. Chakraborty, Applications of the MOORA method for decision making in manufacturing environment, Int. J. Adv. Manuf. Technol. 54 (9–12) (2011) 1155–1166, doi:10.1007/s00170-010-2972-0.
[39] I. Chamodrakas, D. Batis, D. Martakos, Supplier selection in electronic marketplaces using satisficing and fuzzy AHP, Expert Syst. Appl. 37 (1) (2010) 490–498.
[40] C.-T. Chen, Extensions of the TOPSIS for group decision-making under fuzzy environment, Fuzzy Sets Syst. 114 (1) (2000) 1–9.
[41] Y. Chen, Y. Ran, Z. Wang, X. Li, X. Yang, G. Zhang, An extended MULTIMOORA method based on OWGA operator and Choquet integral for risk prioritization identification of failure modes, Eng. Appl. Artif. Intell. 91 (2020) 103605, doi:10.1016/j.engappai.2020.103605.
[42] Z. Chen, M. Lu, X. Ming, X. Zhang, T. Zhou, Explore and evaluate innovative value propositions for smart product service system : A novel graphics-based rough-fuzzy DEMATEL method, J. Cleaner Prod. 243 (2020) 118672, doi:10.1016/j.jclepro.2019.118672.
[43] J.H. Dahooie, E.K. Zavadskas, H.R. Firoozfar, A.S. Vanaki, N. Mohammadi, W.K.M. Brauers, An improved fuzzy MULTIMOORA approach for multi-criteria decision making based on objective weighting method (CCSD) and its application to technological forecasting method selection, Eng. Appl. Artif. Intell. 79 (2019) 114–128, doi:10.1016/j.engappai.2018.12.008.
[44] M.C. Das, B. Sarkar, S. Ray, A framework to measure relative performance of Indian technical institutions using integrated fuzzy AHP and COPRAS methodology, Socioecon. Plann. Sci. 46 (3) (2012) 230–241, doi:10.1016/j.seps.2011.12.001.
[45] S. Dey, A. Kumar, A. Ray, B.B. Pradhan, Supplier selection: Integrated theory using dematel and quality functions deployment methodology, in: Procedia Engineering, 38, 2012, pp. 3560–3565, doi:10.1016/j.proeng.2012.06.411.
[46] H. Ding, L. Benyoucef, X. Xie, A simulation-optimization approach using genetic search for supplier selection, in: Proceedings of the 2003 Winter Simulation Conference, 2, 2003, pp. 1260–1267, doi:10.1109/WSC.2003.1261559. 2003.
[47] Hongwei Ding, L. Benyoucef, X Xie, A simulation optimization methodology for supplier selection problem, Int. J. Computer Integr. Manuf. 18 (2–3) (2005) 210–224, doi:10.1080/0951192052000288161.
[48] X. Ding, J. Zhong, Power Battery Recycling Mode Selection Using an Extended MULTIMOORA Method, Scientific Programming (2018) 2018.
[49] Y. Dorfeshan, S.M. Mousavi, V. Mohagheghi, B. Vahdani, Selecting project-critical path by a new interval type-2 fuzzy decision methodology based on MULTIMOORA, MOOSRA and TPOP methods, Comput. Ind. Eng. 120 (2018) 160–178.
[50] Ö. Ekmekcioğlu, K. Koc, M. Özger, Stakeholder perceptions in flood risk assessment: A hybrid fuzzy AHP-TOPSIS approach for Istanbul, International Journal of Disaster Risk Reduction 60 (2021) 102327, doi:10.1016/j.ijdrr.2021.102327.
[51] S. El Amrani, N.U. Ibne Hossain, S. Karam, R. Jaradat, F. Nur, M.A. Hamilton, J. Ma, Modelling and assessing sustainability of a supply chain network leveraging multi Echelon Bayesian Network, J. Cleaner Prod. 302 (2021) 126855, doi:10.1016/j.jclepro.2021.126855.
[52] A. Fahmi, C. Kahraman, Ü. Bilen, ELECTRE I method using hesitant linguistic term sets: An application to supplier selection, International Journal of Computational Intelligence Systems 9 (1) (2016) 153–167.
[53] A. Fallahpour, E.U. Olugu, S.N. Musa, D. Khezrimotlagh, K.Y. Wong, An integrated model for green supplier selection under fuzzy environment: application of data envelopment analysis and genetic programming approach, Neural Computing and Applications 27 (3) (2016) 707–725, doi:10.1007/s00521-015-1890-3.
[54] R. Fattahi, M. Khalilzadeh, Risk evaluation using a novel hybrid method based on FMEA, extended MULTIMOORA, and AHP methods under fuzzy environment, Saf. Sci. 102 (2018) 290–300.
[55] S.M.A.K. Firouzabadi, M. Ghahremanloo, M. Keshavarz-Ghorabaee, J. Saparauskas, A new group decision-making model based on bwm and its application to managerial problems, Transformations in Business & Economics 18 (2) (2019) 47.
[56] M.M. Fouladgar, A. Yazdani-Chamzini, A. Lashgari, E.K. Zavadskas, Z. Turskis, Maintenance strategy selection using AHP and COPRAS under fuzzy environment, International Journal of Strategic Property Management 16 (1) (2012) 85–104, doi:10.3846/1648715X.2012.666657.
[57] J. Freeman, T. Chen, Green supplier selection using an AHP-Entropy-TOPSIS framework. Supply Chain Management, An International Journal 20 (3) (2015) 327–340, doi:10.1108/SCM-04-2014-0142.
[58] Y.-K. Fu, An integrated approach to catering supplier selection using AHP-ARAS-MCGP methodology, Journal of Air Transport Management 75 (2019) 164–169.
[59] V.S. Gadakh, V.B. Shinde, N.S. Khemnar, Optimization of welding process parameters using MOORA method, Int. J. Adv. Manuf. Technol. 69 (9–12) (2013) 2031–2039, doi:10.1007/s00170-013-5188-2.
