Research Article

Integrated Fuzzy-MSGP Methods for Clothing and Textiles Supplier Evaluation and Selection in the COVID-19 Era

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Supplier selection is an important issue in supply chain management (SCM) which, as with most dimensions of business, has been strongly impacted by the COVID-19 pandemic. Previous research on the clothing and textiles (C&T) industry has overlooked efforts to provide a regular reference method for addressing the problem of supplier selection. This study discusses the COVID-19 pandemic’s impact on, and the relative importance of, supplier selection implementation. This study applied fuzzy techniques for order preference by similarity to ideal solution (TOPSIS) and multisegment goal programming (MSGP) method to the problem of supplier selection and combined these two methods to propose a novel multicriteria decision-making (MCDM) method to be used by C&T companies. It proposes a simple method to provide decision-makers (DMs) with guidelines for supplier selection considering existing constraints on business resources. The advantage of this method is the incorporation of both qualitative and quantitative criteria (e.g., both tangible and intangible resources), which allows DMs to set multisegment aspiration levels (MSALs) for supplier selection. A case study of a C&T manufacturer’s application of the model is also presented.

1. Introduction

In recent years, supplier selection as a sustainable strategy to achieve raw material supply has received more and more attention from both academia and industry [1, 2]. Identifying the right supplier has a strong impact on the efficiency and productivity of a company’s supply chain management (SCM) operations process. Many businesses have sought a strategic method of supplier selection which would increase management effectiveness and overall competitiveness in their industries. Therefore, supplier selection is a strategic point when considering SCM effectiveness. A supplier’s performance relies upon the quality consistency and functional efficiency of the resource it supplies. For example, decision-makers’ (DMs) success or failure in the task of selecting stable suppliers plays an important role in production, marketing, and logistics management [3]. To optimize supply chain operations, questions about how to improve the production capacity, raw fabric quality, and efficacy of services obtained from suppliers have a significant impact on improving the ability of enterprises to meet customer needs. Being able to evaluate suppliers’ procedures is one of the crucial activities for companies to gain a competitive advantage and achieve business goals. For the clothing and textiles (C&T) industry, successful SCM requires effectively managing the coalition of suppliers, distributors, and manufacturers while responding to customer needs [4]. In the context of the C&T supply chain, there are a number of researchers working on different approaches to select suppliers to improve C&T capabilities in the supply chain [5]. For C&T, choosing the right supplier will significantly reduce procurement costs and increase customer satisfaction, thereby enhancing the company’s competitive advantage. Therefore, choosing the best supplier has become a major strategic deliberation for the SCM of many companies, and it is also a key factor for business success.

The COVID-19 pandemic is known to have brought additional difficulties to supplier selection, especially in production sectors such as the C&T industry. The COVID-19 pandemic has created a lot of uncertainty, forcing C&T businesses to modify their general practices and make important changes that will guide them into the future [6].
Moreover, as with all industries, C&T manufacturing must come up with a strategy to deal with the difficulties that the COVID-19 pandemic has brought, and these strategies can be seen as an important factor in the impact of the pandemic on their supplier selection [1]. Issues surrounding survival and growth strategies that C&T companies are forced to address include how to design and develop products that provide value to customers during the pandemic crisis and how to find external help and achieve sustainability goals [6].

The supplier selection process is essentially considered a multicriteria decision-making (MCDM) problem, which is influenced by different tangible and intangible criteria. The MCDM method is commonly used to address a variety of real-life management problems involving multiple criteria and alternative considerations [1, 7]. In recent years, the C&T industry has faced various MCDM problems in clothing products [4]. However, the supplier selection method of C&T businesses generally lacks a formal reference framework. In addition, there are research gaps on how the COVID-19 pandemic is affecting the global economy and how it has become an important factor in sustainable supplier selection such as in the C&T industry. This study aims to fill this gap by proposing a fuzzy MCDM technique for evaluating and selecting optimal suppliers after the COVID-19 outbreak. The advantage of this method comes from its attention to both qualitative criteria, such as quality, service, and pandemic containment, and quantitative criteria, such as product or manufacturing costs, manufacturing hours, and production quantities, which allows DMs to set MSAL for supplier selection. As far as we know, no prior research on C&T SCM has considered this combination when discussing supplier selection. Therefore, this paper offers a novel model of fuzzy-MSGP and presents a comparison of this proposed analytical method with others. It proposes a simple method, which can be calculated using an Excel software tool, to help DMs facing restraints on business resources and provides guidelines for supplier selection in the C&T industry.

2. Literature Review

Given the literature on the supplier evaluation and selection problems, the most relevant studies are reviewed below.

2.1. Supplier Selection Criteria. Recently, supplier selection has received great attention in academic publications. For instance, in examining the C&T industry, Guneri et al. [8] point out that the closeness of the relationship between enterprises, the position and reputation within the industry and past performance, the conflict resolution ability, and delivery time of goods are all important criteria for the evaluation and selection of C&T companies’ suppliers. Liao and Kao [9] propose that, in the process of supplier selection, the business needs to consider price or cost, product quality, goods delivery time, customer service satisfaction, and a supplier’s alignment with organizational needs and objectives. Lin et al. [10] argue that quality stability, cost rationality, service satisfaction, delivery accuracy, and trust are crucial criteria for evaluating suppliers in the electronics industry market. Trapp and Sarkis [11] have developed a novel optimization model that incorporates sustainable choices using the five interest criteria of supplier profitability, downstream relationship closeness, technical capability fit, quality reliability, and conflict resolution. Luthra et al. [12] use several factors: product quality, product cost, product cost discount, delivery flexibility, industry responsiveness, response to demand changes, prepayment discount, capacity assurance, manufacturing flexibility, IT infrastructure penetration, and financial stability to choose suppliers.

