information

MDPI

Article

Fermatean Fuzzy-Based Personalized Prioritization of Barriers to IoT Adoption within the Clean Energy Context

N Sai Snehitha Reddy [1], Raghunathan Krishankumar [1], S Shanmugha Priya [1], Fausto Cavallaro [2,*], Abbas Mardani [3] and Kattur Soundarapandian Ravichandran [4]

[1] Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Coimbatore 641112, Tamil Nadu, India; cb.en.p2cse21010@cb.students.amrita.edu (N.S.S.R.); r_krishankumar@cb.amrita.edu (R.K.); ss_priya@cb.amrita.edu (S.S.P.)
[2] Department of Economics, University of Molise, 86100 Campobasso, Italy
[3] Business School, Worcester Polytechnic Institute (WPI), Worcester, MA 01609-2280, USA; abbas.mardani.edu@gmail.com
[4] Department of Mathematics, Amrita School of Physical Sciences, Amrita Vishwa Vidyapeetham, Coimbatore 641112, Tamil Nadu, India; ks_ravichandran@cb.amrita.edu
* Correspondence: cavallaro@unimol.it

Abstract: Globally, industries are focusing on green habits, with world leaders demanding net zero carbon; clean energy is considered an attractive and viable option. The Internet of things (IoT) is an emerging technology with potential opportunities in the clean energy domain for quality improvement in production and management. Earlier studies on IoTs show evidence that direct adoption of such digital technology is an ordeal and incurs adoption barriers that must be prioritized for effective management. Motivated by the claim, in this paper, the authors attempt to prioritize the diverse adoption barriers with the support of the newly proposed Fermatean fuzzy-based decision framework. Initially, qualitative rating information is collected via questionnaires on barriers and criteria from the circular economy (CE). Later, these are converted to Fermatean fuzzy numbers used by integrated approaches for decision processes. A regret scheme is put forward for determining CE criteria importance, and the barriers are prioritized by using a novel ranking algorithm that incorporates the WASPAS formulation and experts' personal choices during rank estimation. The applicability of the developed framework is testified via a case example. Sensitivity analysis and comparison reveal the merits and limitations of the developed decision model. Results show that labor/workforce skill insufficiency, an ineffective framework for performance, a technology divide, insufficient legislation and control, and lack of time for training and skill practice are the top five barriers that hinder IoT adoption, based on the rating data. Additionally, the criteria such as cost cutting via a reuse scheme, resource circularity, emission control, and scaling profit with green habits are the top four criteria for their relative importance values. From these inferences, the respective authorities in the clean energy sector could effectively plan their strategies for addressing these barriers to promote IoT adoption in the clean energy sector.

Keywords: circular economy; sustainability; regret theory; digital technology; WASPAS method

check for updates

Citation: Reddy, N.S.S.; Krishankumar, R.; Priya, S.S.; Cavallaro, F.; Mardani, A.; Ravichandran, K.S. Fermatean Fuzzy-Based Personalized Prioritization of Barriers to IoT Adoption within the Clean Energy Context. *Information* **2023**, *14*, 309. https://doi.org/10.3390/info14060309

Academic Editors: Luis Martínez López, Lesheng Jin, Zhen-Song Chen, Humberto Bustince and Antonio Jiménez-Martín

Received: 10 February 2023
Revised: 18 May 2023
Accepted: 22 May 2023
Published: 29 May 2023

1. Introduction

Clean energy attracts attention worldwide as nations strive to reduce or eradicate their carbon footprint. In the Paris Accord, world leaders committed to reducing carbon traces from Earth [1]. Recently, India firmly committed to sustainable green/lean development [2] by planning to reduce carbon traces by 45% by the year 2030. This updated agreement truly showcases the concrete focus of the nation towards sustainability. Additionally, the country plans to adopt non-fossil fuels for a 50% share of installed capacity to generate electricity to meet the demand (www.carbonbrief.org, accessed on 3 October 2022). In

2015, India launched the 'Digital India' initiative, which was primarily targeted to scale up the IT sectors and make them an integral part of the nation's development by integrating technologies into diverse fields such as health, environment, economy, and education [3]. The Internet of things (IoTs) is a digital technology applicable in diverse fields such as agriculture, environment, health, and energy [4,5]. IoT is a fast-growing technology in the global market. It can be defined as things connected via the internet by network connection in either wired or wireless format [6].

