International Journal of Industrial Engineering & Production Research June 2024 Vol. 35, No. 3: 1-20
DOI: 10.22068/ijiepr.35.3.1997

RESEARCH PAPER

Raw Material Provider Selection Problem Considering the Digitalization, Circular Economy and Resilience Dimensions: A Case Study

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Received 5 January 2024; Revised 10 March 2024; Accepted 25 May 2024;

ABSTRACT
This study focuses on evaluating potential raw material providers (RMPs) as one of the critical tasks of the logistics managers. In this regard, the literature showed that the simultaneous consideration of resilience, digitalization, and circular economy in the RMP selection problem (RMPSP) has been ignored by previous studies. Therefore, to cover the mentioned gap, this research attempts to study the RMPSP by considering other crucial concepts namely resilience and Circular Economy (CE). For this purpose, by considering a real-world case study in the steel industry, the current work first specifies the indicators of the research problem. Then, the indicators' weights are measured using the stochastic Best-Worst Method (BWM). In the next step, the RMPs are prioritized by developing a novel approach called the stochastic Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). In general, the main objective of this study is to evaluate the performance of the RMPs in the steel industry based on the CE, resilience, and digitalization aspects. According to the achieved results, "Reliability", "Price", "Quality", "Reverse logistics and Waste management", "Information systems usage", and "Restorative Capacity", are identified as the most desirable indicators. Moreover, the results confirm the effectiveness and validation of the developed method.

KEYWORDS: Raw material provider selection; Digitalization; Resilience; Circular economy; Multiple-criteria decision-making.

1. Introduction

In today's competitive and global marketplace, the importance of supply chain (SC) management has been drastically highlighted. Nowadays, practical managers know that they can significantly enhance market share and profits by setting an optimal plan for their SCs [1–4]. In this field, one of the most important research areas is to evaluate the performance of RMPs called as the RMP selection problem (RMPSP). Overall, the RMPSP holds significant importance in supply chain management due to its direct impact on the overall performance, efficiency, and competitiveness of organizations. Selecting the right RMPs is crucial as they play a critical role in determining the quality, cost, and timeliness of inputs and materials that flow through the supply chain. Poor RMP selection can lead to disruptions, delays, quality issues, and increased costs, ultimately affecting the organization's ability to meet customer demands and achieve strategic objectives [5]. The crucial role of the mentioned problem has resulted in conducting considerable papers in this field. Although researchers usually considered functional indicators like delivery time and cost in the traditional approach, their

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attention has dramatically attracted to other important indicators (e.g. resilience and digitalization) in recent years.

In the last decade, the digital industry (DI) and artificial intelligence (AI) have grown significantly. This considerable progress has had an undeniable impact on SC activities and has led to configuring the digital SCs [6]. In general, the concept of a digital supply chain involves the integration of technology and data analytics to optimize the flow of goods, information, and finances across the entire supply chain network. By leveraging digital technologies such as artificial intelligence, blockchain, and the Internet of Things (IoT), organizations can streamline processes, improve visibility, and make more informed decisions in real-time [7]. One of the key advantages of digital supply chains is the ability to enhance collaboration and communication among stakeholders, including RMPs, manufacturers, distributors, and customers. Real-time data sharing and visibility enable better coordination and synchronization of activities, leading to reduced lead times, lower inventory levels, and improved customer satisfaction [8]. Hence, it is necessary to consider the digitalization dimensions in the supply chain management problem.

One of the critically important concepts that has dramatically attracted the attention of researchers after the COVID-19 pandemic is resilience, which is a set of strategies to enhance the ability of a system for dealing with risks [9–11]. In the face of various disruptions such as natural disasters, geopolitical tensions, pandemics, and economic uncertainties, the ability of supply chain to bounce back quickly and effectively from unexpected events is essential for maintaining operational continuity and meeting customer demands. Resilience encompasses the capacity of SCs to anticipate, respond to, adapt to, and recover from disruptions while minimizing negative impacts on performance, costs, and customer satisfaction [12]. Therefore, considering the resilience in the SC management problem seems necessary.

Another crucial concept that plays a crucial role in the nowadays competitive market, especially due to the environmental concerns, is the Circular Economy (CE). In general, the concept of the CE has gained significant traction in today's business environment due to its potential to address pressing environmental concerns and drive sustainable economic growth. In the context of a circular economy, resources are utilized in a closed-loop system, where products are designed, produced, used, and recycled or repurposed in a way that minimizes waste and maximizes resource efficiency. This shift away from the traditional linear "take-make-dispose" model not only reduces the environmental impact of production and consumption but also offers opportunities for cost savings, innovation, and new revenue streams for businesses [13,14]. According to the literature, the transition towards a circular economy is not only a strategic imperative for businesses to mitigate environmental risks but also a pathway towards long-term competitiveness and sustainability in today's dynamic business landscape [15,16]. The mentioned points show the necessity of considering the CE in SC management.

Based on the above-mentioned points, the CE and digitalization indicators play a critically important role in the RMP selection problem. In this regard, in spite of the considerable efforts of researchers to incorporate the mentioned aspects into the RMPSP, the simultaneous consideration of these indicators in the steel RMPSP has been ignored in the literature. Hence, to cover this gap, this article attempts to develop a hybrid decision-making framework to evaluate the RMPs based on the digitalization, resilient, and CE dimensions. In this regard, by considering a real case study in the steel industry, the major indicators and alternatives are specified. Then, the indicators weights are computed using the stochastic BWM. Then, to rank the RMPs, a novel method named the stochastic TOPSIS is developed. In general, the main objectives of this research are as follows: (i) identifying the main indicators of the CE-based digital and resilient RMPSP, (ii) developing an efficient decision-making method to evaluate the RMPs' performance under uncertain environment, (iii) determining the most desirable indicators of the research problem, and (v) determining the best supplier. To reach the research objective, the current article attempts to answer the following research questions: (i) what are the main indicators of the CE, resilience and digitalization dimensions in the RMPSP problem? (ii) how can develop an efficient method to evaluate the performance of the RMPs under uncertain environment? (iii) Which indicators are the best for the research problem? and (v) Which suppliers have the best performance based on the considered indicators?

All in all, developing a novel decision-making method to evaluate the performance of the RMPs according to the CE, resilience, and digitalization aspects in the steel industry is the main advantage of this article in comparison with published works.

The rest of this article has been organized as follows. Section 2 provides the literature review. Section 3 provides the case study and methodology. Section 4 provides the numerical results. Section 5 provides the conclusions.

2. Literature Review

2.1. RMPSP with different dimensions

In this section, we have reviewed some related papers that addressed the RMPSP with digitalization, resilience, or CE dimensions. In this field, [17] incorporated the digitalization and sustainability metrics in the evaluation process of the RMPs. In this regard, the authors determined the major dimensions of the research problem and then proposed an ontology-based approach to evaluate RMPs. [18] proposed a novel hybrid approach for assessing the performance of the RMPs according to the digitalization and resilience dimensions. In this regard, the authors first specified the main criteria and then developed a goal programming-based Fuzzy BWM (FBWM) to determine their importance. In the next step, the authors used the Fuzzy Vise Kriterijumska Optimizacija I Kompromisno Resenje (FVIKOR) to examine the performance of the alternatives. A fuzzy decision-making approach was suggested by [19] for studying the RMPSP based on the digitalization and resilience indicators. The authors specified the main dimensions and then suggested a modified fuzzy decision-making to assess the RMPs according to the considered indicators. [20] addressed the evaluation process of the RMPs based on various criteria consisting of resilience and digitalization. To do this, by utilizing the pairwise comparisons questionnaire, they used the Analytical Hierarchy Process (AHP) method to evaluate the RMPs. [21] focused on the evaluation process of the raw materials providers based on the resilience and digitalization indicators using a machine learning-based model. In this regard, by considering the role of blockchain technology, the authors developed a two-stage model to evaluate RMPs reinforcing SC resilience. On the other side, about evaluating the RMPs based on the CE dimensions, [22] focused on the evaluation process of the RMPs according to the CE indicators. In this regard, the authors selected a real case study and then identified the main dimensions. Afterwards, they proposed a dynamic decision support system by combining the FIS and BWM to assess the RMPs. [23] addressed the RMPSP with the CE criteria under uncertain environment. The authors integrated the BWM, the regret theory, and dual hesitant fuzzy sets to evaluate the performance of the RMPs according to the CE dimensions. [24] investigated the evaluation process of the RMPs by considering the resilience and CE aspects. In the mentioned work, at the outset, the relevant indicators were extracted. Afterwards, the authors proposed a criterion knowledge-based framework to assess the performance of the RMPs. [25] investigated the evaluation process of the RMPs by considering digitalization, sustainability and CE dimensions. The authors computed the criteria's importance using the BWM. In the next step, they evaluated the RMPs using the VIKOR approach. [26] focused on the SC network configuration issue in which the evaluation of the RMPs was conducted according to the CE dimensions. They computed the score of the RMPs according to the CE dimensions employing the interval-valued fuzzy-compromise decision-making approach. In the next step, by suggesting a mathematical model, they designed a SC with the and resilience and sustainability features. [27] studied the RMPSP by considering the digitalization and resilience aspects. For this purpose, the authors developed a fuzzy decision-making framework to measure the importance of the indicators and also assess the performance of the RMPs. They implemented the proposed method in a multinational solar water pump manufacturing company to show its application and efficiency. [28] investigated the resilient RMPSP for the pharmaceutical industry. In this regard, they first identified the main criteria of the research problem and then developed a decision-making method to evaluate the performance of the RMPs based on the considered indicators. [29] focused on the raw material provider selection problem based on the resilience indicators. For this purpose, the authors first determined the most important criteria for the research problem. Then, they used the double normalization-based multi-aggregation to assess the performance of the RMPs. [30] examined the interrelationship between the RMPSP and circular economy. In this way, at the outset, the authors identified the main indicators related to circular economy. Then, they developed a hybrid decision-making method to compute the importance of the indicators and also to evaluate the RMPs' performance.