[60] R. Garg, R. Kumar, S. Garg, MADM-Based Parametric Selection and Ranking of E-Learning Websites Using Fuzzy COPRAS, IEEE Trans. Educ. 62 (1) (2019) 11–18, doi:10.1109/TE.2018.2814611.
[61] A. Gezdur, J. Bhattacharjya, in: Digitization in the Oil and Gas Industry: Challenges and Opportunities for Supply Chain Partners, 506, IFIP Advances in Information and Communication Technology, 2017, pp. 97–103, doi:10.1007/978-3-319-65151-4_9.
[62] S.J. Ghoushchi, S. Yousefi, M. Khazaeili, An extended FMEA approach based on the Z-MOORA and fuzzy BWM for prioritization of failures, Appl. Soft Comput. 81 (2019) 105505, doi:10.1016/j.asoc.2019.105505.
[63] S.S. Goswami, D.K. Behera, Evaluation of the best smartphone model in the market by integrating fuzzy-AHP and PROMETHEE decision-making approach, DECISION 48 (1) (2021) 71–96, doi:10.1007/s40622-020-00260-8.
[64] X. Gou, H. Liao, Z. Xu, F. Herrera, Double hierarchy hesitant fuzzy linguistic term set and MULTIMOORA method: A case of study to evaluate the implementation status of haze controlling measures, Information Fusion 38 (2017) 22–34, doi:10.1016/j.inffus.2017.02.008.
[65] K. Govindan, S. Rajendran, J. Sarkis, P. Murugesan, Multi criteria decision making approaches for green supplier evaluation and selection: A literature review, J. Cleaner Prod. 98 (2015) 66–83, doi:10.1016/j.jclepro.2013.06.046.
[66] K. Govindan, R. Sivakumar, Green supplier selection and order allocation in a low-carbon paper industry: integrated multi-criteria heterogeneous decision-making and multi-objective linear programming approaches, Annals of Operations Research 238 (1–2) (2016) 243–276.
[67] S. Guo, H. Zhao, Fuzzy best-worst multi-criteria decision-making method and its applications, Knowledge-Based Systems 121 (2017) 23–31, doi:10.1016/j.knosys.2017.01.010.
[68] H. Gupta, Assessing organizations performance on the basis of GHRM practices using BWM and Fuzzy TOPSIS, J. Environ. Manage. 226 (2018) 201–216, doi:10.1016/j.jenvman.2018.08.005.
[69] H. Gupta, M.K. Barua, Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS, J. Cleaner Prod. 152 (2017) 242–258.
[70] H. Gupta, M.K. Barua, A framework to overcome barriers to green innovation in SMEs using BWM and Fuzzy TOPSIS, Sci. Total Environ. 633 (2018) 122–139, doi:10.1016/j.scitotenv.2018.03.173.
[71] V. Gupta, P.K. Kapur, D. Kumar, Measuring and evaluating data distribution strategies using an integrated approach of fuzzy based MOORA and AHP, Life Cycle Reliability and Safety Engineering 6 (1) (2017) 37–45.
[72] S.A.S. Haeri, J. Rezaei, A grey-based green supplier selection model for uncertain environments, J. Cleaner Prod. 221 (2019) 768–784, doi:10.1016/j.jclepro.2019.02.193.
[73] Arian Hafezalkotob, A. Hafezalkotob, Comprehensive MULTIMOORA method with target-based attributes and integrated significant coefficients for materials selection in biomedical applications, Materials & Design 87 (2015) 949–959, doi:10.1016/j.matdes.2015.08.087.
[74] Arian Hafezalkotob, A. Hafezalkotob, H. Liao, F. Herrera, An overview of MULTIMOORA for multi-criteria decision-making: Theory, developments, applications, and challenges, Information Fusion 51 (2019) 145–177 December 2018, doi:10.1016/j.inffus.2018.12.002.
[75] Arian Hafezalkotob, A. Hafezalkotob, M.K. Sayadi, Extension of MULTIMOORA method with interval numbers: An application in materials selection, Appl. Math. Modell. 40 (2) (2016) 1372–1386, doi:10.1016/j.apm.2015.07.019.
[76] Ashkan Hafezalkotob, A. Hafezalkotob, A novel approach for combination of individual and group decisions based on fuzzy best-worst method, Appl. Soft Comput. 59 (2017) 316–325, doi:10.1016/j.asoc.2017.05.036.
[77] Ashkan Hafezalkotob, A. Hami-Dindar, N. Rabie, A. Hafezalkotob, A decision support system for agricultural machines and equipment selection: A case study on olive harvester machines, Comput. Electron. Agric. 148 (2018) 207–216.
[78] H. Han, S. Trimi, A fuzzy TOPSIS method for performance evaluation of reverse logistics in social commerce platforms, Expert Syst. Appl. 103 (2018) 133–145, doi:10.1016/j.eswa.2018.03.003.
[79] S. Hashemkhani, Z. Morteza, Y. Edmundas, K. Zavadskas, An extended stepwise weight assessment ratio analysis (SWARA) method for improving criteria prioritization process, Soft Computing (2018) 1992, doi:10.1007/s00500-018-3092-2.
[80] A. Heidarzade, I. Mahdavi, N. Mahdavi-Amiri, Supplier selection using a clustering method based on a new distance for interval type-2 fuzzy sets: A case study, Appl. Soft Comput. 38 (2016) 213–231.
[81] S. Hezer, E. Gelmez, E. Özceylan, Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment, Journal of Infection and Public Health 14 (6) (2021) 775–786, doi:10.1016/j.jiph.2021.03.003.
