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RESEARCH ARTICLE

An Integrated Approach for Assessing Suppliers Considering Economic Sustainability Innovation

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ABSTRACT Innovation plays a key role in improving the sustainability performance of corporations. Limited studies have investigated the economic aspect of sustainable innovation. This article puts forward a decision framework for evaluating economic sustainable innovative suppliers. A new methodology based on fuzzy Full Consistency Method (FFUCOM) and Improved Combinative Distance-based Assessment (ICODAS) is developed and extended using interval rough Dombi-Bonferroni operators. In the developed approach, the FFUCOM is employed to determine the criteria weights, and the ICODAS is responsible for assessing and ranking the suppliers. A case study from the manufacturing sector of an emerging economy is considered for validating the developed framework and decision model. The findings introduce the "*financial resumption of products*" as the most critical economic innovation criterion for evaluating suppliers. Furthermore, the applicability and validity of the proposed model was confirmed through sensitivity analysis.

INDEX TERMS Sustainable innovation, supply chain management, supplier evaluation and selection, full consistency method (FUCOM), combinative distance-based assessment (CODAS).

I. INTRODUCTION

The negative impacts of industrialization on people and nature are apparent. Corporations ought to cooperate to minimize the harmful influence of their operations, taking into account three dimensions of sustainability (e.g., economic, social and environmental) [1]. Sustainable innovation can be described as all the initiatives that improves the sustainability performance. This sort of innovation includes the adoption of new processes, technologies, and materials in the supply chain processes [2]. That is, upgrading the operations to address the adverse environmental effects, provide social benefits, and boost the performance of organizations. In other words, sustainable innovation includes all technological, product, process, and social initiatives that aim at saving energy, preventing pollution and management of waste within supply chains [3]. Applying sustainable innovation is one of the requirements for attaining sustainable development [4].

Considering the limitations at a time of financial restraint, and possible recession in the post-pandemic and war economy, pursuing a net-zero policy requires economic sustainable innovations to secure enough resources for an uninterrupted improvement-a much-needed consideration that motivated the present study. Studies have explored sustainable innovation from various perspectives. Gupta et al. [5] studied the barriers to implementing sustainable supply chain innovation in the manufacturing industry and suggested new strategies to help overcome the barriers. More recently, Munten et al. [6] addressed tensions that may exist in coopetition for sustainable innovation using inputs from experts

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from the automotive industry. Ahmadi et al. [7] investigated the interrelationships among social sustainability innovation criteria.

One of the key elements of supply chains is supplier evaluation. Suppliers play a critical part in supply chains and their performance has a significant impact on the corporation's success [8]. In this situation, firms need to establish external practices related to sustainability and strategies, particularly in the upstream supply chains [9]. From the existing studies, Gupta and Barua [10] investigated the supplier selection problem considering their performance in environmental sustainability innovation. Most recently, Petrudi et al. [11] investigated the social innovation capability of suppliers in the context of COVID-19 epidemic. Thus far, less attention has been paid to the economic aspect of sustainable innovation, particularly in the context of supplier evaluation and selection from emerging economies.

This work addresses this gap by proposing a new evaluation framework and a novel methodology for supplier evaluation and selection considering economic sustainability innovativeness. This article addresses the following questions:

Q1. What considerations determine the sustainable economic innovativeness of a supplier?

Q2. How to assess the supplier's performance with respect to these criteria with the least subjectivity?

This article offers two main contributions. The first contribution of this study is to introduce an economic sustainability innovation framework as a basis for general economic innovation decision-making. The second contribution comes from proposing a novel Multi-Criteria Decision-Making (MCDM) framework, which consists of the Fuzzy FUll COnsistency Method (FFUCOM) and Improved COmbinative Distance-based ASsessment (ICODAS). The FUCOM method is an MCDM method that is employed to subjectively identify the criteria weights, similar to BWM [12], and AHP [13]. Additionally, Compared to other MCDM methods, the FUCOM method has also some advantages: (i) it provides the (n-1) pairwise comparison of factors using not only integers, but also decimal values; (ii) it uses a straightforward algorithm to identify the criteria weights; (iii) it needs a small number of pairwise comparisons of criteria compared to other well-known MCDM models such as AHP and the BWM, with the number of comparison [n (n-1) /2] and [2n-3], respectively; (iv) it minimizes the number of pairwise comparisons by taking transitivity into account in the comparison of pairs of criteria [14]. In this study, the fuzzy FUCOM (FFUCOM) is employed to handle ambiguous and conflicting data using a limited number of pairwise comparison criteria compared to similar fuzzy version. Additionally, this method eliminates the problem of inconsistency as a result of intensive pairwise comparisons [15]. The CODAS was developed for the assessment and selection of the suppliers. According to the CODAS method, Euclidean and taxicab distances are considered when determining which alternative is preferred over another. The strategy is based on identifying the alternative that is further removed from the unfavorable ideal solution. The Euclidean distance is the first distance that is employed. The Taxicab distance is used to find the solution when the Euclidean distance between two alternatives is equal or when it is less than a predefined threshold value [16].

In the developed framework, hereafter named as FFUCOM-ICODAS, a new MCDM concept based on Dombi Bonferroni [17] is introduced to effectively deal with uncertainty and inaccuracy in the supplier evaluation and selection decision, which is based on the utilization of interval rough numbers with an adaptive rough boundary interval. The adaptability of the rough boundary interval is facilitated by employing the hybrid Dombi Bonferroni function. The Bonferroni function [17] is applied to show the interrelationships amongst rough sequences.

The rest of this manuscript is structured as follows. In Section II, the relevant literature regarding sustainable supply chain management, sustainable supplier evaluation and selection, sustainable innovation and the economic dimension is presented. We elaborate on the proposed methodology in Section III. A case application from industry and numerical analysis including the stability analysis of the proposed method is given in Section IV. Section V presents results comparison with other MCDM approaches. Discussion of the findings come next in Section VI. Finally, Section VII presents the Conclusion.

II. LITERATURE REVIEW

This section begins with a review of sustainable supply chain management. Second sub-section presents sustainable supplier evaluation and selection, and the last sub-section focuses on sustainable innovation and the economic dimension.

A. SUSTAINABLE SUPPLY CHAIN MANAGEMENT

Sustainable supply chain management (SSCM) main difference from the conventional supply chain is that it integrates social and environmental factors in decisions and managing the available resources [18]. Although profitability is a key goal, other factors such as social-wellbeing and avoiding a harmful environmental footprint have an impact [19]. Overall, SSCM reduces the supply chain activities damaging influences and helps organizations to establish a competitive advantage [20] and pursue their long-term sustainable development goals. SSCM also has implications for promoting efficiency in firms [21], [22]. SSCM is gradually becoming an integral part of organizations with society and governments asking them to involve sustainability considerations in different parts of their operations [6]. Firms are being held responsible to manage environmental and socio-economic problems through utilization of initiatives related to sustainability [23]. Literature has seen considerable development in supply chain performance improvement considering sustainability criteria [2] with a growing number of articles investigating SSCM [24]. Sustainable supplier evaluation and selection is overviewed in the next sub-section.

B. SUSTAINABLE SUPPLIER EVALUATION AND SELECTION

Sustainable supplier evaluation and selection (SSES) takes into account environmental and social factors compared to conventional supplier selection [8]. An increasing number of firms are utilizing sustainability factors in their supply chain activities and operations, particularly while assessing their suppliers [11]. Selecting the right supplier is an important area of SSCM, which significantly impacts the supply chain performance and the corporates' sustainability [21]. SSES helps organizations to ensure that they have the right resources [20]. SSES incorporates socio-environmental standards into the traditional supplier evaluation. SSES has drawn considerable attention in the academic literature [25], [26]. The present study builds on the previous literature in this area by developing a new typology for investigating the economic aspect of sustainable innovation through supplier evaluation and selection in an emerging economy context. Sustainable innovation and the economic dimension are overviewed in the last sub-section of the literature review.

C. SUSTAINABLE INNOVATION AND THE ECONOMIC DIMENSION

Companies should be innovative and responsive to damaging socio-environmental effects. Sustainable innovation can be applied as a differentiation strategy that establishes competitive advantages over their rivals [4], [9]. Sustainable innovation can be described as new or modified products, processes, services, techniques, and systems that decrease harmful environmental and social impacts and enhance quality of life [10]. Sustainable innovation is a requisite for obtaining sustainable development [27]. Organizations can achieve their sustainability performance targets by applying innovation criteria in their decisions [28]. Sustainable innovation consists of initiatives for ongoing improvement in products and processes, with the target of alleviating their possible damaging socio-environmental effects [26]. To ensure a truly sustainable innovative organization, social, economic, and environmental aspects should be simultaneously considered [5]. Sustainable innovation may involve different components of an organization that are demonstrated through improved financial, market, and environmental performance [29]. It also improves the corporate image, which in turn boosts profitability in the long-term [30]. Literature has introduced an array of factors to be considered in developing a sustainability innovation framework [31]. In particular, social factors such as poverty, corruption, human rights, health, and safety have been investigated [32]. Hermundsdottir and Aspelund [33] suggested that implementing sustainable innovation results in reducing supply chain costs. Sustainable innovation has three dimensions. (e.g., Economic innovation, social innovation, and environmental innovation). In this paper, we only focus on the economic dimension of sustainable innovation, with the target of assessing and ranking several economic sustainable innovative suppliers. In this paper, eleven economic innovation criteria including cost competitive advantage, financial availability for innovation, financial resumption of products, efficiency,producing sustainable products to decrease material utilization, finance in R&D, sustainable product cost reduction, increased sustainability value to clients, productivity, turnover per employee and value-added per employee, were extracted from the literature review and can be found in **Table 1.** Explanation of the proposed methodology can be found in the next Section.

III. METHODOLOGY

A. PRELIMINARIES

Definition 1: Let ς_1 and ς_2 be any of two real numbers. According to [43], the Dombi T-norm and T-conorm between ς_1 and ς_2 are described in Equations (1) and (2), respectively.

$$\Delta_D(\varsigma_1, \varsigma_2) = \frac{1}{1 + \left\{\left((1-\varsigma_1)/\varsigma_1\right)^{\phi} + \left((1-\varsigma_2)/\varsigma_2\right)^{\phi}\right\}^{1/\phi}} \tag{1}$$

$$\Delta_D^c(\varsigma_1, \varsigma_2) = \frac{1}{1 + \left\{\left(\varsigma_1/(1-\varsigma_1)\right)^{\phi} + \left(\varsigma_2/(1-\varsigma_2)\right)^{\phi}\right\}^{1/\phi}} \tag{2}$$

where $\phi > 0$ and $(\varsigma_1, \varsigma_2) \in [0, 1]$.

Definition 2: Let $\chi_1, \chi_2 \geq 0$. Considering $(\varsigma_1, \varsigma_2, \ldots, \varsigma_n)$ as a set of non-negative numbers, Expression (3) is true where BM^{χ_1,χ_2} is called a Bonferroni Mean (BM) operator introduced by [17].

$$BM^{\chi_1,\chi_2}(\varsigma_1, \varsigma_2, \ldots, \varsigma_n) = \left(\frac{1}{n(n-1)} \sum_{x=1}^{n} \left(\varsigma_i^{(x)}\right)^{\chi_1} \sum_{\substack{y=1 \\ y \neq x}}^{n} \left(\varsigma_j^{(y)}\right)^{\chi_2}\right)^{\frac{1}{\chi_1+\chi_2}} \tag{3}$$

Considering the Dombi T-norm and T-conorm, we define the Dombi Bonferroni (DBM) operator as follows.

Theorem 1: Let $(\varsigma_1, \varsigma_2, \ldots, \varsigma_n)$ be a collection of real numbers, then DBM operator is described as in (4), shown at the bottom of the next page, where $f\left(\varsigma_i^{(x)}\right) = \varsigma_i^{(x)} \Big/ \sum_{i=1}^{n} \varsigma_i^{(x)}$ and $f\left(\varsigma_j^{(y)}\right) = \varsigma_j^{(y)} \Big/ \sum_{i=1}^{n} \varsigma_j^{(y)}$ represents additive functions. The Theorem 1 proof is provided in *Appendix A*.