2.2. Steel RMPSP

Here, the articles that studied the RMPSP for the steel industry are reported. In this regard, the TOPSIS method was employed by [31] to evaluate the performance of the RMPs for small scale steel manufacturing unit. To do this, the authors first provided a list of dimensions and then assessed the feasible RMPs based on them using the TOPSIS method. The RMPSP for the steel industry by considering the environmental concerns was addressed by [32]. In this way, the authors extracted the required indicators and then measured their importance using the BWM. Moreover, to assess the performance of the RMPs, they utilized the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. [33] addressed the evaluation process of the RMPs based on the sustainability pillars for the steel industry. For this purpose, they identified the main dimensions according to the literature and then assessed the RMPs applying the taxonomy method. The RMPSP with the sustainability and resilience dimensions was studied by [34]. To this end, they first presented the relevant indicators. Afterwards, the authors employed the BWM for computing the indicators' weights. In the next step, they evaluated the performance of the RMPs applying the TOPSIS method. [35] developed a hybrid method based on a decision-making method and the design of experiment-based metamodel approach to assess the performance of RMPs for the steel industry. [36] investigated the steel supply chain problem based on the sustainability dimensions under uncertainty. In this regard, the authors proposed a multi-objective mathematical model that minimized the total cost and maximizes the efficiency of product production lines. [37] focused on RMPSP for the metal industry using the AHP method. In this regard, the authors first determined the main indicators of the research problem and also the feasible alternatives. Then, they used the AHP approach to evaluate the RMPs' performance.

2.3. Contribution statement

The literature review showed that the RMPSP is one of the trend topics among the researchers and considerable papers have been published in this field in recent years. Nevertheless, despite publishing several academic works in the field of the RMPSP by considering different concepts, some gaps are still observed. In this regard, although there are many articles that focused on the RMPSP for the steel industry (for example see [31], [33], [34], [35]), none of them considered the CE, resilience, and digitalization indicators. Indeed, the previous papers ignored the simultaneous consideration of the CR, resilience, and digitalization aspects in the RMPSPS especially for the steel industry. However, as mentioned in the introduction section, all of the mentioned features (i.e., digitalization, circular economy, and resilience) play a crucial role in the SC management problem, especially in the steel industry. Hence, to bridge the mentioned gaps, this study has focuses on the evaluation process of the RMPs for the steel industry by considering the digitalization, CE, and resilience indicators. For this purpose, first, the main dimensions related to digitalization, CE, and resilience indicators are specified. Then, the potential RMPs are identified. Finally, an integrated stochastic BWM-TOPSIS is developed to prioritize the RMPs based on the considered dimensions. In general, the main contributions of this work can be summarized as follows:

- This is the first study that simultaneously considers the digitalization, resilience, and circular economy dimensions in the RMPSP for the steel industry.
- This research proposes a novel method named the stochastic TOPSIS to evaluate the performance of the RMPs.
- This research focuses on a real-world case study.

3. Case study and Methodology

3.1. Case study and indicators

As aforementioned, this work chooses a case study in the steel industry. In this regard, the steel industry plays a crucial role in the global economy, serving as a foundational pillar for various sectors such as construction, automotive, infrastructure, machinery, and manufacturing. The steel industry is important in economics for several reasons: (i) Job creation: The steel industry creates a significant number of jobs both directly in steel production and indirectly in related industries such as mining, transportation, and manufacturing. (ii) Economic growth: Steel is a key input in many industries, including construction, automotive, and infrastructure development. A strong steel industry is essential for economic growth and development. (ii) Trade balance: Steel is a major export product for many countries, contributing to their trade balance and overall economic performance. And (v) Innovation: The steel industry drives innovation in materials science and engineering, leading to the development of new products and technologies that can benefit other industries. Also, in terms of environmental issues, the steel industry has a significant impact on the environment due to its energy-intensive production processes and greenhouse gas emissions. However, the industry has been working to reduce its environmental footprint through initiatives such as improving energy efficiency, recycling scrap steel, and investing in cleaner technologies. By addressing environmental concerns, the steel industry can contribute to sustainability and mitigate its impact on climate change. Moreover, raw material provider selection is crucial in the steel industry for several reasons: 1. Quality of raw materials: The quality of steel products is highly dependent on the quality of raw materials used in the production process. Selecting reliable and reputable suppliers ensures that the steel produced meets the required standards and specifications. 2. Cost efficiency: Raw material provider selection plays a significant role in determining the cost of raw materials, which directly impacts the overall production costs of steel products. Choosing suppliers that offer competitive prices and favorable terms can help improve cost efficiency and profitability. 3. Supply chain reliability: The steel industry operates on tight production schedules and just-in-time inventory management. Selecting reliable suppliers with a track record of on-time delivery and consistent supply helps ensure uninterrupted production and smooth operations. 4. Technological expertise: Suppliers with advanced technology and expertise in steel production can provide valuable technical support and contribute to innovation in the industry. Partnering with technologically advanced suppliers can help improve product quality and competitiveness. This research selects a company located in Mazandaran province, Iran. This company produces different products like metal deck. The mentioned company has four main RMPs that have been located in different province of Iran. Fig. 1 shows the location of the company and its RMPs.

Fig. 1. A schematic from the position of the company and its suppliers

In the following, we have presented the main aspects and criteria determined in this research (see Table 1). In this regard, we define four different aspects namely general, CE, resilience, and digitalization aspects, each of which has its relevant criteria. It should be noted that we first extract potential indicators and then the experts chosen the most relevant ones.

Tab. 1. The aspects and criteria considered in this research

Aspect	Criteria	Reference
General	Lead-time (C1)	[2,38,39]
	Reputation (C2)	[40,41]
	Price (C3)	[2,38,39]
	Quality (C4)	[40–42]
	Service (C5)	[31,43]
CE	Reverse logistics and Waste management (C6)	[22,24]
	Resource consumption (C7)	[22,24]
	Energy consumption (C8)	[44,45]
	Recyclable raw materials (C9)	[44,45]
	Green packaging (C10)	[46–49]
Resilience	Reliability (C11)	[40,42]
	Extra Inventory (C12)	[40,42]
	Rerouting (C13)	[40,42]
	Restorative Capacity (C14)	[40,50]
	Backup Supplier (C15)	[49,51]
Digitalization	Digital customer relationships (C16)	[52–54]
	Smart factory (C17)	[53,55,56]
	Industry 4.0 technology usage (C18)	[52,53,57]
	Cyber security (C19)	[53,57]
	Information systems usage (C20)	[53,58]

3.2. Stochastic BWM

The Best-Worst Method (BWM) is a decision-making technique developed by [59] that aims to prioritize alternatives based on their perceived best and worst attributes. The main reasons for selecting this method for this study are as follows [40,60]: (i) this approach significantly enhances the reliability, (ii) this method significantly decreases the computational burden, and (iii) this approach can easily combined with other approaches. It should be noted that for k decision-makers and n indicators, the AHP (analytical hierarchy process) method requires $k.\frac{n(n-1)}{2}$ comparisons but the BWM needs only $k.(2n-3)$ comparisons. Since the traditional BWM cannot deal with the uncertain environment of the decision-making problems, researchers have proposed various uncertain versions of the BWM in recent years. One of the recently introduced efficient variant of the BWM is the Stochastic BWM developed by [61]. This method is the extended form of the BWM using scenario-based programming to deal with randomness uncertainty in the business environment. It should be noted that the main reasons for focusing of the scenario-based programming is that according to the literature this type of uncertainty plays an important and crucial role in the decision-making problems [61–63]. In the following, we have briefly defined the Stochastic BWM steps.

Step 1. First of all, the most desirable and least desirable indicators are determined by the decision-makers.

Step 2. The pairwise comparison vectors are formed based on numbers 1-9. In this regard, the decision-makers should form the BO (Best-to-Other) and OW (Other-to-Worst) comparison vectors by comparing the best and worst indicators with the other ones based on numbers 1-9.

