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A Novel Hybrid Gray MCDM Model for Resilient Supplier Selection Problem

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Abstract: The current business climate has generated considerable uncertainty and disrupted supply chain processes. Suppliers have frequently been identified as the primary source of hazards responsible for supply chain disruptions. Using a strategic approach to supplier selection that prioritizes providers with resilience features, mitigating the risk exposure inherent in supply chains is possible. This study proposes a comprehensive gray multiple-criteria decision making (MCDM) method incorporating resilience attributes to supplier selection. To determine criteria weights, the gray PSI and gray BWM methodologies were used, and to evaluate and prioritize resilient providers, the gray MCRAT and gray COBRA methodologies were applied. According to the results obtained by the suggested methodology, the supplier that demonstrated the greatest degree of resilience was determined to be the provider categorized as SPIR 4. The sequential sequence of the SPIR numbers is as follows: SPIR 5, SPIR 1, SPIR 3, SPIR 2, and SPIR 6. The data demonstrate that the developed approach produced accurate results.

Keywords: gray MCRAT; gray PSI; gray BWM; MCDM; resilient supplier selection

MSC: 03B52; 90B50

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1. Introduction

Businesses are becoming increasingly conscious of outsourcing suppliers in today's highly volatile and fiercely competitive business environment. With the advantages of cost-effective labor, higher product quality, and service innovation, businesses are more inclined to outsource portions of their company's activities in the present cutthroat international market. However, the rise of international supply alternatives and strategic outsourcing has exposed supply chains to several disruptive occurrences, such as ecological catastrophes, man-made assaults, and common breakdowns [1].

Resilience, which is an interdisciplinary notion, refers to the capacity of a system to adapt as circumstances shift [2]. It is a new term for supply chains and is described as the capacity of the supply chain to adjust to unforeseen occurrences, react to disturbances, and continue operating [3]. Garza-Reyes [4] revealed that resilience has an impact on the sustainability of supply chains.

Suppliers' resilience is best demonstrated by their capacity to manage risk and outperform competition in the case of interruptions [5]. Therefore, the significance of using resilient suppliers is evident when considering the potential impact that disruptions can have on a company's operations and reputation [6]. By strategically selecting suppliers who possess resilience traits, the risk exposure within supply chains can be minimized [7]. Furthermore, resilient suppliers help businesses maintain continuity during adverse situations by ensuring the timely delivery of goods and services.

Despite its advantages, resilient supplier selection encounters several problems. First, the selection procedure necessitates a thorough evaluation across several aspects, including affordability, capability, and dependability. Another difficulty is deciding which criteria should be given greater importance than others. Thirdly, because supply chains are dynamic, businesses need to make sure that their suppliers can quickly adjust to changing circumstances. To overcome these obstacles and make a successful resilient supplier selection, various approaches have been used by companies, one of which is multi-criteria decision making (MCDM).

Research on the resilient supplier selection issue is scarce. Haldar et al. [8] used the AHP method to fulfil some criteria, followed by the TOPSIS method to try to find the right rating of the resilient suppliers in an automobile component manufacturing company. In a catastrophe scenario, Haldar et al. [9] created a quantitative method using aggregate fuzzy weight and fuzzy TOPSIS to select important suppliers under uncertainty. Using weighted goal programming (WGP) and preemptive goal programming, Chen et al. [10] assessed and investigated resilient suppliers quantitatively for an automotive company. To assist the assessment and selection of resilient providers in a fuzzy setting using the VIKOR technique, Sahu et al. [11] modified an effective decision support system. Sen et al. [12] used a fuzzy MCDM model, including TODIM and PROMETHEE to rank green and resilient suppliers. Ghamari et al. [13] assessed green, resilient suppliers for a steel manufacturing company in Iran using the BWM and TOPSIS methods.

It has been found that the uncertainty conditions in resilient supplier selection have not been adequately addressed by using gray numbers, but empirical studies dealing with uncertainty with gray methods can assist managers in making better decisions in uncertain situations. The application of the gray systems theory in this study offers a range of benefits. It has a robust theoretical framework that addresses the challenges posed by uncertainty and lack of information in modeling [14]. It yields satisfactory outcomes by using less data in comparison to alternative statistical methodologies [15]. One of the primary advantages of gray systems theory in comparison to fuzzy set theory is its ability to account for the presence of fuzziness inside a particular scenario [16].

This study aimed to develop a novel method that considers uncertain situations by using gray theory, performance selection index (PSI), BWM, multiple-criteria ranking by alternative trace (MCRAT), and comprehensive distance-based ranking (COBRA) methods in resilient supplier selection. The gray PSI and gray BWM approaches were used to ascertain the weights of the criteria. The gray MCRAT and gray COBRA methods were used to rank alternatives. To verify and implement the framework proposed by this study, resilient supplier selection was carried out in the textile sector. Resilient supplier selection in this sector is currently a major concern for managers due to the presence of uncertainty and disruptions.

This study makes multiple contributions to the literature. The contributions of this study to the literature are as follows:

- In resilient supplier selection, very little empirical study has been conducted [17]. This study made an effort to close this gap by performing a case study. In this study, a sizable manufacturing company in the textile industry is used as an example to assess and evaluate the supplier's resilience. Therefore, this study contributes to the literature.
- The present work introduces a novel gray MCDM technique, referred to as gray MCRAT. In contrast to competing MCDM approaches, the MCRAT method offers a more streamlined methodology for assessing alternatives across several criteria, yielding dependable, universally applicable, and logically sound outcomes. Regrettably, the conventional MCRAT model cannot effectively address situations involving

uncertainty. Consequently, this work endeavors to provide a novel approach, namely the gray MCRAT technique, to mitigate this limitation.

- A new hybrid gray MCDM method is proposed in this study. These gray MCDM methods have not been used together in the literature before.
- The gray COBRA method ranks options based on the integration of various types of distances from multiple reference points. Thanks to this feature, it yields more reliable results compared to other reference-based MCDM methods (TOPSIS, CODAS, EDAS, etc.). Therefore, in this study, we tried to obtain more reliable results by using two different gray MCDM methods (gray MCRAT and gray COBRA).

The remaining sections of the paper are structured as follows. A review of the relevant research is presented in Section 2. In Section 3, the suggested methodology is explained. Section 4 presents the results of an application, while Section 5 reports a sensitivity analysis aimed at validating the results. Section 6 draws some conclusions and Section 7 dicusses them, summarizing the main implications of this study.

2. Literature Review

Scholars and practitioners have emphasized the importance of selecting suppliers who can withstand disruptions and uncertainties in the supply chain (e.g., [18]). Various criteria have been proposed for evaluating supplier resilience, including financial stability, operational flexibility, geographical location, and collaborative capacity [19]. Researchers have also explored different methodologies for assessing supplier resilience, ranging from qualitative assessments and bibliometric analysis [20], to simulation [21] and quantitative models utilizing mathematical optimization and risk analysis techniques [22]. Moreover, case studies and empirical research have provided insights into the strategies adopted by organizations to enhance the resilience of their supplier networks, such as dual sourcing, inventory buffering, and information-sharing initiatives [23]. Overall, the literature underscores the critical role of resilient supplier selection in mitigating supply chain risks and ensuring business continuity in the face of unforeseen disruptions [24]. Despite the acknowledged importance of supplier resilience in mitigating supply chain risks, empirical studies in this domain remain scant. This study addresses this gap by conducting a comprehensive real-life case study.

Some studies have used a variety of MCDM techniques that might aid businesses in choosing resilient suppliers despite uncertainties and limited information.

Parkouhi and Ghadikolaei [25] suggested a resilient supplier selection method for a wood and paper production company that included a fuzzy ANP and gray VIKOR. They examined alternatives with regard to delivery, adaptability, culture, shared growth, technological advances, relationships, cost, and hazard criteria.

To choose a resilient supplier for a computer manufacturing company, Pramanik et al. [26] suggested a fuzzy MCDM framework that combines AHP, QFD, and TOPSIS with criteria that included quality, turnaround time, dependability, speed of processing, profit margin, excess stock, location division, re-engineering, response time, adaptability, fitting, manufacturing consistency, and average time between failures.

COPRAS technique and interval-valued intuitionistic fuzzy (IVIF) numbers were used by Davoudabadi et al. [27] to present a novel method for resilient supplier selection. They used cost, quality, dependability, performance, and client satisfaction to assess suppliers for an automotive company.

Gan et al. [28] used fuzzy BWM to determine criteria weights and GMO-RTOPSIS to choose the most resilient supplier with criteria that included excess stock, location division, dependability, stability, cooperation, adaptability (re-route and re-organize), and restoring ability.

To estimate the resilience of the suppliers, an ensemble technique incorporating logistic regression, classification and regression tree (CART), and neural network was suggested by Hosseini and Khaled [29] with AHP. Twelve criteria (cost, quality, delivery time, response time, excess inventory, location division, dependability, stability, trustworthiness, adaptability (re-route and re-organize), and restoring ability) were identified to assess the resilience capacities of suppliers and applied to a pipe manufacturer for water and sewerage in the US.