B. MULTI-CRITERIA FRAMEWORK

This study proposes the fuzzy FUCOM algorithm for defining the optimal values of the criteria weights and the interval rough Dombi Bonferroni CODAS methodology for the

TABLE 1. Economic sustainability innovation criteria supported by the literature.

Criteria	Supporting references
Cost competitive advantage	[34], [35]
Financial availability for innovation	[9], [36]
Financial resumption of products	[37], [38]
Efficiency	[7], [39]
Finance in R&D	[39], [40]
Producing sustainable products to decrease material utilization	[41], [35]
Sustainable product cost reduction	[5], [18]
Increased sustainability value to clients	[28], [10]
Turnover per employee	[9], [6]
Value-added per employee	[42], [20]
Productivity	[5], [38]

evaluation stage. **Fig. 1** graphically illustrates the developed methodological structure with its computational procedure detailed below.

Phase I (Identification of Criteria Weights): Developed by [44], Full Consistency Method is a comparison based MCDM method that uses pairwise comparison and variation from maximal consistency to identify the criteria weights. The FUCOM method has the following major advantages; (1) offers evaluation criteria pairwise comparison using not only integers, but also decimal values; (2) employs a simple algorithm to identify the weights of the criteria; (3) requires fewer pairwise comparisons for obtaining criteria weights; (4) considering transitivity in the comparison of pairs of criteria [14], [45]. It minimizes the number of pairwise comparisons compared to other MCDM models such as AHP and BWM with [n (n-1) /2] and [2n-3]. This model has been employed in different application areas such as level crossing selection [46]; Sustainable fuel vehicle selection [15] and location selection for the logistic center [47]. Given that many tactical and operational decisions require rapid appraisal and decision schemes, uncertainty of evaluations is a possibility. In this situation, applications of fuzzy approaches help improve the reliability of the outcomes. Linguistic scales

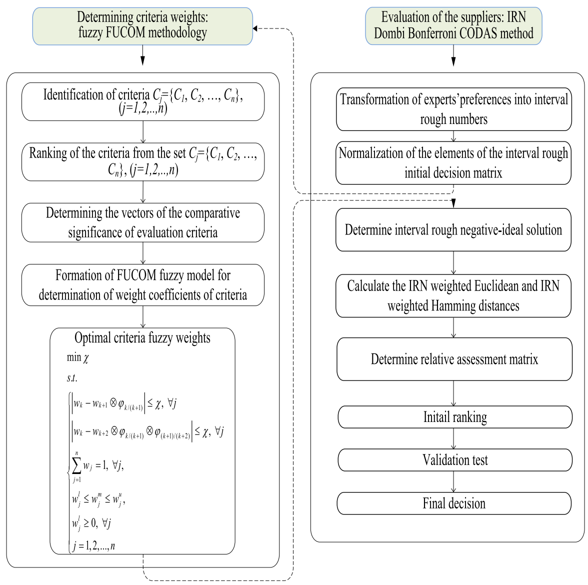

FIGURE 1. The computational procedure of the developed methodology.

based on fuzzy numbers have been widely utilized in the decision analysis context. This study incorporates a fuzzy

$$DBM^{\chi_1,\chi_2,\phi}(\varsigma_1,\varsigma_2,\ldots,\varsigma_n) = \frac{\sum_{t=1}^{n} \varsigma_t}{1+\left\{\frac{1}{\chi_1+\chi_2}\frac{n(n-1)}{\sum_{\substack{x,y=1\\x\neq y}}^{n} \frac{1}{\left(\chi_1\left(\left(1-f\left(\varsigma_i^{(x)}\right)\right)/f\left(\varsigma_i^{(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\varsigma_j^{(y)}\right)\right)/f\left(\varsigma_j^{(y)}\right)\right)^{\phi}\right)}}\right\}^{1/\phi}} \tag{4}$$

linguistic rating system, defined by triangular fuzzy numbers (TFN), to improve FUCOM (see **Table 2**).

The computational procedure of the fuzzy FUCOM method is provided below.

Step 1: After receiving feedback from experts, the average value is used as input. The first rank is given to a criterion that has the highest weight coefficient and the ranking continues until the least significant criterion is determined. The ranking of the criteria in order of importance is presented in Equation (5).

$$C_{j(1)} > C_{j(2)} > \ldots\ldots\ldots\ldots > C_{j(k)} \tag{5}$$

where j is the index of decision criterion (j = 1,2,…,n) and k denotes the rank of the observed criterion. When two or more decision criteria have the same rating, the equality symbol "≥" will replace ">".

Step 2: Decision criteria are compared using linguistic terms in **Table 3**. Comparisons are made based on the first ranked criterion; the most crucial criterion is compared with the remaining decision criteria to assign n-1 fuzzy priority $\tilde{\sigma}_{C_{j(k)}}$. The fuzzy comparative priority specifies the importance of criterion C_(j(k)) importance compared to that of C_(j(k+1)), as formulated in Equation (6).

$$\tilde{\eta}_{k/(k+1)} = \frac{\tilde{\sigma}_{C_{j(k+1)}}}{\tilde{\sigma}_{C_{j(k)}}} \tag{6}$$

In so doing, the fuzzy vector of comparative priorities of the decision criteria is obtained using Equation (7).

$$\tilde{\eta} = \left[\tilde{\eta}_{1/2}, \tilde{\eta}_{2/3}, \ldots\ldots\ldots\ldots, \tilde{\eta}_{k/(k+1)}\right]^T \tag{7}$$

Step 3: To obtain the optimal fuzzy weight coefficients of the decision criteria $[\tilde{\omega}_1, \tilde{\omega}_2, \ldots\ldots\ldots\ldots, \tilde{\omega}_n]^T$, it must meet the following conditions.

Condition 1: The fuzzy weight coefficients associated with the criteria ratio should be equal to their comparative significance, that is:

$$\tilde{\eta}_{k/(k+1)} = \frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+1)}} \tag{8}$$

Condition 2: Considering the condition described in Equation (9), the final fuzzy weight coefficient values should satisfy the mathematical transitivity condition.

$$\tilde{\eta}_{k/(k+1)} \otimes \tilde{\eta}_{(k+1)/(k+2)} = \tilde{\eta}_{(k)/(k+2)} \tag{9}$$

This condition can also be formulated as follows:

$$\tilde{\eta}_{k/(k+1)} \otimes \tilde{\eta}_{(k+1)/(k+2)} = \frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+2)}} \tag{10}$$

Full consistency of $Y = 0$ is only possible when there is full adherence to transitivity between weight coefficients, which can be stated as

$$\frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+1)}} - \tilde{\eta}_{k/(k+1)} = 0 \quad \text{and}$$
$$\frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+2)}} - \tilde{\eta}_{k/(k+1)} \otimes \tilde{\eta}_{(k+1)/(k+2)} = 0 \tag{11}$$

Besides, the values of the criteria weight coefficients $[\tilde{\omega}_1, \tilde{\omega}_2, \ldots\ldots\ldots\ldots, \tilde{\omega}_n]^T$ should be determined in a way that the condition in Equation (12) is satisfied when minimizing Y.

$$\left|\frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+1)}} - \tilde{\eta}_{k/(k+1)}\right| \leq 0 \quad and$$
$$\left|\frac{\tilde{\omega}_k}{\tilde{\omega}_{(k+2)}} - \tilde{\eta}_{k/(k+1)} \otimes \tilde{\eta}_{(k+1)/(k+2)}\right| \leq 0 \tag{12}$$

Finally, the optimum weights of the decision criteria can be obtained by solving the fuzzy nonlinear model in Equation (13).

$$\begin{cases} MIN\ Y \\ s.t. \\ \left|\dfrac{\tilde{\omega}_k}{\tilde{\omega}_{(k+1)}} - \tilde{\eta}_{k/(k+1)}\right| \leq Y, \forall j \\ \left|\dfrac{\tilde{\omega}_k}{\tilde{\omega}_{(k+1)}} - \tilde{\eta}_{k/(k+1)} \otimes \tilde{\eta}_{(k+1)/(k+2)}\right| \leq Y, \forall j \\ \sum_{j=1}^{n} \tilde{\omega}_j = 1, \\ \tilde{\omega}_j = (\tilde{\omega}_j^a, \tilde{\omega}_j^b, \tilde{\omega}_j^c), \\ \tilde{\omega}_j^a \geq 0, \forall j \quad and \quad j = 1, 2, \ldots\ldots\ldots, n \end{cases} \tag{13}$$

In this model $\tilde{\omega}_j = \left(\tilde{\omega}_j^a \leq \tilde{\omega}_j^b \leq \tilde{\omega}_j^c\right)$, and $\tilde{\eta}_{k/(k+1)} = \left(\tilde{\eta}_{k/(k+1)}^a, \tilde{\eta}_{k/(k+1)}^b, \tilde{\eta}_{k/(k+1)}^c\right)$ where $\tilde{\omega}_k$ *and* $\tilde{\eta}_{k/(k+1)}$ are triangular fuzzy numbers with a, b, and c denoting the lower, medium, and upper bounds of the triplet, respectively.

Phase II (Evaluation of the Suppliers): Keshavarz Ghorabaee et al. [16] introduced the basic CODAS method. This study improves the CODAS method using IRNs and nonlinear hybrid Dombi-Bonferroni functions in three major points; (1) Hybrid rough Dombi-Bonferroni functions are used for aggregation of expert preferences; (2) Dombi norms were applied to define the normalized weighted matrix elements; (3) The algorithm was adopted to apply a new concept for explaining the boundary intervals of rough numbers. Applying hybrid rough Dombi-Bonferroni functions allows for evaluating mutual relations between decision attributes and a more flexible decision-making considering the decision- makers' risk attitudes. Furthermore, the application of Dombi T-norms and T-conorms in the CODAS methodology improves the flexibility of the method, which, in turn, contributes to more objective reasoning in a dynamic environment. The computational procedure of the improved CODAS method can be described as follows.

Step 1: Creating an aggregated decision matrix ($\Im$). Suppose that b experts E_e $(e = 1, 2, \ldots, b)$ evaluate a total of m S_i $(i = 1, 2, \ldots, m)$ alternatives. Also, suppose that experts evaluate alternatives with a predefined set of n criteria C_j $(j = 1, 2, \ldots, n)$ using a predefined crisp scale. Then evaluation of alternatives with respect to each criterion by expert

TABLE 2. Weights used for criteria determination scale.

Linguistic term	Importance weight	TFN
Equally important	1	(1,1,1)
Weakly more important	2	(1,2,3)
Moderately more important	3	(2,3,4)
Moderately plus more important	4	(3,4,5)
Strongly more important	5	(4,5,6)
Strongly plus more important	6	(5,6,7)
Very strongly more important	7	(6,7,8)
Very strongly plus more important	8	(7,8,9)
Extremely more important	9	(9,9,9)

TABLE 3. Screened criteria.

Criteria	Description
Decreasing cost of sustainable products (C1)	The corporations' ability to reduce production and logistics costs, and the related overheads.
Availability of financial resources for promoting innovation (C2)	The availability of financial supports for implementing sustainable innovation and related initiatives.
Financial resumption of products (C3)	Employing a variety of activities from reusing and repurposing to recycling, to extend the product value and improve circularity.
Enhanced sustainability value to customers (C4)	Value creation for clients through reducing the price, enhancing the product's functions, among other benefits.
Finance in R&D (C5)	The financial resources accessibility to carry out research and development activities for the design, production, and distribution of sustainable products.
Production of sustainable products for diminishing material consumption (C6)	Applying sustainability standards that reduce material usage in the production and energy usage in the logistics processes.

k is denoted by $\left(\zeta_{ij}^{k};\zeta_{ij}^{k'}\right)$, where $i=1,\ldots,m; j=1,\ldots,n$ and $\zeta_{ij}^{k},\zeta_{ij}^{k'}$ are the linguistic terms.