Step 3. solving a mathematical model presented in Model (1) to compute the indicators' weights.

Step 4. Checking the Consistency Ratio (CR). If the CR is a small number (usually less than 0.1), the achieved results are acceptable. Otherwise, back to Step 2.

The main notations of this method presented in Table 2 and Model (1) is the mathematical formulation of the stochastic BWM.

Tab. 2. The notations of the stochastic BWM

Parameters	
P_s	Probability of scenario s
a_{Bjs}	Comparison vector between the most desirable criterion and other ones under scenario *s*
a_{jWs}	Comparison vector between the least desirable criterion and other ones under scenario *s*
Variables	
ξ_s	The consistency ration (CR) under scenario *s*
ws_{js}	The importance of j^{th} criterion under scenario *s*
w_j	The final importance of the j^{th} criterion

$$\begin{aligned}
&Min \sum_s P_s.\xi_s && \\
&|ws_{Bs} - a_{Bjs}.ws_{js}| \leq \xi_s && \forall j,s \\
&|ws_{js} - a_{jWs}.ws_{Ws}| \leq \xi_s && \forall j,s \\
&\sum_j ws_{js} = 1 && \forall s \\
&w_j = \sum_s P_s.ws_{js} && \forall j \\
&ws_{js}, w_j \geq 0 && \forall j,s
\end{aligned} \tag{1}$$

3.3. Stochastic TOPSIS

One of the widely used approaches in the decision-making area is TOPSIS developed by [64] which aims to find an alternative with most closeness to the ideal solution. The main reasons for selecting the TOPSIS method in this study are as follows: (i) this is an efficient decision-making method that showed an appropriate performance in the RMPSP literature, (ii) this method has simple concepts and is easy to Implement making it understandable for practical managers. There are several versions of the TOPSIS method to cope with uncertainty like fuzzy TOPSIS, grey TOPSIS, etc. In this regard, as aforementioned, the randomness uncertainty is one of the critical parts of the decision-making environment that its role completely exhibited after the COVID-19 pandemic [61,65]. Also, according to the literature, in many real-world cases, the decision-making the process is along with randomness uncertainty [61–63]. Additionally, according to the literature, considering different scenarios in decision-making problems can bring the research problem close to the real-world conditions However, developing the variant of the TOPSIS method that can effectively deal with this type of uncertainty has been rarely addressed in the literature. Hence, motivated by the mentioned issue, the current study develops a new version of the TOPSIS method named the stochastic TOPSIS method. In the following, we have described this approach.

Step 1. Forming the scenario-based decision matrix

Let there are *I* alternatives indexed by *i*, *J* criteria indexed by *j*, and *S* scenarios indexed by *s*. The scenario-based decision matrix (D_{ijs}) can be formed as Table 3. In this matrix, x_{ijs} shows the score of alternative *i* based on criterion *j* under scenario *s*.

Tab. 3. The stochastic decision matrix for the stochastic TOPSIS method

	c_1			c_2			…	c_j		
	s_1	…	s_s	s_1	…	s_s		s_1	…	s_s
a_1	x_{111}	…	x_{11s}	x_{121}	…	x_{12s}	…	x_{1i1}	…	x_{1js}
a_2	x_{211}	…	x_{21s}	x_{221}	…	x_{22s}	…	x_{2i1}	…	x_{2js}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
a_i	x_{i11}	…	x_{i1s}	x_{i21}	…	x_{i2s}	…	x_{ij1}	…	x_{ijs}

Step 2. Calculating the normalized decision matrix

In this step, the normalized decision-matrix (N_{ijs}) is formed using relation (2).

$$n_{ijs} = \frac{x_{ijs}}{\sqrt{\sum_i x_{ijs}^2}};\ n_{ijs} \in N_{ijs} \quad (2)$$

Step 3. Calculating the weighted normalized decision matrix

In this step, by considering $W = \{w_1, w_2, \dots, w_J\}$ as the weights of the indicators, the weighted normalized decision matrix (V_{ijs}) is calculated based on relation (3).

$$v_{ijs} = w_J . n_{ijs};\ v_{ijs} \in V_{ijs} \quad (3)$$

Step 4. Calculating the positive ideal solution (PIS) and negative ideal solution (NIS)

In this step, the PIS and NIS in each scenario are measured according to equations (4) and (5). In the next step,

$$d_s^{max} = \{\max V_{ijs} \,|j\ is\ a\ poitive\ indicator\};\ d_s^{max} = \{\min V_{ijs} \,|j\ is\ a\ negative\ indicator\} \quad (4)$$

$$d_s^{min} = \{\min V_{ijs} \,|j\ is\ a\ poitive\ indicator\};\ d_s^{min} = \{\max V_{ijs} \,|j\ is\ a\ negative\ indicator\} \quad (5)$$

Step 5. Calculating the separation of each alternative from the NIS and PIS solutions

In this step, the separation of each alternative from the NIS and PIS solutions in each scenario are calculated. It should be noted that d_{is}^{+} represents the Euclidean distance of each alternative from the PIS and d_{is}^{-} shows the Euclidean distance of each alternative from the NIS.

$$d_{is}^{+} = \sqrt{\sum_j \left(v_{ijs} - d_s^{max}\right)^2} \quad (6)$$

$$d_{is}^{-} = \sqrt{\sum_j \left(v_{ijs} - d_s^{min}\right)^2} \quad (7)$$

Step 6. Calculating the relative closeness

In this step, the relative closeness (RC) to the ideal solution in each scenario (c_{is}) is measured using relation (8). Eventually, the final RC of the alternatives (fc_i) is calculated using equation (9) where PS_s is the probability of scenario *s*. The alternatives are ranked based on the fc_i . When fc_i is bigger, the rank of alternative *i* is better.

$$c_{is} = \frac{d_{is}^{-}}{d_{is}^{+} + d_{is}^{-}} \quad (8)$$

$$fc_i = \sum_s PS_s . c_{is} \quad (9)$$

Fig. 2 illustrates the framework of this study to better understand the procedure of evaluating the RMPs using the developed hybrid approach. as shown in this figure, at the outset, we identify the main indicators and alternatives according to the experts and literature. Afterwards, the importance of the indicators is computed using the stochastic BWM method. In the next step, the RMPs are assessed using the developed stochastic TOPSIS.