Parkouhi et al. [30] examined resilient supplier selection for paper and wood companies in Iran using the gray DEMATEL approach with criteria such as delivery time, capacity, customization, capability, flexibility, collaboration, and quality.

To address the resilient supplier selection challenge in Logistic 4.0, Hasan et al. [31] utilized fuzzy TOPSIS. The criteria used in this study to assess resilient alternatives were current stock level, delivery time, manufacturing capacity, cost, digital resources, tracing ability, critical nodes, location division, re-engineering, flexibility, automation failures, information management, control of cyber security risks, reliability, visibility, cooperation, restoring ability, adaptability, and agility.

For a corporation that manufactures computer hardware components, Sureeyatanapas et al. [32] used the TOPSIS approach to rank resilient suppliers by response time, excess stock, safe location, stand-by supplier contracts, stability, restoring ability, adaptability, production interruption risk, logistics interruption risk, information loss risk, capacity of production, delivery time, service level, technological ability, company image, quality, and cost.

Waleekhajornlert and Sureeyatanapas [33] identified important criteria such as response time, inventory for safety stock, restoration, innovativeness, and quality for resilient supplier selection in an electronics manufacturing company and ranked alternatives using the expanded TOPSIS technique.

A hybrid MCDM model that combines BWM, WASPAS, and TOPSIS was created by Xiong et al. [34] to find the most resilient green supplier. They used life cycle management, excess inventory, manufacturing division, dependability, restructuring, transportation, storage, collaboration dedication, sustainable design, sustainable purchasing, pollutants production, ecologic packaging, and environmental image as the criteria to assess supplier alternatives.

Leong [35] developed the GRA-BWM-TOPSIS technique to rank resilient suppliers for a food manufacturing company according to seven criteria: quality, lead time, cost, flexibility, visibility, response time, and economic stability.

Nazari-Shirkouhi [36] used Z-number data envelopment analysis (Z-DEA) and artificial neural network (ANN) to present a novel hybrid method for resilient supplier selection in pharmaceutical businesses by combining conventional and resilient criteria.

Tavakoli et al. [37] used a hybrid technique including the Markov chain, QFD, and FBWM methods to rank resilient suppliers for an online department store by location division, restoring ability, adaptability, collaboration, stand-by supplier contracts, excess stock, response time, risk elimination, social rights, dedication to social responsibility, safety at work, environmental design, innovativeness, prevention of pollution, energy conservation, waste disposal, employment of an effective environmental management system, green competences, economic stability, technological ability, dependability, service level, quality, delivery time, and cost.

Nayeri et al. [38] examined sustainable and resilient supplier selection for the health equipment business using the stochastic fuzzy BWM (SFBWM) and the multi-objective model. The results of the study indicated that agility, cost, carbon footprint, quality, robustness, and waste disposal are the most significant factors.

Zhao et al. [39] proposed a comprehensive framework for green resilient supplier selection using rough VIKOR and goal programming. The key criteria for assessing suppliers, as determined by their findings, were the punctual delivery of goods and the capacity to handle crises.

Majumdar et al. [40] examined the concept of the trapezoidal fuzzy TOPSIS approach and its suitability for choosing resilient suppliers in manufacturing sectors during the COVID-19 pandemic. The study revealed that cost, absorbing capability, and social responsibility are the key factors to consider when selecting resilient suppliers.

Tirkolaee et al. [41] developed a new two-phase model that involves neutrosophic fuzzy BWM and WASPAS methods for selecting resilient suppliers in the face of uncertainty. A comprehensive multi-objective optimization approach is then constructed to allocate orders, taking into account resilience ratings, facility dependability, and unpredictable supply and demand.

Agarwal and Nishad [42] provided a fuzzy evaluation based on distance from the average solution (EDAS) that considers the idea of resilience alongside sustainability to address the sustainable ranking of resilient suppliers.

Sun et al. [43] presented a novel MCDM model for resilient supplier selection including probabilistic uncertain linguistic numbers, BWM, and TOPSIS.

Liang et al. [44] utilized fuzzy BWM and an improved wolf pack algorithm to solve resilient supplier selection problems in the energy sector. It was found that product risk and financial and service risks are the most important criteria.

Song et al. [45] assessed resilient suppliers for a retailer in China in two stages. During the first stage, they integrated BWM and evidential reasoning to derive the preference scores of decision makers. During the second stage, they constructed a multi-objective mixed-integer linear programming (MILP) model to identify the optimum alternative.

In summary, these studies demonstrate that resilient supplier selection entails a mix of several techniques and criteria to guarantee supply chain sustainability in the face of disruptive occurrences.

This study suggests a combined gray MCDM framework that takes into account resilience characteristics. Three steps may be identified in the development of this study. The primary assessment criteria, as well as their sub-criteria, were determined in phase one and incorporated into a single framework. The assessment criteria were determined based on the literature review of related papers and interviews with the purchasing managers. To determine the weights of the criteria and sub-criteria in phase two, gray PSI and gray BWM methods were utilized to integrate judgments from decision makers. Gray MCRAT and gray COBRA methods were used in the third phase to assess and rank resilient suppliers according to their performances.

3. Materials and Methods

In this study, a resilient supplier selection was made using a gray hybrid MCDM model consisting of gray PSI, gray BWM, gray MCRAT, and gray COBRA methods. While the weights of the criteria were obtained with the first two methods, the suppliers were ranked with gray MCRAT and gray COBRA methods.

3.1. Gray Numbers

Gray numbers refer to a set of numbers that are continuous and fall inside a range. They were introduced by Julong [46] as a solution for situations that include knowledge that is either ambiguous or only partially understood. A gray number is often represented by a specific collection of integers or a closed range, as defined below.

Definition 1: Presume that $\otimes K = [x, y]$ is a gray number that represents the lowest boundary as a and the maximum boundary as b, where a and b are real numbers.

Definition 2: Presume that $\otimes K_1 = [x, y]$ and $\otimes K_2 = [z, t]$ are two gray numbers, where φ is greater than or equal to 0 and φ belongs to the set of real numbers. The stages are outlined below:

$$\otimes K_1 + \otimes K_2 = [x + z, y + t] \tag{1}$$

$$\otimes K_1 - \otimes K_2 = [x - z, y - t] \tag{2}$$

$$\otimes K_1 \times \otimes K_2 = [min(xz, xt, yz, yt),\ max(xz, xt, yz, yt)] \tag{3}$$

$$\otimes K_1 \div \otimes K_2 = [min(x/z, x/t, y/z, y/t),\ max(x/z, x/t, y/z, y/t)] \tag{4}$$

$$\varphi \otimes K_1 = [\varphi x, \varphi z] \quad (5)$$

Definition 3: The gray possibility degree is described as the degree of likelihood between two gray numbers, denoted as $\otimes K_1$ and $\otimes K_2$.

$$P(\otimes K_1 \geq \otimes K_2) = max\left\{1 - max\left(\frac{t - x}{L(\otimes K_1) + L(\otimes K_2)}, 0\right), 0\right\}, \quad (6)$$

where $L(\otimes K_1) = y - x$ and $L(\otimes K_2) = t - z$ denote lengths.

Definition 4: The correlation between $\otimes K_1$ and $\otimes K_2$ can be expressed as below:

$$If \otimes K_1 = \otimes K_2 \; then \; P(\otimes K_1 \geq \otimes K_2) = 0.5 \quad (7)$$

$$If \otimes K_1 < \otimes K_2 \; then \; P(\otimes K_1 \geq \otimes K_2) < 0.5 \quad (8)$$

$$If \otimes K_1 > \otimes K_2 \; then \; P(\otimes K_1 \geq \otimes K_2) > 0.5 \quad (9)$$

3.2. Gray PSI

The steps of the gray PSI method are shown below [47,48].

Step 1: First, the linguistic values (shown in Table 1) assigned by the decision makers are converted into gray numbers. Table 1 is taken from [49]. These are combined with Equation (10) to obtain a gray decision matrix (⊗B).

$$\otimes B = \left[\otimes b_{ij}\right]_{m \times n}, \quad \otimes b_{ij} = \left[\frac{\sum_{k=1}^{1} b_{ijk}^{l}}{k}, \frac{\sum_{k=1}^{1} b_{ijk}^{u}}{k}\right] \quad (10)$$

Table 1. Linguistic scale and gray numbers.

Linguistic Scale	Gray Numbers
None (N)	[0, 2]
Very low (VL)	[1, 3]
Low (L)	[2, 4]
Moderately low (ML)	[3, 5]
Medium (M)	[4, 6]
Moderately high (MH)	[5, 7]
High (H)	[6, 8]
Very high (VH)	[7, 9]
Extremely high (EH)	[8, 10]

Step 2: This matrix is normalized.

$$\otimes a_{ij} = \begin{cases} \dfrac{\otimes b_{ij}}{max\left(\otimes b_{ij}\right)} = \left[\dfrac{b_{ij}^{l}}{max\left(b_{ij}^{u}\right)}, \dfrac{b_{ij}^{u}}{max\left(b_{ij}^{u}\right)}\right] if \otimes b_{ij} \in BNC \\ \dfrac{min\left(\otimes b_{ij}\right)}{\otimes b_{ij}} = \left[\dfrac{min\left(b_{ij}^{l}\right)}{b_{ij}^{u}}, \dfrac{min\left(b_{ij}^{l}\right)}{b_{ij}^{l}}\right] if \otimes b_{ij} \in NBNC \end{cases} \quad (11)$$

In Equation (11), *BNC* and *NBNC* indicate benefit and non-benefit criteria, respectively. Additionally, $\otimes a_{ij}$ shows the normalized version of $\otimes b_{ij}$.