Considering the obtained values from each expert, k $(1\leq k\leq b)$, two initial matrices $\Im^{k(l)}=\left[\zeta_{ij}^{k(l)}\right]_{m\times n}$ and $\Im^{k(u)}=\left[\zeta_{ij}^{k(u)}\right]_{m\times n}$ should be prepared. On this basis two groups of sequences $\zeta_{ij}^{(l)}=\left\{\zeta_{ij}^{1(l)},\zeta_{ij}^{2(l)},\ldots,\zeta_{ij}^{b(l)}\right\}$ and $\zeta_{ij}^{(u)}=\left\{\zeta_{ij}^{1(u)},\zeta_{ij}^{2(u)},\ldots,\zeta_{ij}^{b(u)}\right\}$ can be distinguished based on which, one can define the lower $\zeta_{ij}^{(l)k}$ and upper interval limit $\zeta_{ij}^{(u)k}$; the class limits should satisfy the condition that $\zeta_{ij}^{(l)1}\leq\zeta_{ij}^{(l)2}\leq,\ldots,\leq\zeta_{ij}^{(l)b},\zeta_{ij}^{(u)1}\leq\zeta_{ij}^{(u)2}\leq,\ldots,\leq\zeta_{ij}^{(u)b}$, $(1\leq i\leq m; 1\leq j\leq n)$. Then two sets containing the lower class $\zeta^{(l)}=(\zeta_{ij}^{(l)1},\zeta_{ij}^{(l)2},\ldots,\zeta_{ij}^{(l)b})$ and the upper class $\zeta^{(u)}=(\zeta_{ij}^{(u)1},\zeta_{ij}^{(u)2},\ldots,\zeta_{ij}^{(u)b})$ are formed. Lower and upper approximation of $\zeta_{ij}^{(l)k}$ and $\zeta_{ij}^{(u)k}$ are defined as follows.

$$\underline{Apr}(\zeta_{ij}^{(l)k})=\bigcup_{1\leq i\leq b}\left\{\varphi\in\Im/\zeta^{(l)}(\varphi)\leq\zeta_{ij}^{(l)k}\right\};\underline{Apr}(\zeta_{ij}^{(u)k})=\bigcup_{1\leq i\leq b}\left\{\varphi\in\Im/\zeta^{(l)}(\varphi)\leq\zeta_{ij}^{(u)k}\right\}\quad(14)$$

$$\overline{Apr}(\zeta_{ij}^{(l)k})=\bigcup_{1\leq i\leq b}\left\{\varphi\in\Im/\zeta^{(l)}(\varphi)\geq\zeta_{ij}^{(l)k}\right\};\overline{Apr}(\zeta_{ij}^{(u)k})=\bigcup_{1\leq i\leq b}\left\{\varphi\in\Im/\zeta^{(l)}(\varphi)\geq\zeta_{ij}^{(u)k}\right\}\quad(15)$$

Given the lower and upper approximations, one can define their lower limits ($\underline{\zeta}_{ij}^{(l)k}$ and $\underline{\zeta}_{ij}^{(u)k}$) and upper limits ($\overline{\zeta}_{ij}^{(l)k}$ and $\overline{\zeta}_{ij}^{(u)k}$) using Equations as in (16)–(19), shown at the bottom of the page.

These Equations transform the expert sequences $\left(\zeta_{ij}^{k}; \zeta_{ij}^{k'}\right)$ into the interval rough number $\zeta_{ij}^{k} = \left(\left[\underline{\zeta}_{ij}^{(l)k}, \overline{\zeta}_{ij}^{(l)k}\right], \left[\underline{\zeta}_{ij}^{(u)k}, \overline{\zeta}_{ij}^{(u)k}\right]\right)$. Notably, the correspondent initial decision matrix $\Im^{k} = \left[\zeta_{ij}^{k}\right]_{m\times n}$ are obtained from every expert, where $\zeta_{ij}^{k} = \left(\left[\underline{\zeta}_{ij}^{(l)k}, \overline{\zeta}_{ij}^{(l)k}\right], \left[\underline{\zeta}_{ij}^{(u)k}, \overline{\zeta}_{ij}^{(u)k}\right]\right)$. Finally, the rough Dombi-Bonferroni interval operator in Equation (20) is used to compute the fusion of expert matrices $\Im^{k}$ and the aggregated initial decision matrix $\Im = [\zeta_{ij}]_{m\times n}$, $\zeta_{ij} = \left(\left[\underline{\zeta}_{ij}^{(l)}, \overline{\zeta}_{ij}^{(l)}\right], \left[\underline{\zeta}_{ij}^{(u)}, \overline{\zeta}_{ij}^{(u)}\right]\right)$ as in (20), shown at the bottom of the next page, where

$$f\left(\zeta_i\right) = \left(\left[f\left(\underline{\zeta}_i^{(l)}\right), f\left(\overline{\zeta}_i^{(l)}\right)\right], \left[f\left(\underline{\zeta}_i^{(u)}\right), f\left(\overline{\zeta}_i^{(u)}\right)\right]\right) = \left(\left[\frac{\underline{\zeta}_i^{(l)}}{\sum_{i=1}^{m}\underline{\zeta}_i^{(l)}}, \frac{\overline{\zeta}_i^{(l)}}{\sum_{i=1}^{m}\overline{\zeta}_i^{(l)}}\right], \left[\frac{\underline{\zeta}_i^{(u)}}{\sum_{i=1}^{m}\underline{\zeta}_i^{(u)}}, \frac{\overline{\zeta}_i^{(u)}}{\sum_{i=1}^{m}\overline{\zeta}_i^{(u)}}\right]\right)$$

represents a rough additive function.

Step 2 (Normalization of the Aggregated Matrix): Equation (21) is employed to calculate the normalized IRN matrix elements $\hat{\Im} = [\hat{\zeta}_{ij}]_{m\times n}$.

$$\hat{\zeta}_{ij} = \begin{cases} \dfrac{\zeta_{ij}}{\zeta^{+}} = \left(\left[\dfrac{\underline{\zeta}_{ij}^{(l)}}{\zeta^{+}}, \dfrac{\overline{\zeta}_{ij}^{(l)}}{\zeta^{+}}\right], \left[\dfrac{\underline{\zeta}_{ij}^{(u)}}{\zeta^{+}}, \dfrac{\overline{\zeta}_{ij}^{(u)}}{\zeta^{+}}\right]\right); & if\ j \in B, \\ \dfrac{\zeta^{-}}{\zeta_{ij}} = \left(\left[\dfrac{\zeta^{-}}{\overline{\zeta}_{ij}^{(u)}}, \dfrac{\zeta^{-}}{\underline{\zeta}_{ij}^{(u)}}\right], \left[\dfrac{\zeta^{-}}{\overline{\zeta}_{ij}^{(l)}}, \dfrac{\zeta^{-}}{\underline{\zeta}_{ij}^{(l)}}\right]\right); & if\ j \in C \end{cases} \tag{21}$$

where $\zeta^{+} = \max\limits_{1\le i\le m}\left(\underline{\zeta}_{ij}^{(u)}\right)$, $\zeta^{-} = \min\limits_{1\le i\le m}\left(\underline{\zeta}_{ij}^{(l)}\right)$.

Step 3 (Computing Weighted Decision Matrix): Equation as in (22), shown at the bottom of the next page, is used to calculate the weighted matrix, where w_j indicates the vector of weight coefficients and $\zeta_{ij} = \left(\left[\underline{\gamma}_{ij}^{(l)}, \overline{\gamma}_{ij}^{(l)}\right], \left[\underline{\gamma}_{ij}^{(u)}, \overline{\gamma}_{ij}^{(u)}\right]\right)$ indicates the elements' weighted normalized matrix $R = \left[\zeta_{ij}\right]_{m\times n}$.

Step 4 (Calculate weighted Euclidean ($\overline{\overline{ED}}_i$) and IRN weighted Hamming ($\overline{\overline{HD}}_i$) distances): Negative Ideal Point (NIP) is the basis of calculating Euclidean

$$\underline{\zeta}_{ij}^{(l)k} = \frac{\sum\limits_{t=1}^{n}\zeta_{ijt}^{(l)k}}{1+\left\{\dfrac{1}{\chi_1+\chi_2}\dfrac{n(n-1)}{\sum\limits_{\substack{x,y=1\\x\neq y}}^{n}\dfrac{1}{\left(\chi_1\left(\left(1-f\left(\zeta_i^{(l)(x)}\right)\right)/f\left(\zeta_i^{(l)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\zeta_j^{(l)(y)}\right)\right)/f\left(\zeta_j^{(l)(y)}\right)\right)^{\phi}\right)}}\right\}^{1/\phi}}\Bigg|\zeta_i^{(l)(x)}, \zeta_j^{(l)(y)} \in \underline{Apr}(\zeta_{ij}^{(l)k}) \tag{16}$$

$$\underline{\zeta}_{ij}^{(u)k} = \frac{\sum\limits_{t=1}^{n}\zeta_{ijt}^{(u)k}}{1+\left\{\dfrac{1}{\chi_1+\chi_2}\dfrac{n(n-1)}{\sum\limits_{\substack{x,y=1\\x\neq y}}^{n}\dfrac{1}{\left(\chi_1\left(\left(1-f\left(\zeta_i^{(u)(x)}\right)\right)/f\left(\zeta_i^{(u)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\zeta_j^{(u)(y)}\right)\right)/f\left(\zeta_j^{(u)(y)}\right)\right)^{\phi}\right)}}\right\}^{1/\phi}}\Bigg|\zeta_i^{(u)(x)}, \zeta_j^{(u)(y)} \in \underline{Apr}(\zeta_{ij}^{(u)k}) \tag{17}$$

$$\overline{\zeta}_{ij}^{(l)k} = \frac{\sum\limits_{t=1}^{n}\zeta_{ijt}^{(l)k}}{1+\left\{\dfrac{1}{\chi_1+\chi_2}\dfrac{n(n-1)}{\sum\limits_{\substack{x,y=1\\x\neq y}}^{n}\dfrac{1}{\left(\chi_1\left(\left(1-f\left(\zeta_i^{(l)(x)}\right)\right)/f\left(\zeta_i^{(l)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\zeta_j^{(l)(y)}\right)\right)/f\left(\zeta_j^{(l)(y)}\right)\right)^{\phi}\right)}}\right\}^{1/\phi}}\Bigg|\zeta_i^{(l)(x)}, \zeta_j^{(l)(y)} \in \overline{Apr}(\zeta_{ij}^{(l)k} \tag{18}$$

$$\overline{\zeta}_{ij}^{(u)k} = \frac{\sum\limits_{t=1}^{n}\zeta_{ijt}^{(u)k}}{1+\left\{\dfrac{1}{\chi_1+\chi_2}\dfrac{n(n-1)}{\sum\limits_{\substack{x,y=1\\x\neq y}}^{n}\dfrac{1}{\left(\chi_1\left(\left(1-f\left(\zeta_i^{(u)(x)}\right)\right)/f\left(\zeta_i^{(u)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\zeta_j^{(u)(y)}\right)\right)/f\left(\zeta_j^{(u)(y)}\right)\right)^{\phi}\right)}}\right\}^{1/\phi}}\Bigg|\zeta_i^{(u)(x)}, \zeta_j^{(u)(y)} \in \overline{Apr}(\zeta_{ij}^{(u)k} \tag{19}$$

and Hamming distances, which is determined using Equation (23).

$$NIP_j = \min_{1\le i\le m}\{\zeta_{ij}\} = \left(\left[\min_{1\le i\le m}\left\{\underline{\gamma}_{ij}^{(l)}\right\}, \min_{1\le i\le m}\left\{\overline{\gamma}_{ij}^{(l)}\right\}\right], \left[\min_{1\le i\le m}\left\{\underline{\gamma}_{ij}^{(u)}\right\}, \min_{1\le i\le m}\left\{\overline{\gamma}_{ij}^{(u)}\right\}\right]\right) \tag{23}$$

where ζ_{ij} represents the weighted normalized matrix elements. On this basis, Euclidean (ED_i) and Hamming distance (HD_i) can be calculated using Equations (24)- (27).