To investigate the issue of identifying suppliers for durable partnerships, Luthra et al. [12] advise a structure using an integrated analytical hierarchy process (AHP) approach. Based on a review of their research results and on the current consensus among experts, they determined the preferred measures to be product price, surrounding cost, raw material quality, presence of a professional health and safety system, and maintenance capability of environmental policies. O’Connor et al. [13] investigated suppliers’ responses to a highly competitive environment under the challenges posed by manufacturing. They divide the conceptual framework for supplier selection into market changes, operational capabilities, and input costs. In contrast, Torgul and Paksoy [14] suggested that six standard deviations should be used for supplier evaluation and selection, including price variation, product quality consistency, delivery time stability, and company performance. Furthermore, Alegoz and Yapicioglu [15] proposed a framework for supplier selection and order allocation. In addition to the impact of volume discounts and express service options, they argue that the supplier’s environmental factors should also be considered. Finally, acquisition strategy, supplier’s development, and assistance with customer relationship management should all be considered, according to the comprehensive framework proposed by Rezaei and Behnamian [3].

2.2. Modifications to Supplier Selection Criteria in Response to the COVID-19 Pandemic. The COVID-19 pandemic has affected the lives and operations of millions of persons in the world, resulting in impacted supply performance, such as delayed delivery times, insufficient order volumes, and controlled demand [1, 16]. During the COVID-19 pandemic, scholars successively published various research papers, especially about the impact of the COVID-19 pandemic on SCM, and provided companies with common and sustainable development goals in supplier selection in order to improve the competitiveness of enterprises [7, 16–22]. For instance, Orji and Ojadi [1] propose an integrated MCDM method to analyze COVID-19 pandemic response strategies and categorize 12 triple bottom line (TBL) criteria for supplier selection into economic, social, and environmental dimensions. They also explore the interrelationships between TBL criteria and sustainable supplier selection. The assorted four criteria are (1) the economic dimension (such as price, product quality, financial capacity, and production system efficiency) [23–25], (2) the environmental dimension (such as green product
design, environmental protection capability, the presence of training facilities, and regular environmental audits) [26, 27], (3) the social dimension (such as discussions of corporate social duty, information sharing, consensus with regulations, and work safety procedures) [17, 28, 29], and (4) pandemic response strategies (such as complying with government policy changes, the use of personal protective equipment, providing forecasts of customer protection needs, and developing business’ economic recovery plans) [16, 17, 30, 31]. In addition, Wang and Chen [32] have applied to the supplier selection problem assessment of the appropriateness of alternative supplier performance while taking into consideration the severity of the pandemic, performance in pandemic containment efforts, the company’s reputation in the industry, and delivery speed and level of buyer-supplier cooperation. Liao et al. [33], Liao and Kao [34], Wang and Chen [32], and Orji and Ojadi [1] summarize the updated supplier selection criteria regarding supplier selection under the post-COVID-19 outbreak which have appeared in the literature, as shown in Table 1.

2.3. Approaches to the Problem of Supplier Selection. When faced with a supplier selection decision, there are a number of techniques that have been applied to solve these MCDM problems. These techniques or methods include techniques for order preference by similarity to ideal solution (TOPSIS), linear programming (LP), multi-choice goal programming (MCGP), data envelopment analysis (DEA), cost-point methods (CPM), analytical hierarchy process (AHP), analytic network process (ANP), multi-objective optimization based on ratio analysis with full multiplicative form (MULTIMOORA), VlseKriterijumska Optimizacija I Kompromiso Resenje (VIKOR), and fuzzy set theory. Recently, the use of varied methods or techniques in the supplier selection has received considerable attention from both academic researchers and industry specialists and this is reflected in recent SCM literature [4].

Ha and Krishnan [35] use a hybrid mold for supplier selection, incorporating AHP and DEA techniques into their research agenda. An integrated fuzzy case-based reasoning and mathematical programming method is proposed by Faez et al. [36]. To help telecom companies select suppliers, Önüt et al. [37] have developed a supplier assessment method based on TOPSIS and ANP methods. Kakogul and Susuz [38] combined AHP and mathematical programming for considering nonlinear integer and multiobjective programming to determine the optimal supplier under quality, cost management, delivery, technology, and other constraints. Liao and Kao [8] used a combination of Taguchi loss function, AHP, and MCGP method to select the most suitable supplier. In addition, for supplier evaluation and selection in SCM, Liao and Kao [34] developed an integrated MCGP and fuzzy TOPSIS technique to assist companies in finding the best suppliers. Dobos and Vörösmarty [39] used DEA to evaluate candidate supplier performance against environmental measures. Büyüközkan and Göçer [40] investigated a new combinatorial intuition-fuzzy MCDM method based on a logical design procedure to efficiently assess and select the most suitable suppliers. Chatterjee and Stević [41] used a two-phase fuzzy-AHP TOPSIS model for supplier evaluation in a manufacturing environment. In addition, Zavadskas et al. [42] addressed a modelling procedure for the selection of a steel pipes supplier by using fuzzy-AHP method. Durmič et al. [43] combined full consistency method (FUCOM) with rough simple additive weighting (SAW) method to create a model for sustainable supplier selection. Cakar and Çavuş [44] applied fuzzy TOPSIS method to supplier selection process in dairy industry. Fu et al. [45] applied a combination of fuzzy-AHP, fuzzy-ARAS (additive ratio assessment), and MSGP methods to assess in-flight duty-free products suppliers’ selection. Chattopadhyay et al. [46] developed a Rough-MABAC-DoE- interval rough analytic hierarchy process-multiplicative border approximation area comparison-