Step 3: The mean value of $\otimes a_{ij}$ for each criterion is obtained as:

$$\otimes \overline{\mathrm{a}}_{\mathrm{ij}} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{m}} \otimes \mathrm{a}_{\mathrm{ij}}}{\mathrm{m}} = \left[\frac{\sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{a}_{\mathrm{ij}}^{\mathrm{l}}}{\mathrm{m}}, \frac{\sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{a}_{\mathrm{ij}}^{\mathrm{u}}}{\mathrm{m}} \right] \tag{12}$$

Step 4: The gray preference value ($\otimes c_j = \left[c_j^l, c_j^u\right]$) is calculated as:

$$\otimes c_j = \sum_{i=1}^{m} \left(\otimes a_{ij} - \otimes \overline{a}_{ij}\right)^2 = \begin{bmatrix} min\left(\sum_{i=1}^{m} \left(a_{ij}^l - \overline{a}_{ij}^l\right)^2, \sum_{i=1}^{m} \left(a_{ij}^u - \overline{a}_{ij}^u\right)^2 \right), \\ max\left(\sum_{i=1}^{m} \left(a_{ij}^l - \overline{a}_{ij}^l\right)^2, \sum_{i=1}^{m} \left(a_{ij}^u - \overline{a}_{ij}^u\right)^2 \right) \end{bmatrix} \tag{13}$$

Step 5: The gray deviation values ($\otimes dv_j$) and criteria gray weights ($\otimes w_{jPS}$) are obtained as:

$$\otimes dv_j = \left[dv_j^l, dv_j^u\right] = \left|1 - \otimes c_j\right| = \left[\left|1 - c_j^u\right|, \left|1 - c_j^l\right|\right] \tag{14}$$

$$\otimes w_{jPS} = \frac{\otimes dv_j}{\sum_{j=1}^{n} \otimes dv_j} = \left[\frac{dv_j^l}{\sum_{j=1}^{n} dv_j^u}, \frac{dv_j^u}{\sum_{j=1}^{n} dv_j^l} \right] \tag{15}$$

After the criteria weights are determined according to the gray PSI method, the gray BWM method is used to determine the subjective gray weights.

3.3. Gray BWM

The gray BWM method's steps are demonstrated below [49].

Step 1: First, decision makers select the best and the worst criteria. Then, they assess other criteria compared to the best and worst criteria. As a result, the gray vectors, "the best compared to the others ($\otimes D_B = \otimes d_{B1}, \otimes d_{B2}, \ldots, \otimes d_{Bn}$)", and "the others compared to the worst ($\otimes D_W = \otimes d_{1W}, \otimes d_{2W}, \ldots, \otimes d_{nW}$)" are produced. The values in Table 1 are used by decision makers in these comparison processes.

Step 2: The ideal gray values of the criteria ($\otimes w_{k1}, \otimes w_{k2}, \ldots, \otimes w_{kn}$) are determined for each decision maker (k).

$$Min \otimes t$$

$$s.t. \begin{cases} \left| \frac{\otimes w_B}{\otimes w_{kj}} - \otimes d_{Bj} \right| \leq \otimes t \\ \left| \frac{\otimes w_{kj}}{\otimes w_W} - \otimes d_{jW} \right| \leq \otimes t \\ \sum_{j=1}^{n} W\left(\otimes w_{kj}\right) = 1 \\ \underline{w}_{kj} \leq \overline{w}_{kj} \\ \underline{w}_{kj} \geq 0 \\ j = 1, \ldots, n \end{cases} \tag{16}$$

where $\otimes t = \left[\underline{t}, \overline{t}\right]$ demonstrates gray numbers, $\underline{t}$ shows the lowest number, and $\overline{t}$ shows the highest number. w_{kj} is the ideal gray value of the criteria, $\underline{w}_{kj}$ refers to the lowest value, and $\overline{w}_{kj}$ refers to the highest value.

$\otimes d_{Bj}$ shows how the best criterion performs compared to other criteria while $\otimes d_{jW}$ shows how other criteria perform compared to the worst criterion. As determined using the following equation, $W\left(\otimes w_{kj}\right)$ is the white value of the gray value w_j.

$$W\left(\otimes w_{kj}\right) = \frac{\left(\underline{w}_{kj} + \overline{w}_{kj}\right)}{2} \tag{17}$$

The concept of gray possibility degree (GPD) must be incorporated into the model, since the optimization in Equation (16) necessitates comparing gray numbers [50]. Therefore, the optimization can be modeled as follows:

$$Min \otimes t$$
$$s.t.\begin{cases} GPD\left\{\left|\frac{\otimes w_B}{\otimes w_{kj}} - \otimes d_{Bj}\right| \leq \otimes t\right\} < 0.5 \\ GPD\left\{\left|\frac{\otimes w_{kj}}{\otimes w_W} - \otimes d_{jW}\right| \leq \otimes t\right\} < 0.5 \\ \sum_{j=1}^{n} W\left(\otimes w_{kj}\right) = 1 \\ \underline{w}_{kj} \leq \overline{w}_{kj} \\ \underline{w}_{kj} \geq 0 \\ j = 1, \ldots, n \end{cases} \tag{18}$$

Equations (19) and (20) are used to determine the GPD value of two gray values (such as $\otimes a$ and $\otimes b$).

$$GPD\{\otimes a \leq \otimes b\} = \frac{max(0, L(\otimes a) + L(\otimes b) - max(0, \overline{a} - \underline{b}))}{L(\otimes a) + L(\otimes b)} \tag{19}$$

$$L(\otimes a) = |\overline{a} - \underline{a}|, L(\otimes b\ ) = \left|\overline{b} - \underline{b}\right| \tag{20}$$

The GPDs must adhere to the following requirements:
$GPD\{\otimes a \leq \otimes b\} = 0.5$ if $\otimes a = \otimes b$,
$GPD\{\otimes a \leq \otimes b\} = 1$ if $\underline{a} > \overline{b}$,
$GPD\{\otimes a \leq \otimes b\} = 0$ if $\overline{a} < \underline{b}$.
If $\otimes a\ and \otimes b$ crossover and $GPD\{\otimes a \leq \otimes b\} < 0.5$ then $\otimes b < \otimes a$,
If $\otimes a\ and \otimes b$ crossover and $GPD\{\otimes a \leq \otimes b\} > 0.5$ then $\otimes a < \otimes b$.
Step 3: The consistency is checked using Equations (21)–(23).

$$CR = \frac{S(\otimes t)}{CI} \tag{21}$$

$$CI^2 - \left(1 + 2\overline{d}_{BW}\right)CI + \left(\overline{d}_{BW}^2 - \overline{d}_{BW}\right) = 0 \tag{22}$$

$$\otimes d_{BW} = \left[\underline{d}_{BW}, \overline{d}_{BW}\right] = \max_j\{\otimes d_{Bj}, \otimes d_{jW}\} \tag{23}$$

The white value of $\otimes t$ is shown as $S(\otimes t)$ in Equation (21).
Step 4: Equations (24)–(26) are applied to generate the final gray weights for the criterion.

$$\otimes w_{jBW} = \left[\underline{w}_{jBW}, \overline{w}_{jBW}\right] \tag{24}$$

$$\underline{w}_{jBW} = \left(\prod_{k=1}^{l} \underline{w}_{kj}\right)^{1/k} \tag{25}$$

$$\overline{w}_{jBW} = \left(\prod_{k=1}^{l} \overline{w}_{kj}\right)^{1/k} \tag{26}$$

Gray combined weights ($\otimes w_{jCM}$) are obtained by combining the gray weights of criteria obtained from the gray BWM method and the gray PSI method using the following equation.

$$\otimes w_{jCM} = \frac{\otimes w_{jPS} \times \otimes w_{jBW}}{\sum_{j=1}^{n} \otimes w_{jPS} \times \otimes w_{jBW}} \tag{27}$$

3.4. Gray MCRAT

The steps of the developed gray MCRAT method are demonstrated below.