[82] N.U.I. Hossain, S.El Amrani, R. Jaradat, M. Marufuzzaman, R. Buchanan, C. Rinaudo, M Hamilton, Modeling and assessing interdependencies between critical infrastructures using Bayesian network: A case study of inland waterway port and surrounding supply chain network, Reliab. Eng. Syst. Saf. 198 (2020) 106898, doi:10.1016/j.ress.2020.106898.
[83] C.-W. Hsu, A.H. Hu, Applying hazardous substance management to supplier selection using analytic network process, J. Cleaner Prod. 17 (2) (2009) 255–264, doi:10.1016/j.jclepro.2008.05.004.
[84] C.-W. Hsu, T.-C. Kuo, S.-H. Chen, A.H. Hu, Using DEMATEL to develop a carbon management model of supplier selection in green supply chain management, J. Cleaner Prod. 56 (2013) 164–172, doi:10.1016/j.jclepro.2011.09.012.
[85] C.-C. Huang, W.-Y. Liang, T.-L. Tseng, P.-H. Chen, The rough set based approach to generic routing problems: case of reverse logistics supplier selection, Journal of Intelligent Manufacturing 27 (4) (2016) 781–795.
[86] C.-L. Hwang, K. Yoon, Multiple Attribute Decision Making, 186, Springer, Berlin Heidelberg, 1981, doi:10.1007/978-3-642-48318-9.
[87] Y.T. İç, An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies, Rob. Comput. Integr. Manuf. 28 (2) (2012) 245–256, doi:10.1016/j.rcim.2011.09.005.

[88] I. Igoulalene, L. Benyoucef, M.K. Tiwari, Novel fuzzy hybrid multi-criteria group decision making approaches for the strategic supplier selection problem, Expert Syst. Appl. 42 (7) (2015) 3342–3356.
[89] A. Ijadi Maghsoodi, M. Mosavat, A. Hafezalkotob, A. Hafezalkotob, Hybrid hierarchical fuzzy group decision-making based on information axioms and BWM: Prototype design selection, Comput. Ind. Eng. 127 (2019) 788–804 March 2018, doi:10.1016/j.cie.2018.11.018.
[90] A. Ijadi Maghsoodi, H. Rasoulipanah, L. Martínez López, H. Liao, E.K. Zavadskas, Integrating interval-valued multi-granular 2-tuple linguistic BWM-CODAS approach with target-based attributes: Site selection for a construction project, Comput. Ind. Eng. 139 (2020) 106147, doi:10.1016/j.cie.2019.106147.
[91] A. Ishizaka, S. Siraj, Are multi-criteria decision-making tools useful ? An experimental comparative study of three methods, European Journal of Operational Research 264 (2) (2018) 462–471, doi:10.1016/j.ejor.2017.05.041.
[92] D. Ivanov, A. Dolgui, A. Das, B. Sokolov, Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility, in: Handbook of ripple effects in the supply chain, Springer, 2019, pp. 309–332.
[93] O. Jadidi, S. Cavalieri, S. Zolfaghari, An improved multi-choice goal programming approach for supplier selection problems, Appl. Math. Modell. 39 (14) (2015) 4213–4222.
[94] V. Jain, A.K. Sangaiah, S. Sakhuja, N. Thoduka, R. Aggarwal, Supplier selection using fuzzy AHP and TOPSIS: a case study in the Indian automotive industry, Neural Computing and Applications 29 (7) (2018) 555–564.
[95] D. Kannan, A.B.L. De Sousa Jabbour, C.J.C. Jabbour, Selecting green suppliers based on GSCM practices: Using Fuzzy TOPSIS applied to a Brazilian electronics company, European Journal of Operational Research 233 (2) (2014) 432–447, doi:10.1016/j.ejor.2013.07.023.
[96] A.K. Kar, A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network, Journal of Computational Science 6 (2015) 23–33.
[97] C. Karaca, A. Ulutaş, Supplier Performance Evaluation by Using SWARA and MULTIMOORA, Economics Management & Econometrics (2017) 137.
[98] P. Karande, S. Chakraborty, A Fuzzy-MOORA approach for ERP system selection, Decision Science Letters 1 (1) (2012) 11–21, doi:10.5267/j.dsl.2012.07.001.
[99] H. Kaur, S. Prakash Singh, Multi-stage hybrid model for supplier selection and order allocation considering disruption risks and disruptive technologies, Int. J. Prod. Econ. 231 (2021) 107830, doi:10.1016/j.ijpe.2020.107830.
[100] A. Kengpol, M. Tuominen, A framework for group decision support systems: an application in the evaluation of information technology for logistics firms, Int. J. Prod. Econ. 101 (1) (2006) 159–171.
[101] M. Keshavarz Ghorabaee, M. Amiri, J. Salehi Sadaghiani, G. Hassani Goodarzi, Multiple criteria group decision-making for supplier selection based on COPRAS method with interval type-2 fuzzy sets, The International Journal of Advanced Manufacturing Technology 75 (5–8) (2014) 1115–1130, doi:10.1007/s00170-014-6142-7.
[102] M. Keshavarz Ghorabaee, E.K. Zavadskas, M. Amiri, A. Esmaeili, Multi-criteria evaluation of green suppliers using an extended WASPAS method with interval type-2 fuzzy sets, J. Cleaner Prod. 137 (2016) 213–229, doi:10.1016/j.jclepro.2016.07.031.
[103] R.N. Keshteli, E. Davoodvandi, Using fuzzy AHP and fuzzy TOPSIS in fuzzy QFD: A case study in ceramic and tile industry of Iran, International Journal of Productivity and Quality Management 20 (2) (2017) 197–216, doi:10.1504/IJPQM.2017.081480.
[104] E. Khanmohammadi, M. Zandieh, T. Tayebi, Drawing a strategy canvas using the fuzzy best–worst method, Global Journal of Flexible Systems Management 20 (1) (2019) 57–75.