a) Euclidean distance (ED_i)

$$ED_i = \sum_{j=1}^{n} d^E\left(\hat{\gamma}_{ij}; NIP_j\right) \tag{24}$$

where as in (25), shown at the bottom of the next page.

b) Hamming distance (HD_i)

$$HD_i = \sum_{j=1}^{n} d^H\left(\hat{\gamma}_{ij}; NIP_j\right) \tag{26}$$

where as in (27), shown at the bottom of the next page.

$$\zeta_{ij} = \left(\left[\frac{\sum_{t=1}^{n}\underline{\zeta}_{ijt}^{(l)}}{\left\{1+\frac{1}{\chi_1+\chi_2}\frac{n(n-1)}{\sum_{\substack{x,y=1\\x\neq y}}^{n}\frac{1}{\chi_1\left(\left(1-f\left(\underline{\zeta}_i^{(l)(x)}\right)\right)/f\left(\underline{\zeta}_i^{(l)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\underline{\zeta}_j^{(l)(y)}\right)\right)/f\left(\underline{\zeta}_j^{(l)(y)}\right)\right)^{\phi}}}\right\}^{1/\phi}}, \frac{\sum_{t=1}^{n}\overline{\zeta}_{ijt}^{(l)}}{\left\{1+\frac{1}{\chi_1+\chi_2}\frac{n(n-1)}{\sum_{\substack{x,y=1\\x\neq y}}^{n}\frac{1}{\chi_1\left(\left(1-f\left(\overline{\zeta}_i^{(l)(x)}\right)\right)/f\left(\overline{\zeta}_i^{(l)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\overline{\zeta}_j^{(l)(y)}\right)\right)/f\left(\overline{\zeta}_j^{(l)(y)}\right)\right)^{\phi}}}\right\}^{1/\phi}}\right], \left[\frac{\sum_{t=1}^{n}\underline{\zeta}_{ijt}^{(u)}}{\left\{1+\frac{1}{\chi_1+\chi_2}\frac{n(n-1)}{\sum_{\substack{x,y=1\\x\neq y}}^{n}\frac{1}{\chi_1\left(\left(1-f\left(\underline{\zeta}_i^{(u)(x)}\right)\right)/f\left(\underline{\zeta}_i^{(u)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\underline{\zeta}_j^{(u)(y)}\right)\right)/f\left(\underline{\zeta}_j^{(u)(y)}\right)\right)^{\phi}}}\right\}^{1/\phi}}, \frac{\sum_{t=1}^{n}\overline{\zeta}_{ijt}^{(u)}}{\left\{1+\frac{1}{\chi_1+\chi_2}\frac{n(n-1)}{\sum_{\substack{x,y=1\\x\neq y}}^{n}\frac{1}{\chi_1\left(\left(1-f\left(\overline{\zeta}_i^{(u)(x)}\right)\right)/f\left(\overline{\zeta}_i^{(u)(x)}\right)\right)^{\phi}+\chi_2\left(\left(1-f\left(\overline{\zeta}_j^{(u)(y)}\right)\right)/f\left(\overline{\zeta}_j^{(u)(y)}\right)\right)^{\phi}}}\right\}^{1/\phi}}\right]\right) \tag{20}$$

$$\hat{\gamma}_{ij} = w_j \cdot \hat{\zeta}_{ij} = \left(\left[\underline{\xi}_{ij}^{(l)} - \frac{\underline{\xi}_{ij}^{(l)}}{1+\left\{w_j\left(\frac{f\left(\underline{\xi}_{ij}^{(l)}\right)}{1-f\left(\underline{\xi}_{ij}^{(l)}\right)}\right)^{\phi}\right\}^{1/\phi}}, \overline{\xi}_{ij}^{(l)} - \frac{\overline{\xi}_{ij}^{(l)}}{1+\left\{w_j\left(\frac{f\left(\overline{\xi}_{ij}^{(l)}\right)}{1-f\left(\overline{\xi}_{ij}^{(l)}\right)}\right)^{\phi}\right\}^{1/\phi}}\right], \left[\underline{\xi}_{ij}^{(u)} - \frac{\underline{\xi}_{ij}^{(u)}}{1+\left\{w_j\left(\frac{f\left(\underline{\xi}_{ij}^{(u)}\right)}{1-f\left(\underline{\xi}_{ij}^{(u)}\right)}\right)^{\phi}\right\}^{1/\phi}}, \overline{\xi}_{ij}^{(u)} - \frac{\overline{\xi}_{ij}^{(u)}}{1+\left\{w_j\left(\frac{f\left(\overline{\xi}_{ij}^{(u)}\right)}{1-f\left(\overline{\xi}_{ij}^{(u)}\right)}\right)^{\phi}\right\}^{1/\phi}}\right]\right) \tag{22}$$

Step 5 (Determine Relative Assessment (RA) matrix and alternatives final ranking): The elements of the RA matrix can be calculated using Equation (28).

$$\eta_{iz} = (ED_i - ED_z) + (\tau\,(ED_i - ED_z) \times (HD_i - HD_z))\,; \quad i, z \in \{1, 2, \ldots, m\} \tag{28}$$

where τ represents the threshold parameter is determined by the expert. Keshavarz Ghorabaee et al. [16] suggested a threshold of 0.02 for describing the initial solution. Finally, the aggregation of the RA matrix's elements results in the assessment score ($\aleph_i$) for every alternative (see Equation (25)).

$$\aleph_i = \sum_{z=1}^{m} \eta_{iz} \tag{29}$$

The dominance of the alternatives is determined according to their $\aleph_i$, with larger values being more desirable.

IV. RESULTS ANALYSIS

A. THE CASE PROBLEM DESCRIPTION

A case study in an emerging economy in the Middle East is conducted to explore the economic sustainable innovativeness considerations in assessing the suppliers. Sustainable development initiatives in the region are still in the early implementation stages [8]. The case company is a leading automotive factory in the region and buys parts and raw material from an array of international suppliers; it was founded several years ago and has been manufacturing various vehicles for the domestic market and exportation to several Asian countries.

A team of five managers from purchasing, maintenance, financial, logistics and production planning departments has agreed to be involved in our study and assist in the assessment. These managers, hereafter named as our experts, had at least 12 years of working experience in the time of interviewing them. In addition to providing insights in the modeling phase of our study, the experts shortlisted their best five suppliers to take part in this work.

B. SCREENING PROCESS

A questionnaire considering the factors listed in **Table 1** was submitted to the experts for review in several rounds. The experts were asked to determine the criteria which were pertinent to their operations by denoting them as either accepted (Yes) or rejected (No). Experts were asked to recommend different or additional economic sustainability innovation factor. The experts agreed that the criteria confirmed by at least three of the panel will be taken into consideration in the next review round. Generally, three rounds were accomplished in the process of screening the criteria, based on which six criteria were selected (see **Table 3**). The same screening approach has been applied in the academic literature [12], [48], where expert input was used to identify whether a particular criterion needs to be considered in the assessment phase.

C. APPLICATION OF FFUCOM-ICODAS

Experts were asked to provide their opinion in both identifying the evaluation criteria weight and scoring the alternatives. In Phase I, experts state their comparative priorities on a scale of [1], [2], [3], [4], [5], [6], [7], [8], and [9] as per their domain knowledge. Their preferences were then converted into corresponding linguistic expressions (see **Table 2**). Next, the criteria were sorted considering the comparative evaluation, as presented in **Table 4.**

As an example, the comparative priorities of economic innovation criteria for Expert 1 have been defined as follows:

$$\tilde{\eta}_{C1/C6} = \tilde{\sigma}_{C1} \big/ \tilde{\sigma}_{C6} = (2, 3, 4) \big/ (1, 1, 1) = (2, 3, 4)$$
$$\tilde{\eta}_{C6/C4} = \tilde{\sigma}_{C6} \big/ \tilde{\sigma}_{C4} = (3, 4, 5) \big/ (2, 3, 4) = (0.75, 1.33, 2.50)$$
$$\tilde{\eta}_{C4/C2} = \tilde{\sigma}_{C4} \big/ \tilde{\sigma}_{C2} = (5, 6, 7) \big/ (3, 4, 5) = (1.00, 1.50, 2.33)$$
$$\tilde{\eta}_{C2/C3} = \tilde{\sigma}_{C2} \big/ \tilde{\sigma}_{C3} = (6, 7, 8) \big/ (5, 6, 7) = (0.86, 1.17, 1.60)$$
$$\tilde{\eta}_{C3/C5} = \tilde{\sigma}_{C3} \big/ \tilde{\sigma}_{C5} = (7, 8, 9) \big/ (6, 7, 8) = (0.88, 1.14, 1.50)$$

Next, the fuzzy vector of the comparative priorities of the decision criteria is calculated,

$$\tilde{\eta} = [(2, 3, 4), (0.75, 1.33, 2.50), (1.00, 1.50, 2.33), (0.86, 1.17, 1.60), (0.88, 1.14, 1.50)]\,.$$

To check if it satisfies the transitivity condition for the final values of the fuzzy weight coefficients, the following conditions has resulted from the relation mathematical transitivity.

$$\begin{aligned}\tilde{\eta}_{C1/C4} &= \tilde{\sigma}_{C1/C6} \otimes \tilde{\sigma}_{C6/C4} \\ &= (2, 3, 4)(0.75, 1.33, 2.50) \\ &= (1.50, 4.00, 10.00) \\ \tilde{\eta}_{C6/C2} &= \tilde{\sigma}_{C6/C4} \otimes \tilde{\sigma}_{C4/C2} \\ &= (0.75, 1.33, 2.50)(1, 1.50, 2.33)\end{aligned}$$

$$d^E\left(\hat{\gamma}_{ij}; NIP_j\right) = \sqrt{\frac{\left\{\underline{\gamma}_{ij}^{(l)} - \underline{NIP}_j\right\}^2 + \left\{\overline{\gamma}_{ij}^{(l)} - \overline{NIP}_j\right\}^2 + \left\{\underline{\gamma}_{ij}^{(u)} - \underline{NIP}_j\right\}^2 + \left\{\overline{\gamma}_{ij}^{(u)} - \overline{NIP}_j\right\}^2}{4}} \tag{25}$$

$$d^H\left(\hat{\gamma}_{ij}; NIP_j\right) = \frac{\left|\underline{\gamma}_{ij}^{(l)} - \underline{NIP}_j\right| + \left|\overline{\gamma}_{ij}^{(l)} - \overline{NIP}_j\right| + \left|\underline{\gamma}_{ij}^{(u)} - \underline{NIP}_j\right| + \left|\overline{\gamma}_{ij}^{(u)} - \overline{NIP}_j\right|}{4} \tag{27}$$

$$
\begin{aligned}
&= (0.75, 2.00, 5.83)\\
\tilde{\eta}_{C4/C3} &= \tilde{\sigma}_{C4/C2} \otimes \tilde{\sigma}_{C2/C3}\\
&= (1.00, 1.50, 2.33)(0.86, 1.17, 1.60)\\
&= (0.86, 1.75, 3.73)\\
\tilde{\eta}_{C2/C5} &= \tilde{\sigma}_{C2/C3} \otimes \tilde{\sigma}_{C3/C5}\\
&= (0.86, 1.17, 1.60)(0.88, 1.14, 1.50)\\
&= (0.75, 1.33, 2.40)
\end{aligned}
$$

Accordingly, the fuzzy nonlinear model shown below is solved to get the optimum fuzzy weights of the criteria. In this model, *a, b*, and *c* represent the lower-, medium-, and upper-bound values of a TFN.