Step 1: First, a gray decision matrix is created.

$$\otimes B = \left[\otimes b_{ij}\right]_{m \times n} \tag{28}$$

Step 2: The gray decision matrix is normalized by utilizing Equation (29) (for benefit criteria) and Equation (30) (for non-benefit criteria).

$$\otimes v_{ij} = \frac{\otimes b_{ij}}{\max(\otimes b_{ij})} = \left[\frac{b_{ij}^{l}}{\max\left(b_{ij}^{u}\right)}, \frac{b_{ij}^{u}}{\max\left(b_{ij}^{u}\right)}\right] \tag{29}$$

$$\otimes v_{ij} = \frac{\min(\otimes b_{ij})}{\otimes b_{ij}} = \left[\frac{\min\left(b_{ij}^{l}\right)}{b_{ij}^{u}}, \frac{\min\left(b_{ij}^{l}\right)}{b_{ij}^{l}}\right] \tag{30}$$

Step 3: Normalized gray values are multiplied with the gray combined weights.

$$\otimes g_{ij} = \otimes w_{jCM} \times \otimes v_{ij} = \left[w_{jCM}^{\mathrm{l}} \times f_{ij}^{l},\ w_{jCM}^{\mathrm{u}} \times f_{ij}^{u}\right] \tag{31}$$

Step 4: The gray optimal alternative is identified.

$$\otimes q_j = max\left(\otimes g_{ij} \middle| 1 \leq j \leq n\right) \tag{32}$$

$$\otimes Q = \{\otimes q_1, \otimes q_2, \ldots \otimes q_n\} \tag{33}$$

Step 5: Gray optimal alternatives are decomposed.

$$\otimes Q = \otimes Q^{max} \cup\ \otimes Q^{min} \tag{34}$$

$$\otimes Q = \{\otimes q_1, \otimes q_2, \ldots \otimes q_k\} \cup\ \{\otimes q_1, \otimes q_2, \ldots \otimes q_h\}; k + h = j \tag{35}$$

Step 6: Alternatives are decomposed.

$$\otimes C = \otimes C^{max} \cup\ \otimes C^{min} \tag{36}$$

$$\otimes C = \{\otimes c_1, \otimes c_2, \ldots \otimes c_k\} \cup\ \{\otimes c_1, \otimes c_2, \ldots \otimes c_h\}; k + h = j \tag{37}$$

Step 7: The gray magnitude of the components is calculated.

$$\otimes Q_k = \left[q_k^l, q_k^u\right] = \left[\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_k^l\right)^2}, \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_k^u\right)^2}\right] \tag{38}$$

$$\otimes Q_h = \left[q_h^l, q_h^u\right] = \left[\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_h^l\right)^2}, \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_h^u\right)^2}\right] \tag{39}$$

The same process is used for each alternative.

$$\otimes C_k = \left[c_k^l, c_k^u\right] = \left[\sqrt{\left(c_1^l\right)^2 + \left(c_2^l\right)^2 + \ldots + \left(c_k^l\right)^2}, \sqrt{\left(c_1^u\right)^2 + \left(c_2^u\right)^2 + \ldots + \left(c_k^u\right)^2}\right] \tag{40}$$

$$\otimes C_h = \left[c_h^l, c_h^u\right] = \left[\sqrt{\left(c_1^l\right)^2 + \left(c_2^l\right)^2 + \ldots + \left(c_h^l\right)^2}, \sqrt{\left(c_1^u\right)^2 + \left(c_2^u\right)^2 + \ldots + \left(c_h^u\right)^2}\right] \tag{41}$$

Step 8: The $\otimes D$ and $\otimes F$ gray matrices are generated. The former indicates the gray values composed of optimal alternative components, and the latter shows the gray values composed of each alternative.

$$\otimes D = \begin{bmatrix} \otimes Q_k & 0 \\ 0 & \otimes Q_h \end{bmatrix} \tag{42}$$

$$\otimes F = \begin{bmatrix} \otimes C_k & 0 \\ 0 & \otimes C_h \end{bmatrix} \tag{43}$$

Step 9: The $\otimes D$ and $\otimes F$ gray matrices are multiplied to acquire the $\otimes Z_i$ matrix indicated in Equation (44).

$$\otimes Z_i = \otimes D \times \otimes F = \begin{bmatrix} \otimes z_{11;i} & 0 \\ 0 & \otimes z_{22;i} \end{bmatrix} \tag{44}$$

Step 10: The gray trace of the matrix $\otimes Z_i$ is acquired as follows.

$$tr(\otimes Z_i) = \otimes z_{11;i} + \otimes z_{22;i} = \left[z^l_{11,i} + z^l_{22,i},\ z^u_{11,i} + z^u_{22,i} \right] \tag{45}$$

In Equation (45), $tr(\otimes Z_i) = \left[Z^l_i, Z^u_i \right]$ shows the gray trace of the Z_i matrix, and this value is transformed into crisp $tr(Z_i)$ using $Z_i = \left(Z^l_i + Z^u_i \right) \times 0.5$. The one with the highest $tr(Z_i)$ value is the best option.

3.5. Gray COBRA

The steps of the gray COBRA technique are listed below [48].

Step 1: A gray decision matrix ($\otimes B$) is created.

$$\otimes B = \left[\otimes b_{ij} \right]_{m \times n} \tag{46}$$

Step 2: The weighted gray matrix ($\otimes T$) is developed by multiplying the gray decision matrix values with the weights ($\otimes w_j$).

$$\otimes T = \left[\otimes t_{ij} \right]_{m \times n}, \tag{47}$$

$$\otimes t_{ij} = \left[\underline{t}_{ij}, \bar{t}_{ij} \right] = \otimes w_{jCM} \times \otimes b_{ij}, \tag{48}$$

Step 3: The reference solutions (PIS, NIS, and AS) are acquired.

$$PIS = \left[\otimes pis_j \right]_{1 \times n}, \otimes pis_j = \left[\underline{pis}_j, \overline{pis}_j \right] = \begin{cases} \left[\max\limits_i \underline{t}_{ij}, \max\limits_i \bar{t}_{ij} \right], for\ j \in J^B \\ \left[\min\limits_i \underline{t}_{ij}, \min\limits_i \bar{t}_{ij} \right], for\ j \in J^C \end{cases} \tag{49}$$

$$NIS = \left[\otimes nis_j \right]_{1 \times n}, \otimes nis_j = \left[\underline{nis}_j, \overline{nis}_j \right] = \begin{cases} \left[\min\limits_i \underline{t}_{ij}, \min\limits_i \bar{t}_{ij} \right], for\ j \in J^B \\ \left[\max\limits_i \underline{t}_{ij}, \max\limits_i \bar{t}_{ij} \right], for\ j \in J^C \end{cases} \tag{50}$$

$$AS = \left[\otimes as_j \right]_{1 \times n}, \otimes as_j = \left[\underline{as}_j, \overline{as}_j \right] = \left\{ \left[\operatorname{mean}\limits_i \underline{t}_{ij}, \operatorname{mean}\limits_i \bar{t}_{ij} \right], for\ j \in J^B, J^C \right. \tag{51}$$

where J^B denotes benefit criteria and J^C denotes non-benefit criteria sets.

Step 4: For each alternative, the gray distances from PIS, NIS, and AS are found.

$$\otimes d(S)_i = \otimes dE(S)_i + \otimes \sigma \times \otimes dE(S)_i \times \otimes dT(S)_i \tag{52}$$

$$\otimes\sigma = \max_i \otimes dE(S)_i - \min_i \otimes dE(S)_i \quad (53)$$

where the correction coefficient is $\otimes\sigma$, S stands for any solution (PIS, NIS, or AS), $\otimes dE(S)_i$ shows the Euclidian distance, and $\otimes dT(S)_i$ shows the taxicab distance.

$$\otimes dE(PIS)_i = \left[\sqrt{max\left(0, \sum_{j=1}^{n}\left(\underline{pis}_i - \bar{t}_{ij}\right)^2\right)}, \sqrt{max\left(0, \sum_{j=1}^{n}\left(\overline{pis}_i - \underline{t}_{ij}\right)^2\right)}\right] \quad (54)$$

$$\otimes dT(PIS)_i = \left[\left|\underline{pis}_i - \bar{t}_{ij}\right|, \left|\overline{pis}_i - \underline{t}_{ij}\right|\right] \quad (55)$$

$$\otimes dE(NIS)_i = \left[\sqrt{max\left(0, \sum_{j=1}^{n}\left(\underline{t}_{ij} - \overline{nis}_i\right)^2\right)}, \sqrt{max\left(0, \sum_{j=1}^{n}\left(\bar{t}_{ij} - \underline{nis}_i\right)^2\right)}\right] \quad (56)$$

$$\otimes dT(NIS)_i = \left[\left|\underline{t}_{ij} - \overline{nis}_i\right|, \left|\bar{t}_{ij} - \underline{nis}_i\right|\right] \quad (57)$$

$$\otimes dE(AS)_i^+ = \left[\sqrt{max\left(0, \sum_{j=1}^{n}\tau^+\left(\underline{t}_{ij} - \overline{as}_i\right)^2\right)}, \sqrt{max\left(0, \sum_{j=1}^{n}\tau^+\left(\bar{t}_{ij} - \underline{as}_i\right)^2\right)}\right] \quad (58)$$

$$\otimes dT(AS)_i^+ = \left[\tau^+, \left|\underline{t}_{ij} - \overline{as}_i\right|, \tau^+\left|\bar{t}_{ij} - \underline{as}_i\right|\right] \text{ where} \quad \tau^+ = \begin{cases} 1\ if\ \otimes as_j < \otimes t_{ij} \\ 0\ if\ \otimes as_j > \otimes t_{ij} \end{cases} \quad (59)$$

$$\otimes dE(AS)^- = \left[\sqrt{max\left(0, \sum_{j=1}^{n}\tau^-\left(\underline{as}_i - \bar{t}_{ij}\right)^2\right)}, \sqrt{max\left(0, \sum_{j=1}^{n}\tau^-\left(\overline{as}_i - \underline{t}_{ij}\right)^2\right)}\right] \quad (60)$$

$$\otimes dT(AS)_i^- = \left[\tau^-, \left|\underline{as}_i - \bar{t}_{ij}\right|, \tau^-\left|\overline{as}_i - \underline{t}_{ij}\right|\right] \text{ where} \quad \tau^- = \begin{cases} 1\ if\ \otimes as_j > \otimes t_{ij} \\ 0\ if\ \otimes as_j < \otimes t_{ij} \end{cases} \quad (61)$$

Step 5: The gray comprehensive distances are determined using Equation (62).

$$\otimes dC_i = \frac{\otimes d(PIS)_i - \otimes d(NIS)_i - \otimes d(AS)_i^+ + \otimes d(AS)_i^-}{4} \quad (62)$$

Step 6: The options are ranked using Equations (19) and (20).

