Ranking Barriers Impeding Sustainability Adoption in Clean Energy Supply Chains: A Hybrid Framework With Fermatean Fuzzy Data

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***Abstract*—In this article, we aim to prioritize barriers hindering sustainability inclusion within clean energy supply chains. Supply chain management is a crucial aspect of the clean energy sector, whereby the global supply chains can be enforced with policies to adopt sustainability/green practices. The literature infers that the adoption of sustainability is not direct, and multiple barriers impede the process, driving researchers to rank these barriers. Previous studies on prioritizing barriers cannot effectively model uncertainty; experts' reliability is directly assigned; interrelationships/hesitation of criteria/experts are usually not considered; and there is a lack of personalized ordering based on individuals' preferences. Motivated by these gaps, the authors put forward an integrated framework with a Fermatean fuzzy set, variance-based criteria importance through intercriteria correlation for determining experts' and criteria weights, and ranking procedure with complex proportional assessment–Copeland for personalized ordering of barriers. The usefulness of the developed approach is testified through a case example. Results infer that wastage/pollution reduction and profit from green production are the two top criteria considered for rating sustainability barriers, while limited governmental policies, monitoring/control issues, and expertise mismatch are the top three barriers impeding sustainability adoption. Finally, sensitivity and comparative analyses are performed to understand the framework's efficacy.**

***Index Terms*—Barriers prioritization, clean energy, complex proportional assessment (COPRAS) method, criteria importance through intercriteria correlation (CRITIC) method, Fermatean fuzzy set (FFS), sustainability.**

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I. Introduction

SUSTAINABILITY refers to the aspect of meeting the demand of the present without affecting the resources for the future [39], [51]. Globally, countries strive hard to achieve sustainable and lean growth, focusing on indicators, strategies, and policies to balance economic and environmental growth [38], [91]. However, the process of inclusion of sustainability is not straightforward since it is associated with different aspects with varying levels of dynamism [31] and different barriers/challenges that can appear, hindering the adoption phase [50], [54]. As per the report from indiabudget.gov.in, (accessed: 10.01.2023), the Government of India came up with diverse initiatives, such as Swachh Bharat, Pradhan Mantri Awas Yojana, Deen Dayal Upadhyay Gram Jyoti Yojana, Beti Bachao Beti Padhao, and alike, by investing billions of dollars toward achieving the various goals of sustainable development nationwide. The core aim of these programs is to meet the ambitious target committed in the Paris Accords by 2030 and promote the nation toward successful achievement of the sustainable development goals.

In this line of thought, it is essential to prioritize different barriers/challenges that can appear during the attempt to incorporate or implement sustainability. The clean energy sector is a promising scope for the world leaders to strike a balance between demand and development in terms of both the environment and economy [86]. As per the report from the International Energy Agency (IEA) (www.iea.org accessed: 14.01.2023), supply chains of the clean energy sector incur a certain level of pollution, of which close to 90% is from material production and technology manufacturing. Although the emission is far less compared with fossil-fuel-based energy, there is an urge for active sustainability to be implemented in the clean energy supply chain division so that net zero emission can be achieved. Sustainable supply chain (SSC) mainly focuses on the performance and integration of entities where the emphasis is on social, economic, and environmental aspects. Specifically, in the clean energy sector, there is immense stress on the economic aspect. Based on the alignment of SSC, it is essential to note that there must be coordination among resources, their flow, and a well-defined concept of sustainability with participation from diverse stakeholders of the system [30]. In general, the realization of a clean energy sustainable supply chain (CESSC) is supported via simulation and modeling based on a system dynamics approach, discrete event simulation, and agent-based modeling. These modeling mechanisms foster the understanding of the dynamism that is in place within the CESSCs.

Decision models are powerful in handling issues concerning CESSCs, and owing to the diverse criteria set involved in the analysis along with the uncertainty, multicriteria decision-making (MCDM) is a viable option [61]. Al-Nory [12] presented an optimization model for guiding the integration of supply chains and clean energy within the smart city context. In similar lines, earlier Balaman and Selim [19] presented optimization models to foster the integration of the heating system of districts by designing CESSCs. Xie et al. [94] put forward the Stackelberg game to model the multiechelon renewable energy supply chains by formulating profit distribution and risk-sharing concepts. Mohammadzadeh and Hasanzadeh [2] prepared a fuzzy-based decision model with an analytical hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS) for evaluating factors in incorporating SSCs within the electricity industry. Sarkar and Seo [72] implemented the Stackelberg game with the Kuhn–Tucker model to better handle the inequality constraint and maximize the profit of energy to understand renewable energy supply chains from the production system context. Haiyun et al. [37] presented quality function deployment-based Mastrocinque et al. [60] came up with a multicriteria fuzzy inference system for evaluating the sustainability aspect within photovoltaic supply chains that are facilitated by Industry 4.0 paradigms in seven countries. Almutairi et al. [11] prepared a gray number-based decision model with "stepwise weight assessment ratio analysis (SWARA)" and "evaluation based on distance from average solution (EDAS)" approaches for assessing barriers that impede blockchain technology adoption within renewable energy supply chains.

Furthermore, Rentizelas et al. [69] applied data envelopment analysis for evaluating biomass supply chains efficiency globally based on multiple criteria. Ahmadi et al. [4] presented a life-cycle assessment and technoeconomic analysis for assessing bioenergy pathways within Canada. Zhang et al. [100] put forward the power-of-pull and structural path analysis for finding the hotsports with respect to supply chains for power conservation within China. Shete et al. [79] applied the AHP method with Pythagorean fuzzy data for assessing the enablers of SSCs within the Indian context. Allman et al. [10] presented a stochastic formulation for optimizing supply chains dealing with biowaste to energy in the states of Minnesota and North Carolina, U.S. Masoomi et al. [59] put forward a fuzzy-based framework with "best worst method (BWM)," "complex proportional assessment (COPRAS)," and "weighted aggregated sum product assessment (WASPAS)" approaches for selecting a strategic supplier to support CESSCs. Azadnia et al. [18] presented BWM for assessing risk with the supply chain of green hydrogen within the European Union context. Wu et al. [93] proposed a dynamic network data envelopment analysis for grading security performance from the context of energy supply chains within seven countries. Masood et al. [58] presented group BWM for grading challenges that affect sustainability and resilience within the energy supply chains in Pakistan based on the sustainable development goals and triple bottom line. Table I provides a summarized view of the contributions from extant models.

According to the above discussion, it is clear that researchers commonly adopt optimization, decision approaches, simulation analysis, and other methods to evaluate diverse entities within the energy supply chain domain. Specifically, it is noted that studies consider MCDM as a tool for grading/prioritizing entities with the clean energy supply chain context. Notably, the inclusion of sustainability within the supply chain of clean energy is not a direct process, and there are diverse barriers that must be modeled by considering rating information from different experts based on certain criteria set. Typically, uncertainty is inevitable in such problems, and representation/modeling of such uncertainty is essential for the rational ordering of barriers as well as proper strategic planning.

Fermatean fuzzy set (FFS) [75] is a type of orthopair fuzzy set that models uncertainty from three dimensions (two explicit and one implicit), such as membership, indeterminacy, and nonmembership with the flexibility parameter $q = 3$ in order to enhance the window of preference elicitation. This allows experts to effectively express their views. Compared with the predecessor models, viz., intuitionistic and Pythagorean fuzzy sets (PFSs),

TABLE I
SUMMARIZED VIEW OF CONTRIBUTIONS: MCDM MODELS FOR CLEAN ENERGY SUPPLY CHAIN

Source(s)	Weight calculati on	Ranking	Application
Mastrocinque et al. [61]		AHP	Sustainable investment decision within CESC
Mohammadzadeh and Hasanzadeh [2]	AHP	TOPSIS	Factor evaluation for CESC
Almutairi et al. [11]	SWARA	EDAS	Barrier grading for blockchain adoption to CESC
Rentizelas et al. [69]		DEA	Efficiency evaluation of biomass supply chain
Masoomi et al. [59]	BWM	WASPAS and COPRAS	Strategic supplier selection for CESC
Azadnia et al. [18]		BWM	Risk assessment in green hydrogen SCs
Wu et al. [93]		Dynamic network DEA	Security performance evaluation of energy SCs
Masood et al. [58]		Group BWM	Barrier grading for sustainability/resilience adoption in energy SCs

Note: AHP is the analytical hierarchy process; TOPSIS is the technique for order of preference by similarity to ideal solution; SWARA is the stepwise weight assessment ratio analysis; EDAS is the evaluation based on distance from average solution; WASPAS is the weighted aggregated sum product assessment; COPRAS is the complex proportional assessment; DEA is the data envelopment analysis; BWM is the best worst method, SC is the supply chain, and CESC is the clean energy supply chain.