<table>
<thead>
<tr>
<th>Table 1: Supplier selection criteria.</th>
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<tbody>
<tr>
<td><strong>Category</strong></td>
</tr>
<tr>
<td>Economic</td>
</tr>
<tr>
<td>(ii) Product quality</td>
</tr>
<tr>
<td>(iv) Production capability/methods</td>
</tr>
<tr>
<td>(vi) Technical/R&amp;D capability</td>
</tr>
<tr>
<td>Social</td>
</tr>
<tr>
<td>Environmental</td>
</tr>
<tr>
<td>(i) Work safety procedures</td>
</tr>
<tr>
<td>(ii) Compliance with policies and regulations</td>
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<tr>
<td>(iii) Information sharing</td>
</tr>
<tr>
<td>(v) Reputation in industry</td>
</tr>
<tr>
<td>(vii) Conflict/problem-solving</td>
</tr>
<tr>
<td>Anxiety</td>
</tr>
<tr>
<td>COVID-19 pandemic response strategies/performan</td>
</tr>
<tr>
<td>(ii) Regular environmental audits</td>
</tr>
<tr>
<td>(iv) Presence of training facilities</td>
</tr>
<tr>
<td>(v) Location</td>
</tr>
<tr>
<td>(vii) Pandemic severity</td>
</tr>
<tr>
<td>(i) Providing personal protective equipment</td>
</tr>
<tr>
<td>(iii) Complicity with regulatory changes</td>
</tr>
<tr>
<td>(v) Management and organization capability</td>
</tr>
<tr>
<td>(i) Pandemic containment capability</td>
</tr>
</tbody>
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...
Step 1. consult a mature field of experts. 
Step 2. In an anonymous manner. 
Step 3. Using different rounds. 
Step 4. with feedback on the results. 
Step 5. Participants can reconsider their position.

Figure 1: The Delphi technique process [51].

design of experiments-) based metamodel for assessing supplier selection in iron and steel industries in 74 countries.

Lahdhir et al. [47] use fuzzy logic methods and AHP to select suitable subcontractors in the apparel supply chain. The most recent research works in supplier selection under COVID-19, such as the work of Kilic and Yalcin [48], combine an improved two-stage fuzzy goal programming (GP) model with fuzzy TOPSIS technique to green supplier selection. Orji and Ojadi [1] integrated MCDM method to analyze the interrelationship between COVID-19 pandemic response strategies and TBL criteria for supplier selection. Their method of MCDM is based on fuzzy set theory, AHP, and MULTIMOORA. Rezaei and Behnamian [3] have adopted a multistage screening algorithm to assess and select suppliers for each period while meeting the company’s targets for continuous improvement and increased effectiveness. This innovative solution provides a selection mechanism to select final suppliers based on their current and previous performance. In addition, Wang and Chen [32] proposed a biobjective AHP-mixed-integer nonlinear programming (MINLP-) genetic algorithm (GA) and applied it to a real-world case of selecting diverse alternative suppliers in the COVID-19 pandemic to evaluate its effectiveness. Therefore, these researchers propose a comprehensive mechanism to appropriately select suitable suppliers, which can be explored in future studies.

However, the information available in real life is inherently inaccurate, ambiguous, or uncertain, so many case study models may be partially flawed and inaccurate due to this lack of preciseness [49]. Therefore, DMSs also need to make controversial judgments based on variable and unclear information. For the selection of suppliers, enterprises often face a high level of uncertainty and ambiguity in actual instances of decision-making. Under these circumstances, fuzzy set theory (FST) is the most efficient method that can be used to deal with uncertainty and ambiguity in the decision-making process. Using TOPSIS method’s logic and simple mathematics is the best way to solve MCDM issues and may be effectively developed to handle and close the gap in supplier selection models. Chen et al. [50] use a fuzzy set theory based MCDM approach to analyze SCM cases and apply linguistic values to evaluate the ratings and weights of supplier selection criteria.

Within the COVID-19 scenario, the main motivation and aim of this paper is to develop an integrated MSGP and fuzzy TOPSIS reference model to solve the problem of multiobjective supplier evaluation and selection under conditions of resource constraints. First, the Delphi technique (see Figure 1) was used to obtain the supplier selection criteria. Second, the linguistic values presented in triangular fuzzy numbers (TFN) are used to measure criteria ratings and weights of the supplier. Third, an FST-based hierarchical multimodel is used, and the closeness coefficient (CC) of each supplier is obtained by using the fuzzy positive ideal and negative ideal solutions. Finally, a fuzzy MSGP model based on supplier tangible constraints (objectives) is constructed for selecting the best supplier by using LINGO 11 software. The integrated procedure is shown in Figure 2.

The rest of this paper is organized as follows. Section 3 presents the proposed fuzzy TOPSIS and MSGP methods. Section 4 presents an integrated approach to the supplier selection problem using fuzzy TOPSIS and MSGP through a case application. Finally, research conclusions and recommendations for future research are provided in Section 5.

3. The Proposed Methodology

3.1. Fuzzy TOPSIS. In real life, the decision-making process involves many problems and may not be fully and correctly implemented due to the ambiguity, inaccuracy, imprecision, and uncertainty of available data [49]. In this situation, fuzzy set theory (FST) is proposed to employ linguistic variables in the supplier selection process [37, 49, 50]. The above basic concepts (i.e., fuzzy numbers and linguistic variables) will be defined in the next subsection.

To solve some nonstatistical uncertainty problems, FST is proposed to incorporate linguistic variables into the decision-making process [52]. Here a real fuzzy number A is described as a fuzzy subset of the real number x with the membership function \( \mu_A(x) \) that represents uncertainty. A positive triangular fuzzy number \( \tilde{m} \) can be defined as \((m_1, m_2, m_3)\), as shown in Figure 3. The membership function \( \mu_{\tilde{m}}(x) \) is defined as follows [34]:

\[
\mu_{\tilde{m}}(x) = \begin{cases} 
0, & x \leq m_1, \\
(1 - \frac{x - m_1}{m_2 - m_1}), & m_1 \leq x \leq m_2, \\
1 - \frac{m_3 - x}{m_3 - m_2}, & m_2 \leq x \leq m_3, \\
0, & x \geq m_3.
\end{cases}
\]

(1)

Taking any two positive TFNs \( \tilde{m} = (m_1, m_2, m_3) \) and \( \tilde{n} = (n_1, n_2, n_3) \) together with a positive number \( k \), some main operations of fuzzy numbers \( \tilde{m} \) and \( \tilde{n} \) can be expressed as follows:

\[
\tilde{m}(+)\tilde{n} = (m_1 \oplus n_1, m_2 \oplus n_2, m_3 \oplus n_3),
\]

(2)

\[
\tilde{m}(-)\tilde{n} = (m_1 \odot n_1, m_2 \odot n_2, m_3 \odot n_3),
\]

(3)

\[
\tilde{m}(\times)\tilde{n} = (m_1 \otimes n_1, m_2 \otimes n_2, m_3 \otimes n_3),
\]

(4)
This case can be defined as the following sets: (1) a set of $k$ DMs called $A = (A_1, A_2, \ldots, A_k)$; (2) a set of $m$ possible candidates called $S = (S_1, S_2, \ldots, S_m)$; (3) a set of $n$ criteria called $C = (C_1, C_2, \ldots, C_n)$; and (4) a set of performance ratings of $A_i$ ($i = 1, 2, \ldots, m$) with respect to criteria $C_j$ ($j = 1, 2, \ldots, n$) called $X = \{x_{ij}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n\}$, with a set of importance weights of each criterion $w_i = (i = 1, 2, \ldots, n)$.