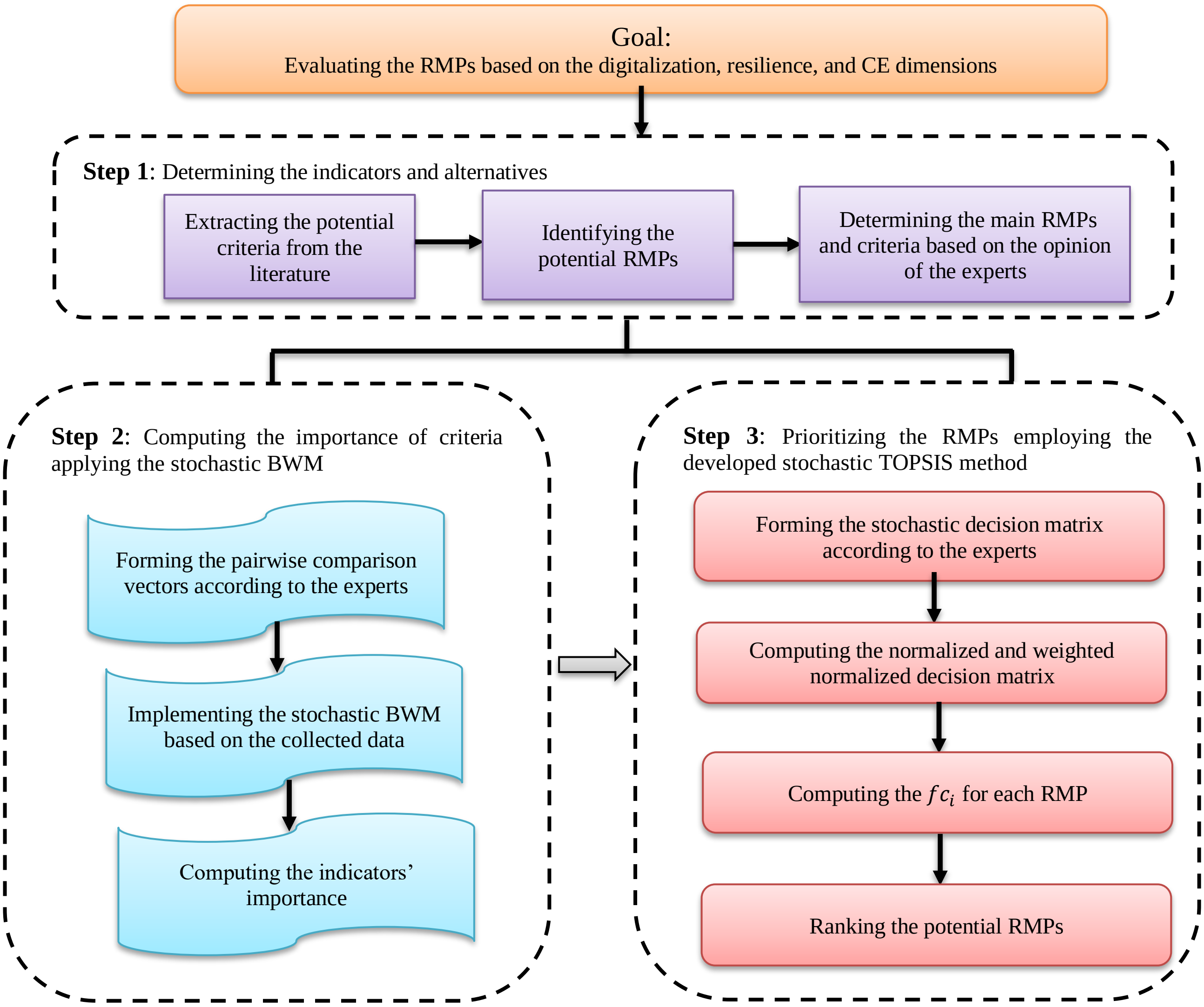


Fig. 2. The research framework

4. Computational Results

In this section, the numerical results are presented. In this regard, it should be noted that the required data are gathered based on the opinion of the experts of the considered case study. In this way, three groups of experts have formed according to their qualifications and experience, and the relevant questionnaires are dispatched among them to form the comparison vectors of the SBWM and the decision matrix of the STOPSIS approach.

4.1. Results of the stochastic BWM

To compute the weights of the indicators using the stochastic BWM approach, the pairwise comparison vectors have been formed based on the average of the options of the experts. To this end, inspired by the literature, we have defined three scenarios namely optimistic (e.g., economic prosperity conditions), most possible (e.g., normal conditions), and pessimistic (e.g., disruption conditions) scenarios. It should be noted that $P_{s1} = 0.25$ $P_{s2} = 0.5$, and $P_{s3} = 0.25$. A sample of questionnaire has been provided in the Appendix. Table 4 demonstrates the weights of indicators obtained by the stochastic BWM. Based on this table, "Price" and "Quality" were determined as the most desirable criteria for the general aspect. Additionally, "Reverse logistics and Waste management" and "Recyclable raw materials" were determined as the most desirable criteria for the CE aspect. Furthermore, "Reliability" and "Restorative Capacity" were determined as the most desirable criteria for the resilience aspect. Also, "Information systems usage" and "Cyber security" were determined as the most desirable criteria for the digitalization aspect. Finally, among all dimensions of the research problem, "Reliability", "Price", "Quality", "Reverse logistics and Waste management", "Information systems usage", "Restorative

Capacity", and "Energy consumption" were determined as the best ones.

Tab. 4. The weights of the aspects and indicators

Aspect	W^{Aspect}	Criterion	$IW^{Criterion}$	Final weight ($W^{Aspect} \times IW^{Criterion}$)
General	0.2513	Lead-time	0.2010	0.05051
		Reputation	0.1950	0.04900
		Price	0.2035	0.05114
		Quality	0.2031	0.05104
		Service	0.1974	0.04961
CE	0.2500	Reverse logistics and Waste management	0.2040	0.05100
		Resource consumption	0.2021	0.05053
		Energy consumption	0.2021	0.05053
		Recyclable raw materials	0.2014	0.05035
		Green packaging	0.1904	0.04760
Resilience	0.2511	Reliability	0.2044	0.05132
		Extra Inventory	0.2000	0.05022
		Rerouting	0.1938	0.04866
		Restorative Capacity	0.2018	0.05067
		Backup Supplier	0.2000	0.05022
Digitalization	0.2476	Digital customer relationships	0.1892	0.04685
		Smart factory	0.2000	0.04952
		Industry 4.0 technology usage	0.2018	0.04997
		Cyber security	0.2039	0.05049
		Information systems usage	0.2051	0.05078

4.2. Results of the stochastic TOPSIS

In this section, we have presented the outputs of the developed stochastic TOPSIS. In this way, Table 5 shows the stochastic decision matrix in which the score of RMPs based on each criterion has been given according to 1-9 numbers. It should be noted that, in this section, inspired by the literature, we have defined three scenarios namely optimistic, most possible, and pessimistic scenarios. It should be noted that $P_{s1} = 0.25$ $P_{s2} = 0.5$, and $P_{s3} = 0.25$. Also, Tables 6 and 7 respectively demonstrate the normalized decision matrix and the weighted normalized decision matrix. After the calculations using equations (2)-(9), the values of fc_i are computed and presented in Table 8. According to this table, the ranking of the RMPs are as follows: A1>A2>A4>A3>A5.

Tab. 5. The stochastic decision matrix

	C1			C2			C3			C4			C5			C6			C7			C8			C9			C10		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	7	5	4	6	4	3	4	3	2	6	4	3	6	4	3	8	6	5	4	3	2	4	3	2	8	7	6	9	7	5
A2	8	6	5	7	5	4	5	3	2	7	5	4	5	3	2	7	5	6	4	3	2	5	4	3	8	7	5	7	5	3
A3	9	7	6	7	5	4	6	4	3	6	4	3	6	4	3	6	4	3	5	3	2	9	7	6	5	3	2	7	5	4
A4	8	6	4	6	4	3	7	5	4	5	3	2	5	3	2	6	4	3	4	2	1	8	5	4	5	3	2	6	4	3
A5	9	7	6	6	4	3	6	4	3	6	4	3	4	2	1	6	4	3	4	2	1	7	5	4	6	4	3	5	3	2

	C11			C12			C13			C14			C15			C16			C17			C18			C19			C20		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	8	7	6	6	5	4	6	4	3	8	6	4	8	6	5	8	6	5	8	6	5	6	4	3	8	6	5	7	5	4
A2	7	5	4	9	7	6	7	5	4	8	6	5	9	8	7	8	7	6	8	6	5	5	3	2	8	6	5	7	6	5
A3	7	5	4	5	3	2	6	4	3	5	3	2	7	5	4	7	4	3	8	6	5	5	3	2	7	5	4	8	6	4
A4	8	6	5	5	3	2	7	5	4	4	2	1	7	5	4	9	8	7	9	7	6	6	4	3	6	4	3	9	8	7
A5	7	5	4	8	6	4	8	6	5	5	3	2	6	5	4	9	7	5	9	7	6	5	3	2	5	3	2	7	6	4

Tab. 6. The normalized decision-matrix

	C1			C2			C3			C4			C5			C6			C7			C8			C9			C10		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	0.38	0.36	0.35	0.42	0.40	0.39	0.45	0.44	0.44	0.45	0.44	0.44	0.37	0.31	0.23	0.33	0.26	0.18	0.53	0.57	0.61	0.46	0.47	0.50	0.43	0.42	0.40	0.38	0.35	0.38
A2	0.44	0.43	0.44	0.49	0.51	0.52	0.37	0.33	0.29	0.52	0.55	0.58	0.46	0.46	0.46	0.41	0.38	0.35	0.53	0.57	0.61	0.40	0.40	0.30	0.43	0.42	0.40	0.46	0.46	0.44
A3	0.49	0.50	0.53	0.49	0.51	0.52	0.45	0.44	0.44	0.45	0.44	0.44	0.55	0.62	0.69	0.49	0.51	0.53	0.44	0.43	0.41	0.51	0.55	0.59	0.43	0.42	0.40	0.54	0.58	0.49
A4	0.44	0.43	0.35	0.42	0.40	0.39	0.52	0.55	0.58	0.37	0.33	0.29	0.46	0.46	0.46	0.49	0.51	0.53	0.35	0.29	0.20	0.46	0.40	0.40	0.43	0.42	0.40	0.46	0.46	0.44
A5	0.49	0.50	0.53	0.42	0.40	0.39	0.45	0.44	0.44	0.45	0.44	0.44	0.37	0.31	0.23	0.49	0.51	0.53	0.35	0.29	0.20	0.40	0.40	0.40	0.51	0.56	0.60	0.38	0.35	0.49

	C11			C12			C13			C14			C15			C16			C17			C18			C19			C20		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	0.31	0.48	0.50	0.51	0.36	0.29	0.21	0.39	0.37	0.35	0.39	0.34	0.27	0.43	0.43	0.42	0.44	0.41	0.42	0.43	0.42	0.41	0.50	0.52	0.55	0.52	0.54	0.56	0.41	0.36
A2	0.46	0.42	0.41	0.40	0.44	0.44	0.43	0.46	0.46	0.46	0.48	0.51	0.54	0.43	0.43	0.42	0.44	0.48	0.50	0.43	0.42	0.41	0.41	0.39	0.37	0.52	0.54	0.56	0.41	0.43
A3	0.62	0.42	0.41	0.40	0.44	0.44	0.43	0.39	0.37	0.35	0.48	0.51	0.54	0.43	0.43	0.42	0.38	0.27	0.25	0.43	0.42	0.41	0.41	0.39	0.37	0.45	0.45	0.45	0.47	0.43
A4	0.46	0.48	0.50	0.51	0.44	0.44	0.43	0.46	0.46	0.46	0.39	0.34	0.27	0.43	0.43	0.42	0.49	0.55	0.58	0.48	0.49	0.50	0.50	0.52	0.55	0.39	0.36	0.34	0.53	0.57
A5	0.31	0.42	0.41	0.40	0.53	0.58	0.64	0.52	0.55	0.58	0.48	0.51	0.54	0.50	0.51	0.53	0.49	0.48	0.42	0.48	0.49	0.50	0.41	0.39	0.37	0.32	0.27	0.23	0.41	0.43