FFS can yield a broader preference space with the representation of a cognitive restrictive constraint that sets a bound between the degree of preference and degree of nonpreference, which is not present in the neutrosophic or spherical fuzzy forms. For instance, in FFS and other orthopair fuzzy forms, the degree of membership (preference) and the degree of nonmembership (nonpreference) cannot be 1 simultaneously, that is $\mu = \upsilon = 1$. This is because of the constraint $0 \leq \mu^q + \upsilon^q \leq 1$ with q taking up values as 1, 2, or 3 depending on the orthopair form. Neutrosophic and spherical fuzzy forms are also interesting and can be explored in the future. Specifically, the orthopair fuzzy forms, such as FFS, have one implicit and two explicit dimensions for modeling uncertainty, where the implicit dimension is a derivative of the two explicit dimensions. Readers can refer to the definition given below for clarity.

The rest of this article is organized as follows. The literature review pertaining to barrier grading and Fermatean fuzzy is provided in Section II along with the research gaps, contributions, and rationale behind the contribution. In Section III, the methodology is discussed with detailed steps for each entity. In Section IV, a case example is presented to understand the usefulness of the model. Sensitivity measurement and comparison with other models are provided in Section V to understand the efficacy of the developed model. The results and discussion are described in Section VI, which adds intuitive value to the research work. Finally, Section VII concludes this article.

II. Literature Review

A. Prioritization Models for Grading Barriers

This section describes the existing models in the literature that tackle the challenges of grading barriers affecting different green and sustainable activities. As discussed earlier, identifying the barriers is essential to support policymakers and experts in strategic planning and development. Shah et al. [76] evaluated barriers that affect clean energy adoption in Pakistan by developing fuzzy AHP with a Delphi approach. Farooque et al. [103] presented a fuzzy "decision-making trial and evaluation laboratory (DEMATEL)" to evaluate the barriers that hinder the life cycle in the context of blockchain. Chen et al. [22] assessed the e-waste system barriers under the fuzzy context, using integrated BMW and TOPSIS schemes. Lamba et al. [55] presented a fuzzy-based AHP procedure for evaluating barriers in the e-commerce sector associated with the reverse logistics domain. Mahdiyar et al. [56] put forward the Delphi approach with BWM in the fuzzy environment for barrier assessment in a green roof setup. Bui et al. [20] adopted the Delphi approach to evaluate the barriers that hinder practical waste management. Khandelwal and Barua [45] used the fuzzy AHP model to rank the barriers that affect supply chains in the circular economy context in the Indian plastic industry. Tavana et al. [88] introduced a barrier assessment approach with fuzzy context, along with entropy and "multiobjective optimization on the basis of ratio analysis (MOORA)" as an improvement mechanism in the manufacturing sector. Solangi et al. [85] developed fuzzy-based AHP-TOPSIS for assessing barriers to renewable energy adoption within Pakistan. Upadhyay et al. [90] prioritized the barriers associated with isolation during the corona virus (COVID-19) epidemic by using fuzzy AHP.

Karam et al. [42] recently prepared a combined Delphi-AHP scheme in the fuzzy context to rank barriers that impede horizontal collaborative transport. Rasty et al. [67] assessed barriers associated with trust features in online shopping, using an intuitionistic fuzzy "failure mode and effect analysis" model. Other scholars have proposed integrated models for prioritizing solutions that could tackle the barriers in the sustainability fields [13], [45], [46], [83]. Dhingra et al. [26] developed a fuzzy AHP model for assessing barriers that do not allow offshore wind energy adoption. Rejeb et al. [68] integrated Delphi with BWM to prioritize barriers that affect blockchain adoption with the circular economy aspect. Singh et al. [84] proposed a gray-DEMATEL approach for assessing barriers that hamper the product life-cycle phase in a manufacturing organization. Krishankumar et al. [50] used the nonlinear fuzzy context along with variance-based COPRAS to assess barriers in sustainable operations. Govindan et al. [34] devised an extension to BWM in the fuzzy context, utilizing DEMATEL and supermatrix for prioritizing the barriers in the circular economy aspect. Ashour et al. [14] developed a parsimonious-cybernetic fuzzy AHP model to rank barriers that affect sustainability in interior decorations/architectures. Kumar et al. [52] adopted fuzzy AHP to assess barriers that disturb the implementation of lean-six-sigma in the context of Industry 4.0. Abdul et al. [1] developed a spherical Pythagorean fuzzy-based AHP model to rank barriers that do not allow ecopreneurship to adopt renewable energy technology. Krishankumar and Pamucar [49] provided a decision approach combining criteria importance through intercriteria correlation (CRITIC) and WASPAS for ranking barriers affecting clean energy adoption with orthopair data. Einy-Sarkalleh et al. [28] prioritized barriers within the Iranian car industry by extending "measurement alternatives and ranking according to compromise solution (MARCOS)" to the fuzzy context. Kaswan et al. [43] introduced BWM for assessing barriers that hinder green lean-six-sigma adoption. Chisale and Lee [23] presented AHP with TOPSIS under a fuzzy context for ranking barriers and remedies to accelerate clean energy adoption in Malawi. Naseem et al. [63] ranked barriers that affect blockchain implementation based on a fuzzy AHP approach for the revenue logistics domain.

B. Fermatean Fuzzy Decision Models

This section provides a review of extant decision models under the FFS context. Inception [15] proposed the "intuitionistic fuzzy set (IFS)," which is an orthopair fuzzy set with the sum of membership and nonmembership that is less than or equal to unity. Later, Yager [95] came up with the "PFS" as an improvement of IFS by allowing experts to flexibly express choices based on the condition that the sum of the squares of membership and nonmembership is less than or equal to unity. In this line of extension, Senapati and Yager [75] provided FFS that is more flexible than IFS and PFS, which allows broader information to be expressed with the constraint as the sum of cubic membership and nonmembership that is less than or equal to unity.

Driven by flexibility, many researchers have adopted FFS for MCDM. Keshavarz-Ghorabaee et al. [44] extended the WASPAS approach for ranking suppliers in the green construction context by considering FFS preferences. Akram et al. [8] presented Einstein-ordered weighted operators for aggregation of FFS, using the operator for sanitizer selection to reduce the spread of COVID-19. Aydemir and Yilmaz Gunduz [16] put forward a novel Dombi aggregation-based TOPSIS method under the FFS context for MCDM. Deng and Wang [24] developed an integrated entropy-based evidence measure under the FFS context for MCDM. Hadi et al. [36] presented Hamacher-based fusion operators under the FFS context, applying the same for cyclone disaster assessment. Shahzadi et al. [78] introduced novel operators under the Hamacher generators for the aggregation of FFSs along with some properties and used the operator for MCDM. Shahzadi et al. [78] provided interactive Hamacher operators along with their properties for aggregation of FFS data, using the method for medical applications. Gul [35] extended "simple additive weight," "viekriterijumsko kompromisno rangiranje," and "additive ratio assessment (ARAS)" methods under FFS. The study also presents a detailed discussion on the set, showcasing its usefulness in the selection of a viable laboratory for COVID-19 testing. Singh and Pant [82] presented a combinative distance-based assessment (CODAS) approach for identifying the best tax schemes for public transit based on FFS-based data.

Recently, Korucuk et al. [48] prepared a SWARA-COPRAS integrated approach for assessing green digital marketing strategies in the context of twin transition with FFS-based preference information. Zhou et al. [102] developed a model that extends the "elimination et choice translating reality" approach to FFS for MCDM application. Simic et al. [81] proposed an FFS-based combined compromise solution (CoCoSo) approach to evaluate urban transport in Serbia. Mishra et al. [62] presented "CRITIC" together with both EDAS and score measures in order to assess reverse logistic providers within the sustainability aspect. Lai et al. [104] came up with a "CoCoSo" approach for blockchain evaluation by considering hesitant FFS-based preferences. Ali and Ansari et al. [9] proposed a Fermatean fuzzy bipolar set, along with operational laws and an aggregation function, for the appropriate selection of surgeon robots. Yang et al. [96] put forward an integrated weighted distance-based TOPSIS under the FFS context for the selection of viable green low-carbon ports. Deng and Wang [25] presented a novel distance measure along with their properties and features, which was used for pattern recognition and medical diagnosis. Akram et al. [7] presented Hamacher operators with the "CODAS" method under the FFS context and tested the method in the rank of construction companies and McDonald's franchises. Rong et al. [70] prepared a MARCOS-based decision model with the FFS context to be used in the logistic distribution center evaluation within the cold supply chain domain. Tan et al. [87] developed a prospect theory-based "multiattribute border approximation area comparison" for risk assessment in investment applications. Akram et al. [7] put forward the Hamy operator and weighted Hamy operator under the two-tuple FFS and discussed its properties along with its usage in MCDM. Aytekin et al. [17] ranked warehousing companies in the pharmaceutical field by extending WASPAS and entropy to FFS. Akram et al. [7] came up with the MOORA approach for FFS to select a suitable intelligent manufacturer system that could enable effective manufacturing and design. Gonzales et al. [33] presented DEMATEL with the "maximum mean de-entropy" approach for barrier evaluation that hinders the adoption of education 4.0 in the Philippines. Saha et al. [71] introduced Delphi-based double normalized MARCOS models in the FFS context for warehouse selection in the automotive sector. Akram et al. [7] proposed a Fermatean fuzzy soft expert set and discussed some useful properties of the set along with its extension in selecting suitable brands for solar panels. Zeng et al. [99] put forward a new distance measure and discussed its properties in the FFS context along with the formulation of the TOPSIS method for low-carbon cities evaluation. Wang et al. [92] devised an occupational risk assessment, considering MARCOS with prospect theory in the context of Fermatean fuzzy Fine–Kinney. Hooshangi et al. [40] developed geographic information system (GIS)-based Fermatean fuzzy TOPSIS for location assessment to set up solar farms in Iran. Seikh and Mandal [73] extended the "preference ranking organization method for enrichment and evaluation" approach with SWARA under the interval version of Fermatean fuzzy number (FFNs) for biomedical waste management. Similarly, Mandal and Seikh [57] presented a TOPSIS approach under the interval version of FFNs for sustainable development application. Zaman et al. [97] applied a TOPSIS method under a complex FFN context for selecting a suitable English-language instructor. Gocer [32] extended the ARAS approach to the interval variant of FFNs for the rational selection of renewable energy technology in Turkey. Qi et al. [64] proposed a novel covering induced by a rough set for the Fermatean fuzzy context and presented the precision parameter to facilitate the selection of charging stations for electric vehicles in an Indian city.