Production and distribution of clean energy to satisfy its demand involve a crucial play of consistent interconnection between diverse entities, and embedding IoT technology in the clean energy field is a convenient and reasonable approach to achieving success [7,8]. Driven by this train of thought, many IoT vendors prepare themselves for the new and emerging use case of implementing IoT in the clean energy sector. Specifically, the launch of the 'Digital India' initiative and the updated Paris Accord indicate a promising opportunity for sustainable and global development in India. A scheme called "Atal Mission for Rejuvenation and Urban Transformation" (AMRUT), launched in 2015 in India, focused on the transformation of cities for better living by adopting innovative solutions actively supported by digital technologies [9]. In the process of developing smart cities with active and well-connected businesses, clean energy plays a substantial role, and there arises a need for energy at a feasible cost, in sufficient quantity, and in a clean manner.

Although there is interest in embedding IoT in the clean energy sector, its direct adoption is an ordeal, as it involves diverse barriers/challenges that hinder adoption. From the stakeholders' point of view, it is essential to rank these barriers for a better understanding of the severity of these barriers/challenges so that strategies can be planned and implemented to resolve the challenges/barriers easily. Mardani et al. [10] prepared a SWOT analysis-based decision approach for ranking technologies based on diverse barriers. Further, Cui et al. [11] assessed different IoT organizations based on diverse barriers under the Pythagorean decision framework. Driven by these studies, in this paper, the authors plan to rank barriers that hinder IoT adoption within clean energy sectors by proposing a new decision framework under the Fermatean fuzzy context. As discussed above, there is an urge to rank such barriers to promote their success within their respective sectors. The rating of these barriers is accompanied by circular economy (CE) criteria, which actively promotes sustainability and supports the rating of IoT adoption barriers. CE follows the theme of zero waste and aims to make the waste of one resource into another. Complementing the linear economy that follows the 'take–make–use–dispose' theme, CE follows the 'take–make–use–dispose' theme, eradicating wastage in the system. CE obeys the 4 Rs, viz., reuse, reduce, recycle, and remove. Some critical components of CE are the product service system, cradle to cradle, industrial economy, performance economy, etc. [12].

Motivation and Research Contributions

Some research gaps that can be identified in the barrier ranking frameworks are: (i) experts expect a broader/flexible window for expressing their opinions; (ii) hesitation in preference elicitation by experts is not captured adequately; (iii) the nature of criteria is not considered during weight calculation; and (iv) personal choices of experts are not considered during rank estimation of IoT adoption barriers. To circumvent these gaps, specific research contributions are made in the present work, and they are presented in a nutshell below:

- Initial qualitative rating data from experts via questionnaires are converted to Fermatean fuzzy data (FFD) [13], which not only offers flexibility to experts in terms of opinion sharing from both preference and non-preference aspects but also helps to model uncertainty better by using three grades of uncertainty viz., membership, hesitancy, and non-membership as claimed in [13]. The inequality constraint $a^3 + b^3 \leq 1$ (a is the membership grade and b is the non-membership grade) allows flexibility in the orthopair values, thereby providing a window for experts to express their opinions effectively compared to fuzzy set, intuitionistic, and Pythagorean fuzzy sets. Based on the discussion with experts regarding the quantification of the qualitative terms for the degree of preference and non-preference, the conversion is made by adhering to the constraint of FFD.

- Weights of criteria are determined methodically by presenting a regret measure, which not only captures the hesitation of experts but also considers the nature of criteria during weight assessment.
- A new ranking algorithm is developed by considering the formulation of "weighted aggregated sum product assessment" (WASPAS) and personal choices from experts to obtain personalized ordering of barriers, which not only provides a sense of personalization but also adds rationality to the decision process by considering the rating for each criterion and their overall opinion for a particular option (barrier in this case).
- Further, a case example of barriers to IoT adoption in the clean energy sector within India is demonstrated to understand the model's usefulness.
- Finally, sensitivity analysis for weight values followed by a comparison of the proposed model with extant models from both the application and method perspectives is performed to understand the merits and limitations of the current work.