As stated above, a decision-making problem matrix can be expressed as follows:

$$
\bar{x} = \begin{bmatrix}
\bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\
\bar{x}_{21} & \bar{x}_{22} & \cdots & \bar{x}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{x}_{m1} & \bar{x}_{m2} & \cdots & \bar{x}_{mn}
\end{bmatrix},
$$

$$
\bar{w} = [\bar{w}_1, \bar{w}_2, \ldots, \bar{w}_n],
$$

where $\bar{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\bar{w}_j = (\bar{w}_{j1}, \bar{w}_{j2}, \bar{w}_{j3})$, $i = 1, 2, 3, \ldots, m$, $j = 1, 2, 3, \ldots, n$.

Make the fuzzy rating and importance weight of the $k$th DM be $\bar{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$ and $\bar{w}_{jk} = (\bar{w}_{jk1}, \bar{w}_{jk2}, \bar{w}_{jk3})$, where $i = 1, 2, \ldots, m$, $j = 1, 2, 3, \ldots, n$ respectively.

Thus, the aggregated fuzzy ratings $\bar{x}_{ij}$ of alternatives for each criterion, can be obtained as $\bar{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, where $a_{ij} = \min\{a_{ijk}\}$, $b_{ij} = 1/K \sum_{k=1}^{K} b_{ijk}$, and $c_{ij} = \max\{c_{ijk}\}$, and the aggregated fuzzy weights, $\bar{w}_j$, of each criterion can be obtained as $\bar{w}_j = (\bar{w}_{j1}, \bar{w}_{j2}, \bar{w}_{j3})$, where $w_{j1} = \min\{w_{jk1}\}$, $w_{j2} = 1/K \sum_{k=1}^{K} w_{jk2}$, and $w_{j3} = \max\{w_{jk3}\}$ [50].

According to a brief discussion of fuzzy set theory, the normalized fuzzy decision matrix can be expressed as

$$
\bar{R} = [\bar{r}_{ij}],
$$

$$
\bar{r}_{ij} = \left(\frac{a_{ij}}{c_j}, \frac{b_{ij}}{c_j}, \frac{c_{ij}}{c_j}\right),
$$

$$
\bar{c}_j^* = \max c_{ij},
$$

where $\bar{c}_j^*$ is the normalized value of $\bar{c}_j = (a_{ij}, b_{ij}, c_{ij})$, which is obtained as follows:

If the $j$th criterion is a benefit, then

$$
\bar{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right),
$$

and $\bar{c}_j^* = \max c_{ij}$.

If the $j$th criterion is a cost, then

$$
\bar{r}_{ij} = \left(\frac{a_{ij}}{c_j}, \frac{a_{ij}}{c_j}, \frac{b_{ij} - a_{ij}}{c_j}\right),
$$

where $a_{ij} = \min a_{ij}$.

According to the normalized fuzzy decision matrix, the weighted normalized fuzzy decision matrix can be constructed as follows:

$$
\bar{V} = [\bar{v}_{ij}]_{mn},
$$

where $\bar{v}_{ij} = \bar{x}_{ij} \odot \bar{w}_{ij}$, $i = 1, 2, 3, \ldots, m$, $j = 1, 2, 3, \ldots, n$.

After constructing the weighted normalized fuzzy decision matrix, a fuzzy positive ideal solution (FPIS; $S^*$) and
fuzzy negative ideal solution (FNIS; \( S^- \)) can be calculated as follows:

\[
S^- = \left\{ \left( \max_i v_{ij} \mid j \in J \right), \left( \min_i v_{ij} \mid j \in J' \right) \right\},
\]

\[
= (\bar{v}^-_1, \bar{v}^-_2, \ldots, \bar{v}^-_n), \quad i = 1, 2, \ldots, m, \quad j = 1, 2, 3, \ldots, n,
\]

where \( v^*_j = \max_i v_{ij} \) and \( \bar{v}^-_i = \min_i v_{ij} \). In addition, \( J \) is associated with benefit criteria, but \( J' \) is associated with cost criteria.

The distance of each alternative from \( S^* \) and \( S^- \) can be calculated as

\[
d^*_i = \sum_{j=1}^{n} d(\bar{v}_i, v^*_j), \quad i = 1, 2, \ldots, m,
\]

(15)

\[
d^-_i = \sum_{j=1}^{n} d(\bar{v}_i, v^-_j), \quad i = 1, 2, \ldots, m,
\]

(16)

where \( d(\cdot, \cdot) \) represents the distance measured between two fuzzy numbers.

Then, according to the distance from the fuzzy positive ideal solution (FPIS) \( S^* \) and the fuzzy negative ideal solution (FNIS) \( S^- \), the closeness coefficient \( (CC_i) \) of each supplier can be obtained as follows:

\[
CC_i = \frac{d^-_i}{(d^*_i + d^-_i)}, \quad i = 1, 2, \ldots, m,
\]

(17)

where the \( CC_i \) range belongs to the closed interval zone to one (say \([0, 1]\)) and \( i = 1, 2, \ldots, m \).