C. Research Gaps and Contributions

Based on the review of barrier prioritization models provided in Section III, certain challenges/gaps were noted, such as follows.

1) Uncertainty is not effectively modeled, and subjective randomness can be better handled.
2) Hesitation of experts along with variability in the distribution of choices is not adequately captured.
3) Interactions among criteria are not rationally modeled.
4) Importance of experts is not considered during the criteria weight calculation.
5) Ordering of barriers based on individual's opinions/preferences is lacking.

Table II gives a summarized view of the identified gaps and issues in the earlier barrier ranking models.

In order to circumvent these challenges, the contributions of this article are as follows.

1) FFS is used as the preference information, where the rating data in the qualitative form are converted into FFS based on the respective forms.
2) The importance of experts is methodically calculated by presenting the variance measure.
3) A weighted CRITIC scheme is put forward to determine the weights of the criteria that are methodically under the FFS context.

TABLE II
RESEARCH GAPS INFERRED FROM THE EXTANT BARRIER RANKING MODELS

Source(s)	Experts' hesitation	Criteria interactions	Flexible uncertainty modeling	Inclusive criteria/ experts	Personalized ranking
Shah et al. [76]	N/C	N/C	No	N/C	N/C
Faroque et al. (2020)	N/C	Considered	No	N/C	N/C
Chen et al. [22]	N/C	N/C	No	N/C	N/C
Khandelwal and Barua [45]	N/C	N/C	No	N/C	N/C
Upadhyay et al. [90]	N/C	N/C	No	N/C	N/C
Karam et al. [42]	N/C	N/C	No	N/C	N/C
Dhingra et al. [26]	N/C	N/C	No	N/C	N/C
Singh et al. [84]	N/C	Considered	No	N/C	N/C
Govindan et al. [34]	N/C	Considered	No	N/C	N/C
Abdul et al. [1]	N/C	N/C	Moderate	N/C	N/C
Einy-Sarkalleh et al. [28]	N/C	N/C	No	N/C	N/C
Kaswan et al. [43]	N/C	N/C	No	N/C	N/C

Note: N/C is not considered.

4) Ranking of barriers is performed in a bidirectional fashion considering both individual and cumulative opinions and by developing a new ranking algorithm with the COPRAS–Copeland mechanism.

In this work, the problem statement of focus is to develop an integrated decision model that could prioritize barriers hindering sustainability adoption in clean energy supply chains by reducing human intervention and uncertainty. Specifically, the rationale behind the contributions mentioned above is as follows.

1) FFS has a broader window size compared with its predecessor orthopair variants. Notably, FFS can model uncertainty from three phases: membership grade, nonmembership grade, and hesitancy grade. As a result, uncertainty is rationally modeled, and subjective randomness is reasonably reduced.
2) Works by the authors in [41] and [47] reveal the urge for methodical weight determination for criteria and experts. Besides, the hesitation of experts is rationally captured along with the interactions of criteria, which drives authors to present these procedures.
3) The CRITIC approach is considered in this model rather than other methods, such as "AHP," "analytical network process (ANP)," "method-based on the removal effect of criteria (MEREC)," "simultaneous evaluation of criteria and alternatives (SECA)," and so on.
   a) The CRITIC approach is less computationally complex compared with other methods that either involve pairwise comparison (such as AHP/ANP) or constrained optimization model (such as SECA) or loop-based calculation owing to the removal concept of MECREC.
   b) Also, the CRITIC approach does not involve consistency check and repair mechanism, which is a crucial issue with AHP/ANP.
   c) Furthermore, the overhead of constraint elicitation is avoided in CRITIC.
   d) Apart from these points, CRITIC approach considers the hesitation of experts as well as the interrelationship among criteria, which is lacking in methods, such as AHP, ANP, and MEREC. Based on these inferences, the CRITIC approach is considered in the present decision model.
4) The COPRAS method has the ability to rationally consider the criteria type during rank estimation, the Copeland strategy, and the inclusion of criteria and experts' weights that supposxsrt the ordering of barriers, providing ranking from both the individual and cumulative perspectives.

To clarify the methodical contributions of the developed model, we present the following points.

1) Weights of experts are determined methodically using the variance approach by reflecting the attitudinal trait of risk aversion.
2) Weights of criteria are determined methodically by the CRITIC approach that embeds the importance of experts into the formulation.
3) Ranking barriers from both the individualistic and holistic perspectives are formulated by presenting an algorithm integrating COPRAS and Copeland's strategy.

III. METHODOLOGY

A. Preliminaries

Basic concepts related to orthopair fuzzy sets are given as follows.

Definition 1 [15]: YH is a fixed set, and $NH \subset YH$ is also fixed. Then, $\overline{NH}$ is an IFS in YH such that

$$\overline{NH} = \{yh, \mu_{\overline{NH}}(yh), \upsilon_{\overline{NH}}(yh) | yh\epsilon YH\} \quad (1)$$

where $\mu_{\overline{NH}}(yh)$, $\upsilon_{\overline{NH}}(y\,h)$, and $\pi_{\overline{NH}}\ (yh) = 1 - (\mu_{\overline{NH}}(yh) + \upsilon_{\overline{NH}}(yh))$ are the grades of membership, nonmembership, and indeterminacy, respectively, and $\mu_{\overline{NH}}(yh)$, $\upsilon_{\overline{NH}}(yh)$, and $\pi_{\overline{NH}}(yh)$ are the values ranging between 0 and 1, and $\mu_{\overline{NH}}(yh) + \upsilon_{\overline{N?H}}(yh) \leq 1$.

Definition 2 [74]: YH is a fixed set and $yh \in YH$. Then, the FFS UX on YH is considered as follows:

$$UX = \{yh, \mu_{UX}(yh), \upsilon_{UX}(yh) | yh\epsilon YH\} \quad (2)$$

where $\mu_{UX}(yh), \upsilon_{UX}(yh)$ range between 0 and 1, being referred by grades of membership and nonmembership. Besides, $0 \leq (\mu_{UX}(yh))^3 + (\upsilon_{UX}(yh))^3 \leq 1$. Indeterminacy grade $\pi_{UX}(yh)$ is calculated as $1 - ((\mu_{UX}(yh))^3 + (\upsilon_{UX}(yh))^3)$ and it must be noted that the indeterminacy grade is in the unit interval.

Note 1: In this study, $UX = (\mu_x, \upsilon_x)\ \forall x = 1, 2, \ldots, \tau$ is referred as FFN, and collectively they form FFS. The reasons for considering FFNs as preference information over other fuzzy extensions, such as IFS [15], PFS [95], and hesitant fuzzy set (HFS) [89], are as follows.

1) The FFN offers a broader window for preference expression compared with the earlier variants viz., IFS and PFS.
2) Although HFS can offer multiple values for a particular instance, the FFNs have an orthopair representation for modeling uncertainty that presents both the membership as well as nonmembership grades along with the hesitation grade, which is derived from the former two grades, which is lacking in HFS.

For clarity, consider an example where an expert rates a teacher for the suitability to increased pay, the expert provides the value as an orthopair, say (0.85, 0.65). Now IFS and PFS forms are not suitable owing to the mismatch of the constraints: $0 \leq (\mu_{UX}(yh))^1 + (\upsilon_{UX}(yh))^1 \leq 1$ for IFS and $0 \leq (\mu_{UX}(yh))^2 + (\upsilon_{UX}(yh))^2 \leq 1$ for PFS. Furthermore, HFS cannot accept an orthopair. As a result, FFS is a suitable preference style that the expert can use for representing the degree of membership and nonmembership in a flexible manner.