4. Application

The application of this method was carried out in a medium-sized Turkish textile company. This company has more than 1000 employees and sends its products abroad. The products manufactured by this company include men's shirts and men's trousers. The highest authority managers of the company and the managers who know the suppliers best participated in the research. Therefore, six managers of this company were interviewed. The features of the six managers participating in the study are presented in Table 2.

Table 2. Managers' features.

Managers	Duty	Graduation	Experience (Years)
Mngr1	CEO	Business	25
Mngr2	CFO	Business	22
Mngr3	Operation Manager	Industrial Engineering	10
Mngr4	Assistant Operation Manager	Industrial Engineering	2
Mngr5	Purchasing Manager	Industrial Engineering	14
Mngr6	Logistics Manager	Industrial Engineering	10

Firstly, a literature review was conducted and the criteria that would be appropriate for the study were determined. Then, these criteria were listed and presented to the managers. The managers determined which criteria to be used in the study by majority vote. Managers identified three main criteria and twelve sub-criteria. The main criteria and sub-criteria are presented in Table 3. Then, these managers were asked to identify suppliers. Managers identified six suppliers. All of these suppliers produce fabric, but the SPIR 2 and SPIR 4 suppliers also subcontract production. While the number of employees at the SPIR 1 and SPIR 4 suppliers is approximately 400, the number of employees at the other suppliers is approximately 300.

Table 3. Main criteria and sub-criteria.

Main Criteria	Sub-Criteria	Sources
Operational criteria (OC)	Cost	[10,11,25,27,29,31–33,35–37]
	Delivery time (DT)	[10,13,25,26,29–33,35–37]
	Quality (Q)	[10,11,13,25–27,29,30,32,33,35–37]
	Technological abilities (TA)	[13,25,32,33,36,37]
Resilience criteria (RESC)	Risk awareness as an aid to increase resilience capacity (RAA)	[36,37]
	Restorative capacity (REC)	[28,29,31–33,37]
	Strategic stock for crises holding capacity (STS)	[11,12,32,33]
	Capacity to invest in bumpers (CAPI)	[11,12]
	Flexibility of supplier (FLES)	[25,30,31,35]
Relationship criteria (RELSC)	Reputation (REP)	[13,33]
	Financial stability (FS)	[13,35,37]
	Communication and transparency (COT)	[30,31]

Only two of the determined sub-criteria (cost and DT) are defined as non-beneficial, while the other criteria are defined as beneficial. First, the managers (Mngrs) evaluated the suppliers' performance in the criteria with the linguistic data in Table 1. These linguistic data were then converted into gray numbers. Then, using Equation (10), the numbers given by the management were combined, and the gray decision matrix was created. Table 4 shows the gray decision matrix.

Table 4. Gray decision matrix.

Suppliers ↓ Criteria →	Cost	DT	Q	TA	RAA	REC
SPIR 1	[4, 6]	[4.1667, 6.1667]	[3.5, 5.5]	[6, 8]	[6, 8]	[5.8333, 7.8333]
SPIR 2	[4, 6]	[4, 6]	[3.8333, 5.8333]	[6, 8]	[5.8333, 7.8333]	[5, 7]
SPIR 3	[4, 6]	[3.6667,5.6667]	[3.6667, 5.6667]	[6.3333, 8.3333]	[6.1667, 8.1667]	[4.3333, 6.3333]
SPIR 4	[5.6667, 7.6667]	[2.1667, 4.1667]	[5.3333, 7.3333]	[6.5, 8.5]	[6.5, 8.5]	[6, 8]
SPIR 5	[5.5, 7.5]	[2.5, 4.5]	[5.1667, 7.1667]	[6.5, 8.5]	[6.1667, 8.1667]	[5.3333, 7.3333]
SPIR 6	[4.6667, 6.6667]	[4.1667, 6.1667]	[4, 6]	[5.8333, 7.8333]	[5.3333, 7.3333]	[4.1667, 6.1667]
Suppliers ↓ Criteria →	**STS**	**CAPI**	**FLES**	**REP**	**FS**	**COT**
SPIR 1	[5, 7]	[4.5, 6.5]	[5.3333, 7.3333]	[5.5, 7.5]	[5.6667, 7.6667]	[6.3333, 8.3333]
SPIR 2	[4.1667, 6.1667]	[4.3333, 6.3333]	[5.6667, 7.6667]	[4.3333, 6.3333]	[5.5, 7.5]	[6, 8]
SPIR 3	[4.6667, 6.6667]	[4.6667, 6.6667]	[6, 8]	[4.1667, 6.1667]	[5.6667, 7.6667]	[6, 8]
SPIR 4	[5.5, 7.5]	[4.8333, 6.8333]	[6.3333, 8.3333]	[6.3333, 8.3333]	[6.6667, 8.6667]	[6.5, 8.5]
SPIR 5	[5.1667, 7.1667]	[5.1667, 7.1667]	[5.3333, 7.3333]	[5.6667, 7.6667]	[6.3333, 8.3333]	[6.5, 8.5]
SPIR 6	[5, 7]	[4.8333, 6.8333]	[5.6667, 7.6667]	[4.5, 6.5]	[5.6667, 7.6667]	[5.8333, 7.8333]

By applying the equations of the gray PSI method to the gray decision matrix, the gray weights of the criteria were obtained according to the gray PSI method. Table 5 presents the results of the gray PSI method.

Table 5. The results of gray PSI.

Results ↓	Criteria →	Cost	DT	Q	TA	RAA	REC
	$\otimes dv_j$	[0.9027, 0.9766]	[0.7848, 0.9728]	[0.9414, 0.9414]	[0.9943, 0.9943]	[0.9892, 0.9892]	[0.9551, 0.9551]
	$\otimes w_{jPS}$	[0.0770, 0.0853]	[0.0670, 0.0849]	[0.0803, 0.0822]	[0.0849, 0.0868]	[0.0844, 0.0864]	[0.0815, 0.0834]
Results ↓	**Criteria →**	**Cost**	**DT**	**Q**	**TA**	**RAA**	**REC**
	$\otimes dv_j$	[0.9815, 0.9815]	[0.9917, 0.9917]	[0.9891, 0.9891]	[0.9450, 0.9450]	[0.9854, 0.9854]	[0.9943, 0.9943]
	$\otimes w_{jPS}$	[0.0838, 0.0857]	[0.0846, 0.0866]	[0.0844, 0.0864]	[0.0807, 0.0825]	[0.0841, 0.0860]	[0.0849, 0.0868]

Managers identified the best and worst criteria for the gray BWM method. They then determined the gray vectors ($\otimes D_B$ and $\otimes D_W$) using the linguistic values in Table 1. Afterward, using Equations (16)–(20), the gray weights of the criteria were found according to the gray BWM method. Then, the gray weights found for each manager were combined with Equations (25) and (26). Table 6 shows the criteria weights according to the gray BWM method.

Table 6. The results of gray BWM.