[105] K. Korpela, J. Hallikas, T. Dahlberg, Digital supply chain transformation toward blockchain integration, in: Proceedings of the 50th Hawaii International Conference on System Sciences, 2017.
[106] C.-Y. Ku, C.-T. Chang, H.-P. Ho, Global supplier selection using fuzzy analytic hierarchy process and fuzzy goal programming, Quality & Quantity 44 (4) (2009) 623–640, doi:10.1007/s11135-009-9223-1.
[107] A. Kumar, A. A, H Gupta, Evaluating green performance of the airports using hybrid BWM and VIKOR methodology, Tourism Management 76 (2020) 103941, doi:10.1016/j.tourman.2019.06.016.
[108] R.J. Kuo, S.Y. Hong, Y.C. Huang, Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection, Appl. Math. Modell. 34 (12) (2010) 3976–3990, doi:10.1016/j.apm.2010.03.033.
[109] A.C. Kutlu, M. Ekmekçioğlu, Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP, Expert Syst. Appl. 39 (1) (2012) 61–67, doi:10.1016/j.eswa.2011.06.044.
[110] S. Li, W. Zeng, Risk analysis for the supplier selection problem using failure modes and effects analysis (FMEA), Journal of Intelligent Manufacturing 27 (6) (2016) 1309–1321.
[111] W. Liang, G. Zhao, C. Hong, Selecting the optimal mining method with extended multi-objective optimization by ratio analysis plus the full multiplicative form (MULTIMOORA) approach, Neural Computing and Applications (2018) 1–16.
[112] C.-N. Liao, Y.-K. Fu, L.-C. Wu, Integrated FAHP, ARAS-F and MSGP methods for green supplier evaluation and selection, Technological and Economic Development of Economy 22 (5) (2016) 651–669.
[113] M. Lin, C. Huang, Z. Xu, MULTIMOORA based MCDM model for site selection of car sharing station under picture fuzzy environment, Sustainable Cities and Society 53 (2020) 101873, doi:10.1016/j.scs.2019.101873.
[114] A. Liu, Y. Xiao, X. Ji, K. Wang, S.-B. Tsai, H. Lu, J. Cheng, X. Lai, J. Wang, A novel two-stage integrated model for supplier selection of Green fresh product, Sustainability 10 (7) (2018) 2371.
[115] A. Liu, Y. Xiao, H. Lu, S.-B. Tsai, W. Song, A fuzzy three-stage multi-attribute decision-making approach based on customer needs for sustainable supplier selection, J. Cleaner Prod. 239 (2019) 118043.
[116] H.-C. Liu, X.-J. Fan, P. Li, Y.-Z. Chen, Evaluating the risk of failure modes with extended MULTIMOORA method under fuzzy environment, Eng. Appl. Artif. Intell. 34 (2014) 168–177, doi:10.1016/j.engappai.2014.04.011.
[117] C. Lo, D. Chen, C. Tsai, K. Chao, Service Selection Based on Fuzzy TOPSIS Method, in: 2010 IEEE 24th International Conference on Advanced Information Networking and Applications Workshops, 2010, pp. 367–372, doi:10.1109/WAINA.2010.117.
[118] H.-W. Lo, J.J.H. Liou, H.-S. Wang, Y.-S. Tsai, An integrated model for solving problems in green supplier selection and order allocation, J. Cleaner Prod. 190 (2018) 339–352.
[119] J. Lu, S. Zhang, J. Wu, Y. Wei, COPRAS METHOD FOR MULTIPLE ATTRIBUTE GROUP DECISION MAKING UNDER PICTURE FUZZY ENVIRONMENT AND THEIR APPLICATION TO GREEN SUPPLIER SELECTION, Technological and Economic Development of Economy 27 (2) (2021) 369–385, doi:10.3846/tede.2021.14211.
[120] J. Luan, Z. Yao, F. Zhao, X. Song, A novel method to solve supplier selection problem: Hybrid algorithm of genetic algorithm and ant colony optimization, Math. Comput. Simul 156 (2019) 294–309.
[121] S. Luthra, K. Govindan, D. Kannan, S.K. Mangla, C.P. Garg, An integrated framework for sustainable supplier selection and evaluation in supply chains, J. Cleaner Prod. 140 (2017) 1686–1698.
[122] M. Mahdiloo, R.F. Saen, K.-H. Lee, Technical, environmental and eco-efficiency measurement for supplier selection: An extension and application of data envelopment analysis, Int. J. Prod. Econ. 168 (2015) 279–289.
[123] M.A. Makhesana, Application of improved complex proportional assessment (COPRAS) method for rapid prototyping system selection, Rapid Prototyping Journal 21 (6) (2015) 671–674, doi:10.1108/RPJ-03-2014-0027.
[124] E. Manavalan, K. Jayakrishna, A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4 . 0 requirements, Comput. Ind. Eng. 127 (2019) 925–953 November 2018, doi:10.1016/j.cie.2018.11.030.
[125] A. Mardani, E. Kazimieras, Z. Khalifah, N. Zakuan, A review of multi-criteria decision-making applications to solve energy management problems : Two decades from 1995 to 2015, Renewable Sustainable Energy Rev. 71 (2017) 216–256 July 2015, doi:10.1016/j.rser.2016.12.053.
[126] A. Mardani, M. Nilashi, N. Zakuan, N. Loganathan, S. Soheilirad, M.Z.M. Saman, O. Ibrahim, A systematic review and meta-Analysis of SWARA and WASPAS methods: Theory and applications with recent fuzzy developments, Appl. Soft Comput. 57 (2017) 265–292, doi:10.1016/j.asoc.2017.03.045.
[127] C.L. Martins, M.V. Pato, Supply chain sustainability: A tertiary literature review, J. Cleaner Prod. 225 (2019) 995–1016, doi:10.1016/j.jclepro.2019.03.250.