Definition 3 [75]: UX_1 and UX_2 are two FFNs. Arithmetic operations with FFNs are given by

$$\eta\, UX_2 = \left(\left(1 - \left(1 - \mu_2^3\right)^\eta\right)^{1/3}, \upsilon_2^\eta\right)\ ,\ \eta > 0 \tag{3}$$

$$UX_1^\eta = \left(\mu_1^\eta, \left(1 - \left(1 - \upsilon_1^3\right)^\eta\right)^{1/3}\right)\ ,\ \eta > 0 \tag{4}$$

$$UX_1 \oplus UX_2 = \left(\left(1 - \left(1 - \mu_1^3\right)\left(1 - \mu_2^3\right)\right)^{1/3}, \upsilon_1\upsilon_2\right) \tag{5}$$

$$UX_1 \otimes UX_2 = \left(\mu_1\mu_2, \left(1 - \left(1 - \upsilon_1^3\right)\left(1 - \upsilon_2^3\right)\right)^{1/3}\right). \tag{6}$$

Definition 4 [74]: UX_1 and UX_2 are two FFNs. Score and accuracy measures are given by

$$A\ (UX_2) = \mu_2^3 + \upsilon_2^3 \tag{7}$$

$$S\ (UX_2) = \mu_2^3 - \upsilon_2^3. \tag{8}$$

It can be seen that (3)–(8) are operations with FFNs, being referred as scalar multiplication, power multiplication, ring sum, ring product, accuracy, and score, respectively.

Based on (7) and (8), the FFNs can be compared and the rule is given as follows:

1) IF $S(UX_1) < S(UX_2)$, THEN $UX_1 < UX_2$;
2) IF $S(UX_1) > S(UX_2)$, THEN $UX_1 > UX_2$;
3) IF $S\ (UX_1) = S(UX_2)$, THEN
   a) IF $A(UX_1) < A(UX_2)$, THEN $UX_1 < UX_2$;
   b) IF $A(UX_1) > A(UX_2)$, THEN $UX_1 > UX_2$;
   c) IF $A\ (UX_1) = A(UX_2)$, THEN $UX_1 = UX_2$.

B. Calculation of Weights/Importance

This section primarily focuses on the weight calculation of experts and criteria based on a methodical procedure in order to reduce subjectivity and biases. To support the theory, the studies of the authors in [41] and [47] can be referred to, as they emphasize the crucial importance of methodical weight estimation. In MCDM, weight calculation is a crucial stage, and it can be seen that these weights influence the rationality of ranking candidates or alternatives (barriers in this case) [82].

Driven by this claim, researchers have proposed methods for weight estimation with two main categories, namely with no a priori information and with partial information. Specifically, in the former context, there is no overhead of partial information about the entity. Comparatively, the latter context is considered when experts have some dilute opinion about an entity. In this work, it is assumed that no a priori information is available with respect to criteria and experts.

Popular methods in the former context include AHP [61], DEMATEL [33], entropy [54], and SWARA [66], which increase complexity during the implementation because of the pairwise comparison, and also they cannot handle interactions of entities and hesitation of experts. To overcome this issue, authors have introduced variance measures along with weighted CRITIC. Moreover, CRITIC [27] is a promising method in the weight assessment sector that is able to capture the interrelationship among criteria and variability in the distribution. The intuitive idea of considering the importance of experts in criteria weight calculations makes this a promising procedure. A stepwise procedure for weight estimation is given as follows.

Step 1: Construct Z matrices of order $Q \times V$ with qualitative terms. Based on the tabular values, these terms are converted to FFN.

Step 2: Determine the accuracy of FFN, by using (7), based on the data from Step 1. The matrix order is retained as in Step 1.

Step 3: The following equation is applied to determine the variance vector by considering data from Step 2:

$$vr_j^l = \frac{\sum_j \left(\frac{\sum_{i=1}^{Q}\left(A(UX_{ij}) - \overline{A(UX_j)}\right)^2}{Q-1}\right)}{\sum_l \left(\sum_j \left(\frac{\sum_{i=1}^{Q}\left(A(UX_{ij}) - \overline{A(UX_j)}\right)^2}{Q-1}\right)\right)} \tag{9}$$

where $\overline{A(UX_j)}$ is the average value.

Step 4: Calculate the net information associated with each expert, which can be normalized to determine expert weight by using (10). A vector of $1 \times Z$ is obtained as weight values

$$EW_l = \frac{\sum_{j=1}^{V}\left(1 - vr_j^l\right)}{\sum_{l=1}^{Z}\left(\sum_{j=1}^{V}\left(1 - vr_j^l\right)\right)} \tag{10}$$

where EW_l is the weight of the expert.

Step 5: Form Z opinion vectors of order $1 \times V$ by considering qualitative terms for criteria, which are further converted to FFN based on tabular values.

Step 6: Calculate the accuracy of FFN by applying (7). Include the experts' importance, in order to obtain weighted accuracy by using the following equation:

$$SA_{lj} = EW_l \cdot A\left(UX_{lj}\right) \tag{11}$$

where SA_{lj} is the weighted accuracy.

Step 7: Determine the interaction factor among criteria, by considering (12). A symmetric square matrix of order $V \times V$ is obtained as follows:

$$r_{xy} = \frac{\sum_{l=1}^{Z}\left(\left(SA_{lj} - \overline{SA_j}\right)_x \cdot \left(SA_{lj} - \overline{SA_j}\right)_y\right)}{\sqrt{\sum_{l=1}^{Z}\left(SA_{lj} - \overline{SA_j}\right)_x^2 \cdot \sum_{l=1}^{Z}\left(SA_{lj} - \overline{SA_j}\right)_y^2}} \tag{12}$$

where x and y are any two criteria, and $\overline{SA_j}$ is the average of weighted accuracy.

Step 8: Criteria weights are calculated by using (13) by considering the information associated with the criterion. A vector of $1 \times V$ is obtained as the weight values

$$CW_j = \frac{\sigma_j^2 . \sum_y r_{xy}}{\sum_{j=1}^{V}\left(\sigma_j^2 . \sum_y r_{xy}\right)} \tag{13}$$

where σ_j^2 is the variance measure, and CW_j is the weight of criteria.

Equation (13) is used to calculate the weight vector, where each value ranges between 0 and 1, summing to unity.

C. Ranking Algorithm

This section discusses a ranking algorithm for ordering/ranking barriers that hinder supply chain sustainability operations. In the context of MCDM, ranking is a crucial concept that aims to select a suitable candidate from an entire set by determining their rank values. COPRAS is one such elegant and effective ranking method that actively considers both the criteria type and strategic values of experts during rank estimation [98]. Moreover, the method is simple and provides an understanding of complex proportions from different angles to determine the rank values [27], [101].

Driven by these features, an algorithm for ranking is proposed by considering the idea of the COPRAS method and Copeland strategy. The focus is mainly on obtaining individual expert's rankings based on her/his preferences. The procedure for the algorithm is given as follows.

Step 1: Consider Z matrices of $Q \times V$ order from Section III–B as input to the ranking model.

Step 2: Apply (7) to determine the accuracy of the FFN from Step 1. Z matrices of $Q \times V$ are obtained.

Step 3: Apply (14)–(16) to determine the COPRAS ranking parameters for each expert's decision matrix:

$$R1 = \sum_{j=1}^{V1} CW_j \cdot A\left(UX_{ij}\right) \tag{14}$$

$$R2 = \sum_{j=1}^{V2} CW_j \cdot A\left(UX_{ij}\right) \tag{15}$$

$$R3 = \beta R1 + (1-\beta)\left(\frac{\sum_i R2}{R2 + \sum_i \frac{1}{R2}}\right) \tag{16}$$

where $V1$, $V2$, and β are the number of benefit criteria, the number of cost criteria, and the strategy values ranging from 0 to 1.

It must be noted that (14)–(16) are applied for the preference data from each expert, so the rank values of barriers can be determined based on the individual's data. To further determine the net rank of the barrier and the final ordering, Copeland strategy procedure is provided as follows.

Step 4: Net rank of barriers is determined by using (17)–(19)

$$T1 = \sum_{l=1}^{Z} EW_l . o_i \tag{17}$$

$$T2 = T1_{\max} - T1 \tag{18}$$

$$T3 = T1 - T2 \tag{19}$$

where o_i is the rank order of barrier i.

Accordingly, the COPRAS–Copeland integrated ranking algorithm was developed to achieve personalized ordering of barriers based on the individual expert's ratings/preferences along with the combined ordering of barriers. Notably, the popular COPRAS method determines rank values by actively considering criteria type and complex proportional measures from different angles. Moreover, COPRAS is a simple and elegant approach for rank determination. Likewise, the Copeland strategy is a powerful rank aggregation measure that yields cumulative ordering of barriers based on the rank order from individual experts' data. Besides, the combination allows consideration of both criteria and experts' weights in the rank determination process. The sense of personalization along with holistic ranking is supported by the COPRAS–Copeland ranking procedure. The benefits of these two approaches motivated the authors to combine them in order to formulate a ranking algorithm for ranking barriers that hinder sustainability inclusion within the clean energy supply chains.

Fig. 1 shows the architecture of the developed framework. Initially, questionnaires were developed and given to a panel of experts for data collection. Later, these preferences were converted to their respective FFNs. Opinions on criteria were considered, as explained in Section III–B, to determine the weights of criteria. Decision matrices from experts were used to calculate the importance of experts, which were used as input to formulae the criteria weights. The procedure, as discussed in Section III–B, was applied to the weight assessment of both criteria and experts. These vectors were considered as input along with decision matrices for rank estimation. Personalized and cumulative rank values were determined for barriers, and ordering was done accordingly. The personalized ranking was obtained through the algorithm, as presented in Section III–C, which was further considered within the Copeland strategy to determine the cumulative ordering of barriers.