The rest of this article is organized in the following fashion. The literature review of existing models for barrier prioritization and Fermatean fuzzy-based models for the decision process is provided in Section 2. The methodology is explained stepwise in Section 3, where the basic concepts are provided along with the detailed procedure for criteria weight determination and personalized ranking of barriers hindering IoT adoption. Section 4 offers a case example demonstrating the developed framework's applicability. Comparison from both the application and method point of view is presented in Section 5, and finally, a conclusion with future direction to research is given in Section 6.

2. Literature Review

2.1. Decision Models for Barriers Ranking

In recent times, barrier ordering and selection is becoming crucial owing to their significance in the net growth of an organization. As nations firmly commit to reducing carbon traces, sustainability is becoming a key factor [14,15]. However, in practical cases, adopting components such as technologies, sustainable operations, and green habits is indirect, and critical barriers hinder adoption. Table 1 presents a brief summary of such barrier selection using decision approaches to show the earlier works in the respective field.

Table 1. Summarized view of different barrier assessment decision models in the literature.

Source	Application	Methods Proposed	No of Alternatives	No of Criteria	Whether Sensitivity Analysis Is Done or Not	Whether Comparative The Analysis Is Done or Not	Fuzzy Set Used
[11]	IoT barriers	CoCoSo SWARA	4	25	Yes	No	PFS
[12]	Sustainability barriers	AHP ELECTRE	15	9	No	Yes	Fuzzy set
[16]	Offshore outsourcing barriers evaluation	AHP	3	10	Yes	No	Interval fuzzy set
[17]	Supply chain management barriers	ELECTRE	6	9	No	Yes	IFS

Table 1. *Cont.*

Source	Application	Methods Proposed	No of Alternatives	No of Criteria	Whether Sensitivity Analysis Is Done or Not	Whether Comparative The Analysis Is Done or Not	Fuzzy Set Used
[18]	IoT barriers in manufacturing industry	AHP TOPSIS	10	13	No	Yes	Fuzzy set
[19]	Sustainable consumption barriers	ANP	20	4	No	Yes	Fuzzy set
[20]	Industry 4.0 implementation barriers	SWARA WASPAS	6	5	Yes	No	Fuzzy set
[21]	Waste management barriers	COCOSO	15	4	Yes	Yes	FFS
[22]	Hydrogen up-site barriers	WASPAS COPRAS	14	4	No	Yes	IFS
[23]	Blockchain in CE adoption barriers	ANP	14	7	Yes	Yes	HFLTS
[24]	Prioritization of barriers in Indian manufacturing industries	AHP ANP	15	4	Yes	No	Fuzzy set
[25]	Spray painting robot barriers	SWARA COCOSO	6	7	No	Yes	IFS
[26]	Tourism barrier evaluation	DEMATEL ISM	17	4	No	Yes	IFS
[27]	CE barriers	CoCoSo	15	5	Yes	No	Fuzzy set
[10]	Digital technology barrier selection	SWARA WASPAS	4	24	Yes	Yes	HFS

Note: IFS—intuitionistic fuzzy set, PFS—Pythagorean fuzzy set, AHP—analytical hierarchy process, ANP—analytic network process, SWARA—stepwise weight assessment ratio analysis, WASPAS—weighted aggregated sum product assessment, ELECTRE—elimination and choice expressing reality, CoCoSo—Combined Compromise Solution method, HFLTS—hesitant fuzzy linguistic term set, DEMATEL—decision-making trial and evaluation laboratory, ISM—interpretive structural modeling, COPRAS—complex proportion assessment, and FFS—Fermatean fuzzy set.