Expert 1 (C1-C4) $\rightarrow$

$$
\min \chi
$$

$$
s.t.\ \begin{cases}
\left|\frac{w_1^l}{w_2^u} - 0.67\right| \le \chi;\ \left|\frac{w_1^m}{w_2^m} - 1.00\right| \le \chi;\ \left|\frac{w_1^u}{w_2^l} - 1.5\right| \le \chi;\\
\left|\frac{w_2^l}{w_3^u} - 2.33\right| \le \chi;\ \left|\frac{w_2^m}{w_3^m} - 4.00\right| \le \chi;\ \left|\frac{w_2^u}{w_3^l} - 6.72\right| \le \chi;\\
\left|\frac{w_3^l}{w_4^u} - 0.78\right| \le \chi;\ \left|\frac{w_3^m}{w_4^m} - 1.00\right| \le \chi;\ \left|\frac{w_3^u}{w_4^l} - 1.29\right| \le \chi;\\
\left|\frac{w_1^l}{w_3^u} - 1.56\right| \le \chi;\ \left|\frac{w_1^m}{w_3^m} - 4.00\right| \le \chi;\ \left|\frac{w_1^u}{w_3^l} - 10.07\right| \le \chi;\\
\left|\frac{w_2^l}{w_4^u} - 1.81\right| \le \chi;\ \left|\frac{w_2^m}{w_4^m} - 4.00\right| \le \chi;\ \left|\frac{w_2^u}{w_4^l} - 8.64\right| \le \chi;\\
(w_1^l + 4 \cdot w_1^m + w_1^u)/6 + (w_2^l + 4 \cdot w_2^m + w_2^u)/6\\
+(w_3^l + 4 \cdot w_3^m + w_3^u)/6 = 1;\ w_j^l \le w_j^m \le w_j^u,\\
\quad \forall j = 1, 2, \ldots, n\\
w_j^l, w_j^m, w_j^u \ge 0, \forall j = 1, 2, \ldots, n
\end{cases}
$$

LINGO 19.0 software was employed for solving above model, the optimal fuzzy weights of Expert 1 is:

$$
\begin{aligned}
\tilde{\omega}_{C1} &= (0.240, 0.483, 0.586)\ \tilde{\omega}_{C2}\\
&= (0.033, 0.0973, 0.112)\ \tilde{\omega}_{C3} = (0.047, 0.096, 0.096\\
\tilde{\omega}_{C4} &= (0.063, 0.127, 0.127)\ \tilde{\omega}_{C5}\\
&= (0.068, 0.109, 0.109)\ \tilde{\omega}_{C6} = (0.134, 0.144, 0.144)
\end{aligned}
$$

This procedure is completed considering the inputs from all experts. When solving the models, he objective values (Y) are around 0, indicating that there is a high level of consistency in the outcomes. Optimal fuzzy weights results and Average Optimal Fuzzy Weights (AOFW) of six criteria are summarized in **Table 5**. To obtain the corresponding average crisp value, the Graded Mean Integration Representation (GMIR), which is an effective defuzzification method, is employed to develop the fuzzified TFNs of the criteri.Given $\tilde{\omega}_k = (a_k, b_k, c_k)$ as a TFN, GMIR $R(\tilde{\omega}_k)$ can be computed using $R(\tilde{\omega}_k) = \frac{a_k+4b_k+c_k}{6}$. The global fuzzy values of the criterion weights and the average crisp weights are shown in **Fig. 2** and **Fig. 3**, respectively. The results of the F-FUCOM model show that "*Financial resumption of products (C3)*", with the weight of 0.190, is the most critical economic sustainability innovation criterion for evaluating suppliers and "*Enhanced sustainability value to customers (C4)*", with the weight of 0.100, is the least important criterion identified by experts. Criteria were ranked from the most- to least-significant, as follows:

$$
\omega_{C3} > \omega_{C2} = \omega_{C5} = \omega_{C6} > \omega_{C1} > \omega_{C4}
$$

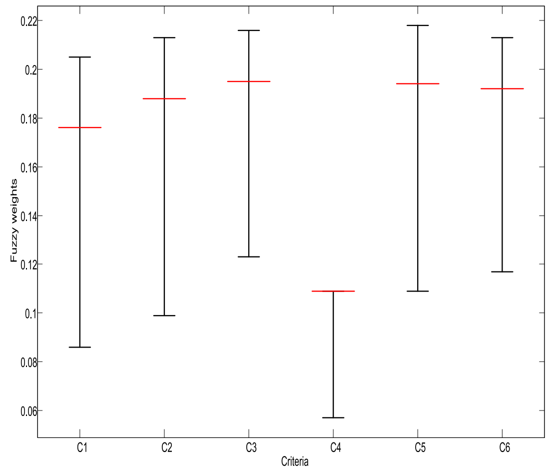

FIGURE 2. Final fuzzy values of weighting coefficients.

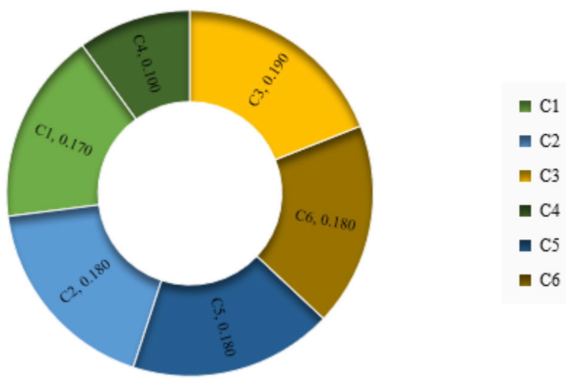

FIGURE 3. Average crisp weight for each criterion.

In the next phase, the interval rough Dombi-Bonferroni CODAS model is applied for evaluating suppliers. In the case study, five suppliers $S_i\ (i = 1, 2, \ldots, 5)$ are considered for the evaluation. Given the outcomes of phase I, the experts $E_e\ (e = 1, 2, \ldots, 5)$ expressed their preferences using a five-point scale: 1 – Very Low, 2 – Low, 3 – Medium, 4 – High, 5 – Very High. The computational procedure is summarized below.

The decision matrices are established by processing the inputs, shown in **Table 6**, where the experts presented their evaluation of alternatives using assessments pairs $\left(\zeta_{ij}^k; \zeta_{ij}^{k'}\right)$, $1 \le k \le 5$ such that uncertainty and imprecision in expert assessments is alleviated. If $\zeta_{ij}^k = \zeta_{ij}^{k'}$, there are no uncertainties in the expert assessment, while $\zeta_{ij}^k \ne \zeta_{ij}^{k'}$ indicates that there is a certain level of uncertainty/imprecisions, which is defined by the assessment interval (AI), $AI_{ij} = \zeta_{ij}^{k'} - \zeta_{ij}^k$.

TABLE 4. Comparative linguistic evaluation for each decision-maker.

DM1	Ranking	C1> C6> C4> C2> C3> C5					
	Criteria	C1	C6	C4	C2	C3	C5
	Linguistic terms	EI	MI	MMI	SMI	VMI	VSI
	TFN	(1, 1, 1)	(2, 3, 4)	(3,4,5)	(5,6,7)	(6,7,8)	(7,8,9)
DM2	Ranking	C5> C3> C4> C2> C1> C6					
	Criteria	C5	C3	C4	C2	C1	C6
	Linguistic terms	EI	MI	MMI	SMI	VMI	VSI
	TFN	(1, 1, 1)	(2, 3, 4)	(3,4,5)	(5,6,7)	(6,7,8)	(7,8,9)
DM3	Ranking	C2> C3> C5> C1> C4> C6					
	Criteria	C2	C3	C5	C1	C4	C6
	Linguistic terms	EI	MI	MMI	SI	VMI	EMI
	TFN	(1, 1, 1)	(2, 3, 4)	(3,4,5)	(4,5,6)	(6,7,8)	(9,9,9)
DM4	Ranking	C6> C5> C2> C1> C3> C4					
	Criteria	C6	C5	C2	C1	C3	C4
	Linguistic terms	EI	MI	SI	SMI	VMI	VSI
	TFN	(1,1,1)	(2, 3, 4)	(4,5,6)	(5,6,7)	(6,7,8)	(7,8,9)
DM5	Ranking	C3> C2> C6> C5> C4> C1					
	Criteria	C3	C2	C6	C5	C4	C1
	Linguistic terms	EI	MI	MMI	SMI	VMI	EMI
	TFN	(1,1,1)	(2, 3, 4)	(3,4,5)	(5,6,7)	(6,7,8)	(9,9,9)

Higher AI_{ij} values are indicative of greater uncertainty, and vice versa. On this basis, we noticed a significant level of uncertainty in the expert evaluations.

Next, Equations (14)- (19) are used to transform the estimation pairs $\left(\zeta_{ij}^{k};\zeta_{ij}^{k'}\right)$, $1 \le k \le 5$ from **Table 6** into interval rough numbers; *Appendix B* elaborates on the transformation procedure. Finally, the interval rough Dombi-Bonferroni function is used to aggregate the IRN values from the expert into the initial decision matrix $\Im = \left[\zeta_{ij}\right]_{5\times 6}$, which is illustrated in **Table 7**. In the aggregation of interval rough sequences, it is assumed that $\chi_1 = \chi_2 = \phi = 1$. After the transformation of the estimation pairs from **Table 7**, an example of the interval rough expert estimates (position S1-C1 of the initial matrix) is provided below.

$$\zeta_{11}^{1} = ([1.41, 2.27], [1.86, 3.43]);$$

$$\zeta_{11}^{2} = ([1.64, 3.00], [2.18, 4.00]);$$

$$\zeta_{11}^{3} = ([1.00, 1.64], [1.00, 2.18]);$$

$$\zeta_{11}^{4} = ([1.00, 1.64], [1.59, 2.62]);$$

$$\zeta_{11}^{5} = ([1.41, 2.27], [1.59, 2.62]).$$

The aggregation is done using Equation (16) as follows:
(1) Calculating the sequences of additive rough functions.

$$f\left(\underline{\zeta}_{11}^{(l)1}\right) = 2/6.46 = 0.218; f\left(\underline{\zeta}_{11}^{(l)2}\right) = 1.64/6.46 = 0.254; \ldots;$$

$$f\left(\underline{\zeta}_{11}^{(l)5}\right) = 1.141/6.46 = 0.218;$$

$$f\left(\overline{\zeta}_{11}^{(l)1}\right) = 2.27/10.83 = 0.210; f\left(\overline{\zeta}_{11}^{(l)2}\right) = 3/10.83 = 0.277; \ldots;$$

$$f\left(\overline{\zeta}_{11}^{(l)5}\right) = 2.27/10.83 = 0.210;$$

$$f\left(\underline{\zeta}_{11}^{(u)1}\right) = 1.86/8.21 = 0.122; f\left(\underline{\zeta}_{11}^{(u)2}\right) = 2.18/8.21 = 0.265; \ldots;$$

$$f\left(\underline{\zeta}_{11}^{(u)5}\right) = 1.59/8.21 = 0.193;$$

$$f\left(\overline{\zeta}_{11}^{(u)1}\right) = 3.43/14.84 = 0.231; f\left(\overline{\zeta}_{11}^{(u)2}\right) = 2.18/14.84 = 0.147; \ldots;$$

$$f\left(\overline{\zeta}_{11}^{(u)5}\right) = 2.62/14.84 = 0.176;$$

TABLE 5. Optimal fuzzy weights for all experts.