IV. Case Example—Barrier Ranking in Sustainability Context

In this section, the usefulness of the developed framework is demonstrated through an example of barrier ranking in the context of sustainability adoption in the clean energy supply chain sector. As discussed earlier, clean energy is an attractive

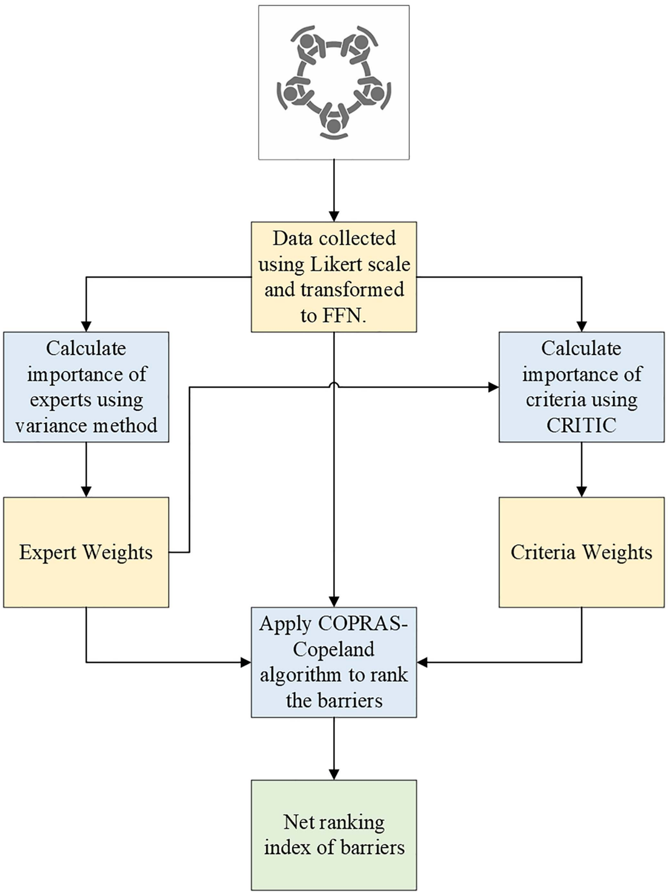

Fig. 1. Barrier grading with an integrated approach.

option to which world leaders are transforming their countries as a means to satisfy demand and achieve sustainability and green growth. However, supply chains of this sector incur a certain level of environmental problems, regarding both material production and technology manufacturing, which sets back the ideology of net zero carbon. In order to fill this gap, the enforcement of sustainability operations within supply chains would help the promotion of this objective. Owing to the implicit dynamic nature, the adoption is not direct and has some barriers/challenges.

Consider an energy firm that primarily focuses on clean energy-related component buildings as well as the promotion of power production from clean energy. This company recently conducted its annual meeting, in which the agenda was to analyze the increase in growth and action-driven plans to be implemented for the next five years. Different board-level members shared their views based on market research, and thematic discussions with scholars took place. As a result, it was inferred that the firm significantly reduced its carbon footprint when compared with the fossil-fuel-based power alternative. However, it was noted that some indirect aspects hinder the net zero carbon theme, posing a certain level of challenge to the firm in doing so. Mainly, both component building and resource utilization mechanisms need to increase their sustainability in order to help India achieve its ambitious goal of 45% reduction of carbon trace in the Paris Accords. Indeed, this is the responsibility of each sector in order to actively focus on achieving this common goal and to correct their strategies for greater sustainable development.

Along these lines, the clean energy sector has the advantage of reducing carbon emissions to a great extent. However, if they could also improve sustainability in other indirectly related aspects, they could potentially achieve the net zero carbon emission objective. Moreover, researchers have shown that the process is not direct, and barriers pop up during such initiatives. One idea is to prioritize the barriers so that both policymakers and experts can plan their strategies on more critical and high-priority barriers, which will increase the pace toward sustainability. For this purpose, the energy firm assigned four experts with specializations in diverse fields, including a senior professor from the sustainability science division, a manager from the energy firm, an employee from the financial department, and a researcher from the R&D clean energy division. Moreover, these professionals have 7–8 years of expertise in their respective fields. The panel collected diverse challenges/barriers from different kinds of literature according to their personal expertise. Based on the voting, 12 barriers are shortlisted for this case example. These barriers were rated over circular economy (CE) criteria identified in the literature, with nine criteria being considered for the rating of the barriers. In this study, the 12 barriers include funds insufficiency, legislation, monitoring, and control issues, improper investment, ineffective integration strategy/framework, expertise mismatch, issues with waste treatment, material-based energy, job reskilling/upskilling issues, ineffective quality of resources, limited governmental policies, lack of support from management, and limited awareness to Industry 4.0; and the 9 criteria are green design, waste/pollution reduction, sustainable logistics, profit from green production, green purchase, job growth, cost, resource wastage, and emission.

Furthermore, the procedure for ranking barriers is presented in the following text. For simplicity, let T_1, T_2, T_3, and T_4 be four experts that rate 12 barriers M_1, $M_2,\ldots,$ and M_{12}, based on nine criteria F_1, $F_2,\ldots,$ and F_9. Let us consider the following Likert scales for rating along with their FFNs—first, *for rating barriers based on criteria:* absolutely high (AH) – (0.90, 0.10), very high (VH) – (0.80, 0.60), moderately high (MH) – (0.80, 0.65), high (H) – (0.75, 0.60), neutral (N) – (0.50, 0..50), low (L) – (0.60, 0.70), moderately low (ML) – (0.70, 0.80), very low (VL) – (0.60, 0.90), and absolutely low (AL) – (0.01, 0.98)—and second, *for rating criteria:* absolutely highly preferred (A.H.P) – (0.90, 0.10), very highly preferred (VHP) – (0.80, 0.60), moderately highly preferred (MHP) – (0.80, 0.65), highly preferred (HP) – (0.75, 0.60), neutral preference (NP) – (0.50, 0.50), less preferred (LP) – (0.60, 0.70), moderately less preferred (MLP) – (0.70, 0.80), very less preferred (VLP) – (0.60, 0.90), and absolutely less preferred (ALP) – (0.01, 0.98).

Step 1: Obtain decision matrices of order 12 × 9 from four experts in the qualitative form, which can later be converted to FFNs.

Table III gives the rating of barriers over CE criteria from each expert's point-of-view, which are Likert-scale values that are converted to FFNs using the values provided above. These matrices were utilized in the procedure, as discussed in Section III–B, to determine the importance of experts.

TABLE III
BARRIERS RATING ON CRITERIA

M	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
T_1									
M_1	N	MH	ML	N	H	N	ML	N	MH
M_2	N	H	H	ML	ML	L	L	L	VH
M_3	MH	VL	H	N	H	MH	MH	ML	ML
M_4	N	H	H	H	H	ML	MH	H	MH
M_5	H	MH	H	ML	ML	ML	N	VH	H
M_6	H	H	N	MH	MH	ML	H	N	H
M_7	VL	L	MH	N	ML	H	VL	N	ML
M_8	MH	L	L	L	ML	MH	VH	L	VH
M_9	VL	VH	H	ML	VH	L	L	ML	L
M_{10}	L	N	H	L	N	L	MH	L	ML
M_{11}	VL	VL	ML	H	N	VL	MH	L	N
M_{12}	VL	VL	ML	ML	MH	ML	L	L	H

TABLE IV
CRITERIA CHOICES FROM EXPERTS

T	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
T_1	LP	NP	VLP	LP	HP	HP	HP	NP	MLP
T_2	VLP	NP	HP	NP	LP	MHP	MHP	MHP	LP
T_3	NP	MLP	HP	LP	HP	VLP	MHP	LP	HP
T_4	VLP	MLP	MHP	VHP	LP	LP	MHP	LP	HP

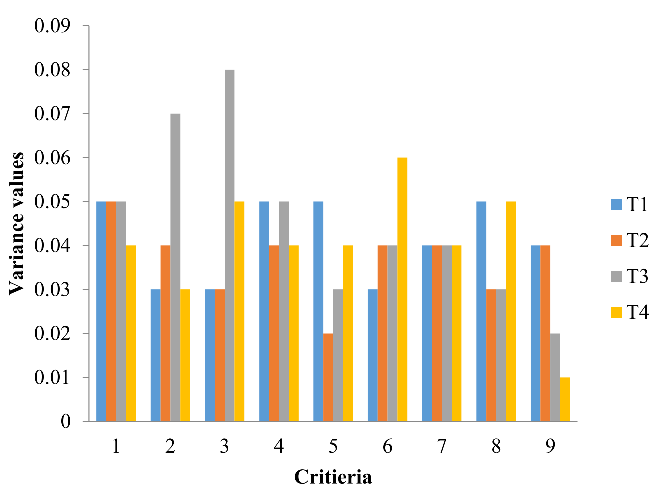

Fig. 2. Variance values based on the experts' data.