Table 2 shows the need for the proposed decision model by pointing out the research gaps in the extant barrier prioritization decision models from the literature. It can be noted from Table 2 that IFS, PFS, and FFS can express both preference and non-preference values, unlike the classical fuzzy set and its interval variants. Additionally, among IFS, PFS, and FFS, from [13], it is clear that FFS has a broader scope/window for choice/views expression as they have a constraint as $\mu^3 + \upsilon^3 \leq 1$, which allows membership grade and non-membership grade to take values such as (0.95, 0.10) and (0.80, 0.70), which are not acceptable by PFS and IFS. So, FFS has a high level of broadness compared to other fuzzy forms discussed in Table 1. Table 2 supports the research gaps mentioned in Section 1 and motivates the authors to propose some research contributions presented in Section 1.

Table 2. Summarized view of research gaps in extant barrier prioritization models.

Sources	Expressing Both Preference and Non-Preference	Level of Broadness for Choice Expression	Experts' Hesitation during Weight Calculation	Criteria Type during Weight Calculation	Personalized Ranking
[11]	Yes	Moderate	Not considered	Not considered	No
[12]	No	No	Not considered	Not considered	No
[16]	No	No	Not considered	Not considered	No
[17]	Yes	Low	Not considered	Not considered	No
[18]	No	No	Not considered	Not considered	No
[19]	No	No	Not considered	Not considered	No
[20]	No	No	Not considered	Not considered	No
[21]	Yes	High	Not considered	Not considered	No
[22]	Yes	Low	Not considered	Not considered	No
[23]	No	No	Not considered	Not considered	No
[24]	No	No	Not considered	Not considered	No
[25]	Yes	Low	Not considered	Not considered	No
[26]	Yes	Low	Yes	Not considered	No
[27]	No	No	Not considered	Not considered	No
[10]	No	No	Not considered	Not considered	No
Proposed	Yes	High	Yes	Yes	Yes

2.2. Fermatean Fuzzy-Based Decision Models

To overcome the issues in the fuzzy set, Atanassov [28] developed the intuitionistic fuzzy set (IFS) that could represent uncertainty in three dimensions: membership, non-membership, and hesitancy. However, the IFS was limited in terms of a window for preference expression. In order to expand the idea, [29] put forward the Pythagorean fuzzy set (PFS), which offered extended flexibility to experts for sharing her/his preferences. However, still, some restrictions prevailed in the process of preference elicitation, which was addressed by Senapati and Yager [13] via the Fermatean fuzzy set (FFS), which raised the powers of membership and non-membership to three allowing the FFS to offer expanded window size for preference elicitation. Soon after, FFS gained attraction from researchers in the decision-making fields, and in this section, we briefly present the FFS-based decision models. Keshavarz-Ghorabaee et al. [30] presented FFS-based WASPAS green supplier selection in a construction zone. Sahoo [31] performed bride selection with the help of FFS-based TOPSIS and newly developed score functions. Some new operational laws were implemented with an extension to WPM for FFS-based decision making [32]. Additionally, some weighted aggregation functions from the arithmetic and geometric context were proposed along with their fundamental properties to show their potential in group decision making [33]. Similarity measures are newly developed for performing pattern recognition with FFS [34]. Further, distance/knowledge measures are presented under the FFS context for enhancing the theoretical base of the generic orthopair structure. Akram et al. [35] developed aggregation functions such as ordered weighted average and Einstein version of weighted average under the FFS context for sanitizer selection to reduce COVID-19 spread among communities. Silambarasan [36] presented some new operational laws with their properties and analytical proof to build a theoretical foundation of FFS with a significant focus on implication operators.

Furthermore, Gul [37] made lab selection for COVID-19 testing under the FFS context using the SAW and VIKOR rank methods. Aydin [38] extended the MABAC approach to