Criteria ↓ Mngrs →	Mngr1	Mngr2	Mngr3	Mngr4	Mngr5	Mngr6	Combined Weights	$\otimes w_{jBW}$
OC	[0.550, 0.685]	[0.640, 0.735]	[0.083, 0.125]	[0.154, 0.185]	[0.083, 0.125]	[0.100, 0.167]	[0.268, 0.337]	-
RESC	[0.204, 0.250]	[0.194, 0.260]	[0.563, 0.694]	[0.704, 0.769]	[0.688, 0.760]	[0.542, 0.683]	[0.482, 0.570]	-
RELSC	[0.111, 0.200]	[0.071, 0.100]	[0.222, 0.313]	[0.077, 0.111]	[0.156, 0.188]	[0.217, 0.292]	[0.142, 0.200]	-
Cost	[0.385, 0.633]	[0.197, 0.273]	[0.469, 0.594]	[0.160, 0.203]	[0.197, 0.280]	[0.324, 0.513]	[0.288, 0.416]	[0.077, 0.140]
DT	[0.139, 0.231]	[0.045, 0.062]	[0.158, 0.188]	[0.522, 0.624]	[0.062, 0.086]	[0.211, 0.294]	[0.190, 0.247]	[0.051, 0.083]
Q	[0.167, 0.308]	[0.545, 0.610]	[0.198, 0.281]	[0.160, 0.203]	[0.495, 0.610]	[0.211, 0.294]	[0.296, 0.384]	[0.079, 0.130]
TA	[0.061, 0.077]	[0.131, 0.136]	[0.050, 0.062]	[0.056, 0.072]	[0.131, 0.140]	[0.066, 0.088]	[0.083, 0.096]	[0.022, 0.032]
RAA	[0.472, 0.563]	[0.036, 0.052]	[0.145, 0.167]	[0.250, 0.440]	[0.250, 0.421]	[0.174, 0.214]	[0.221, 0.309]	[0.107, 0.176]
REC	[0.145, 0.181]	[0.165, 0.214]	[0.145, 0.167]	[0.179, 0.250]	[0.171, 0.219]	[0.174, 0.214]	[0.163, 0.207]	[0.079, 0.118]
STS	[0.121, 0.139]	[0.428, 0.510]	[0.145, 0.167]	[0.069, 0.125]	[0.171, 0.219]	[0.054, 0.071]	[0.165, 0.205]	[0.079, 0.117]
CAPI	[0.067, 0.097]	[0.165, 0.214]	[0.079, 0.133]	[0.125, 0.134]	[0.066, 0.094]	[0.174, 0.214]	[0.112, 0.148]	[0.054, 0.084]
FLES	[0.104, 0.111]	[0.107, 0.110]	[0.367, 0.487]	[0.179, 0.250]	[0.171, 0.219]	[0.286, 0.424]	[0.202, 0.267]	[0.097, 0.152]
REP	[0.121, 0.138]	[0.563, 0.694]	[0.083, 0.125]	[0.171, 0.200]	[0.067, 0.091]	[0.146, 0.179]	[0.192, 0.238]	[0.027, 0.048]
FS	[0.763, 0.807]	[0.222, 0.313]	[0.130, 0.143]	[0.633, 0.729]	[0.761, 0.807]	[0.738, 0.792]	[0.541, 0.598]	[0.077, 0.120]
COT	[0.071, 0.100]	[0.083, 0.125]	[0.732, 0.787]	[0.100, 0.167]	[0.127, 0.148]	[0.063, 0.083]	[0.196, 0.235]	[0.028, 0.047]

The gray weights of the criteria obtained by the gray PSI method and the gray weights of the criteria found by the gray BWM method were combined with Equation (26). Table 7 presents the gray weights of the criteria according to the gray PSI ($\otimes w_{jPS}$) and gray BWM ($\otimes w_{jBW}$) methods and the combined gray weights ($\otimes w_{jCM}$).

After finding the combined gray weights, the gray MCRAT method was used to evaluate the performance of the suppliers. By applying Equations (29) and (30) to the gray decision matrix in Table 4, the gray normalized decision matrix was obtained. Table 8 presents the gray normalized decision matrix.

Table 7. Combined gray Weights of criteria.

Weights ↓ Criteria →	Cost	DT	Q	TA	RAA	REC
$\otimes w_{jPS}$	[0.0770, 0.0853]	[0.0670, 0.0849]	[0.0803, 0.0822]	[0.0849, 0.0868]	[0.0844, 0.0864]	[0.0815, 0.0834]
$\otimes w_{jBW}$	[0.0770, 0.1400]	[0.0510, 0.0830]	[0.079, 0.130]	[0.022, 0.032]	[0.107, 0.176]	[0.079, 0.118]
$\otimes w_{jCM}$	[0.0564, 0.1884]	[0.0320, 0.1115]	[0.0602, 0.1664]	[0.0179, 0.044]	[0.0847, 0.2386]	[0.0602, 0.1554]
Weights ↓ Criteria →	**STS**	**CAPI**	**FLES**	**REP**	**FS**	**COT**
$\otimes w_{jPS}$	[0.0838, 0.0857]	[0.0846, 0.0866]	[0.0844, 0.0864]	[0.0807, 0.0825]	[0.0841, 0.086]	[0.0849, 0.0868]
$\otimes w_{jBW}$	[0.079, 0.117]	[0.054, 0.084]	[0.097, 0.152]	[0.027, 0.048]	[0.077, 0.120]	[0.028, 0.047]
$\otimes w_{jCM}$	[0.063, 0.157]	[0.0433, 0.1146]	[0.0771, 0.2057]	[0.0207, 0.0612]	[0.0611, 0.1617]	[0.0226, 0.0644]

Table 8. Gray normalized decision matrix.

Suppliers ↓ Criteria →	Cost	DT	Q	TA	RAA	REC
SPIR 1	[0.6667, 1]	[0.3514, 0.52]	[0.4773, 0.75]	[0.7059, 0.9412]	[0.7059, 0.9412]	[0.7292, 0.9792]
SPIR 2	[0.6667, 1]	[0.3611, 0.5417]	[0.5227, 0.7955]	[0.7059, 0.9412]	[0.6863, 0.9216]	[0.625, 0.875]
SPIR 3	[0.6667, 1]	[0.3824, 0.5909]	[0.5, 0.7727]	[0.7451, 0.9804]	[0.7255, 0.9608]	[0.5417, 0.7917]
SPIR 4	[0.5217, 0.7059]	[0.52, 1]	[0.7273, 1]	[0.7647, 1]	[0.7647, 1]	[0.75, 1]
SPIR 5	[0.5333, 0.7273]	[0.4815, 0.8667]	[0.7046, 0.9773]	[0.7647, 1]	[0.7255, 0.9608]	[0.6667, 0.9167]
SPIR 6	[0.6, 0.8571]	[0.3514, 0.52]	[0.5455, 0.8182]	[0.6863, 0.9216]	[0.6274, 0.8627]	[0.5208, 0.7708]
Suppliers ↓ Criteria →	**STS**	**CAPI**	**FLES**	**REP**	**FS**	**COT**
SPIR 1	[0.6667, 0.9333]	[0.6279, 0.907]	[0.6400, 0.8800]	[0.6600, 0.9000]	[0.6538, 0.8846]	[0.7451, 0.9804]
SPIR 2	[0.5556, 0.8222]	[0.6046, 0.8837]	[0.6800, 0.9200]	[0.5200, 0.7600]	[0.6346, 0.8654]	[0.7059, 0.9412]
SPIR 3	[0.6222, 0.8889]	[0.6512, 0.9302]	[0.7200, 0.9600]	[0.5000, 0.7400]	[0.6538, 0.8846]	[0.7059, 0.9412]
SPIR 4	[0.7333, 1]	[0.6744, 0.9535]	[0.7600, 1]	[0.7600, 1]	[0.7692, 1]	[0.7647, 1]
SPIR 5	[0.6889, 0.9556]	[0.7209, 1]	[0.6400, 0.8800]	[0.6800, 0.9200]	[0.7308, 0.9615]	[0.7647, 1]
SPIR 6	[0.6667, 0.9333]	[0.6744, 0.9535]	[0.6800, 0.9200]	[0.5400, 0.7800]	[0.6538, 0.8846]	[0.6863, 0.9216]

Then, the weighted, normalized gray matrix was achieved using Equation (31). Using Equations (32)–(37), gray optimal alternatives, decomposed gray optimal alternatives, and decomposed alternatives were obtained, respectively. The gray magnitude components were calculated using Equations (38) and (39). Table 9 demonstrates these values.

Table 9. The gray magnitude components.

$\otimes Q_k$	[0.1328, 0.4742]
$\otimes Q_h$	[0.0411, 0.2189]

After obtaining gray magnitude components, first, the values for each alternative were found using Equations (40) and (41). Then, ⊗D and ⊗F gray matrices were created, and the gray trace of the matrix was calculated using Equations (44) and (45). The gray trace matrix was converted to a crisp trace matrix. Table 10 shows these results and the rankings of the suppliers.

According to the results of the gray MCRAT method, the most resilient supplier was determined as the supplier coded as SPIR 4. This supplier is followed by SPIR 5, SPIR 1, SPIR 3, SPIR 2 and SPIR 6, in that order.

Table 10. The results of gray MCRAT.

Suppliers ↓ Results →	$\otimes C_k$	$\otimes C_h$	$\otimes z_{11;i}$	$\otimes z_{22;i}$	$tr(\otimes Z_i)$	$tr(Z_i)$	Rankings
SPIR 1	[0.1161, 0.4282]	[0.0392, 0.1971]	[0.0154, 0.2031]	[0.0016, 0.0431]	[0.0170, 0.2462]	0.1316	3
SPIR 2	[0.1117, 0.4174]	[0.0393, 0.1978]	[0.0148, 0.1979]	[0.0016, 0.0433]	[0.0164, 0.2412]	0.1288	5
SPIR 3	[0.1153, 0.4267]	[0.0395, 0.1996]	[0.0153, 0.2023]	[0.0016, 0.0437]	[0.0169, 0.2460]	0.1315	4
SPIR 4	[0.1324, 0.4729]	[0.0338, 0.1736]	[0.0176, 0.2242]	[0.0014, 0.038]	[0.0190, 0.2622]	0.1406	1
SPIR 5	[0.1231, 0.4484]	[0.0338, 0.1676]	[0.0163, 0.2126]	[0.0014, 0.0367]	[0.0177, 0.2493]	0.1335	2
SPIR 6	[0.1111, 0.4151]	[0.0356, 0.1716]	[0.0148, 0.1968]	[0.0015, 0.0376]	[0.0163, 0.2344]	0.1254	6

After obtaining the results of the gray MCRAT method, the gray COBRA method was started. First, the weighted gray values were obtained using Equation (48). Then, the reference solutions were obtained using Equations (49)–(51). Then, gray distance values were obtained by applying Equations (54)–(61). The values are shown in Table 11.