### 3.2. Multisegment Goal Programming (MSGP).

Goal programming (GP) is a multobjective analysis method that arranges decision-making problems when objectives have been assigned to all attribute resources and the DM is interested in minimizing unachieved comparable objectives [54]. As the DM seeks the best solution from a set of feasible choices, the model can consider many simultaneous objectives. However, there may be many MSALs present, such as more is better or less is better [55, 56]. These typical MSGP problems cannot be solved using traditional GP methods. Liao [54] proposed an MSGP method to solve the MSAL problem, where the DM can set multiple aspiration levels for each segment goal, and the achievement function of MSGP is as follows:

\[
\min Z = \sum_{i=1}^{m} w_i (d^*_i + d^-_i),
\]

(18)

\[
s.\ t. \ f_i(x) + d^*_i - d^-_i = g_i, \quad i = 1, 2, \ldots, n,
\]

\[
f_i(x) = \sum_{j=1}^{m} s_{ij} B_{ij}(b) \cdot x_i,
\]

(19)

where \( s_{ij}, B_{ij}(b) \in R_i(x), \quad i = 1, 2, \ldots, n, \)

\[
d^*_i, d^-_i \geq 0, \quad i = 1, 2, \ldots, n,
\]

\[
X \in F \quad (F \text{ is a feasible set}),
\]

where \( w_i \) represents the weight attached to the deviation and \( d^*_i \) is the deviation from the target value \( g_i \).

\[
d^*_i = \max(0, f_i(x) - g_i),
\]

(20)

\[
d^-_i = \max(0, g_i - f_i(x)),
\]

(21)

which denote under- and overachievements of the \( i \)th goal, respectively; \( s_{ij} \) is a decision variable coefficient that represents the MSAL of \( j \)th segment of \( i \)th goal, \( B_{ij}(b) \) represents a function of a binary serial number, and \( R_i(x) \) is the function of resource limitations.

The MSGP model can be reformulated with the following type states [34]:

\[
\min S = w_i (d^*_i + d^-_i), w_i (e^*_i + e^-_i),
\]

(23)

\[
s.\ t. \sum_{j=1}^{m} s_{ij} B_{ij}(b) \cdot x_i + d^*_i - d^-_i = g_i, \quad i = 1, 2, \ldots, n,
\]

(24)

\[
= \frac{1}{L_i} \left( b_i s_{ij}^{\max} + (1 - b_i) s_{ij}^{\min} \right) - e^*_i + e^-_i
\]

\[
= 1 + \frac{\left( s_{ij}^{\max} \text{or } s_{ij}^{\min} \right)}{L_i}, \quad i = 1, 2, \ldots, n,
\]

(25)

\[
s_{ij} B_{ij}(b) \in R_i(x), \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, m,
\]

(26)

\[
b_i \in \{0, 1\}, \quad i = 1, 2, \ldots, n,
\]

(27)

\[
d^*_i, d^-_i, e^*_i, e^-_i \geq 0, \quad i = 1, 2, \ldots, n,
\]

(28)

\[
X \in F \quad (F \text{ is a feasible set}),
\]

(29)

where \( L_i = s_{ij}^{\max} - s_{ij}^{\min} \) and all other variables are defined as the same for the MSGP model.

### 3.3. Proposed Fuzzy-MSGP Approach.

This study proposes a fuzzy-TOPSIS integrated MSGP method to address the supplier selection problem. The MSGP model not only considers the DM’s experience and preferences for supplier selection within the qualitative criteria but also includes various tangible constraints, including quantitative criteria such as business budget (e.g., cost), supplier capability, and delivery time. Furthermore, the fuzzy TOPSIS approach helps to translate the DM’s preferences and experiences into salient results by applying linguistic values to measure each standard and alternative supplier. Integrating fuzzy-TOPSIS with MSGP allows DMs to apply both qualitative and quantitative criteria to each supplier, helping DMs identify suppliers that will meet customer requirements. From Liao’s [54] concept, MSGP allows DMs to set MSALs for every
segment target to avoid underestimation or overestimation in the decision-making process. The multisegment decision algorithm flow for supplier selection using fuzzy-TOPSIS and MSGP methods and using equations in Figure 4 is shown as follows.

4. Case Study of Supplier Selection

4.1. Case Background Description. According to the 2020 report of the International Textile Manufacturers Federation [57], average orders and expected turnover in the C&T industry decreased by 42% and 32%, respectively [6]. In this environment, the supplier selection model is used by large C&T companies such as ABC. Although ABC typically has multiple suppliers, most are similar and may be affected by the same risks during the COVID-19 pandemic. Pandemic related risks include reduced capacity for cross-border shipping, problems caused by port congestion, and backlogs on goods from regular suppliers [32]. To minimize these risks, ABC needs to find a diversified way to select suppliers. At the same time, the COVID-19 pandemic provides opportunities for ABC to introduce more sustainable elements into their underlying supply chain networks for increased marketing competitiveness. The chief executive officer (CEO) asked senior management to select a major C&T material supplier to support new product development to improve competitiveness in the Chinese market. Therefore, ABC established a supplier selection decision-making committee, which includes the CEO, epidemiologists, and purchasing managers.

The committee of three DMs ($D_1$, $D_2$, and $D_3$) is formed to select a best supplier from four qualified candidates ($S_1$, $S_2$, $S_3$, and $S_4$) by applying the Delphi technique. Following ABC’s procurement strategy, the first work was to identify the factors that influence supplier selection success and performance under the COVID-19 pandemic.

A review of company documents revealed that, in the process of selecting alternative suppliers, the committee made decisions based on the five following criteria:

(i) Financial stability ($C_1$),
(ii) Product quality ($C_2$),
(iii) Company reputation ($C_3$),
(iv) Pandemic containment capability ($C_4$),
(v) Personal protective equipment ($C_5$).

Fuzzy-TOPSIS is prioritized by the DM’s judgment and evaluation of the relative importance of qualitative multiple
Examining the impact of COVID-19 on supplier selection in clothing and textiles company

4.2. Application of the Proposed Methodology. This method of integration applying fuzzy-TOPSIS and MSGP to solve the problem of supplier selection and the process is outlined as follows.