Fig. 2 provides the variance value associated with each criterion based on experts' data, by applying (9), and based on (10). Subsequently, the weights of experts were calculated as 0.25, 0.23, 0.28, and 0.24, respectively.

Step 2: Form a matrix of 4×9 for criteria weight estimation by considering linguistic rating. The procedure in Section III–B is applied to determine the criteria weights.

Rating data were converted to FFN based on the value presented above. Criteria weights yielded a 1×9 vector in the unit interval, by considering opinions from Table IV and the importance vector from Step 1. The heatmap of the interactions among criteria in Fig. 3 is a 9×9 correlation plot that represents the correlation between each pair of criteria. The variance and interaction values were used to calculate the information that was further normalized to obtain the criteria weights. By applying (12) and (13), the weights of criteria were determined to be 0.12, 0.28, 0.08, 0.25, 0.01, 0.04, 0.05, 0.15, and 0.05, respectively.

A vector of 1×9 was calculated as the weights of criteria, and the weight parameters were determined based on the data/rating from Table IV and the correlation heatmap from Fig. 3. Finally, the weight vector was obtained using the procedure in Section III–B. It must be noted that the weights of experts are considered a parameter for the criteria weight calculation. Considering the variance approach and data from Table III, the experts' weights were calculated. The procedure of the expert weight calculation is also given in Section III–B.

Step 3: Apply the procedure in Section III-V, along with data from Step 1 and weights from Step 2, to determine the ordering of barriers.

$R3$ was calculated for each barrier based on each expert's rating data by applying (16). Values from (14) and (15) were given as input to (16), where β was set to 0.50. The last column in Table V presents the ordering of barriers based on rating data

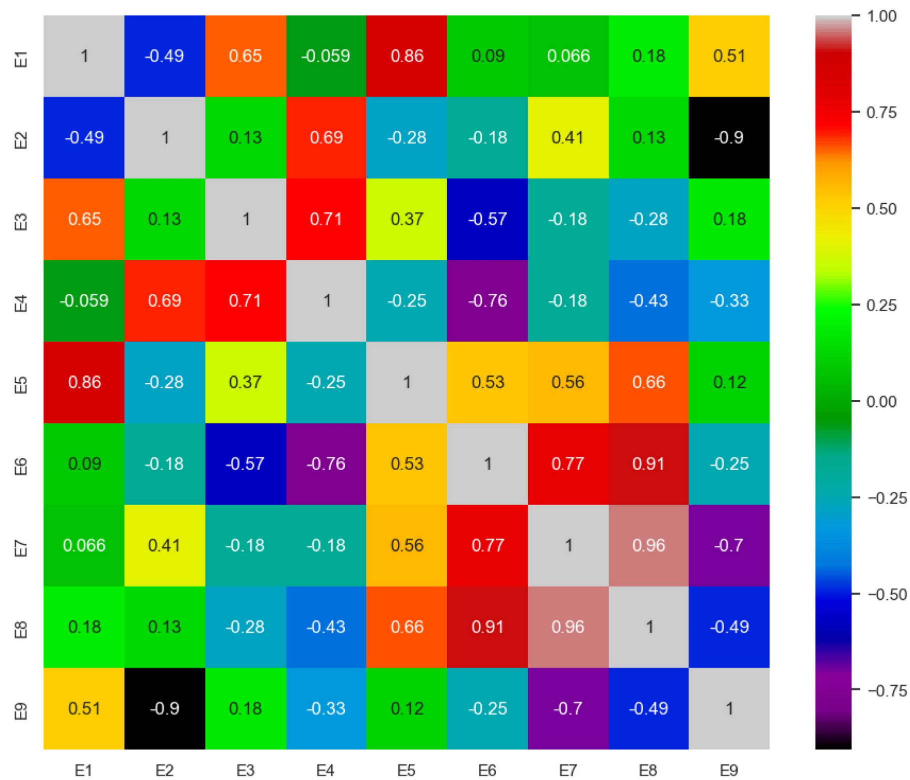

Fig. 3. Interaction values of criteria—(E1 is the green design, E2 is the waste/pollution reduction, E3 is the sustainable logistics, E4 is the profit from green production, E5 is the green purchase, E6 is the job growth, E7 is the cost, E8 is the resource wastage, and E9 is the emission).

TABLE V
RANK ALGORITHM PARAMETERS

M	$R1$	$R2$	$R3$	Order
		T_1		
M_1	5.03	2.65	2	3
M_2	5.11	2.71	1.25	6
M_3	5.07	2.73	1.75	4
M_4	5.17	2.79	0.75	9
M_5	5.31	2.82	0.5	10,11
M_6	5.30	2.64	0.5	10,11
M_7	4.98	2.61	2.25	2
M_8	5.14	2.76	1	8
M_9	5.35	2.69	0.25	12
M_{10}	4.93	2.70	2.5	1
M_{11}	5.10	2.66	1.25	7
M_{12}	5.07	2.68	1.5	5

from each expert, which is: $M_{10} \succ M_3 \succ M_6 \succ M_{12} \succ M_2 \succ M_7 \succ M_1 \succ M_8 \succcurlyeq M_{11} \succ M_5 \succcurlyeq M_9 \succ M_4$. This ordering is considered to be the cumulative ordering based on the Copeland strategy. Readers are recommended to refer to the Appendix for a deeper discussion on the Copeland strategy calculation from (17) to (19).

V. SENSITIVITY MEASURE AND COMPARISON WITH OTHER MODELS

This section describes the effectiveness of the integrated proposed model based on the sensitivity measures of strategy values and criteria weights. This analysis systematically considers unit step-size values for strategies, also known as an intra-analysis, and new weight vectors via rotation of weights' values, otherwise called an interanalysis. The intra-analysis was performed with the actual weights of criteria that were obtained from the procedure in Section III–B. Subsequently, four graphs were obtained with respect to the four experts' preference data. The graphs in Fig. 4(a)–(d) show the rank values at different strategy values. Regarding the interanalysis case, considering different sets of criteria weights, rank orders are presented based on the Copeland strategy in Fig. 5 .

Fig. 4(a)–(d) presents the intracase sensitivity analysis in which the strategy values are altered with unit step size from 0.1 to 0.9. It must be noted that when the strategy value is in the range [0.1, 0.5), the benefit-type criteria are given less priority than the cost-type criteria. Likewise, when the value is in the range (0.5, 0.9], the cost-type criteria are given less priority than the benefit-type criteria. When the strategy value is 0.50, the priority between cost and benefit types is equal. Based on these strategy values, the $R3$ values were calculated to yield a vector of 1×12 order. It is noted from the figures that, as the strategy value changes, the ordering of barriers is altered, which clearly induces competition among the barriers

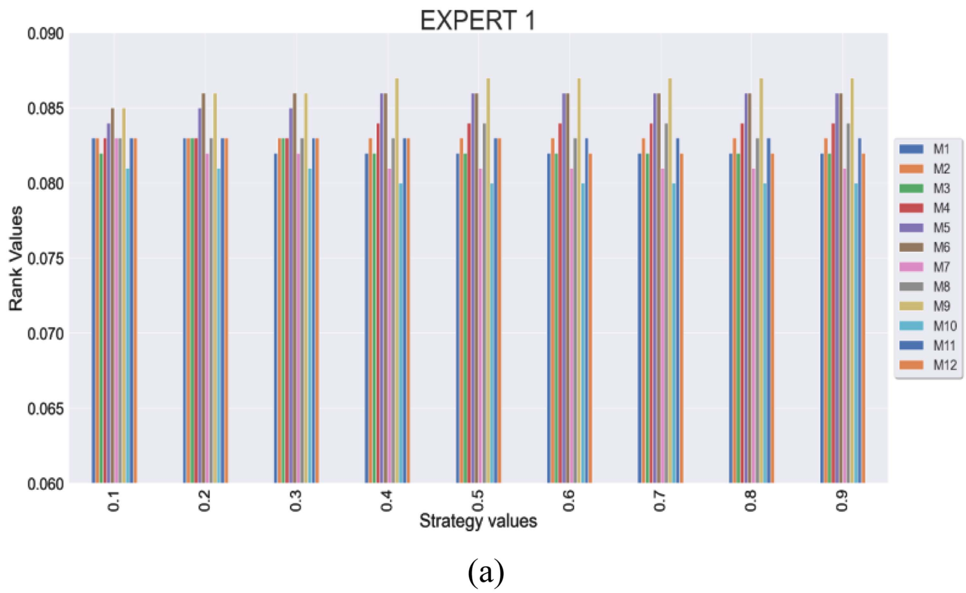

Fig. 4. Sensitivity analysis—Intra case (a)–(d) refers to four experts.