FFS under a multi-expert context to demonstrate the model's usefulness in the decision process via an illustrative example. Deng and Wang [39] presented distance measures under FFS to improve a theoretical aspect of FFS and showcased its usefulness in the decision process. Recently, Jeevaraj [40] presented the interval variant of FFS and showcased its theoretical benefit in decision making. Krishankumar et al. [41] performed zero carbon material evaluation in a construction zone by adopting a FFS-based integrated approach with CRITIC-COPRAS. Mishra et al. [42] presented another variant of FFS with interval hesitant context and extended the COPRAS approach to perform desalination technique selection. Hadi et al. [43] presented the Hamacher version of aggregation functions and weighted forms for promoting group decisions with FFS. Krishankumar et al. [44] came up with SWOT-based comprehensive method under the FFS context for ranking IoTSPs for enabling sustainable transportation in urban regions. Kirisci [45] proposed FFS-based aggregation operators with fundamental properties for the rational evaluation of infectious diseases. Sindhu et al. [46] prepared FFS-based TOPSIS for Dengue disease evaluation. Ali and Ansari [47] developed Fermatean fuzzy bipolar soft models and theoretical and practical foundations and applied the model for surgeon robot evaluation.

3. Methodology

3.1. Preliminaries

Consider some basic concepts related to IFS and FFS in this section.

Definition 1 [48]: *T is a fixed set, and $Q \subset T$ is also fixed. Then, $\overline{Q}$ is an IFS in T such that,*

$$\overline{Q} = \left\{t, \mu_Q(t), v_{\overline{Q}}(t) \middle| t \epsilon T\right\} \tag{1}$$

where $\mu_{\overline{Q}}(t)$, $v_{\overline{Q}}(t)$, and $\pi_{\overline{Q}}(t) = 1 - \left(\mu_{\overline{Q}}(t) + v_{\overline{Q}}(t)\right)$ are in the unit interval and are referred to as the membership, non-membership, and hesitancy grades, $\mu_{\overline{Q}}(t) + v_{\overline{Q}}(t) \le 1$.

Definition 2 [13]: *T is as before and $t \in T$. Then, the FFS FF on T is considered as,*

$$FF = \{t, \mu_{FF}(t), v_{FF}(t) | t \epsilon T\} \tag{2}$$

where $\mu_{FF}(t), v_{FF}(t)$ are in the range 0 to 1 and termed as grades of membership and non-membership. Moreover, $0 \le (\mu_{FF}(t))^3 + (v_{FF}(t))^3 \le 1$.

Note 1: *$FF = (\mu_\alpha, v_\alpha) \forall \alpha = 1, 2, \ldots, \tau$ is called Fermatean fuzzy number (FFN). Collectively, of FFN is FFS. IFS and FFS are special cases on q-rung orthopair fuzzy set and at $q = 1$, IFS is obtained and at $q = 3$, FFS is obtained.*

Definition 3 [49]: *FF_1 and FF_2 are two FFNs. Arithmetic operations with FFN are given by,*

$$FF_1 \bigoplus FF_2 = \left(\left(1 - \left(1 - \mu_1^3\right)\left(1 - \mu_2^3\right)\right)^{1/3}, v_1 v_2\right) \tag{3}$$

$$FF_1^\rho = \left(\mu_1^\rho, \left(1 - \left(1 - v_1^3\right)^\rho\right)^{1/3}\right), \rho > 0 \tag{4}$$

$$\rho \times FF_2 = \left(\left(1 - \left(1 - \mu_2^3\right)^\rho\right)^{1/3}, v_2^\rho\right), \rho > 0 \tag{5}$$

$$FF_1 \bigotimes FF_2 = \left(\mu_1 \mu_2, \left(1 - \left(1 - v_1^3\right)\left(1 - v_2^3\right)\right)^{1/3}\right) \tag{6}$$

$$S(FF_2) = \mu_2^3 - v_2^3 \tag{7}$$

$$A(FF_2) = \mu_2^3 + v_2^3 \tag{8}$$

where Equations (3)–(8) describe the addition, power function, scalar multiplication, multiplication, score, and accuracy.

ρ is the scalar quantity used in Equations (4) and (5) for power function and scalar multiplication, respectively. By applying the ρ value to the FFN, we get an output, which is also an FFN and ρ can take any value greater than 0. For ease of understanding of the operation, an example is considered.

It must be noted that in the sense of arithmetic operation, ρ is some scalar quantity greater than 0, but in the decision-making process, ρ is considered as the weight of entities such as experts or criteria. Consider an example below to understand the working of the operator.