First, the three DMs (say $D_1$, $D_2$, and $D_3$) used the linguistic variables shown in Table 2 to measure the importance weights of the five suppliers (say $S_1$, $S_2$, $S_3$, $S_4$, and $S_5$); the results of the weights are shown in Table 3.

In addition, the three DMs rated suppliers according to each criterion using the linguistic variables shown in Table 4; the rating results are shown in Table 5.

In Tables 3 and 5, the linguistic evaluation is converted into triangular fuzzy numbers (TFN), and then a fuzzy decision matrix is constructed and the fuzzy weights of each criterion are determined, as shown in Table 6.

Here, Table 6 is used to construct a normalized fuzzy decision matrix as shown in Table 7. Using the normalized fuzzy decision matrix in Table 8, the weighted normalized fuzzy decision matrix is constructed as shown in Table 8.

The FPIS and FNIS can be determinable from equations (13) and (14) as $S^* = [(1, 1, 1), (0.7, 0.7, 0.7), (1, 1, 1), (0.9, 0.9, 0.9), (1, 1, 1)]$, and $S^- = [(0.15, 0.15, 0.15), (0.03, 0.03, 0.03), (0.15, 0.15, 0.15), (0.09, 0.09, 0.09), (0.15, 0.15, 0.15)]$.

Therefore, we can obtain the distance of each supplier to FPIS and FNIS according to each criterion, as shown in Table 9.

From Table 9, we can obtain the closeness coefficients (say $CC_i$) of each supplier: $CC_1 = 0.526$, $CC_2 = 0.531$, $CC_3 = 0.547$, and $CC_4 = 0.514$, as shown in Table 10.

Finally, according to the closeness coefficient ($CC_i, i = 1, 2, 3, 4$) of each supplier, which can be obtained from Table 10, the best supplier $S_2$ is determined. Similar to the research by Liao and Kao [34], supplier weights were used to maximize the closeness coefficient in the objective function among eight suppliers.

Moreover, in this case, based on the sales records of the past six years and on ABC’s sales forecast, ABC’s CEO, Marketing Manager, and Purchasing Manager identified four goals to meet the company strategy, namely, selected the supplier with the highest weight ($G_1$), with low delivery time ($G_2$), with the lower budget cost ($G_3$), and with the appropriate level of purchasing demand ($G_4$):

(i) $G_1$: $f_1(x) = 1$ to maximize the supplier’s weight objective;
(ii) $G_2$: $f_2(x) \leq 140$ hours per year in order to minimize supplier lead times;
(iii) $G_3$: $f_3(x) \leq 54,200$ ($1,000$ dollars) to minimize total purchase cost;
Table 5: Rating four candidates by DMs according to five criteria.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Suppliers</th>
<th>Decision-makers (DMs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$D_1$</td>
</tr>
<tr>
<td>$C_1$</td>
<td>$S_1$</td>
<td>(3, 5, 7)</td>
</tr>
<tr>
<td></td>
<td>$S_2$</td>
<td>(5, 7, 9)</td>
</tr>
<tr>
<td></td>
<td>$S_3$</td>
<td>(9, 10, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_4$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td>$C_2$</td>
<td>$S_1$</td>
<td>(1, 3, 5)</td>
</tr>
<tr>
<td></td>
<td>$S_2$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_3$</td>
<td>(9, 10, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_4$</td>
<td>(3, 5, 7)</td>
</tr>
<tr>
<td>$C_3$</td>
<td>$S_1$</td>
<td>(9, 10, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_2$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_3$</td>
<td>(3, 5, 7)</td>
</tr>
<tr>
<td></td>
<td>$S_4$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td>$C_4$</td>
<td>$S_1$</td>
<td>(5, 7, 9)</td>
</tr>
<tr>
<td></td>
<td>$S_2$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_3$</td>
<td>(3, 5, 7)</td>
</tr>
<tr>
<td></td>
<td>$S_4$</td>
<td>(5, 7, 9)</td>
</tr>
<tr>
<td>$C_5$</td>
<td>$S_1$</td>
<td>(5, 7, 9)</td>
</tr>
<tr>
<td></td>
<td>$S_2$</td>
<td>(7, 9, 10)</td>
</tr>
<tr>
<td></td>
<td>$S_3$</td>
<td>(5, 7, 9)</td>
</tr>
<tr>
<td></td>
<td>$S_4$</td>
<td>(7, 9, 10)</td>
</tr>
</tbody>
</table>

Table 6: Fuzzy decision matrix and fuzzy weights for four candidates.

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>(3, 7.7, 10)</td>
<td>(1, 7.3, 10)</td>
<td>(5, 9, 10)</td>
<td>(5, 9, 10)</td>
<td>(3, 8.7, 10)</td>
</tr>
<tr>
<td>$S_2$</td>
<td>(3, 6.3, 9)</td>
<td>(3, 7.7, 10)</td>
<td>(7, 9, 10)</td>
<td>(3, 7, 10)</td>
<td>(5, 8.3, 10)</td>
</tr>
<tr>
<td>$S_3$</td>
<td>(7, 9.7, 10)</td>
<td>(9, 10, 10)</td>
<td>(3, 6.3, 9)</td>
<td>(3, 6.3, 10)</td>
<td>(5, 7.7, 10)</td>
</tr>
<tr>
<td>$S_4$</td>
<td>(3, 7.7, 10)</td>
<td>(3, 7.3, 10)</td>
<td>(3, 7, 10)</td>
<td>(5, 8.3, 10)</td>
<td>(5, 6.3, 9)</td>
</tr>
<tr>
<td>Weights</td>
<td>(0.5, 0.83, 0.9)</td>
<td>(0.3, 0.5, 0.7)</td>
<td>(0.5, 0.8, 1)</td>
<td>(0.3, 0.67, 1)</td>
<td>(0.5, 0.83, 1)</td>
</tr>
</tbody>
</table>

Table 7: The normalized decision matrix.