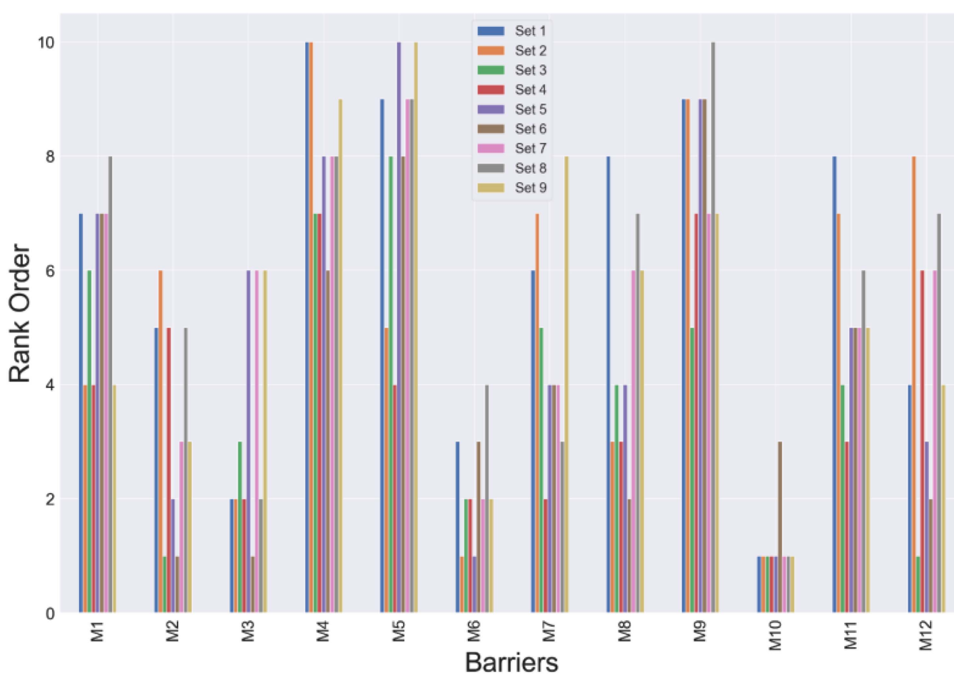

Fig. 5. Sensitivity analysis—Intercase.

and the close/competitive rating provided by each expert in terms of the significance or cruciality of the barrier, which if circumvented could promote faster and effective implementation of sustainability within clean energy supply chains. It is also observed that the highest priority and lowest priority barriers retain the spot intact even after adequate changes are made to the strategy values. Barriers M_9 and M_{10} are the top and bottom priority barriers based on the rating information from T_1. Likewise, barriers M_8 and M_6 are the top and bottom priority barriers based on the rating information from T_2. From the data given by T_3, M_4 and M_3 are the top and bottom priority barriers. Finally, based on the rating data from T_4, M_{11} and M_{10} are the top and bottom priority barriers. In a similar manner, the ordering of barriers with respect to changes in strategy values and rating information from each expert can be inferred from Fig. 4(a)–(d).

Since nine criteria were considered in this study, we formed nine sets, each of order 1×9 with set generation enabled via rotation operation. To understand the process, let us consider three criteria with weights of 0.2, 0.3, and 0.5. Set 1 is (0.2, 0.3, 0.5); set 2 is (0.5, 0.2, 0.3); and set 3 is (0.3, 0.5, 0.2). Likewise, when we have nine criteria, there are nine values that

TABLE VI
DIFFERENT FEATURES FROM THE PROPOSED AND OTHER BARRIER RANKING MODELS

Proposed	Kumar et al. [54]	Shah et al. [76]	Chen et al. [22]	Rasty et al. [67]	Kumar et al. [52]	Dhingra et al. [26]
Input						
FFN	Fuzzy	Fuzzy	Fuzzy	IFS	Fuzzy	Fuzzy
Experts' importance						
Yes – calculated	No	No	No	No	No	No
Experts' hesitation						
Captured	No	No	No	No	No	No
Distribution dynamism						
Captured	No	No	No	No	No	No
Criteria interrelationship						
Captured	No	No	No	No	No	No
Role of experts' weights						
Ranking and criteria weights	No	No	No	No	No	No
Criteria nature						
Considered	Considered	No	Considered	No	No	No
Personalized ranking						
Allowed	No	No	No	No	No	No
Uncertainty modeling						
Three dimensions	One dimension	One dimension	One dimension	Three dimension	One dimension	One dimension
Choice expression						
Broad	Narrow	Narrow	Narrow	Narrow	Narrow	Narrow

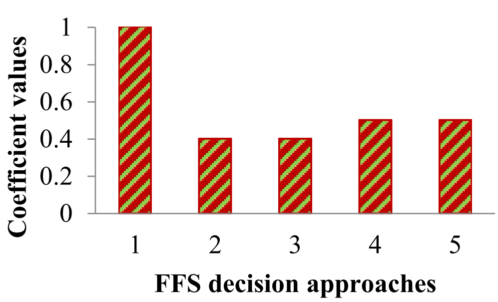

Fig. 6. Uniqueness measure—(X-axis 1 – Proposed versus Proposed; 2 – Proposed versus Akram et al. [8]; 3 – Proposed versus Deng and Wang [24]; 4 – Proposed versus Mishra et al. [62]; 5 – Proposed versus Aytekin et al. [17]).

form the weight vector. Now by rotation, we can form nine sets of a weight vector that are utilized for intercase sensitivity analysis. In Fig. 5, the legends set 1 to set 9 denote this idea. Fig. 5 also reveals competition among the barriers, which is inferred via the different ordering of barriers when looking at different criteria sets. Intuitively, it can be noted that these orders reveal the importance of criteria weights that influence the ordering of barriers. Based on the majority principle, M_{10} is observed as the most crucial barrier to be addressed to better promote sustainable operations in clean energy supply chains. Similarly, M_4 is the least focused barrier, indicating that the strategies for addressing this barrier can be flexible and less stringent, as it may not cause a huge hindrance in sustainability operations. Such intuitive thoughts are possible via the sensitivity analysis of strategy and criteria weight values. Specifically, it is seen that M_{10} is a barrier of high importance, while M_4 is less important. Based on the calculated criteria weight set and Fig. 4(a)–(d), the inference holds true to a considerable extent. However, when criteria weights are rotated, the competition among barriers is apparent, and there is variation in the importance of barriers. As a result, such a sensitivity analysis is essential to better understand the effect of barriers on sustainability operations to aid stakeholders in effectively planning strategies.

Apart from the sensitivity measure, a comparison of a method-based decision model and application-based models was conducted. Specifically, models proposed by the authors in [22], [26], [52], [54], [67], and [76] were considered for comparison with the proposed model, which can help better understand the features of the developed framework.

Table VI offers a summarized view of the features of barrier ranking models. Further innovative aspects of the proposed model are detailed as follows.

1) FFS is a generic orthopair set that can easily offer flexibility to experts to express their opinions in a broader space of expression. Apart from this, the uncertainty can be modeled in three aspects: truth, falsity, and hesitancy grades.
2) Unlike extant models, human intervention is reduced to avoid inaccuracies and biases during the decision process. Methodical calculation of entities is enforced in the proposed model.
3) The hesitation of experts during preference expression, as well as variability in choice sharing, can be captured by the developed model, which is clearly lacking in previous models.

4) Practical MCDM problems have interrelationship/tradeoffs within the criteria set and can be modeled via the proposed approach, whereas the existing approaches less explore it.
5) Since experts are a substantial component of MCDM, their importance is applied in rank estimation and weight estimation, which is unique compared with other models.
6) Finally, rank estimation is triggered by cumulative perception and individual preferences, which offers a sense of personalization that is typically missing in earlier barrier prioritization models.

Besides these promising features, we also consider methodical perception. Moreover, methods proposed by the authors in [8], [17], [24], and [62] were compared with the developed approach in terms of uniqueness and broadness. In the uniqueness measure, the data were given to each approach, and then the rank values were determined and further ordered. The results were sent to Spearman correlation to determine the coefficient values with respect to the proposed method versus other approaches. The computed coefficient values were calculated as 1.0, 0.40, 870, 0.40, 0.50, and 0.50, respectively, which are presented in Fig. 6 in the graphical form. From these values, it can be noted that the developed approach is unique compared with other approaches in terms of formulation by allowing consideration of both individual and cumulative ordering of barriers based on experts; preference data.

From the point-of-view of ranking influence, the proposed model provides both cumulative ordering and personalized ordering of barriers. This capability intuitively delivers significant information to policymakers to decide on the importance and criticality of a specific barrier from both the individual expert's perception and aggregated perception, thereby getting the feel of atomic-level grading of barriers and the holistic grading of barriers. Intuitively, such a model will promote better feedback mechanism and implementable actions.