Example 1: *Let FF_1 be an FFN with value (0.75, 0.80) with scalar quantity cases such as $\rho = 0.4$ and $\rho = 7$, for instance. Now Equations (4) and (5) are applied to determine the power value and scalar multiplication value.*

$$FF_1^\rho = \left(\mu_1^\rho, \left(1 - \left(1 - v_1^3\right)^\rho\right)^{1/3}\right) = \left(0.75^{0.4}, \left(1 - \left(1 - 0.8^3\right)^{0.4}\right)^{1/3}\right) = (0.89, 0.63)$$

(0.89, 0.63) is an FFN as the sum of cubes of 0.89 and 0.65 yields 0.96 as a result that is less than or equal to 1.

$$FF_1^\rho = \left(\mu_1^\rho, \left(1 - \left(1 - v_1^3\right)^\rho\right)^{1/3}\right) = \left(0.75^7, \left(1 - \left(1 - 0.8^3\right)^7\right)^{1/3}\right) = (0.13, 0.99)$$

(0.13, 0.99) is an FFN as the sum of cubes of 0.13 and 0.99 yields 0.99 as a result that is less than or equal to 1.

$$\rho \times FF_1 = \left(\left(1 - \left(1 - \mu_1^3\right)^\rho\right)^{1/3}, v_1^\rho\right) = \left(\left(1 - \left(1 - 0.75^3\right)^{0.4}\right)^{1/3}, 0.8^{0.4}\right) = (0.58, 0.91)$$

(0.58, 0.91) is an FFN as the sum of cubes of 0.58 and 0.91 yields 0.96 as a result that is less than or equal to 1.

$$\rho \times FF_1 = \left(\left(1 - \left(1 - \mu_1^3\right)^\rho\right)^{1/3}, v_1^\rho\right) = \left(\left(1 - \left(1 - 0.75^3\right)^7\right)^{1/3}, 0.8^7\right) = (0.99, 0.21)$$

(0.99, 0.21) is an FFN as the sum of cubes of 0.99 and 0.21 yields 0.99 as a result that is less than or equal to 1.

From Example 1, it is clear that for different values of ρ greater than 0, we obtain values that are FFNs. This way, the scalar quantity is used to determine the power function and scalar multiplication of FFN.

3.2. Weight Etimation by Regret Measure

This section proposes a novel approach for weight calculation of criteria used in the decision process for rating alternatives. In general, weight estimation is a crucial step in the decision process, as it helps understand the relative importance of criteria, which typically influences the ordering of alternatives. Mostly, weight determination is seen as either with no a priori information or with partial information. In the first case (no a priori information), weights are determined by using approaches such as the analytical hierarchy process [50], entropy [51], stepwise weight assessment ratio analysis [52], and the best–worst approach [53]. These approaches can determine weights without any a priori information about criteria. However, in the second case, information about criteria in the form of inequality constraints is required to determine the weights. In practical decision-making situations, specific applications offer partial information about each criterion from the experts' point of view, which must be considered in the weight calculation process. At that time, mathematical models were developed that generally considered constrained optimization models [54].

Among the two prominent cases, the second case incurs an implicit overhead by embedding partial information in the calculation process, mitigated in the first case. In the present study, we consider the first case for weight determination. Though extant models determine weights, hesitation is not well captured during weight determination, and the nature of the criteria needs to be considered during the calculation phase. To better resolve the issues, the regret measure is put forward under the FFS context, which determines weights by considering the nature of criteria and hesitation of experts during preference articulation. Apart from these features, the attitude of experts in the form of weight information is embedded into the regret model for a rational assessment of weight values. A vector of experts' weights is considered along with the criterion opinion vectors from each expert to determine weights of criteria based on the procedure presented below:

Step 1: Form R vectors of $1 \times G$ order by considering qualitative terms, which are then transformed to FFN based on values from the table.

Step 2: Determine accuracy values by applying Equation (8) to the FFN from Step 1. It must be noted that the matrix order remains intact, and an accuracy matrix is obtained. Calculate weighted accuracy by multiplying experts' weight and accuracy values, a vector $R \times 1$ multiplied with G vectors of $R \times 1$.