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>(0.3, 0.77, 1)</td>
<td>(0.1, 0.73, 1)</td>
<td>(0.5, 0.9, 1)</td>
<td>(0.5, 0.9, 1)</td>
<td>(0.3, 0.87, 1)</td>
</tr>
<tr>
<td>$S_2$</td>
<td>(0.3, 0.63, 0.9)</td>
<td>(0.3, 0.77, 1)</td>
<td>(0.7, 0.9, 1)</td>
<td>(0.3, 0.7, 1)</td>
<td>(0.5, 0.83, 1)</td>
</tr>
<tr>
<td>$S_3$</td>
<td>(0.7, 0.97, 1)</td>
<td>(0.9, 1, 1)</td>
<td>(0.3, 0.63, 0.9)</td>
<td>(0.3, 0.63, 1)</td>
<td>(0.5, 0.77, 1)</td>
</tr>
<tr>
<td>$S_4$</td>
<td>(0.3, 0.77, 1)</td>
<td>(0.3, 0.73, 1)</td>
<td>(0.3, 0.7, 1)</td>
<td>(0.5, 0.83, 1)</td>
<td>(0.5, 0.63, 0.9)</td>
</tr>
</tbody>
</table>

Table 8: The weighted normalized decision matrix.

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>(0.15, 0.64, 1)</td>
<td>(0.03, 0.37, 0.7)</td>
<td>(0.25, 0.72, 1)</td>
<td>(0.15, 0.6, 1)</td>
<td>(0.15, 0.67, 1)</td>
</tr>
<tr>
<td>$S_2$</td>
<td>(0.15, 0.53, 0.9)</td>
<td>(0.09, 0.38, 0.7)</td>
<td>(0.35, 0.72, 1)</td>
<td>(0.09, 0.47, 1)</td>
<td>(0.25, 0.69, 1)</td>
</tr>
<tr>
<td>$S_3$</td>
<td>(0.35, 0.81, 1)</td>
<td>(0.27, 0.5, 0.7)</td>
<td>(0.15, 0.51, 0.9)</td>
<td>(0.09, 0.42, 1)</td>
<td>(0.25, 0.64, 1)</td>
</tr>
<tr>
<td>$S_4$</td>
<td>(0.15, 0.64, 1)</td>
<td>(0.09, 0.37, 0.7)</td>
<td>(0.15, 0.56, 1)</td>
<td>(0.15, 0.56, 1)</td>
<td>(0.25, 0.53, 0.9)</td>
</tr>
</tbody>
</table>

Table 9: Distances between FPIS (and FNIS) and suppliers’ ratings.

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>$d(S_1, S^*)$</td>
<td>0.53</td>
<td>0.43</td>
<td>0.46</td>
<td>0.47</td>
</tr>
<tr>
<td>$S_2$</td>
<td>$d(S_2, S^*)$</td>
<td>0.56</td>
<td>0.40</td>
<td>0.41</td>
<td>0.53</td>
</tr>
<tr>
<td>$S_3$</td>
<td>$d(S_3, S^*)$</td>
<td>0.39</td>
<td>0.27</td>
<td>0.57</td>
<td>0.55</td>
</tr>
<tr>
<td>$S_4$</td>
<td>$d(S_4, S^*)$</td>
<td>0.53</td>
<td>0.40</td>
<td>0.55</td>
<td>0.48</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>$d(S_1, S^-)$</td>
<td>0.49</td>
<td>0.43</td>
<td>0.59</td>
<td>0.60</td>
</tr>
<tr>
<td>$S_2$</td>
<td>$d(S_2, S^-)$</td>
<td>0.48</td>
<td>0.44</td>
<td>0.60</td>
<td>0.57</td>
</tr>
<tr>
<td>$S_3$</td>
<td>$d(S_3, S^-)$</td>
<td>0.63</td>
<td>0.49</td>
<td>0.48</td>
<td>0.56</td>
</tr>
<tr>
<td>$S_4$</td>
<td>$d(S_4, S^-)$</td>
<td>0.57</td>
<td>0.43</td>
<td>0.54</td>
<td>0.59</td>
</tr>
</tbody>
</table>
(iv) \( G_i \): \( f_4(x) \leq 2,900 \) ($100 dollars), and the current epidemic prevention cost is maintained.

Moreover, the coefficients of variables in the model were calculated from the ABC database based on records from the past six years.

Data for the epidemic prevention cost, unit material costs, and the delivery time levels of the four candidate suppliers \( S_1, S_2, S_3, \) and \( S_4 \) are shown as follows (Table 11):

The functions and parameters related to ABC’s supplier selection problem are shown as follows:

### Table 10: The results of \( CC_i \).

<table>
<thead>
<tr>
<th>( d^*_i )</th>
<th>( d^*_i )</th>
<th>( d^<em>_i + d^</em> )</th>
<th>( CC_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.69</td>
<td>2.42</td>
<td>5.12</td>
<td>0.526</td>
</tr>
<tr>
<td>2.68</td>
<td>2.37</td>
<td>5.05</td>
<td>0.547</td>
</tr>
<tr>
<td>2.73</td>
<td>2.26</td>
<td>4.99</td>
<td>0.531</td>
</tr>
<tr>
<td>2.62</td>
<td>2.48</td>
<td>5.11</td>
<td>0.514</td>
</tr>
</tbody>
</table>

### Table 11: The data for four candidate suppliers based on three criteria.

<table>
<thead>
<tr>
<th>( S_1 )</th>
<th>( S_2 )</th>
<th>( S_3 )</th>
<th>( S_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epidemic prevention cost ($100)</td>
<td>2700</td>
<td>3600</td>
<td>2500</td>
</tr>
<tr>
<td>Unit material costs ($1000)</td>
<td>$10-$12</td>
<td>9</td>
<td>15</td>
</tr>
<tr>
<td>Delivery time levels (days/time)</td>
<td>0.355</td>
<td>0.04-0.047</td>
<td>0.06-0.073</td>
</tr>
</tbody>
</table>