[128] C.R. Matawale, S. Datta, S.S. Mahapatra, Supplier selection in agile supply chain, Benchmarking: An International Journal 23 (7) (2016) 2027–2060, doi:10.1108/BIJ-07-2015-0067.
[129] R.K. Mavi, M. Goh, N. Zarbakhshnia, Sustainable third-party reverse logistic provider selection with fuzzy SWARA and fuzzy MOORA in plastic industry, Int. J. Adv. Manuf. Technol. 91 (5–8) (2017) 2401–2418, doi:10.1007/s00170-016-9880-x.
[130] DW Miller, M S., Decisions and Operations and Research, 2nd Edition, Prentice-Hall Inc., Englewood Cliffs (N.J.), 1969.
[131] K.S. Moghaddam, Fuzzy multi-objective model for supplier selection and order allocation in reverse logistics systems under supply and demand uncertainty, Expert Syst. Appl. 42 (15–16) (2015) 6237–6254.
[132] N.A. Nabeeh, M. Abdel-basset, A Aboelfetouh, Neutrosophic Multi-Criteria Decision Making Approach for IoT-Based Enterprises, IEEE Access 7 (2019) 59559–59574, doi:10.1109/ACCESS.2019.2908919.
[133] S. Nallusamy, D. Sri Lakshmana Kumar, K. Balakannan, P.S. Chakraborty, MCDM tools application for selection of suppliers in manufacturing industries using AHP, Fuzzy Logic and ANN, Int. J. Eng. Res. Afr. 19 (2016) 130–137.
[134] M. Nasiri, J. Ukko, M. Saunila, T. Rantala, Managing the digital supply chain: The role of smart technologies, 96–97, Technovation, 2020, doi:10.1016/j.technovation.2020.102121.
[135] K. Nourianfar, G.A. Montazer, A fuzzy MCDM approach based on COPRAS method to solve supplier selection problems, in: The 5th Conference on Information and Knowledge Technology, 2013, pp. 231–235, doi:10.1109/IKT.2013.6620070.
[136] M.O. Okwu, L.K. Tartibu, Sustainable supplier selection in the retail industry: A TOPSIS-and ANFIS-based evaluating methodology, International Journal of Engineering Business Management 12 (2020) 1847979019899542.
[137] R.K. Oliver, M.D. Webber, Supply-chain management: logistics catches up with strategy, Outlook 5 (1) (1982) 42–47.
[138] H. Omrani, A. Alizadeh, A. Emrouznejad, Finding the optimal combination of power plants alternatives: A multi response Taguchi-neural network using TOPSIS and fuzzy best-worst method, J. Cleaner Prod. 203 (2018) 210–223, doi:10.1016/j.jclepro.2018.08.238.
[139] G. Oswald, M. Kleinemeier, Shaping the digital enterprise, Springer International Publishing, Cham, 2017.
[140] A. ÖZBEK, A. YILDIZ, Digital Supplier Selection for a Garment Business Using Interval Type-2 Fuzzy TOPSIS, 3, TEKSTİL VE KONFEKSİYON, 2020, doi:10.32710/tekstilvekonfeksiyon.569884.
[141] H.N. Perera, J. Hurley, B. Fahimnia, M. Reisi, The human factor in supply chain forecasting: A systematic review, European Journal of Operational Research 274 (2) (2019) 574–600, doi:10.1016/j.ejor.2018.10.028.

[142] A. Pflaum, G. Prockl, F. Bodendorf, H. Chen, The Digital Supply Chain of the Future: Technologies, Applications and Business Models, in: Proceedings of the 51st Hawaii International Conference on System Sciences, 2018, pp. 4179–4181. 10.24251/HICSS.2018.492.
[143] G. Polat, E. Eray, An integrated approach using AHP-ER to supplier selection in railway projects, Procedia Engineering 123 (2015) 415–422.
[144] M.A. Quddus, N.U. Ibne Hossain, M. Mohammad, R.M. Jaradat, M.S. Roni, Sustainable network design for multi-purpose pellet processing depots under biomass supply uncertainty, Comput. Ind. Eng. 110 (2017) 462–483, doi:10.1016/j.cie.2017.06.001.
[145] S. Rahimi, A. Hafezalkotob, S.M. Monavari, A. Hafezalkotob, R. Rahimi, Sustainable landfill site selection for municipal solid waste based on a hybrid decision-making approach: Fuzzy group BWM-MULTIMOORA-GIS, J. Cleaner Prod. 248 (2020) 119186, doi:10.1016/j.jclepro.2019.119186.
[146] K. Rathi, S. Balamohan, A Mathematical Model for Subjective Evaluation of Alternatives in Fuzzy Multi-Criteria Group Decision Making Using COPRAS Method, Int. J. Fuzzy Syst. 19 (5) (2017) 1290–1299, doi:10.1007/s40815-016-0256-z.
[147] P. Ren, Z. Xu, X. Gou, Pythagorean fuzzy TODIM approach to multi-criteria decision making, Applied Soft Computing Journal 42 (2016) 246–259 https://doi.org/10.1016/j.asoc.2015.12.020.
[148] J. Rezaei, Best-worst multi-criteria decision-making method, Omega 53 (2015) 49–57.
[149] J. Rezaei, O. Kothadiya, L. Tavasszy, M. Kroesen, Quality assessment of airline baggage handling systems using SERVQUAL and BWM, Tourism Management 66 (2018) 85–93, doi:10.1016/j.tourman.2017.11.009.
[150] Şahin, R. (2019). COPRAS Method with Neutrosophic Sets BT - Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets (C. Kahraman & İ. Otay (eds.); pp. 487–524). Springer International Publishing, doi:10.1007/978-3-030-00045-5_19.