Tab. 7. Weighted normalized decision matrix

	C1			C2			C3			C4			C5			C6			C7			C8			C9			C10		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	0.019	0.018	0.018	0.020	0.020	0.019	0.023	0.023	0.022	0.023	0.023	0.022	0.018	0.015	0.011	0.017	0.013	0.009	0.027	0.029	0.031	0.023	0.024	0.025	0.022	0.021	0.020	0.018	0.016	0.015
A2	0.022	0.022	0.022	0.024	0.025	0.026	0.019	0.017	0.015	0.026	0.028	0.030	0.023	0.023	0.023	0.021	0.020	0.018	0.027	0.029	0.031	0.020	0.020	0.015	0.022	0.021	0.020	0.022	0.022	0.022
A3	0.025	0.025	0.027	0.024	0.025	0.026	0.023	0.023	0.022	0.023	0.023	0.022	0.027	0.031	0.034	0.025	0.026	0.027	0.022	0.022	0.021	0.026	0.028	0.030	0.022	0.021	0.020	0.025	0.027	0.029
A4	0.022	0.022	0.018	0.020	0.020	0.019	0.027	0.028	0.030	0.019	0.017	0.015	0.023	0.023	0.023	0.025	0.026	0.027	0.018	0.014	0.010	0.023	0.020	0.020	0.022	0.021	0.020	0.022	0.022	0.022
A5	0.025	0.025	0.027	0.020	0.020	0.019	0.023	0.023	0.022	0.023	0.023	0.022	0.018	0.015	0.011	0.025	0.026	0.027	0.018	0.014	0.010	0.020	0.020	0.020	0.026	0.028	0.030	0.018	0.016	0.015

	C11			C12			C13			C14			C15			C16			C17			C18			C19			C20		
	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3	s1	s2	s3
A1	0.025	0.025	0.026	0.018	0.015	0.011	0.019	0.018	0.017	0.020	0.017	0.014	0.022	0.022	0.021	0.020	0.019	0.020	0.021	0.021	0.020	0.025	0.026	0.027	0.026	0.027	0.028	0.021	0.018	0.018
A2	0.022	0.021	0.021	0.022	0.022	0.021	0.022	0.022	0.022	0.024	0.026	0.027	0.022	0.022	0.021	0.020	0.022	0.023	0.021	0.021	0.020	0.021	0.020	0.018	0.026	0.027	0.028	0.021	0.022	0.023
A3	0.022	0.021	0.021	0.022	0.022	0.021	0.019	0.018	0.017	0.024	0.026	0.027	0.022	0.022	0.021	0.018	0.013	0.012	0.021	0.021	0.020	0.021	0.020	0.018	0.023	0.023	0.023	0.024	0.022	0.018
A4	0.025	0.025	0.026	0.022	0.022	0.021	0.022	0.022	0.022	0.020	0.017	0.014	0.022	0.022	0.021	0.023	0.026	0.027	0.024	0.024	0.025	0.025	0.026	0.027	0.020	0.018	0.017	0.027	0.029	0.032
A5	0.022	0.021	0.021	0.027	0.029	0.032	0.025	0.027	0.028	0.024	0.026	0.027	0.025	0.026	0.027	0.023	0.022	0.020	0.024	0.024	0.025	0.021	0.020	0.018	0.016	0.014	0.011	0.021	0.022	0.018

Tab. 8. The value of fc_i for each alternative

Alternative	fc_i
A1	0.89673
A2	0.86514
A3	0.80871
A4	0.81971
A5	0.80142

4.3. Performance of the stochastic BWM

To demonstrate the efficiency of the employed stochastic BWM, we have compared its outputs with the outputs of the other methods. In this research, we compare the achieved results with the fuzzy BWM and the fuzzy AHP methods. Fig. 3 compares the importance of the indicators obtained by different methods. As can be seen in this figure, there is a significant similarity among the obtained results that confirms the validity and efficiency of the employed approach. On the other side, these methods (i.e., stochastic BWM, fuzzy BWM, and fuzzy AHP) have been compared based on the CR metric in Fig. 4. As shown in this figure, the employed stochastic BWM has the best performance based on the CR metric.

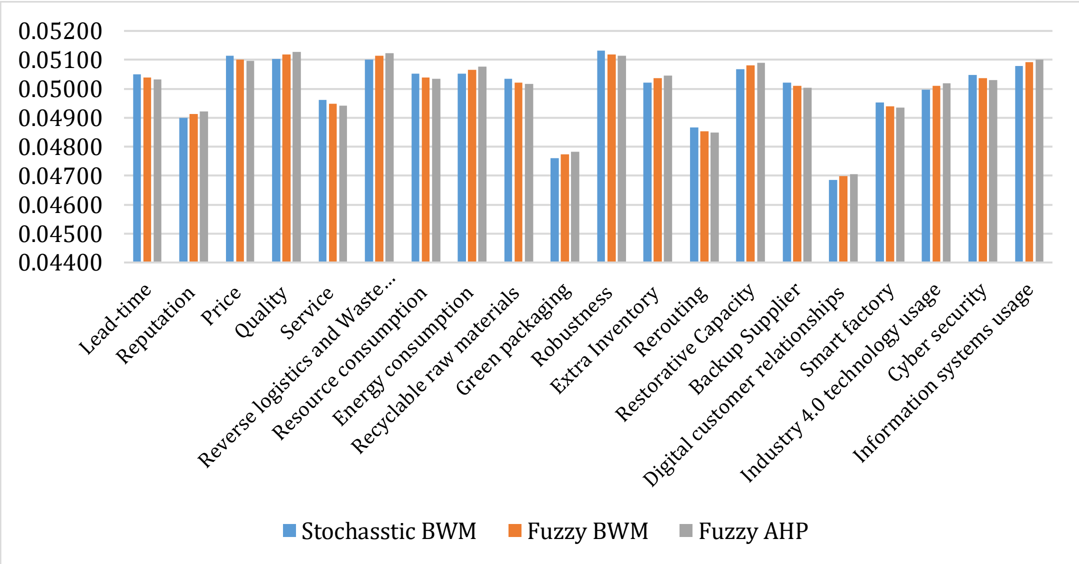


Fig. 3. The comparison between the weights of indicators achieved by different methods