CR	DM1	DM2	DM3	DM4	DM5	AOFW
C1	(0.24,0.483,0.586)	(0.047,0.096,0.096)	(0.039,0.118,0.14)	(0.037,0.097,0.116)	(0.069,0.087,0.087)	(0.086,0.176,0.205)
C2	(0.033,0.0973,0.112)	(0.033,0.097,0.112)	(0.244,0.492,0.588)	(0.053,0.107,0.107)	(0.136,0.147,0.147)	(0.099,0.188,0.213)
C3	(0.047,0.096,0.096)	(0.134,0.144,0.144)	(0.134,0.147,0.147)	(0.053,0.093,0.093)	(0.245,0.493,0.598)	(0.123,0.195,0.216)
C4	(0.063,0.127,0.127)	(0.063,0.127,0.127)	(0.044,0.089,0.089)	(0.066,0.105,0.106)	(0.048,0.0984,0.0984)	(0.057,0.109,0.109)
C5	(0.068,0.109,0.109)	(0.24,0.483,0.586)	(0.063,0.129,0.129)	(0.14,0.151,0.151)	(0.0339,0.099,0.115)	(0.109,0.194,0.218)
C6	(0.134,0.144,0.144)	(0.067,0.109,0.11)	(0.063,0.08,0.08)	(0.259,0.496,0.604)	(0.0648,0.129,0.129)	(0.117,0.192,0.213)

(2) Calculation of Dombi sequences.

$$\frac{1-f\left(\underline{\zeta}_{11}^{(l)1}\right)}{f\left(\underline{\zeta}_{11}^{(l)1}\right)} = 3.58; \frac{1-f\left(\underline{\zeta}_{11}^{(l)2}\right)}{f\left(\underline{\zeta}_{11}^{(l)2}\right)} = 2.93; \ldots; \frac{1-f\left(\overline{\zeta}_{11}^{(u)5}\right)}{f\left(\overline{\zeta}_{11}^{(u)5}\right)} = 4.67$$

(3) Calculation of the aggregate values using the Dombi-Bonferroni function, as shown in the equation at the bottom of the next page.

A similar aggregation procedure is applied for the remainder of the elements of the initial decision matrix. In the next step, the elements of the aggregated matrix are normalized, as shown in the equation at the bottom of the next page.

On this basis, the weighted normalized IRN matrix can be obtained by multiplying the weight coefficients by the Dombi values of the elements in the normalized matrix, as shown in the equation at the bottom of the next page, where the element γ_{11} are defined as follows.

$$\hat{\gamma}_{11} = \begin{cases} \underline{\gamma}_{11}^{(l)} = 0.298 - \dfrac{0.298}{1+\left\{0.1658\left(\frac{0.127}{1-0.127}\right)^1\right\}^{1/1}} = 0.007; \\ \overline{\gamma}_{11}^{(l)} = 0.496 - \dfrac{0.496}{1+\left\{0.1658\left(\frac{0.145}{1-0.145}\right)^1\right\}^{1/1}} = 0.014; \\ \underline{\gamma}_{11}^{(u)} = 0.375 - \dfrac{0.375}{1+\left\{0.1658\left(\frac{0.111}{1-0.111}\right)^1\right\}^{1/1}} = 0.008; \\ \overline{\gamma}_{11}^{(u)} = 0.682 - \dfrac{0.682}{1+\left\{0.1658\left(\frac{0.152}{1-0.152}\right)^1\right\}^{1/1}} = 0.020; \end{cases}$$
$$= ([0.007, 0.014], [0.008, 0.020])$$

As a final step, Euclidean (ED_i) and Hamming (HD_i) distances are calculated based on negative ideal points as follows.

$$NIP_1 = ([0.007, 0.014], [0.008, 0.020]);$$
$$NIP_2 = ([0.011, 0.018], [0.021, 0.025]);$$
$$NIP_3 = ([0.013, 0.026], [0.023, 0.031]);$$
$$NIP_4 = ([0.006, 0.009], [0.012, 0.017]);$$
$$NIP_5 = ([0.011, 0.026], [0.021, 0.031]);$$
$$NIP_6 = ([0.009, 0.018], [0.010, 0.028]).$$

$$ED_i = \begin{array}{c} S1 \\ S2 \\ S3 \\ S4 \\ S5 \end{array} \begin{bmatrix} 0.047 \\ 0.057 \\ 0.112 \\ 0.079 \\ 0.040 \end{bmatrix}; \quad HD_i = \begin{array}{c} S1 \\ S2 \\ S3 \\ S4 \\ S5 \end{array} \begin{bmatrix} 0.040 \\ 0.053 \\ 0.105 \\ 0.073 \\ 0.033 \end{bmatrix}$$

As an example, the first element of the Euclidean distance ED_1 and Hamming distance HD_1 are obtained using $ED_1 = \sum_{j=1}^{6} (0.00 + 0.0216 + 0.0095 + 0.0038 + 0.0117 + 0.0002) = 0.047$ and $HD_1 = \sum_{j=1}^{6}(0.00 + 0.0201 + 0.0067 + 0.0031 + 0.0104 + 0.0001) = 0.040$, respectively. where, , as shown in the equation at the bottom of the next page, and, as shown in the equation at the bottom of the next page.

Given the Euclidean and Hamming distances, the elements of the RA matrix obtained are calculated.

$$RA = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \end{array} \begin{array}{c} \begin{array}{ccccc} S_1 & S_2 & S_3 & S_4 & S_5 \end{array} \\ \begin{bmatrix} 0.000 & -0.011 & -0.130 & -0.064 & 0.006 \\ 0.011 & 0.000 & -0.107 & -0.041 & 0.017 \\ 0.130 & 0.107 & 0.000 & 0.065 & 0.144 \\ 0.064 & 0.041 & -0.065 & 0.000 & 0.079 \\ -0.006 & -0.017 & -0.144 & -0.079 & 0.000 \end{bmatrix} \end{array}$$

where element η_{12} in the RA matrix is calculated by $\eta_{12} = (0.047 - 0.057) + (0.02 \cdot (0.047 - 0.057) \cdot (0.040 - 0.053)) = -0.011$.

Given $\tau = 0.02$ as the threshold parameter, summing the elements of the RA matrix results in the assessment score of the alternatives; $\aleph_i = \begin{array}{c} S1 \\ S2 \\ S3 \\ S4 \\ S5 \end{array} \begin{bmatrix} -0.198 \\ -0.120 \\ 0.445 \\ 0.119 \\ -0.246 \end{bmatrix}$. The dominance of the suppliers is now defined based on $\aleph_i$ values, where the alternative with the highest score is preferred, S3 $>$ S4 $>$ S2 $>$ S1 $>$ S5, and S3 is identified as the best-performing supplier.

D. STABILITY ANALYSIS

In this subsection, the stability of the obtained solution is verified against input changes considering two measures, the threshold parameter (τ) and the values of the stabilization parameters of the Dombi Bonferroni function. It is of particular interest to analyze the influence of the parameter changes and subjectivity on the decision outcomes.

Phase I (Threshold Parameter (τ)): The threshold parameter $\tau \in [0, 1]$ is used to calculate RA elements. Keshavarz Ghorabaee et al. [16] suggested to use $\tau = 0.02$ for defining the initial elements of the RA matrix. Given the subjectivity involved in defining this parameter, 100 alternative scenarios were considered to analyze its impact. In the first scenario, the value of $\tau = 0.00$ was considered and the subsequent scenarios increased by 0.01. The dependency of the assessment score on changing the threshold parameter is shown in **Fig. 4**.

It can be observed that the assessment score of alternatives is dependent on the value of the threshold parameter only in a certain interval. That is, for values between 0 and 0.07, the assessment score of alternatives S3 and S4 is decreasing

$$\zeta_{11} = \begin{cases} \underline{\zeta}_{11}^{(l)} = \dfrac{1.00 + 1.00 + 1.41 + 1.41 + 1.64}{1 + \left\{ \frac{1}{1+1} \frac{5(5-1)}{\left(\frac{1}{5.46} + \frac{1}{5.46}\right)^1 + \left(\frac{1}{5.46} + \frac{1}{3.58}\right)^1 + \ldots + \left(\frac{1}{2.93} + \frac{1}{3.58}\right)^1 + \left(\frac{1}{2.93} + \frac{1}{3.58}\right)^1} \right\}^{1/1}} = 1.27; \\ \ldots \\ \overline{\zeta}_{11}^{(\hat{u})} = \dfrac{2.18 + 2.62 + 2.62 + 3.43 + 4.00}{1 + \left\{ \frac{1}{1+1} \frac{5(5-1)}{\left(\frac{1}{5.81} + \frac{1}{4.67}\right)^1 + \left(\frac{1}{5.81} + \frac{1}{4.67}\right)^1 + \ldots + \left(\frac{1}{2.71} + \frac{1}{4.67}\right)^1 + \left(\frac{1}{2.71} + \frac{1}{3.33}\right)^1} \right\}^{1/1}} = 2.89. \end{cases}$$
$$= ([1.27, 2.11], [1.59, 2.89])$$

$$\overline{\Im} = \begin{array}{c} \\ S1 \\ S2 \\ S3 \\ S4 \\ S5 \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_5 \end{array} \\ \begin{bmatrix} ([0.298, 0.496], [0.375, 0.682]) & ([0.657, 0.836], [0.670, 1.000]) & \ldots & ([0.286, 0.516], [0.376, 0.741]) \\ ([0.481, 0.826], [0.729, 1.000]) & ([0.395, 0.576], [0.655, 0.748]) & \ldots & ([0.280, 0.585], [0.510, 0.821]) \\ ([0.557, 0.808], [0.781, 0.985]) & ([0.366, 0.722], [0.638, 0.994]) & \ldots & ([0.577, 0.780], [0.799, 1.000]) \\ ([0.542, 0.744], [0.781, 0.985]) & ([0.673, 0.909], [0.843, 0.968]) & \ldots & ([0.280, 0.585], [0.510, 0.821]) \\ ([0.479, 0.544], [0.721, 0.845]) & ([0.399, 0.637], [0.588, 0.872]) & \ldots & ([0.375, 0.603], [0.608, 0.824]) \end{bmatrix} \end{array}$$

$$R = \begin{array}{c} \\ S1 \\ S2 \\ S3 \\ S4 \\ S5 \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_5 \end{array} \\ \begin{bmatrix} ([0.007, 0.014], [0.008, 0.020]) & ([0.039, 0.041], [0.028, 0.047]) & \cdots & ([0.010, 0.018], [0.010, 0.028]) \\ ([0.020, 0.041], [0.032, 0.045]) & ([0.013, 0.018], [0.027, 0.025]) & \cdots & ([0.009, 0.024], [0.020, 0.035]) \\ ([0.027, 0.039], [0.037, 0.044]) & ([0.011, 0.030], [0.025, 0.047]) & \cdots & ([0.046, 0.046], [0.054, 0.054]) \\ ([0.026, 0.033], [0.037, 0.044]) & ([0.041, 0.050], [0.047, 0.044]) & \cdots & ([0.009, 0.024], [0.020, 0.035]) \\ ([0.019, 0.017], [0.031, 0.031]) & ([0.013, 0.023], [0.021, 0.035]) & \cdots & ([0.017, 0.026], [0.029, 0.035]) \end{bmatrix} \end{array}$$

$$d^E(\zeta_{11}; NIP_1)) = \sqrt{\frac{\{0.007 - 0.007\}^2 + \{0.014 - 0.014\}^2 + \{0.008 - 0.008\}^2 + \{0.020 - 0.020\}^2}{4}} = 0.00$$

$$d^H(\zeta_{11}; NIP_1)) = \frac{|0.007 - 0.007| + |0.014 - 0.014| + |0.008 - 0.008| + |0.020 - 0.020|}{4} = 0.00$$

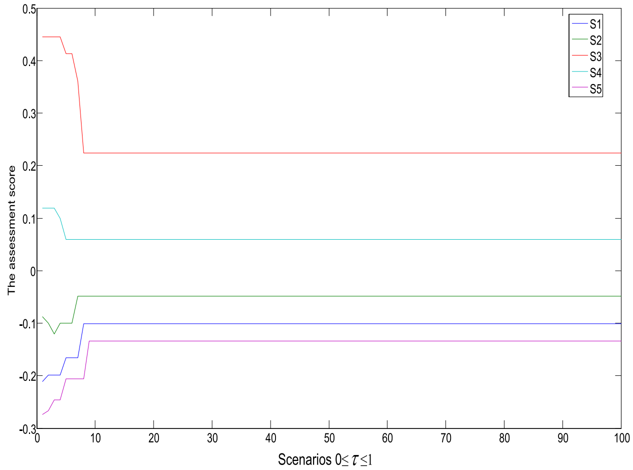

FIGURE 4. **Influence of threshold parameter τ on the ranking results.**

and those of S2, S1, and S5 is increasing. For the rest of the values, i.e. $0.07 < \tau \leq 1.0$, there are no changes in the assessment score of the alternatives. Therefore, it can be concluded that the threshold parameter affects the stability of the initial solution, but the initial solution does not depend on its value. It is worthwhile emphasizing that the results cannot be generalized; the results in future studies, applying our developed method, may require a similar analysis.