[151] A.K. Sahu, S. Datta, S.S. Mahapatra, Evaluation and selection of resilient suppliers in fuzzy environment, Benchmarking: An International Journal 23 (3) (2016) 651–673, doi:10.1108/BIJ-11-2014-0109.
[152] N. Sakib, N.U. Ibne Hossain, F. Nur, S. Talluri, R. Jaradat, J.M. Lawrence, An assessment of probabilistic disaster in the oil and gas supply chain leveraging Bayesian belief network, Int. J. Prod. Econ. 235 (2021) 108107, doi:10.1016/j.ijpe.2021.108107.
[153] X. Sang, X. Liu, An interval type-2 fuzzy sets-based TODIM method and its application to green supplier selection, J. Oper. Res. Soc. 67 (5) (2016) 722–734.
[154] D.K. Sen, S. Datta, S.S. Mahapatra, Dominance based fuzzy decision support framework for g-resilient (ecosilient) supplier selection: an empirical modelling, Int. J. Sustainable Eng. 10 (6) (2017) 338–357, doi:10.1080/19397038.2017.1286410.
[155] Z. Seyedghorban, H. Tahernejad, R. Meriton, G. Graham, Supply chain digitalization: past, present and future, Production Planning & Control 31 (2–3) (2020) 96–114, doi:10.1080/09537287.2019.1631461.
[156] J. Seyedmohammadi, F. Sarmadian, A.A. Jafarzadeh, M.A. Ghorbani, F. Shahbazi, Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops, Geoderma 310 (2018) 178–190 November 2016, doi:10.1016/j.geoderma.2017.09.012.
[157] H. Shabanpour, S. Yousefi, R.F. Saen, Forecasting efficiency of green suppliers by dynamic data envelopment analysis and artificial neural networks, J. Cleaner Prod. 142 (2017) 1098–1107.
[158] I.M. Sharaf, Global Supplier Selection with Spherical Fuzzy Analytic Hierarchy Process, in: Decision Making with Spherical Fuzzy Sets, Springer, 2021, pp. 323–348.
[159] M. Sharma, S. Joshi, Digital supplier selection reinforcing supply chain quality management systems to enhance firm's performance, The TQM Journal, ahead-of-p(ahead-of-print), 2020, doi:10.1108/TQM-07-2020-0160.
[160] A. Shemshadi, H. Shirazi, M. Toreihi, M.J. Tarokh, A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting, Expert Syst. Appl. 38 (10) (2011) 12160–12167, doi:10.1016/j.eswa.2011.03.027.
[161] L. Shen, L. Olfat, K. Govindan, R. Khodaverdi, A. Diabat, A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences, Resour. Conserv. Recycl. 74 (2013) 170–179.
[162] P. Shojaei, S.A. Seyed Haeri, S. Mohammadi, Airports evaluation and ranking model using Taguchi loss function, best-worst method and VIKOR technique, Journal of Air Transport Management 68 (2018) 4–13, doi:10.1016/j.jairtraman.2017.05.006.
[163] D. Simić, V. Svirčević, S. Simić, A hybrid evolutionary model for supplier assessment and selection in inbound logistics, Journal of Applied Logic 13 (2) (2015) 138–147.
[164] R.K. Singh, S. Modgil, Supplier selection using SWARA and WASPAS – a case study of Indian cement industry, Measuring Business Excellence 24 (2) (2020) 243–265, doi:10.1108/MBE-07-2018-0041.
[165] P. Sirisawat, T. Kiatcharoenpol, Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers, Computers and Industrial Engineering 117 (2018) 303–318 April 2017, doi:10.1016/j.cie.2018.01.015.
[166] B. Sohrabi, K. Tahmasebipur, I. Raeesi Vanani, Designing a Fuzzy Expert System for ERP Selection, Industrial Management Journal 3 (6) (2011) 39–58.
[167] Y.A. Solangi, C. Longsheng, S.A.A. Shah, Assessing and overcoming the renewable energy barriers for sustainable development in Pakistan: An integrated AHP and fuzzy TOPSIS approach, Renewable Energy 173 (2021) 209–222, doi:10.1016/j.renene.2021.03.141.
[168] H. Souzangarzadeh, M.J. Rezvani, A. Jahan, Selection of optimum design for conical segmented aluminum tubes as energy absorbers: Application of MULTIMOORA method, Appl. Math. Modell. 51 (2017) 546–560.
[169] D Stanujkic, D. Karabasevic, E.K. Zavadskas, W.K.M. Brauers, An extension of the MULTIMOORA method for solving complex decision-making problems based on the use of interval-valued triangular fuzzy numbers, Transformations in Business and Economics 14 (2B) (2015) 355–375. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84954450231&partnerID=40&md5=fef9ebb6ff5bc6c3c29f5e0b87a5e088
[170] Stanujkic, Dragisa, & Karabasevic, D. (2019). A Bipolar Fuzzy Extension of the MULTIMOORA Method. 30(1), 135–152.
[171] Ž. Stević, D. Pamučar, M. Vasiljević, G. Stojić, S. Korica, Novel integrated multi-criteria model for supplier selection: Case study construction company, Symmetry 9 (11) (2017) 279.
[172] A. Subramanian, K.J. Yermal, S. Hemaraju, S. Ananth, Effectiveness of Digitalized Supply Chain During 2020 COVID-19 Pandemic: Case Studies, International Journal of Research in Engineering, Science and Management 4 (6) (2021) 39–43.
[173] C.C. Sun, A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods, Expert Syst. Appl. 37 (12) (2010) 7745–7754, doi:10.1016/j.eswa.2010.04.066.
[174] P. Sureeyatanapas, K. Sriwattananusart, T. Niyamosoth, W. Sessomboon, S. Arunyanart, Supplier selection towards uncertain and unavailable information: An extension of TOPSIS method, Operations Research Perspectives 5 (2018) 69–79.