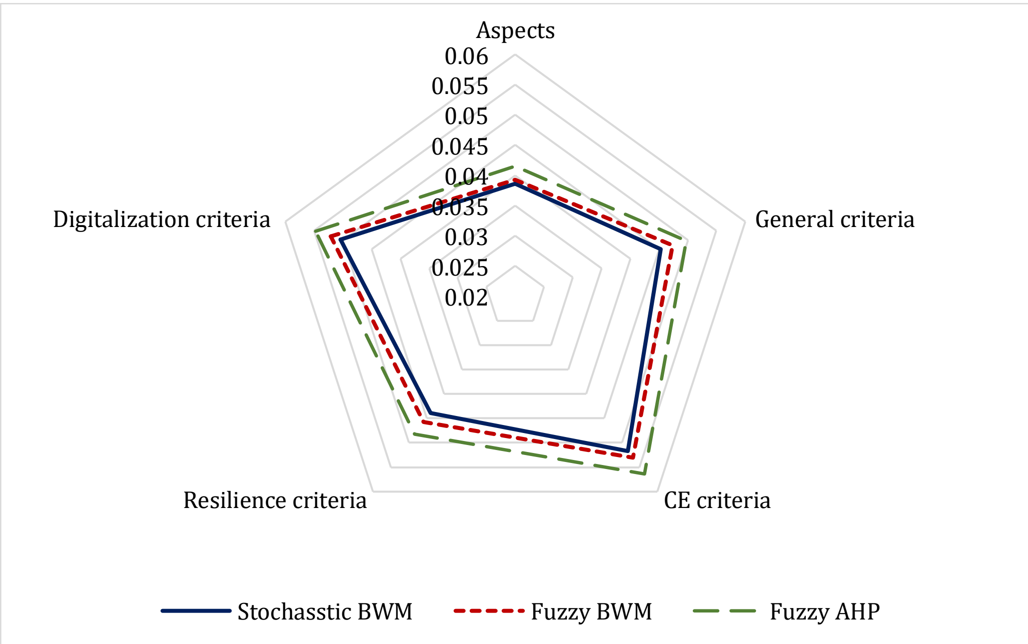


Fig. 4. The comparison between the value of the CR obtained by different methods

4.4. Performance of the stochastic TOPSIS

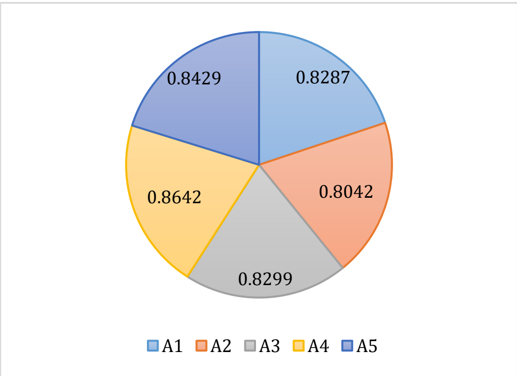
To show the validity and performance of the proposed stochastic BWM, we have compared its results with the results of other methods (TOPSIS, Fuzzy TOPSIS, VIKOR, and stochastic VIKOR). Table 9 shows the obtained results. It should be noted that the stochastic VIKOR is a recently introduced method developed by [65]. Also, we have defined the stages of the VIKOR method in the Supplementary Materials. As can be seen in this table, in all methods, RMPs #A1 and #A2 have been selected as the most appropriate ones, which shows the validation and efficiency of the developed approach. A1>A2>A4>A3>A5.

Tab. 9. The ranking of RMPs based on different approaches

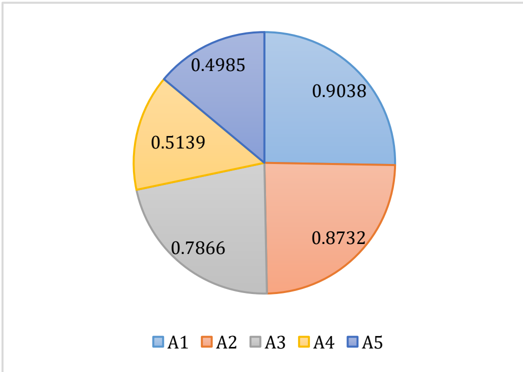
Method	Ranking of the strategies				
	RMP 1	RMP 2	RMP 3	RMP 4	RMP 5
Stochastic TOPSIS	1	2	4	3	5
TOPSIS	1	2	4	3	5
Fuzzy TOPSIS	1	2	3	4	5
VIKOR	1	2	3	4	5
Stochastic VIKOR	1	2	4	3	5

4.5. Evaluating the RMPs in different modes

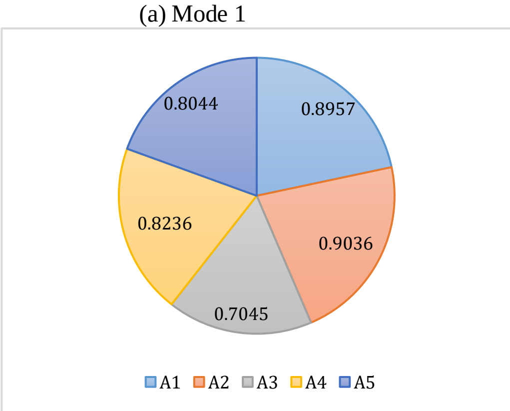
In this section, we have assessed the performance of the RMPs in different modes. To this end, we have considered 5 modes as follows: (Mode 1) Assessing the RMPs according to the general aspect, (Mode 2) Assessing the RMPs according to the CE aspect, (Mode 3) Assessing the RMPs according to the resilience aspect, (Mode 4) Assessing the RMPs according to the digitalization aspect, and (Mode 5) Assessing the RMPs by simultaneous consideration of the CE, general, resilience, and digitalization aspects. Fig. 5 shows the value of fc_i for each RMP in each mode. Based on this figure, in Mode 1, RMP #4 has the best performance. Also, in Mode 2, RMP #1 has the best performance. On the other hand, in Mode 3, RMP #2 has the best performance. Moreover, in Mode 4, RMP #5 has the best performance. Finally, for the research problem (Mode 5) RMPs #1 and #2 have the best performance.



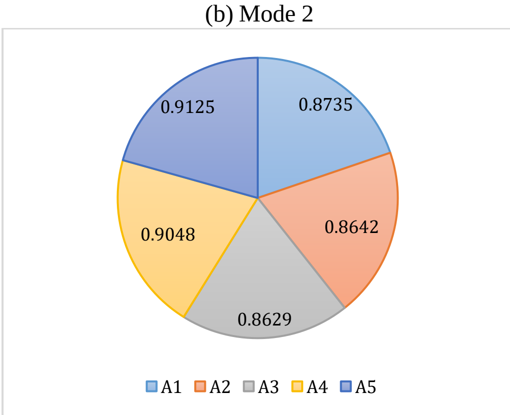
(a) Mode 1



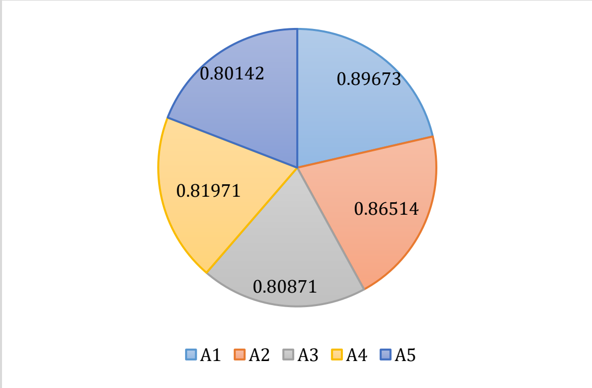
(b) Mode 2



(c) Mode 3



(d) Mode 4



(e) Mode 5

Fig. 5. The score of RMPs in different modes

4.6. Findings and discussions

Since one of the critical challenges of practical managers in the SC field is to evaluate the potential RMPs, the present work has addressed the RMPSP for the steel industry by considering three crucial concepts namely CE, digitalization, and resilience. In this regard, the current work develops a novel hybrid method by combining the stochastic BWM and stochastic TOPSIS approaches. In this way, after specifying the main aspects and RMPs, the stochastic BWM has been employed to calculate the indicators' importance. In the next step, to prioritize the potential RMPs, a new variant of the TOPSIS method called the stochastic TOPSIS has been developed. Based on the achieved outputs, "Price" and "Quality" have been identified as the best criteria for the general aspect. Additionally, "Reverse logistics and Waste management" and "Recyclable raw materials" have been identified as the best criteria for the CE aspect. Furthermore, "Reliability" and "Restorative Capacity" have been identified as the best criteria for the resilience aspect. Also, "Information systems usage" and "Cyber security" have been identified as the best criteria for the digitalization aspect. Eventually, "Reliability", "Price", "Quality", "Reverse logistics and Waste management", "Information systems usage", "Restorative Capacity", and "Energy consumption" have been identified as the best criteria for the research problem. Also, according to the results of the developed stochastic TOPSIS, the prioritizing of the RMPs was as follows: A1>A2>A4>A3>A5.

Moreover, to examine the reliability, validity, and performance of the developed hybrid approach, we have compared its results with the results of the traditional methods. In this regard, based on the obtained results, the weights of the indicators calculated by different methods were similar, which confirms the validity and efficiency of the employed stochastic BWM. Also, the results showed that the applied stochastic BWM has outperformed other methods based on the CR metric showing its reliability. Furthermore, we have prioritized the RMPs using different methods and the achieved results demonstrated that in all methods the best RMPs were the same, which shows the validity and robustness of the developed stochastic TOPSIS.

4.7. Managerial insights

Besides the theoretical merits of each academic research, its practical aspects are also important. Therefore, in this section, we have presented the main managerial implications of the current article. Overall, this work has focused on one of the critical tasks of practical managers; i.e., the evaluation of the performance of the RMPs, by considering three crucial concepts namely digitalization, circular economy, and resilience. To this end, the current study has presented a novel hybrid decision-making method. This research can provide a nice vision to practical managers for understanding the digitalization, circular economy, and resilience concepts. Also, since this work has presented a list of indicators for the mentioned concepts, managers can see the most important dimensions related to the mentioned concepts (i.e., digitalization, circular economy, and resilience) and implement them in their business. By reading this work, managers can understand that an extreme focus on traditional indicators (e.g., cost and delivery time) is unacceptable in today's competitive and global marketplace. Nowadays, if managers want to gain a competitive advantage and also enhance their market share, they should consider other crucial indicators like resilience and digitalization. Also, since this work has studied the research problem under uncertainty, it can help managers to be familiar with the way of dealing with the uncertain environment of the business environment.