Table 11. The gray distances.

Suppliers ↓ Results →	$\otimes dE(PIS)_i$	$\otimes dT(PIS)_i$	$\otimes dE(NIS)_i$	$\otimes dT(NIS)_i$
SPIR 1	[0, 3.1088]	[8.4111, 9.5717]	[0, 2.9565]	[6.1089, 6.5393]
SPIR 2	[0, 3.1338]	[8.0775, 9.6971]	[0, 2.8809]	[6.2257, 6.2355]
SPIR 3	[0, 3.1028]	[8.2052, 9.6453]	[0, 2.9518]	[6.2064, 6.2779]
SPIR 4	[0, 3.0558]	[9.5202, 9.1648]	[0, 3.2536]	[5.8575, 7.2300]
SPIR 5	[0, 3.1196]	[9.0005, 9.3598]	[0, 3.0684]	[5.9412, 7.0107]
SPIR 6	[0, 3.1868]	[8.2078, 9.6556]	[0, 2.8341]	[6.1979, 6.3287]
Suppliers ↓ Results →	$\otimes dE(AS)_i^+$	$\otimes dT(AS)_i^+$	$\otimes dE(AS)_i^-$	$\otimes dT(AS)_i^-$
SPIR 1	[0, 1.4374]	[2.7028, 3.0267]	[0, 2.5207]	[5.6557, 6.1949]
SPIR 2	[0, 0.5588]	[0.4791, 0.5588]	[0, 2.8151]	[7.7901, 8.5441]
SPIR 3	[0, 1.9654]	[3.2493, 3.4222]	[0, 2.1287]	[5.0544, 5.7221]
SPIR 4	[0, 3.1150]	[7.9531, 9.4371]	[0, 0.5377]	[0.3544, 0.5377]
SPIR 5	[0, 2.7120]	[6.9815, 7.8131]	[0, 1.2899]	[1.4588, 1.7043]
SPIR 6	[0, 1.5099]	[2.7933, 2.9396]	[0, 2.4552]	[5.5396, 6.1883]

The gray comprehensive distances were calculated using Equations (52), (53), and (62). The suppliers were ranked using Equations (19) and (20). Table 12 indicates the results of the gray COBRA method.

Table 12. The results of gray COBRA.

Suppliers ↓ Results →	$\otimes d(PIS)_i$	$\otimes d(NIS)_i$	$\otimes d(AS)_i^+$	$\otimes d(AS)_i^-$	$\otimes dC_i$	Rankings
SPIR 1	[−90.9295, 97.9360]	[−54.7926, 57.7491]	[−2.4310, 14.9893]	[−43.9587, 10.9174]	[−51.9066, 41.5192]	4
SPIR 2	[−92.8612, 99.9756]	[−50.9114, 53.7923]	[−0.1745, 1.5314]	[−67.7098, 15.7486]	[−53.9737, 41.7025]	3
SPIR 3	[−91.4517, 98.4746]	[−52.5186, 55.4704]	[−3.7583, 22.9166]	[−34.2900, 8.6786]	[−51.0322, 40.8575]	5
SPIR 4	[−88.8968, 95.7632]	[−66.6666, 69.9202]	[−16.4260, 94.6837]	[−0.8140, 0.6932]	[−63.5787, 44.8872]	1
SPIR 5	[−89.2255, 96.1698]	[−60.9649, 64.0333]	[−11.8400, 68.7156]	[−6.1885, 2.4720]	[−57.0407, 42.8617]	2
SPIR 6	[−94.0262, 101.2434]	[−50.8315, 53.6655]	[−2.4802, 15.3359]	[−42.7711, 10.6250]	[−51.4497, 41.2950]	6

According to the results of gray COBRA, the most resilient supplier was determined to be the supplier coded as SPIR 4. This supplier is followed by SPIR 5, SPIR 2, SPIR 1, SPIR 3 and SPIR 6, in that order. According to Table 12, there are minor differences between the results of the gray COBRA method and the developed gray MCRAT method. Therefore, the results of the two methods are combined with the Borda count method. In the Borda count method, the lowest ranked option is given “0” points, while the highest ranked option is given “n − 1” points. This is intended to rank each method used. These points are then added up. The option with the highest total score is placed in first place, while the option with the second highest total score is placed in the second place, and so on [51]. Table 13 presents the results of the Borda count method and the final rankings of suppliers.

Table 13. The results of Borda count Method.

Suppliers ↓ Results →	Gray MCRAT	Borda Count Number	Gray COBRA	Borda Count Number	Borda Count Total Number	Final Rankings
SPIR 1	3	3	4	2	5	3
SPIR 2	5	1	3	3	4	4
SPIR 3	4	2	5	1	3	5
SPIR 4	1	5	1	5	10	1
SPIR 5	2	4	2	4	8	2
SPIR 6	6	0	6	0	0	6

According to the final rankings obtained using the Borda count method, the most resilient supplier was determined to be SPIR 4, followed by SPIR 5, SPIR 1, SPIR 2, SPIR 3, and SPIR 6, in that order. To check whether the developed the gray MCRAT method obtains accurate results, the gray MCRAT method was compared with other gray MCDM methods (gray ARAS, gray COPRAS, gray MOORA, gray COBRA, gray CODAS, gray EDAS, and gray TOPSIS). Table 14 presents the results of the developed gray MCRAT method and other gray MCDM methods.

Table 14. The Results of Gray MCDM Methods.

Suppliers ↓ Results →	Gray MCRAT	Gray ARAS	Gray COPRAS	Gray MOORA	Gray COBRA	Gray CODAS	Gray EDAS	Gray TOPSIS
SPIR 1	3	3	3	3	4	3	3	4
SPIR 2	5	5	5	5	3	4	4	3
SPIR 3	4	4	4	4	5	5	5	5
SPIR 4	1	1	1	1	1	1	1	1
SPIR 5	2	2	2	2	2	2	2	2
SPIR 6	6	6	6	6	6	6	6	6

The gray MCRAT method, which was developed using the results of the gray MCDM methods, and the gray COPRAS, gray ARAS, and gray MOORA methods yielded the same rankings. Although there are minor differences between the gray MCRAT method and gray TOPSIS and gray COBRA methods, the Spearman correlation coefficient between the gray MCRAT method and these two methods was determined to be 0.829. On the other hand, although there are very small differences between the gray MCRAT method and the gray CODAS and gray EDAS methods, the Spearman correlation coefficient between the gray MCRAT method and these two methods was determined to be 0.943. Based on these results, it can be stated that the developed gray MCRAT method acquired accurate results.

5. Sensitivity Analysis and Validation

In this section, it is determined whether or not the gray MCRAT method developed in this study is sensitive to changes in the weights of the sub-criteria. In this study, a sensitivity analysis was performed by changing the weights of the sub-criteria. The weights of the three sub-criteria with the highest weights (cost, RAA, and FLES) were reduced, resulting in a total of thirty-six scenarios. The following equation [52] was used in the sensitivity analysis.

$$W_{n\gamma} = (1 - W_{n\delta})\frac{W_\gamma}{(1 - W_n)} \tag{63}$$

In Equation (63), $W_{n\gamma}$ denotes the weight of the sub-criterion at a new value and W_γ is the sub-criterion's original value. Additionally, W_n represents the original weight of the sub-criterion with a reduced value and $W_{n\delta}$ denotes the reduced sub-criterion weight [52]. Firstly, thirty-six scenarios were formed. However, when no major changes were observed in these scenarios, four extra scenarios were added. In the first three scenarios, the weights of two sub-criteria were taken as zero. In S37, the weights of the cost and RAA sub-criteria were taken as zero, while rankings of zero were applied to cost and FLES in S38 and to RAA and FLES in S39. In the last scenario, the weights of all three sub-criteria were taken as zero. Thus, sensitivity analysis was performed with a total of forty scenarios. Figure 1 shows the results of the sensitivity analysis.