Phase II (Stabilization Parameter ($\chi 1$, $\chi 2$, and ϕ)): Parameters χ_1 and χ_2 are applied to define the rough Bonferroni function and the parameter ϕ determines the Dombi norms. As stated before, the hybrid rough Dombi Bonferroni function transforms expert estimates into interval rough equivalents with a rough boundary interval representing the difference between lower and upper limits in the rough sequences. $X_1 = \chi_2 = \phi = 1$ was considered for computing the initial values of the interval rough sequences in the initial decision matrix and the initial values of the rough boundary interval. **Fig. 5** shows the dependence of the assessment score in alternatives S1 and S3 considering the change in χ_1 and χ_2. The parameter changes were analyzed in interval $1 \leq \chi_1$ and $\chi_2 \leq 100$. A similar relationship exists for the assessment score of other alternatives, as shown in **Fig. 6.**

Results show that increasing the χ_1 and χ_2 results in a change in the values of criterion. But, notwithstanding having a considerable gain in information uncertainty, there was no indication of deviating from the primary solution. Therefore, we can be sure that the outcome is stable regardless of the risk level in the decision-making process. In a similar approach, 100 alternative scenarios were considered for ϕ to analyze the impact parameter change in interval $1 \leq \phi \leq 100$; results are provided in **Fig.** 7. A similar dependence analysis with the remaining alternatives is provided in **Fig. 8**. The results from **Fig. 8** show that the supplier 3 and supplier 4 kept their dominance throughout the scenarios and supplier 5 remained the worst supplier. However, supplier 2 and supplier 1 exchanged their ranking in interval $54 \leq \phi \leq 100$.

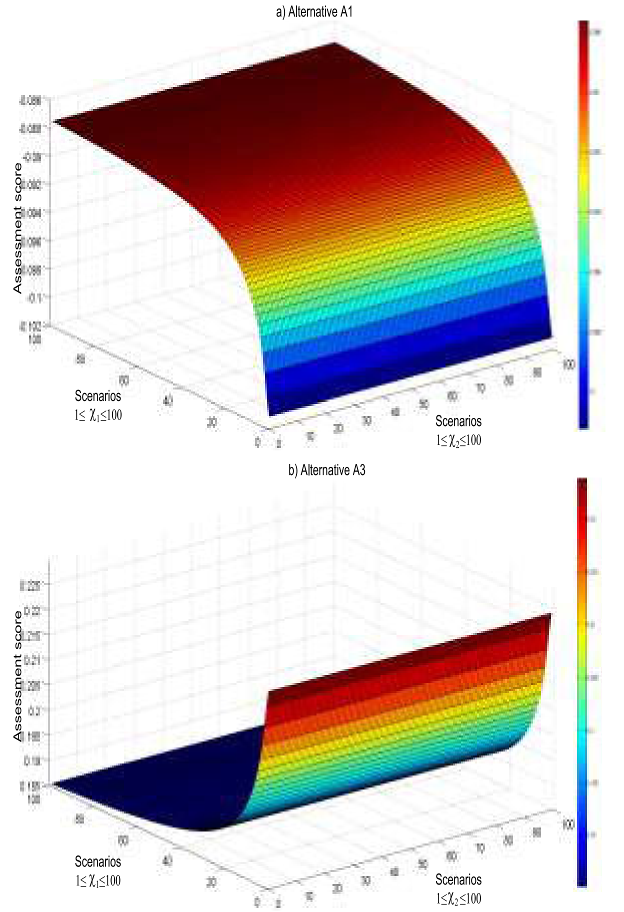

FIGURE 5. **Dependence of the assessment score (alternatives S1 and S3) on χ_1 and χ_2 changes.**

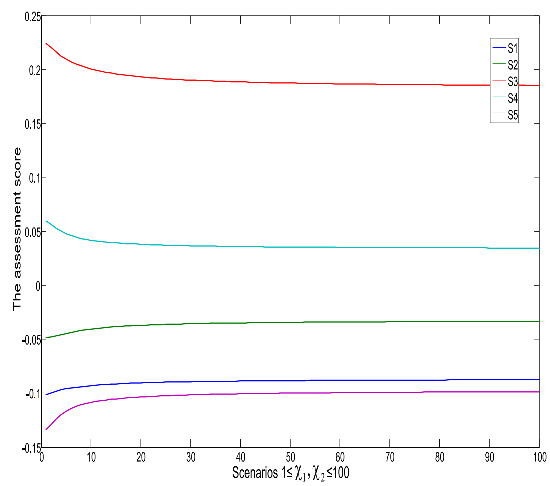

FIGURE 6. **Dependence of the assessment score on stabilization parameter changes (χ_1 and χ_2).**

V. COMPARING RESULTS WITH OTHER MCDM APPROACHES

This section compares the interval rough Dombi CODAS results with other methodologies developed to solve the supplier selection problem. For comparison, four studies with different approaches were selected as benchmarks: 1) fuzzy TOPSIS methodology [10]; 2) BWM-PROMETHEE

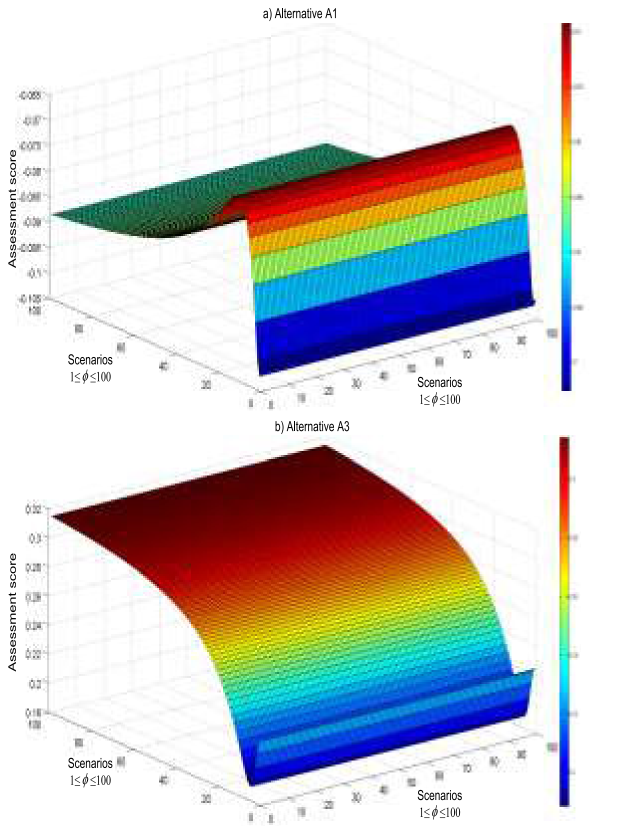

FIGURE 7. Assessment score dependence (alternatives S1 and S3) on ϕ changes.

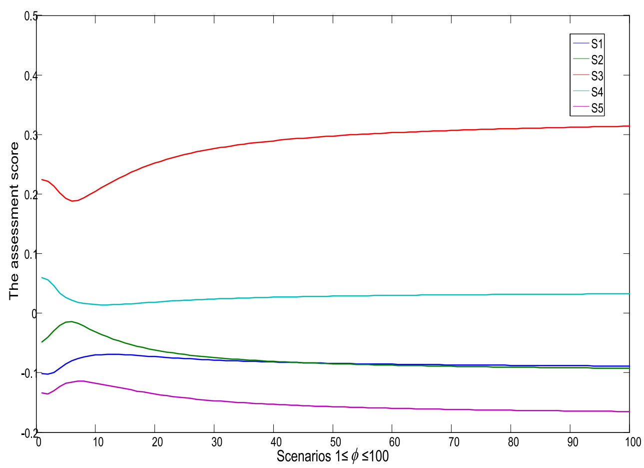

FIGURE 8. Dependence of the assessment score on the stabilization parameter changes (ϕ).

methodology [9]; 3) group grey-BWM and improved grey relational analysis (Group GBWM-IGRA) [11] and 4) fuzzy Entropy-MULTIMOORA methodology [49]. The selected approaches were applied under the same conditions and data set as the interval rough Dombi CODAS multi-criteria framework. Minor modifications of the data set were made when applying the fuzzy approach since triangular fuzzy numbers were employed in the fuzzy TOPSIS and MULTIMOORA methods. Data modification was reflected in the definition of the modal value—the modal value was adopted in the middle of the rough interval. The mentioned changes were formal and could not affect the deviation of the final criterion functions to any extent. **Fig. 9** compares the results of the mentioned multi-criteria approaches. From **Fig. 9**, we can see that applying the discussed multi-criteria techniques leads to similar results. A full correlation of results was obtained with fuzzy TOPSIS and MULTIMOORA methods, which is expected since they are based on the same approach for treating uncertainty. More significant deviations appeared with the BWM-PROMETHEE methodology compared to other techniques. Deviations in the BWM-PROMETHEE method are a consequence of ignoring uncertainty and inaccuracy in the information based on which decisions are made. However, the dominance of the first-ranked alternative (A3) and second-ranked alternative (A4) was confirmed for all methodologies, while alternative A5 represents the worst alternative in the considered set. The most significant differences in ranks appear with the third-ranked (A2) and fourth-ranked (A1) alternatives. **Table 8** presents a comparative analysis of the applied methodologies by looking at their advantages and disadvantages.

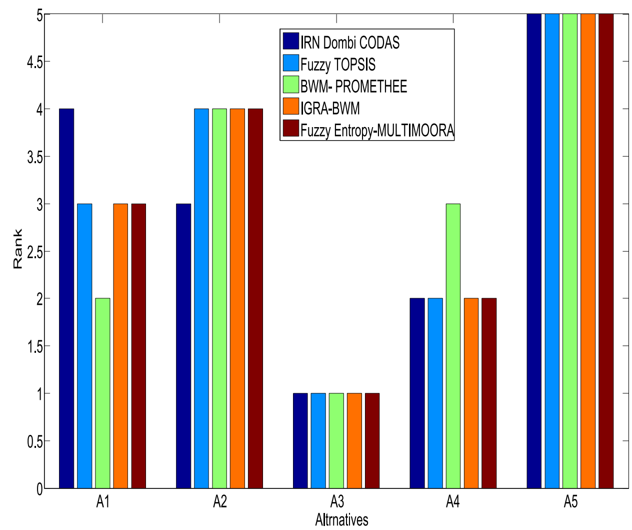

FIGURE 9. Comparison of alternative ranking.

One of the essential advantages of the interval rough Dombi CODAS methodology compared to other methodologies from **Table 8** is the application of flexible nonlinear Dombi functions to manipulate group information. On the other hand, Fuzzy TOPSIS, BWM-PROMETHEE, Group GBWM-IGRA, and Fuzzy entropy-MULTIMOORA models use linear functions that, in certain situations, can lead to a violation of the stability and quality of the obtained solution. Since interval rough Dombi functions enable flexible decision-making due to decision-makers' risk attitude, the presented Dombi CODAS methodology is more general and more flexible compared to other methodologies.

Interval rough Dombi CODAS framework overcome the limitations of traditional fuzzy and grey numbers. Adaptive interval rough intervals improve the objectivity of decision-making since the footprint of uncertainty in the

TABLE 6. Expert's evaluation of the alternatives.