4.8. Theoretical implications

This work has focused on the raw material provider selection problem based on the digitalization, resilience, and CE dimensions under uncertainty. In this regard, this article has developed a hybrid stochastic decision-making framework to determine the best indicators and evaluate the RMPs. The main theoretical contributions of this work can be divided into two main parts as follows: (i) the simultaneous consideration of the CE, resilience, and digitalization indicators in the RMPSP for the steel industry and (ii) developing the stochastic TOPSIS method. About the first theoretical implication, owing to the key role of the CE, resilience and digitalization in today's global and competitive marketplace, this research has aimed to consider these aspects in the RMPSP. In this way, a list of indicators relevant to the CE, resilience and digitalization including four criteria and 20 sub-criteria has been provided. This list can help research to be familiar with the main indicators of evaluating the RMPs based on the CE and digitalization aspects. Moreover, about the second theoretical contribution, this work has proposed a novel method called the stochastic TOPSIS to evaluate the performance of the RMPs. It should be noted that the obtained results confirm the efficiency and applicability of the developed approach.

Overall, the proposed approach and findings of this article contribute to the existing body of knowledge in the field of raw material provider selection and supply chain management based on the following points. First of all, this study has incorporated the CE, resilience, and digitalization dimensions into the steel raw material provider selection problem for the first time. Due to the critically important role of the steel industry in the financial and environmental issues of many countries, improving the evaluation process of suppliers by considering some crucial dimensions like digitalization, resilience, and CE can significantly enhance the efficiency of the supply chain. Also, since this work has proposed a novel decision-making method to evaluate the RMPs in an uncertain environment, it can help supply chain managers to deal with the uncertainty of the business environment, especially in the supplier evaluation process.

5. Conclusions

5.1. Concluding remarks

The current work addressed the RMPs evaluation process by considering three important features namely digitalization, circular economy, and resilience. To do this, at the outset, this research specified the major indicators and also the feasible RMPs. Afterwards, the importance of criteria was measured utilizing the stochastic BWM approach. In the next step, this research developed a novel method called the stochastic TOPSIS to evaluate the performance of the RMPs. To demonstrate the application of the proposed approach, a real-world case study in the steel industry was investigated. The achieved results demonstrated that "Reliability", "Price", "Quality", "Reverse logistics and Waste management", "Information systems usage", "Restorative Capacity", and "Energy consumption" were the best indicators. Moreover, according to the outputs, the prioritizing of the RMPs was as follows: A1>A2>A4>A3>A5. Furthermore, the performance and effectiveness of the developed method was assessed by comparing its outputs with the outputs of the traditional approaches. The obtained results confirmed the reliability, validity and effectiveness of the proposed approach.

5.2. Research limitations and future suggestions

Since the research limitations are an integral part of each academic study, we have presented the main research limitations of this study in this section. In this way, one of the limitations of this study is to investigate the research problem only under randomness uncertainty. In this regard, future researchers can study the current problem under mixed uncertainty (e.g., fuzzy-scenario). Also, this work has ignored some crucial aspects of SC management like agility. Therefore, future articles can add other dimensions like agility and sustainability to the current work. Finally, this work has neglected the historical data. In this regard, it is recommended that future works to develop data-driven models to investigate the research problem using historical data.

References

[1] Nayeri S, Torabi SA, Tavakoli M, Sazvar Z. A multi-objective fuzzy robust stochastic model for designing a sustainable-resilient-responsive supply chain network. J Clean Prod (2021), p. 127691.

[2] Fazlollahtabar H, Kazemitash N. Design of Fazl-Tash novel method for sustainable resilient comprehensive supplier selection problem. Kybernetes (2021).

[3] Fazlollahtabar H, Ahmadiahangar R. Profit analytics in disruption risk for electrical energy supply network considering cost-oriented big data. Energy Environ (2024), p. 0958305X231225599.

[4] Asrol M, Arief M, Gunawan H. Analysis of Green Supply Chain Management Factors for Improving Firm Performance in Food Industry TT -. IUST Vol. 34, (2023), pp. 1-12.

[5] Alora A, Gupta H. Supplier selection among manufacturing companies based on their MSME partners' supply chain finance adoption capability using BWM and VIKOR. J Bus Ind Mark (2024).

[6] Umar M, Khan SAR, Yusliza MY, Ali S, Yu Z. Industry 4.0 and green supply chain practices: an empirical study. Int J Product Perform Manag (2021).

[7] Gharaibeh L, Eriksson KM, Lantz B, Matarneh S, Elghaish F. Toward digital construction supply chain-based Industry 4.0 solutions: scientometric-thematic analysis. Smart Sustain Built Environ Vol. 13, (2024), pp. 42-62.

[8] Frederico GF. Towards a Supply Chain 4.0 on the post-COVID-19 pandemic: a conceptual and strategic discussion for more resilient supply chains. Rajagiri Manag J (2021).

[9] Namdar J, Torabi SA, Sahebjamnia N, Nilkanth Pradhan N. Business continuity-inspired resilient supply chain network design. Int J Prod Res Vol. 59, (2021), pp. 1331-67.

[10] harwati harwati, maria sri asih anna, maya sopha bertha. Analysis and Prioritizing Capability in the Halal Resilience Supply Chain: A Fuzzy AHP Approach TT -. IUST Vol. 34, (2023), pp. 1-18.

[11] Khezeli M, Najafi E, Haji Molana M, Seidi M. A Mathematical Model for Sustainable and Resilient Supply Chain by Considering Synchronization in the Production and Distribution Network TT -. IUST Vol. 33, (2022), pp. 1-34.

[12] Abisoye KI, Adebimpe OA, Oladokun VO. Towards flood resilient supply chain systems A facility location model for flood-prone communities. Handb. Flood Risk Manag. Community Action, Routledge; (2024), pp. 222-33.

[13] Chrispim MC, Mattsson M, Ulvenblad P. The underrepresented key elements of Circular Economy: A critical review of assessment tools and a guide for action. Sustain Prod Consum Vol. 35, (2023), pp. 539-58.

[14] Ávila-Gutiérrez MJ, Martín-Gómez A, Aguayo-González F, Córdoba-Roldán A. Standardization framework for sustainability from circular economy 4.0. Sustainability Vol. 11, (2019), p. 6490.

[15] Martinho VJPD. Insights into circular economy indicators: Emphasizing dimensions of sustainability. Environ Sustain Indic Vol. 10, (2021), p. 100119.

[16] Hysa E, Kruja A, Rehman NU, Laurenti R. Circular economy innovation and environmental sustainability impact on economic growth: An integrated model for sustainable development. Sustainability Vol. 12, (2020), p. 4831.

[17] Zekhnini K, Cherrafi A, Bouhaddou I, Benabdellah AC. Suppliers Selection Ontology for Viable Digital Supply Chain Performance. IFIP Int. Conf. Adv. Prod. Manag. Syst., Springer; (2021), p. 622-631.

[18] Rostami O, Tavakoli M, Tajally A, GhanavatiNejad M. A goal programming-based fuzzy best–worst method for the viable supplier selection problem: a case study. Soft Comput Vol. 27, (2023), pp. 2827-2852.

[19] Stojanović I, Puška A, Selakovic M, Shafia S, Shamout M, Erceg D. Selection of Viable Suppliers for Project Organizations During the Long-Term Disruption of Supply Chains Using IMF

SWARA. Oper Res Eng Sci Theory Appl (2023), p. 6.

[20] Chaouni Benabdellah G, Bennis K, Chaouni Benabdellah A, Zekhnini K. Resilient Sustainable Supplier Selection Criteria Assessment for Economics Enhancement in Industry 4.0 Context. IFIP Int. Conf. Prod. Lifecycle Manag., Springer; (2021), p. 194-208.

[21] Liang D, Fu Y, Garg H. A novel robustness PROMETHEE method by learning interactive criteria and historical information for blockchain technology-enhanced supplier selection. Expert Syst Appl Vol. 235, (2024), p. 121107.

[22] Alavi B, Tavana M, Mina H. A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy. Sustain Prod Consum Vol. 27, (2021), pp. 905-20.

[23] Bai C, Zhu Q, Sarkis J. Circular economy and circularity supplier selection: a fuzzy group decision approach. Int J Prod Res (2022), pp. 1-24.

[24] Echefaj K, Charkaoui A, Cherrafi A, Garza-Reyes JA, Khan SAR, Chaouni Benabdellah A. Sustainable and resilient supplier selection in the context of circular economy: an ontology-based model. Manag Environ Qual An Int J Vol. 34, (2023), pp. 1461-89.

[25] Kusi-Sarpong S, Gupta H, Khan SA, Chiappetta Jabbour CJ, Rehman ST, Kusi-Sarpong H. Sustainable supplier selection based on industry 4.0 initiatives within the context of circular economy implementation in supply chain operations. Prod Plan Control Vol. 34, (2023), pp. 999-1019.

[26] Foroozesh N, Karimi B, Mousavi SM, Mojtahedi M. A hybrid decision-making method using robust programming and interval-valued fuzzy sets for sustainable-resilient supply chain network design considering circular economy and technology levels. J Ind Inf Integr Vol. 33, (2023), p. 100440.

[27] Li YL, Tsang YP, Wu CH, Lee CKM. A multi-agent digital twin–enabled decision support system for sustainable and resilient supplier management. Comput Ind Eng Vol. 187, (2024), p. 109838.