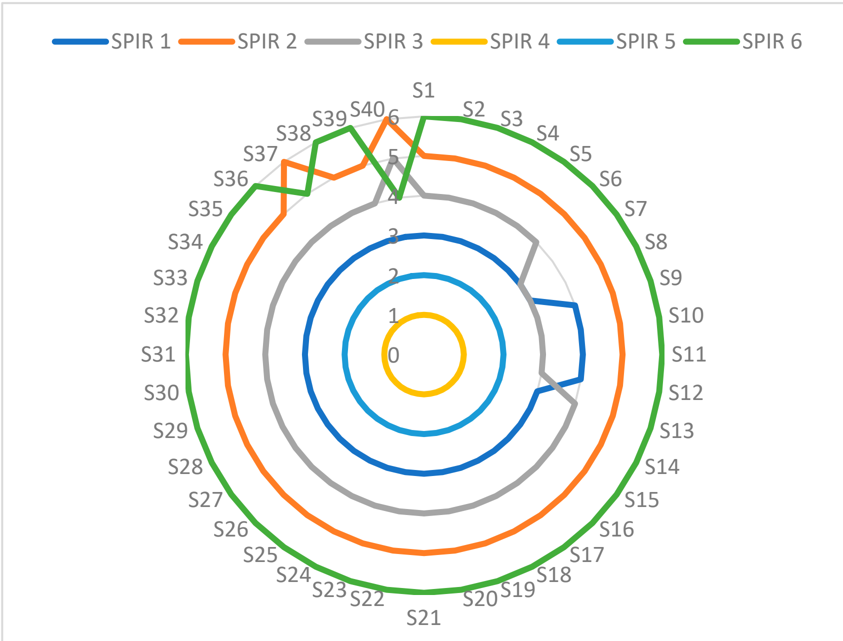

Figure 1. The results of the sensitivity analysis.

According to Figure 1, SPIR 1 decreased from third place to fourth place between S9 and S12, while SPIR 3 moved from fourth place to third place between S7 and S12. In S37 and S40, SPIR 2 decreased from fifth place to sixth place, while SPIR 6 increased from sixth place to fifth place in S37 and from sixth place to fourth place in S40. While the position of SPIR 3 did not change in S37, it dropped by one place from fourth place to fifth place in S40. As can be seen, except for the ranks of the SPIR 4 and SPIR 5 suppliers, the ranks of the other suppliers changed with the changes in the weights of the sub-criteria. This shows that the results of the gray MCRAT method will change depending on the changes that may occur in the weights of the sub-criteria.

The managers participating in the study were shown the results of the proposed model and asked to evaluate the consistency of this result. The managers gave a score between one (very inconsistent) and ten (very consistent). Mngr1, Mngr3, Mngr5, and Mngr6 gave it nine points, Mngr2 gave it eight points, and Mngr4 gave it ten points. The average of the total scores obtained was nine. This result shows that the proposed method is consistent and valid.

6. Conclusions

The ability of suppliers to effectively handle risk and outperform competitors during periods of disruption is a key indicator of their resilience. Hence, the need to use resilient suppliers becomes apparent when contemplating the possible ramifications that interruptions might have on a company's operational efficiency and image. However, insufficient attention has been given to addressing the uncertainty associated with the selection of resilient suppliers. Therefore, empirical research using gray methodologies has the potential to aid managers in making more informed choices when faced with uncertain circumstances. This study proposes a comprehensive gray MCDM paradigm that incorporates resilience attributes. To ascertain the relative importance of the criteria and sub-criteria in the second phase, the gray PSI and gray BWM methodologies were used. Gray MCRAT and gray COBRA methodologies evaluated and prioritized resilient providers based on their respective performances. The implementation of gray MCDM was conducted at a medium-sized Turkish textile firm. The aforementioned corporation has a workforce exceeding 1000 individuals and engages in the exportation of its goods. The firm's product line includes men's shirts and pants.

Based on the findings deriving from the gray MCRAT approach, the provider exhibiting the highest level of resilience was identified as the supplier classified with SPIR 4. It is followed by SPIR 5, SPIR 1, SPIR 3, SPIR 2, and SPIR 6, in that order. The findings of gray COBRA demonstrated that the provider exhibiting the highest level of resilience was the supplier coded as SPIR 4. It is sequentially followed by SPIR 5, SPIR 2, SPIR 1, SPIR 3, and SPIR 6. As can be seen, there are slight disparities in the outcomes obtained from gray COBRA and gray MCRAT. Therefore, the outcomes of the two techniques were aggregated using the Borda count technique. With the Borda count approach, the provider with the highest resilience level was SPIR 4. Subsequently, SPIR 5, SPIR 1, SPIR 2, SPIR 3, and SPIR 6 were ranked in descending order of resilience.

Finally, to assess the accuracy of the gray MCRAT technique, a comparative analysis was conducted with other gray MCDM methods. The findings of the gray MCRAT approach yielded consistent ranks with the gray COPRAS, gray ARAS, and gray MOORA methods. While there are some variations among the gray MCRAT technique, gray TOPSIS method, and gray COBRA method, the Spearman correlation coefficient between the gray MCRAT method and the latter two methods was determined to be 0.829. However, it should be noted that despite minor variations, the gray MCRAT approach has a Spearman correlation value of 0.943 when compared to gray CODAS and gray EDAS methods. The findings show that the gray MCRAT technique, which was established, yielded precise outcomes.

In this study, a test was carried out to establish whether or not the results of the developed gray MCRAT method change depending on a change in the weights of the criteria, using forty scenarios. According to the results of the sensitivity analysis, the developed gray MCRAT method is sensitive to changes in the weights of the criteria. The managers participating in the study were shown the result of the proposed model and asked to evaluate its consistency. According to the results of this analysis, the proposed model is consistent and valid.

In this study, unlike many studies in the literature, the weights of both subjective and objective criteria were included in the calculations. Additionally, the gray MCRAT method was developed in this study. It offers a more streamlined methodology for assessing alternatives across several criteria than competing gray MCDM methods. This results in dependable, universally applicable, and logically sound outcomes. The gray COBRA method was also used in this study. The gray COBRA method is unparalleled in its ability to rank options based on the integration of various types of distances from multiple reference points. This feature sets it apart from other reference-based MCDM methods, including TOPSIS, CODAS, and EDAS, and ensures it delivers more reliable results. Based on the above, it can be said that this study has reached stronger and more rigorous results.

Despite the constraints imposed by interaction limitations, the gray number approach is still limited in determining a fraction of the available solution range, particularly when dealing with undesirable parameter values. Therefore, one may use the suggested technique using fuzzy numbers, rough set theory, and neutrosophic numbers. The weightings and ratings of criteria by decision makers are subjective and contingent upon their expertise and understanding of the company, its procedures, and other relevant factors. Hence, the subjective inclinations of decision makers towards certain traits may have influenced the outcomes. Subsequent investigations may expand upon the suggested model by developing a multi-stage framework that takes into account the sub-criteria of each criterion that contributes to resilience. The resilience criteria may be integrated with other environmental criteria to tackle the sustainability concerns related to suppliers. The suggested MCDM framework for the resilient supplier selection may also be used in several sectors, including environmental issues, entertainment, energy, infrastructure, and others.

7. Discussion and Implications

This study focused on the management of supply chain disruptions, which is an important challenge facing today's business world. In particular, the recent increase in uncertainties and disruptions in supply chain processes are challenging businesses more and more. The fact that these disruptions are often caused by suppliers is one of the most important obstacles that businesses face when managing their supply chains. Supply chain disruptions can lead to operational efficiency losses, customer dissatisfaction, and even financial losses. Therefore, the supplier selection process, which is critical for businesses, should be handled with great care.

The findings of the study show that resilience characteristics play a critical role in supplier selection. The developed gray MCDM model emerged as an effective tool to objectively evaluate supplier selection and prioritize resilience attributes. This method can enhance enterprises' ability to manage supply chain risks and strengthen their operational resilience.

In this study, the gray BWM method was used to find the subjective weights of the criteria. Gray BWM obtains the weights of the criteria by making fewer comparisons compared to the gray AHP method. Additionally, the gray PSI method was used to obtain the objective weights of the criteria. The gray PSI method has simpler computing steps compared to the gray CRITIC and gray entropy methods.

In this study, the gray MCRAT method was developed. In contrast to competing gray MCDM approaches, the gray MCRAT method offers a more streamlined methodology to assess alternatives across several criteria, resulting in dependable, universally applicable, and logically sound outcomes.

The gray COBRA method was also used in this study. The gray COBRA method is distinguished by its capacity to rank options based on the integration of various types of distances from multiple reference points. This feature allows it to achieve more reliable results than other reference-based MCDM methods, including TOPSIS, CODAS, and EDAS, among others.

In short, in this study, we endeavored to obtain more reliable results by utilizing two distinct gray MCDM methods (gray MCRAT and gray COBRA).

It can be argued that by applying the proposed method, businesses can manage their supply chain processes more effectively and be better prepared for potential disruptions. However, for this approach to be successful, enterprises should pay more attention to resilience characteristics in supplier selection and adopt advanced decision-making methods.

The results of this study emphasize that businesses should consider resilience characteristics in supplier selection to improve their supply chain management strategies. The use of the gray MCDM method provides important guidance to businesses for this purpose. Considering resilience characteristics in supplier selection can enhance the competitive advantage of businesses and strengthen their long-term sustainability.

Furthermore, this study calls on academics and researchers to develop new and innovative research methods in the field of supply chain management. Further research and methodologies are needed to overcome the current challenges in dealing with supply chain disruptions. Advances in this area can help businesses build stronger and more resilient supply chain systems and support global economic stability.

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