### Table 12: The fuzzy-MSGP model in this case.

Min \( Z = d_1^* + d_2^* + d_3^* + d_4^* + d_1^* + d_2^* + d_3^* + d_4^* + e_1^* + e_2^* + e_3^* + e_4^* + e_5^* + e_6^* + e_7^* + e_8^* \)

s.t. \( 0.526x_1 + 0.547x_2 + 0.531x_3 + 0.514x_4 - d_1^* - d_2^* = 1 \)
\( 0.035x_1 + (0.047b_1 + 0.04(1-b_1)) + x_2 + (0.073b_2 + 0.06(1-b_2)) \) \( x_3 + 0.03x_4 - d_3^* - d_4^* \leq 130 \)
\( (1/0.007) (0.047b_1 + 0.04(1-b_1)) - e_1^* + e_1 = 6.7 \)
\( (1/0.013) (0.073b_2 + 0.06(1-b_2)) - e_1^* + e_1 = 5.6 \)
\( 12b_1 + 10(1-b_1)x_1 + 9x_2 + 15x_3 + (8b_4 + 6(1-b_4)) \) \( x_4 - d_3^* - d_4^* \leq 54,200 \)
\( 1/2 \) \( 12b_1 + 10(1-b_1) \) \( -e_1^* + e_1 = 6 \)
\( 1/2 \) \( 8b_4 + 6(1-b_4) \) \( -e_1^* + e_1 = 4 \)
\( 2700x_1 + 3600x_2 + 2500x_3 + 3200x_4 - d_1^* + d_2^* \leq 2,900 \)
\( b_i \in [0,1], i = 1,2,..,4 \)
\( d_1^*, d_2^* \geq 0, i = 1,2,..,4 \)
\( e_1^*, e_2^* \geq 0, i = 1,2,..,4 \)

1. Weights goal: \( f_1 (X) = 0.586x_1 + 0.543x_2 + 0.555x_3 + 0.545x_4 \geq 1 = 1 \)
2. Delivery time goal: \( f_2 (X) = 0.025x_1 + [0.04, 0.048]x_2 + 0.06, 0.073]x_3 + 0.03x_4 \leq 140 \)
3. Total purchase cost goal: \( f_3 (X) = [10, 12]x_1 + 9x_2 + 15x_3 + [6, 8]x_4 \leq 54,200 \)
4. Epidemic prevention cost goal: \( f_4 (X) = 2700x_1 + 3600x_2 + 2500x_3 + 3200x_4 \leq 2900 \)

Using the above target and the data given by ABC, a fuzzy-MSGP model and its description can be established.
The fuzzy-MSGP model in this case is as follows (Table 12):
All variables are nonnegative.

This fuzzy-TOPSIS and MSGP model of supplier selection as used by ABC can be solved by using LINGO 11.0 (see Figure 6) [58]; the optimal solution is identified in seconds (computertime) on a Pentium(R) 4 CPU 2.00 GHz based microcomputer as \( x_1, x_2, x_3, \) and \( x_4 \) (say \( S_1, S_2, S_3, \) and \( S_4 \)) = 0, 0, 0, 1, and 0. From these results, we can understand that supplier \( S_3 \) is the best selection for ABC.

### 5. Conclusion

Supplier selection is an important decision-making activity and the key to an enterprise gaining a competitive advantage. In order to achieve this goal, DM should adopt effective methods and standards to select suitable and stable suppliers. Likewise, during the COVID-19 pandemic, it is necessary to address the issues of how to seek sustainable partners to improve the competitiveness of enterprises and how to make careful selection of suitable suppliers [1]. Through qualitative content analysis and case studies, this research provides actionable strategies for the C&T industry to address the impact of the COVID-19 outbreak. However, the C&T industry lacks a frame of reference for selecting suppliers and this issue has been overlooked in past research. This paper proposes a novel model of fuzzy-TOPSIS and MSGP that provides DMs with a simple method and guidelines for supplier selection considering existing constraints on their business’s resources.

Generally, supplier evaluation and selection are vague and uncertain. Using this approach, fuzzy set theory helps to make DM’s preferences and experiences salient by using linguistic values to evaluate each supplier’s criteria. Given that there may be many MSALs in management practice, a multisegment approach is best suited for this type of decision-making. Additionally, this integrated approach allows the DM to set up MSALs for the problem of supplier selection. For example, in Table 10, \( S_2 \) is determined to be the best supplier (closeness coefficient; \( CC_i = 0.547 \)); however, when fuzzy-TOPSIS and MSGP methods are integrated, the best supplier is identified as \( S_3 \). The reason for this difference is the consideration of both qualitative and quantitative criteria in supplier selection.

The contributions of this paper are threefold: (1) A fuzzy-MSGP model was proposed and the integrated advantage of this method to identify the relationship between qualitative (intangible) criteria and quantitative (tangible) criteria for supplier selection was tested. For example, Table 13 presents a comparison between this proposed analytical method and other methods. (2) This paper proposed an efficient and simple method, which can be calculated with a common Excel software tool, to help DMs choose the best supplier to meet their needs. (3) The current proposed model offers relevant guidelines for supplier selection for DMs in the C&T industry allowing the managers of C&T departments to successfully implement robust supplier selection by developing key criteria where there is a constraint on business resources.

While this study does present some limitations, such as the selection of industry suppliers, it successfully utilizes fuzzy-TOPSIS and MSGP as proposed research methods for research evaluation. Therefore, this paper also invites future research on this topic which can utilize other MCDMs, such as analytic network process, structural equation modelling (SEM) or interpretive structural modelling, FUCOM-Rough SAW model (e.g., [43]), fuzzy ARAS, MSGP methods (e.g., [45]), and a Rough-MABAC-DoE-based metamodel (e.g., [46]), to estimate the criteria for supplier selection presented in the current case, after which a comparison can be made with the results acquired in this study. Furthermore, the research presented in this paper can be extended in substantial ways; the proposed method can address various marketing and management MCDM issues, such as logistics and marketing, or C&T product development and design issues when faced with inaccuracies, ambiguities, and uncertainties in the information available.

### Data Availability

All data generated or analyzed during this study are included in the published article.

### Conflicts of Interest

The author declares that there are no conflicts of interest.
References