[28] Sheykhzadeh M, Ghasemi R, Vandchali HR, Sepehri A, Torabi SA. A hybrid decision-making framework for a supplier selection problem based on lean, agile, resilience, and green criteria: a case study of a pharmaceutical industry. Environ Dev Sustain (2024), pp. 1-28.

[29] Aal SIA. A Multi-Criteria Decision Making Model for Sustainable and Resilient Supplier Selection and Management. Neutrosophic Syst with Appl Vol. 15, (2024), pp. 33-45.

[30] Faheem R, Mittal R, Jain A, Sharma S, Kannan D, Jha PC. Sustainable circular supplier selection for textile manufacturing industries in India: An integrated WINGS-MABAC approach. Clean Logist Supply Chain (2024), p. 100147.

[31] Kumar S, Kumar S, Barman AG. Supplier selection using fuzzy TOPSIS multi criteria model for a small scale steel manufacturing unit. Procedia Comput Sci Vol. 133, (2018), pp. 905-12.

[32] Javad MOM, Darvishi M, Javad AOM. Green supplier selection for the steel industry using BWM and fuzzy TOPSIS: a case study of Khouzestan steel company. Sustain Futur Vol. 2, (2020), p. 100012.

[33] Xiao L, Zhang S, Wei G, Wu J, Wei C, Guo Y, et al. Green supplier selection in steel industry with intuitionistic fuzzy Taxonomy method. J Intell Fuzzy Syst Vol. 39, (2020), pp. 7247-58.

[34] Ghamari R, Mahdavi-Mazdeh M, Ghannadpour SF. Resilient and

sustainable supplier selection via a new framework: a case study from the steel industry. Environ Dev Sustain (2021), pp. 1-39.

[35] Chattopadhyay R, Das PP, Chakraborty S. Development of a rough-MABAC-DoE-based metamodel for supplier selection in an iron and steel industry. Oper Res Eng Sci Theory Appl Vol. 5, (2022), pp. 20-40.

[36] Askary M, Makui A, Tajik M. A robust multi-objective MIP model to optimize the supply chain of steel industry taking into account the sustainability approach. RAIRO-Operations Res Vol. 58, (2024), pp. 1059-91.

[37] Firdantara ZN, Qurtubi Q, Setiawan D. Supplier Selection Modeling and Analysis in the Metal Casting Industry Using Analytical Hierarchy Process. Adv Sustain Sci Eng Technol Vol. 6, (2024), p. 2402012.

[38] Fallahpour A, Olugu EU, Musa SN, Wong KY, Noori S. A decision support model for sustainable supplier selection in sustainable supply chain management. Comput Ind Eng Vol. 105, (2017), pp. 391-410.

[39] Alamroshan F, La'li M, Yahyaei M. The green-agile supplier selection problem for the medical devices: a hybrid fuzzy decision-making approach. Environ Sci Pollut Res (2021), pp. 1-19.

[40] Fallahpour A, Nayeri S, Sheikhalishahi M, Wong KY, Tian G, Fathollahi-Fard AM. A hyper-hybrid fuzzy decision-making framework for the sustainable-resilient supplier selection problem: a case study of Malaysian Palm oil industry. Environ Sci Pollut Res (2021), pp. 1-21.

[41] Fallahpour A, Kazemi N, Molani M, Nayyeri S, Ehsani M. An Intelligence-Based Model for Supplier Selection Integrating Data Envelopment Analysis and Support Vector Machine. Iran J Manag Stud Vol. 11, (2018), pp. 209-41.

[42] Amindoust A. A resilient-sustainable based supplier selection model using a hybrid intelligent method. Comput Ind Eng Vol. 126, (2018), pp. 122-35.

[43] Chakraborty S, Chattopadhyay R, Chakraborty S. An integrated D-MARCOS method for supplier selection in an iron and steel industry. Decis Mak Appl Manag Eng (2020), Vol. 3, pp. 49-69.

[44] Muneeb SM, Asim Z, Hajiaghaei-Keshteli M, Abbas H. A multi-objective integrated supplier selection-production-distribution model for re-furbished products: Towards a circular economy. Renew Sustain Energy Rev Vol. 175, (2023), p. 113156.

[45] Ali H, Zhang J, Shoaib M. A hybrid approach for sustainable-circular supplier selection based on industry 4.0 framework to make the supply chain smart and eco-friendly. Environ Dev Sustain (2023), pp. 1-38.

[46] Bai C, Sarkis J. Integrating sustainability into supplier selection with grey system and rough set methodologies. Int J Prod Econ Vol. 124, (2010), pp. 252-64.

[47] Bai C, Sarkis J, Wei X. Addressing key sustainable supply chain management issues using rough set methodology. Manag Res Rev (2010).

[48] Sarkis J, Meade LM, Presley AR. Incorporating sustainability into contractor evaluation and team formation in the built environment. J Clean Prod Vol. 31, (2012), pp. 40-53.

[49] Fallahpour A, Wong KY, Rajoo S, Fathollahi-Fard AM, Antucheviciene J, Nayeri S. An integrated approach for a sustainable supplier selection based on Industry 4.0 concept. Environ Sci Pollut Res (2021), pp. 1-19.

[50] Solgi O, Gheidar-Kheljani J, Dehghani E, Taromi A. Resilient supplier selection in complex products and their subsystem supply chains under uncertainty and risk disruption: A case study for satellite components. Sci Iran Vol. 28, (2021), pp.

1802–16.

[51] Nayeri S, Khoei MA, Rouhani-Tazangi MR, GhanavatiNejad M, Rahmani M, Tirkolaee EB. A data-driven model for sustainable and resilient supplier selection and order allocation problem in a responsive supply chain: A case study of healthcare system. Eng Appl Artif Intell Vol. 124, (2023), p. 106511.

[52] ÖZBEK A, Yildiz A. Digital supplier selection for a garment business using interval type-2 fuzzy topsis. Text Appar Vol. 30, (2020), pp. 61-72.

[53] Tas MA, Akcan S. Selecting a Green, Agile and Industry 4.0 Supplier With the Fuzzy-Swara-Bwm Integrated Method (2021).

[54] Schuh G, Anderl R, Gausemeier J, ten Hompel M, Wahlster W. Industrie 4.0 maturity index. Manag Digit Transform Companies Munich Herbert Utz (2017).

[55] Ghobakhloo M. Industry 4.0, digitization, and opportunities for sustainability. J Clean Prod Vol. 252, (2020), p. 119869.

[56] Sharma M, Joshi S. Digital supplier selection reinforcing supply chain quality management systems to enhance firm’s performance. TQM J (2020).

[57] Lichtblau K, Stich V, Bertenrath R, Blum M, Bleider M, Millack A, et al. Industrie 4.0 Readiness. IMPULS-Stiftung for mechanical engineering, plant engineering, and information technology (2015).

[58] Schumacher A, Erol S, Sihn W. A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. Procedia Cirp Vol. 52, (2016), pp. 161-6.

[59] Rezaei J. Best-worst multi-criteria decision-making method. Omega Vol. 53, (2015), pp. 49-57.

[60] Kazemitash N, Fazlollahtabar H, Abbaspour M. Rough best-worst method for supplier selection in biofuel companies based on green Criteria. Oper Res Eng Sci Theory Appl (2021), Vol. 4, pp. 1-12.

[61] Nayeri S, Sazvar Z, Heydari J. Towards a responsive supply chain based on the industry 5.0 dimensions: A novel decision-making method. Expert Syst Appl Vol. 213, (2023), p. 119267.

[62] Foley L, Ball L, Hurst A, Davis J, Blockley D. Fuzziness, incompleteness and randomness; classification of uncertainty in reservoir appraisal. Pet Geosci Vol. 3, (1997), pp. 203-9.

[63] Abdo H, Flaus J-M. Uncertainty quantification in dynamic system risk assessment: a new approach with randomness and fuzzy theory. Int J Prod Res Vol. 54, (2016), pp. 5862-85.

[64] Hwang C-L, Yoon K. Methods for multiple attribute decision making. Mult. Attrib. Decis. Mak., Springer; (1981), pp. 58-191.

[65] Noruzi M, Naderan A, Zakeri JA, Rahimov K. A Novel Decision-Making Framework to Evaluate Rail Transport Development Projects Considering Sustainability under Uncertainty. Sustainability (2023), Vol. 15, p. 13086.

Appendix

Tab. A. 1. An example from a comparison vector between the best indicator and other ones

Expert	Indicator	C1			C2			C3			C4		
	Scenario	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
1	The best criterion												
2													
3													
Average													

Tab. A. 2. An example from a comparison vector between the worst indicator and other ones

		The worst criterion Expert			
		1	2	3	Average
Indicator	Scenario				
C1	S1				
	S2				
	S3				
C2	S1				
	S2				
	S3				
C3	S1				
	S2				
	S3				
C4	S1				
	S2				
	S3				

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