The discrimination ability of the developed framework was realized based on the simulation study performed with 300 matrices generated using the programming language Python, where each matrix was of order 12×9 with criteria weights obtained from the earlier section. These matrices were given as input to other FFS-based decision models, such as those introduced by the authors in [8], [17], [24], and [62]. The rank values were determined for the barriers via these approaches, and the variance of the ranks was obtained for all 300 rank vectors calculated by each approach. The rating information from experts was aggregated using the simple weighted geometry operator for the extant models, and for the proposed framework, the rank values were aggregated using the operator with weights of experts obtained from Section IV. Specifically, 300 variance values were determined for each model based on the matrix set considered for the experiment, which is plotted in Fig. 7. From the figure, it is clear that the proposed model is capable of generating broad rank values compared with its counterparts, making the model effective for discrimination of barriers. This eventually helps experts and policymakers to better understand the priorities of each barrier and make plans accordingly to alleviate the crucial barriers with the defined resources available. Moreover, Fig. 7 indicates that the proposed model can most effectively discriminate barriers, followed

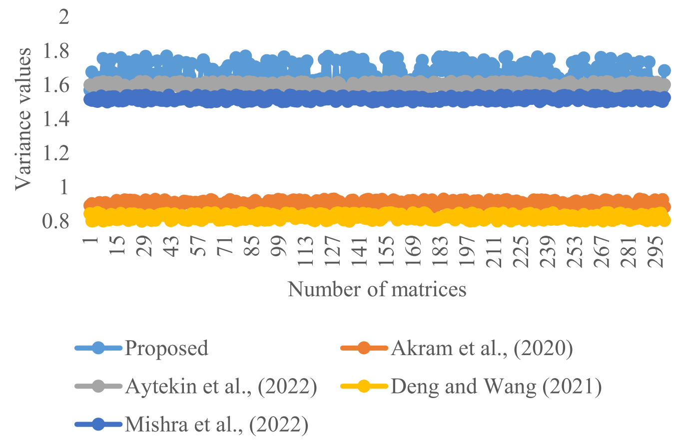

Fig. 7. Broadness analysis of rank values from the proposed and other models.

by the models presented by the authors in [17], [62], and so on.

VI. Results and Discussion

The developed model puts forward an integrated approach with the intention to reduce human intervention and handle uncertainty effectively. Prioritization of barriers helps organizations to better plan strategies with the availability of a finite amount of time and budget. Contrarily, if the barriers are not prioritized, spending time and money to circumvent a low-priority barrier might turn out costly for the organization. In this regard, there is an urge for grading barriers so as to obtain an ordering of these barriers/challenges.

To do so, this research work considered CE criteria that are useful for rating barriers from an expert's point-of-view. Typically, the criteria have different importance values, which vary from one expert to another, thus posing effects on the final ranking. As a result, a methodical approach was followed in this work for calculating the weights of criteria. Specifically, the developed model has the following merits.

1) Flexible modeling of uncertainty with FFNs.
2) Methodical determination of experts as well as criteria weights to reduce bias and inaccuracies.
3) Model hesitation during preference articulation by experts by considering all data points unlike the extreme value approaches and later determine the distribution behavior of rating/preferences.
4) Captures interactions among criteria and considers the importance of experts during weight assessment.
5) Determines both cumulative and personalized rank orders based on each expert's rating information.

Such advantages are lacking or less explored in extant barrier ranking models and add value to the decision process with reduced human intervention, bias, and subjectivity. Furthermore, it must be noted that "wastage/pollution reduction" is considered to be the most important criterion with a weight value of 0.28, followed by "profit from green production (0.25)," "resource wastage (0.15)," "green design (0.12)," and so on. Based on these criteria weights, the barriers were graded. Section IV provides the weight vector and rank values of CE criteria and barriers. Table IV presents the rating from each expert on criteria, which were converted to FFNs based on the respective values, as presented in Section IV. By applying (11), the weighted accuracy matrix of 4×9 order was obtained. Equations (12) and (13) were applied to get the correlation matrix and criteria weight vector. The 9×9 correlation matrix was obtained from (12), and then (13) was used to get the weights of criteria in the unit interval with 1×9 as the order. Fig. 3 depicts the correlation values obtained for all nine criteria, which are used by (13) for determining the weights of criteria.

From the barrier ranking, it is inferred that "limited governmental policies (M_{10})" is the top ranked barrier based on the rating data given by experts. It can be noted that attractive policies and incentives from the government would seriously impact the adoption of sustainability in firms in the clean energy sector, as these policies will provide clear guidelines and direction for firms to effectively realize the success in terms of sustainability adoption. Moreover, these policies could include incentive-based plans that would motivate firms to expedite their transformation. Following this, "monitoring and control issues (M_3)" are the second ranked barriers based on the data from experts. Ideally, there is no clear metric for monitoring the sustainability aspect in the firm, and there is little or no mechanism to control sustainability. As a result, the adoption is affected in firms. Later, in the rank series, we found that "expertise mismatch (M_6)," "limited awareness to Industry 4.0 (M_{12})," and "legislation (M_2)" also hinder sustainability adoption in the clean energy sector. Notably, these barriers also are crucial for the firms, and as a result, the policymakers and experts must devise strategies to tackle or counter these barriers. These top five barriers affect the sustainability adoption within the clean energy sector according to the rating data provided by experts. Considering the rank orders of barriers in Section IV, policymakers can devise strategies for these barriers based on the budget and available time. The last two barriers are "insufficient quality of resources (M_9)" and "improper investment (M_4)," which could be given little attention, owing to the limited amount of time and budget for carrying out the strategies for different barriers that hinder sustainability adoption. Based on the data from experts, these two barriers are placed last in the rank list. Intuitively, it can be noted that with little changes to strategies or small improvement to the existing strategy, these two barriers can be addressed compared with the earlier top five barriers in the rank list that require considerable amount of time and budget to work the strategy for effectively alleviating those barriers.

From the application context, we present the top ranked barriers and high importance criteria. This helps stakeholders gain an understanding of the decision entities and plan the system accordingly to meet the current demand of prioritizing barriers that hinder sustainability adoption within clean energy supply chains. From the method context, the focus is to reduce human intervention, which incurs bias and subjectivity and cannot be alleviated without reducing the intervention rate. Although certain readers might feel the model to be complex, it is worth noting that the methodical determination of decision parameters, such as experts' weights, criteria weights, and ranks of barriers, reduces human intervention, subsequently decreasing bias/subjectivity. Considering the impact of the developed model, the following points should be considered.

1) Uncertainty is better modeled with the help of FFN by flexibly expanding the preference window for the membership and nonmembership degrees.
2) Weights of experts and criteria are methodically determined and are considered to be crucial for the decision process.
3) Experts' hesitation during preference articulation is captured along with interactions of criteria, which are significant cues that support decision making.
4) Individualistic ranking of barriers based on each expert's rating data is a novel and crucial phase of ranking along with the cumulative ordering of barriers.

The sense of personalization and better planning for a particular barrier can be intuitively influenced by the two-stage ordering of barriers, in which the expertwise ordering is finally aggregated to obtain the cumulative ordering. When it comes to recommending the proposed model to industry expert or practitioner, it is important to note that the stakeholders need some training in uncertainty modeling to understand the data articulation and data modeling mechanism. Also, some training is needed in terms of the implementation procedure to comprehend the working of the model, which would help stakeholders effectively utilize the system for rational and supportive decision making. Specifically, the authors recommend using such frameworks for improved decision making with reduced human-driven bias and error along with a support of mathematical basis for arriving at a particular decision. This would further allow stakeholders to revert back to the system for feedback and scope of improvement based on a better understanding of the obtained decision. Despite the complexity of the model in terms of implementation, which could be alleviated with some training, it serves as a supplementary decision tool for managers and practitioners in the decision-making process.

VII. Conclusion

In this article, we presented a novel framework in the clean energy domain, which intends to rank different barriers that affect the adoption of sustainability practices in the context of clean energy supply chains. Although clean energy is a promising alternative for energy satisfaction and reduced carbon emissions, certain habits and practices in the overall supply chain model prevent the sector from net zero carbon. In this study, a methodical approach was devised to rank the hindering factors/barriers that could be mitigated to achieve net zero aspirations. The developed model primarily focuses on reduced human intervention and determining the rank order in a methodical manner to avoid subjective biases.

The comparison results clearly show the uniqueness of the proposed model in terms of application perspective, and from the methodical point-of-view, the importance of criteria weights and the competition among barriers are showcased. Inter/intrasensitivity analyses demonstrate the crucial aspect of weights and strategy values, and the competition among barriers is inferred based on the Copeland strategy. Furthermore, the correlation measure clarifies the uniqueness of the decision model, which attempts to formulate ranks based on individual and cumulative perceptions.

Despite these merits, the following limitations were observed.

1) Unavailability of preference cannot be handled.
2) Data consistency cannot be repaired.
3) Choice-driven grading of barriers is not presently possible.

Certain managerial implications are as follows.

1) Uncertainty is handled from three zones, and experts gain flexibility in opinion sharing compared with other orthopair sets.
2) Methodical determination of entities avoids both biases and inaccuracies in the process.
3) The developed system handles subjective randomness.
4) A ready-to-use tool that could be used by stakeholders to obtain supportive decisions with the adequate mathematical background to support decisions is put forward.
5) Some training of stakeholders is expected for better usage of this tool.

Despite the promising results of the presented model, its limitations should be addressed in further study. Besides, the developed model can be used for different MCDM tasks related to sustainability and green practices, including energy source selection, energy location selection, stakeholder selection, and green component/design selection, among others. Also, the current problem of barrier selection can be modeled to different fuzzy variants, such as hesitant fuzzy context, probabilistic versions of orthopair, neutrosophic variant, spherical fuzzy form, and so on. Apart from these MCDM paradigms, recommendation concepts and preference learning aspects could be integrated to achieve decisions/consensus at bigger scales.

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