Expert 1							Expert 2						
Alt.	C1	C2	C3	C4	C5	C6	Alt.	C1	C2	C3	C4	C5	C6
S1	(2;3)	(3;3)	(2;4)	(1;2)	(4;5)	(2;3)	S1	(3;4)	(4;5)	(4;5)	(2;3)	(2;3)	(1;2)
S2	(3;4)	(1;2)	(4;5)	(2;3)	(3;4)	(4;5)	S2	(4;4)	(2;3)	(3;4)	(4;5)	(2;3)	(1;2)
S3	(2;3)	(1;2)	(2;3)	(4;5)	(3;4)	(2;3)	S3	(2;3)	(3;4)	(3;4)	(2;3)	(3;3)	(4;5)
S4	(4;5)	(4;4)	(4;5)	(3;4)	(4;5)	(4;5)	S4	(3;4)	(3;3)	(1;2)	(2;3)	(2;3)	(1;2)
S5	(2;3)	(2;3)	(3;4)	(1;2)	(3;4)	(3;4)	S5	(2;3)	(2;2)	(2;3)	(3;4)	(1;2)	(3;4)
Expert 3							Expert 4						
Alt.	C1	C2	C3	C4	C5	C6	Alt.	C1	C2	C3	C4	C5	C6
S1	(1;1)	(2;2)	(3;4)	(4;5)	(1;2)	(3;4)	S1	(1;2)	(3;3)	(1;3)	(3;4)	(4;5)	(1;1)
S2	(4;5)	(2;3)	(1;2)	(3;4)	(4;5)	(3;4)	S2	(3;4)	(3;3)	(3;3)	(2;3)	(3;4)	(1;2)
S3	(3;4)	(3;4)	(4;5)	(3;4)	(2;3)	(3;4)	S3	(4;5)	(1;2)	(2;3)	(4;5)	(4;4)	(4;5)
S4	(2;3)	(2;3)	(4;4)	(2;3)	(3;4)	(3;4)	S4	(2;3)	(3;4)	(3;4)	(2;4)	(2;3)	(2;3)
S5	(3;5)	(1;2)	(2;3)	(4;5)	(1;2)	(1;2)	S5	(2;3)	(4;5)	(4;4)	(1;2)	(3;4)	(3;4)
Expert 5													
Alt.	C1	C2	C3	C4	C5	C6							
S1	(2;2)	(3;4)	(2;3)	(2;3)	(3;4)	(3;4)							
S2	(1;2)	(2;3)	(3;4)	(3;4)	(1;2)	(2;3)							
S3	(4;4)	(4;5)	(4;5)	(2;3)	(2;3)	(3;4)							
S4	(3;4)	(4;4)	(2;3)	(1;3)	(2;3)	(1;2)							
S5	(2;3)	(2;3)	(1;2)	(4;5)	(4;5)	(2;3)							

TABLE 7. Aggregated initial decision matrices.

Alt.	**C1**	**C2**	**C3**
S1	([1.27,2.11], [1.59,2.89])	([2.59,3.30], [2.64,3.95])	([1.59,2.89], [3.32,4.18])
S2	([2.04,3.51], [3.09,4.24])	([1.56,2.27], [2.58,2.95])	([2.02,3.22], [2.77,4.16])
S3	([2.37,3.43], [3.32,4.18])	([1.45,2.85], [2.52,3.92])	([2.37,3.43], [3.39,4.46])
S4	([2.30,3.16], [3.32,4.18])	([2.65,3.59], [3.33,3.82])	([1.73,3.41], [2.77,4.16])
S5	([2.03,2.31], [3.06,3.59])	([1.57,2.51], [2.32,3.44])	([1.59,2.89], [2.65,3.59])
Alt.	**C4**	**C5**	**C6**
S1	([1.59,2.89], [2.64,3.95])	([1.73,3.41], [2.82,4.45])	([1.31,2.37], [1.73,3.41])
S2	([2.30,3.16], [3.32,4.18])	([1.69,3.13], [2.77,4.16])	([1.29,2.69], [2.34,3.78])
S3	([2.37,3.43], [3.39,4.46])	([2.30,3.16], [3.14,3.60])	([2.65,3.59], [3.68,4.60])
S4	([1.56,2.27], [3.14,3.60])	([2.13,2.91], [3.14,3.95])	([1.29,2.69], [2.34,3.78])
S5	([1.46,3.10], [2.55,4.18])	([1.45,2.85], [2.52,3.92])	([1.73,2.77], [2.80,3.79])

interval rough approach retains uncertainties and imprecisions from expert preferences. Employing interval rough numbers eliminates the need for additional information used to determine the uncertainty, which is required in other

TABLE 8. The comparisons of MCDM methods.

MCMD method	Characteristics of the MCDM method			
	Flexible membership degree	Flexible boundary intervals	Flexible decision-making due to decision makers' risk attitude	Flexibility in real-world applications
Interval rough Dombi CODAS	Yes	Yes	Yes	Yes
Fuzzy TOPSIS	No	No	Partially	Partially
BWM- PROMETHEE	No	Yes	No	Partially
Group GBWM-IGRA	No	No	No	Partially
Fuzzy entropy-MULTIMOORA	No	No	Partially	Partially

interval number approaches. This preserves the quality of existing data in group decision-making. Besides, experts' perceptions are more objectively expressed in an aggregated matrix. In contrast to the fuzzy set theory, the application requires the definition of a partial membership function without clear boundaries of the set. With interval rough numbers, the boundary area of the set is used to express ambiguities. In fuzzy theory and probability theory, the degree of indeterminacy is defined based on an assumption.

On the other hand, in interval rough numbers (IRN), the indeterminacy is defined based on an approximation that represents the basic concept of rough set theory. In the interval rough numbers, only internal knowledge, (i.e., operational data), is used and there is no need to rely on assumption models. With IRN, the uncertainty footprint is described according to the internal uncertainties and imprecisions in the original data set.

Fuzzy TOPSIS and MULTIMOORA methods use fuzzy numbers with predefined boundaries of fuzzy sets for processing uncertainty. That is why, in the mentioned approaches, it is necessary to apply aggregation operators for the fusion of group information, which leads to the generalization of information in the decision matrix. It is similar to the BWM-PROMETHEE and Group GBWM-IGRA models. On the other hand, the adaptability of the IRN Dombi CODAS framework is reflected in the retention of the initial uncertainties in the decision matrix. Also, the adaptability of the IRN Dombi CODAS methodology is reflected in the possibility of adjusting the stabilization parameters of the nonlinear Dombi functions. By varying the stabilization parameters, the decision-maker simulates a different risk attitude. Considering the above justifications, one can conclude that the proposed multi-criteria approach is superior for solving real-world problems in dynamic decision environments.

VI. DISCUSSION AND IMPLICATIONS

We observed that the financial resumption of products, with a weight of 0.190, is the most important economic innovation criterion in evaluating suppliers for this corporation. This is particularly relevant in the developing economies where the financial resources are comparatively limited. Reducing resource consumption, reusing the used resources, and repurposing them can all benefit the company by reducing the production expenses. Besides, taking back the recycled material into the production process, i.e. closing the loop, financially benefits the consumer in additional to the company. Financial resumption becomes even more significant when taking into account the long-term impact of this criterion in the future state of the other criteria. For example, the capital saved in the production process can be allocated to promoting innovation and injecting more funds for the research and development activities. On the other hand, the saved funds can be employed in adjusting the supply chain strategy. For example, the corporation can offer a higher level of cost-effectiveness through reducing product prices or improving responsiveness by providing better quality products and services. Several past studies support this finding and highlight the importance of this criterion in promoting economic sustainability innovation [37].

Availability of financial resources for promoting innovation, finance in R&D, and production of sustainable products for diminishing material consumption, with the weight of 0.180, were placed in the second position in the criteria ranking. Costs incurred that are relevant to suppliers are important, especially for suppliers assessed based on their environmental management performance. Suppliers with efficient financial backgrounds are absorbed to innovative and new ideas to diminish their products negative environmental impacts. Suppliers with adequate capital facilitate the R&D activities. Besides, they may invest in human resources training and development in terms of sustainable processes and technologies. [10], [50]. Powerful economic support assists firms to invest in new technologies and attract experts from outside corporations for decreasing waste and processes improvement. Moreover, with economic backing, companies can invest in new energy-efficient substances and reverse cycling, hence the overall substance requirements and waste is diminished [51]. In a study conducted by Ahmadi et al. [9], availability of financial resources for promoting innovation and finance in R&D were identified as significant economic innovation criteria and were ranked as second and third, among twenty innovation criteria, which support our findings.

In addition to the usefulness of our findings for improving economic sustainability, this research has implications for improving supply chain resilience. The supply chain entities that are impacted by financial crisis and/or disruptions need to recover to a similar, or even better state through reducing the operational costs and creating additional financial means. Supply chains that are supplied by highly innovative suppliers are less susceptible to running out of the necessary supplies in critical market situations. On the other hand, economic innovativeness provides funds for improving other aspects of sustainability in the supply process. Given the long-term impact of the economic innovativeness of the suppliers, one can conclude that the corporations should put more effort in improving innovativeness by investing on supplier development and training programs.

This study has the following implications for the academic research. The economic innovativeness is the backbone of addressing social and environmental sustainability. However, its impact on sustainability plus considerations, i.e. the technological and political aspects is less tangible and requires further investigation. Our findings may inspire future studies for the development of political innovativeness criteria and investigating their relationships with other dimensions of sustainable innovation. Although the technological innovativeness has long been the subject of many studies, deeper analysis of such criteria in the sustainable supplier evaluation context is rather understudied. In particular, new criteria should be introduced to evaluate the benefits of the adaptation of new disruptive technologies, like 3D printing and blockchain, in the supplier innovativeness context. Finally, the academics may benefit from adopting the economic innovativeness factors for evaluating the third-party logistics service providers.

VII. CONCLUSION

Supplier evaluation and selection considering innovation criteria helps companies to enhance their sustainability performance and pursue sustainable development goals more effectively. This study is a primary work for introducing an economic innovation framework and a novel methodology suitable for assessing suppliers. A literature review was used to introduce the initial list of economic innovation criteria. The criteria were then screened through several rounds of interviews with experts to establish a decision framework. A novel methodology based on fuzzy-FUCOM integrated with an improved version of CODAS, ICODAS, was developed for the assessment and selection of the suppliers. Inputs from a case study with five experienced managers were applied to analysis the applicability of the developed assessment framework and methodology. The financial resumption of products was confirmed as the most important economic innovation criterion. The developed method showed to effectively reduce the subjectivity impact on the results. Overall, this study helps managers to better understand the economic aspect of sustainable innovation while assessing their supply chain partners.

There are certain limitations to this paper, which calls for a deeper analysis of the subject. (1) The first limitation is that few experts from one corporation in one developing economy participated in the article. Therefore, the findings cannot be easily generalized to other industry situations. This study sets the foundation for further research on the economic innovation. Future works can use our findings as a basis for studying other sectors or emerging economies to evaluate the suppliers with respect to economic innovation performance. It is expected to see different or additional economic innovation criteria in other contexts. (2) From the methodological viewpoint, our method does not account for interaction and interrelationships between criteria, which offers a worthwhile direction to pursue. (3) Future studies may integrate Z-numbers for addressing the uncertainty of the decision and experts' confidence in the assessment. Besides, rough numbers can be integrated into FFUCOM for aggregating the experts' opinions in group decision-making, and consensus. (4) One may extend our investigation by including order allocation among the top-ranked suppliers. (5) Finally, this research focused only on the economic dimension of sustainability innovation. Future studies could investigate environmental, political/law, and technological aspects and their impact on the socio- economic innovativeness criteria.

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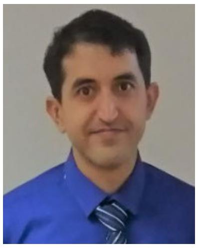

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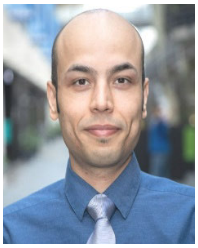

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