[175] M H Tabatabaei, M. Amiri, M. Ghahremanloo, M. Keshavarz-Ghorabaee, E.K. Zavadskas, J. Antucheviciene, Hierarchical Decision-making using a New Mathematical Model based on the Best-worst Method, A Draft of the INTERNATIONAL JOURNAL of COMPUTERS COMMUNICATIONS & CONTROL 2014 (2016) (2013) 669.
[176] Mohammad Hashemi Tabatabaei, A Bazrkar, Providing a Model for Ranking Suppliers in the Sustainable Supply Chain Using Cross Efficiency Method in Data Envelopment Analysis, Brazilian Journal of Operations & Production Management 16 (1) (2019) 43–52.
[177] M. Tavana, Euclid: strategic alternative assessment matrix, Journal of Multi-Criteria Decision Analysis 11 (2) (2002) 75–96.
[178] M. Tavana, CROSS: a multicriteria group-decision-making model for evaluating and prioritizing advanced-technology projects at NASA, Interfaces 33 (3) (2003) 40–56.
[179] M. Tavana, A subjective assessment of alternative mission architectures for the human exploration of Mars at NASA using multicriteria decision making, Computers & Operations Research 31 (7) (2004) 1147–1164.
[180] M. Tavana, S. Banerjee, Evaluating strategic alternatives: an analytical model, Computers & Operations Research 22 (7) (1995) 731–743.
[181] M. Tavana, A. Hatami-Marbini, A group AHP-TOPSIS framework for human spaceflight mission planning at NASA, Expert Syst. Appl. 38 (11) (2011) 13588–13603, doi:10.1016/j.eswa.2011.04.108.
[182] M. Tavana, D.T. Kennedy, P. Joglekar, A group decision support framework for consensus ranking of technical manager candidates, Omega 24 (5) (1996) 523–538.
[183] M. Tavana, M. Keramatpour, F.J. Santos-Arteaga, E. Ghorbaniane, A fuzzy hybrid project portfolio selection method using data envelopment analysis, TOPSIS and integer programming, Expert Syst. Appl. 42 (22) (2015) 8432–8444.
[184] M. Tavana, Z. Li, M. Mobin, M. Komaki, E. Teymourian, Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS, Expert Syst. Appl. 50 (2016) 17–39.
[185] M. Tavana, F. LoPinto, J.W. Smither, A hybrid distance-based ideal-seeking consensus ranking model, Advances in Decision Sciences (2007) 2007.
[186] M. Tavana, A. Shaabani, S. Mansouri Mohammadabadi, N. Varzgani, An integrated fuzzy AHP- fuzzy MULTIMOORA model for supply chain risk-benefit assessment and supplier selection, International Journal of Systems Science: Operations & Logistics (2020) 1–24, doi:10.1080/23302674.2020.1737754.
[187] M Tavana, A. Shaabani, F.J. Santos-Arteaga, N. Valaei, An integrated fuzzy sustainable supplier evaluation and selection framework for green supply chains in reverse logistics, Environmental Science and Pollution Research, 2021, doi:10.1007/s11356-021-14302-w.
[188] Tian, Z., Zhang, H., Wang, J., Wang, J., & Chen, X. (2015). Multi-criteria decision-making method based on a cross-entropy with interval neutrosophic sets, doi:10.1080/00207721.2015.1102359.
[189] S.E. Torkayesh, A. Iranizad, A.E. Torkayesh, M.N. Basit, APPLICATION OF BWM-WASPAS MODEL FOR DIGITAL SUPPLIER SELECTION PROBLEM: A CASE STUDY IN ONLINE RETAIL SHOPPING, Journal of Industrial Engineering and Decision Making 1 (1) (2020) 12–23, doi:10.31181/jiedm200101012t.
[190] G. Torlak, M. Sevkli, M. Sanal, S. Zaim, Analyzing business competition by using fuzzy TOPSIS method: An example of Turkish domestic airline industry, Expert Syst. Appl. 38 (4) (2011) 3396–3406, doi:10.1016/j.eswa.2010.08.125.
[191] E. Turanoglu Bekar, M. Cakmakci, C Kahraman, Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis, Journal of Business Economics and Management 17 (5) (2016) 663–684, doi:10.3846/16111699.2016.1202314.
[192] A. Ulutas, Using of Fuzzy SWARA and Fuzzy ARAS Methods to Solve Supplier Selection Problem, in: Theoretical and Applied Mathematics in International Business, IGI Global, 2020, pp. 136–148.
[193] B. Vahdani, S.M. Mousavi, R. Tavakkoli-Moghaddam, Group decision making based on novel fuzzy modified TOPSIS method, Appl. Math. Modell. 35 (9) (2011) 4257–4269, doi:10.1016/j.apm.2011.02.040.
[194] S. Vinodh, R. Anesh Ramiya, S.G. Gautham, Application of fuzzy analytic network process for supplier selection in a manufacturing organisation, Expert Syst. Appl. 38 (1) (2011) 272–280, doi:10.1016/j.eswa.2010.06.057.
[195] J. Wang, Q. Ma, H.-C. Liu, A meta-evaluation model on science and technology project review experts using IVIF-BWM and MULTIMOORA, Expert Syst. Appl. 168 (2021) 114236, doi:10.1016/j.eswa.2020.114236.
[196] P. Wang, Z. Zhu, Y. Wang, A novel hybrid MCDM model combining the SAW, TOPSIS and GRA methods based on experimental design 345 (2016) 27–45, doi:10.1016/j.ins.2016.01.076.

[197] W. Wang, X. Liu, Y. Qin, A fuzzy Fine-Kinney-based risk evaluation approach with extended MULTIMOORA method based on Choquet integral, Comput. Ind. Eng. 125 (2018) 111–123, doi:10.1016/j.cie.2018.08.019.
[198] T.-C. Wen, K.-H. Chang, H.-H. Lai, Integrating the 2-tuple linguistic representation and soft set to solve supplier selection problems with incomplete information, Eng. Appl. Artif. Intell. 87 (2020) 103248.
[199] Z. Xu, J. Qin, J. Liu, L. Martínez, Sustainable supplier selection based on AHPSort II in interval type-2 fuzzy environment, Information Sciences 483 (2019) 273–293.
[200] V. Yadav, M.K. Sharma, Multi-criteria supplier selection model using the analytic hierarchy process approach, Journal of Modelling in Management 11 (1) (2016) 326–354, doi:10.1108/JM2-06-2014-0052.
[201] M. Yazdani, A. Alidoosti, E.K. Zavadskas, Risk Analysis of Critical Infrastructures Using Fuzzy Copras, Economic Research-Ekonomska Istraživanja 24 (4) (2011) 27–40, doi:10.1080/1331677X.2011.11517478.
[202] M. Yazdani, A. Alidoosti, E.K. Zavadskas, Risk Analysis of Critical Infrastructures Using Fuzzy Copras, Economic Research-Ekonomska Istraživanja 24 (4) (2015) 27–40, doi:10.1080/1331677x.2011.11517478.
[203] M. Yazdani, P. Chatterjee, D. Pamucar, M.D. Abad, A risk-based integrated decision-making model for green supplier selection, Kybernetes, 2019.
[204] M. Yazdani, P. Chatterjee, A.E. Torkayesh, An Integrated AHP-QFD-Based Compromise Ranking Model for Sustainable Supplier Selection, in: Handbook of Research on Interdisciplinary Approaches to Decision Making for Sustainable Supply Chains, IGI Global, 2020, pp. 32–54.
[205] M. Yazdani, P. Chatterjee, E.K. Zavadskas, S. Hashemkhani Zolfani, Integrated QFD-MCDM framework for green supplier selection, J. Cleaner Prod. 142 (2017) 3728–3740, doi:10.1016/j.jclepro.2016.10.095.
[206] M. Yazdani, S. Hashemkhani Zolfani, E.K. Zavadskas, New integration of MCDM methods and QFD in the selection of green suppliers, Journal of Business Economics and Management 17 (6) (2016) 1097–1113.
[207] F. Ye, An extended TOPSIS method with interval-valued intuitionistic fuzzy numbers for virtual enterprise partner selection, Expert Syst. Appl. 37 (10) (2010) 7050–7055, doi:10.1016/j.eswa.2010.03.013.
[208] X.-Y. You, J.-X. You, H.-C. Liu, L. Zhen, Group multi-criteria supplier selection using an extended VIKOR method with interval 2-tuple linguistic information, Expert Syst. Appl. 42 (4) (2015) 1906–1916.
[209] C. Yu, Z. Zou, Y. Shao, F. Zhang, An integrated supplier selection approach incorporating decision maker's risk attitude using ANN, AHP and TOPSIS methods (2019).
[210] X. Yu, S. Zhang, X. Liao, X. Qi, ELECTRE methods in prioritized MCDM environment, Information Sciences 424 (2018) 301–316, doi:10.1016/j.ins.2017.09.061.
[211] L.A. Zadeh, Fuzzy sets, Information and Control 8 (3) (1965) 338–353, doi:10.1016/S0019-9958(65)90241-X.
[212] N. Zarbakhshnia, H. Soleimani, H. Ghaderi, Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria, Appl. Soft Comput. 65 (2018) 307–319, doi:10.1016/j.asoc.2018.01.023.
[213] E.K. Zavadskas, J. Antucheviciene, Multiple criteria evaluation of rural building's regeneration alternatives, Build. Environ. 42 (1) (2007) 436–451, doi:10.1016/j.buildenv.2005.08.001.
[214] E.K. Zavadskas, R. Bausys, B. Juodagalviene, I. Garnyte-Sapranaviciene, Model for residential house element and material selection by neutrosophic MULTIMOORA method, Eng. Appl. Artif. Intell. 64 (2017) 315–324.
[215] E.K. Zavadskas, A. Kaklauskas, V. Sarka, The new method of multicriteria complex proportional assessment of projects, Technological and Economic Development of Economy 1 (3) (1994) 131–139.
[216] Zekhnini, K., Cherrafi, A., Bouhaddou, I., Benghabrit, Y., & Garza-Reyes, J. A. (2020). Supplier selection for smart supply chain: An adaptive fuzzy-neuro approach.
[217] J. Zhang, L. Li, J. Zhang, L. Chen, G. Chen, Private-label sustainable supplier selection using a fuzzy entropy-VIKOR-based approach, Complex & Intelligent Systems (2021) 1–18.
[218] J. Zhang, D. Yang, Q. Li, B. Lev, Y. Ma, Research on Sustainable Supplier Selection Based on the Rough DEMATEL and FVIKOR Methods, Sustainability 13 (1) (2020) 88, doi:10.3390/su13010088.
[219] R.L.J.W.H. Zhang, A multi-criteria decision-making method based on single-valued trapezoidal neutrosophic preference relations with complete weight information, Neural Computing and Applications (2017), doi:10.1007/s00521-017-2925-8.
[220] Y. Zhang, L.V Yaqiong, T.U. Lei, H.O.U. Yueqiu, Intelligent Logistics Supplier Selection Based On Improved Agglomerative Hierarchical Clustering Algorithm, in: 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), 1, 2019, pp. 1309–1314.
[221] H. Zhao, J.-X. You, H.-C. Liu, Failure mode and effect analysis using MULTIMOORA method with continuous weighted entropy under interval-valued intuitionistic fuzzy environment, Soft Comput. 21 (18) (2017) 5355–5367.
[222] Z. Zhi-guang, A VIKOR Method for Supplier Selection, Journal of Gansu Lianhe University (Natural Science Edition) 5 (2012) 7.