Step 3: Calculate two measures, viz., Von Neumann measure and regret measure by applying Equations (9) and (10). Ideally, the order of the matrix from both equations is $R \times G$.

$$NU_{lj} = \left(Q_{lj}\right)^{a} \tag{9}$$

$$TY_{lj} = 1 - e^{-b \times NU_{lj}} \tag{10}$$

where a and b are parameters reflecting risk aversion and regret aversion coefficient with the range 0 to 1 that influences the Von Neumann and regret measures, respectively, and $Q_{lj} = \lambda_l \times A\left(FF_{lj}\right)$ with $A\left(FF_{lj}\right)$ being the accuracy value of FFN FF_{lj}, λ_l being the weight value of expert l. It must be noted that the greater the value of a and b, the greater will be the aversion to risk and regret, respectively.

The accuracy measure adopted in Equation (9) is a weighted accuracy value that embeds the attitude of experts formulated in the form of weights in the unit interval, and this intuitively provides a sense of rationale in the weight determination process, since experts play a significant role in data elicitation both for criteria and alternatives, which in this case would be CE criteria and barriers. Typically, the experts' attitudes would influence the decision process, and so the authors attempted to adopt the same in the proposed formulation.

Step 4: Use the values from Step 3 to determine utility values associated with each criterion to form a vector of $1 \times G$. Equation (11) is adopted to calculate the criteria utility.

$$TI_j = \sum_{l=1}^{R}\left(NU_{lj} + TY_{lj} - NU_j^{*}\right) \tag{11}$$

where TI_j is the utility value for criterion j and NU_j^{*} is the maximum for j from the benefit type and minimum for j from the cost type.

Step 5: Normalize the vector from Step 4 to estimate the weight vector, which is of $1 \times G$ order. The values range from 0 to 1 and sum to one.

$$W_j = \frac{TI_j}{\sum_{j=1}^{G} TI_j} \tag{12}$$

where W_j is the weight value of criterion j.

From Equation (12), the weight vector of $1 \times G$ can be obtained that depicts the relative importance of the criteria that would be used further in the next section to determine the rank values of barriers that hindered the adoption of IoT in clean energy sectors.

3.3. Rank Algorithm for Ordering Barriers

This section proposes a novel algorithm for ordering barriers that hinder IoT adoption in the clean energy sector based on rank values. As we know, ranking is a potential phase in the decision process that helps arrange the alternatives in a certain order so that the selection of suitable alternatives becomes possible. Intuitively, it can be inferred that though experts provide her/his rating for an alternative over a set of criteria, they tend to pose an implicit overall choice for the set of candidate alternatives, which is considered crucial information in the decision process [55].

Driven by the claim, in this section, the authors propose a new ranking algorithm by considering the formulation of WASPAS and experts' choice vectors. This offers not only a sense of rationality towards decision making but also a feeling of personalization in terms of ranking that is lacking in extant models. Specifically, the authors consider a choice vector representing experts' personal choice on each alternative. Since this is essential information, embedding this into the ranking algorithm aids in rational decision making. WASPAS method is considered in the formulation of the ranking algorithm, and it can be seen that WASPAS is (i) a simple and elegant approach for rank estimation; (ii) it determines the final rank of alternatives by considering both the weighted sum and weighted product values of each alternative with a linear combination mechanism; (iii) also, strategy values are considered during rank estimation that in some sense reflects the experts' decision behavior with the principle of strategy value greater than 0.50 corresponds to optimistic behavior, less than 0.50 corresponds to suspicious behavior, and equal to 0.50 corresponds to neutral behavior.

Motivated by these features, the procedure for personalized ordering of barriers is presented below:

Step 1: H barriers are rated qualitatively over G criteria to form *a* $H \times G$ rating matrix, which is further transformed into an FFN decision matrix based on tabular values.

Step 2: Determine the weighted FFN by adopting Equation (5) based on the data from Step 1 and a choice vector of $1 \times H$, with h_i being the choice associated with barrier i. Later, determine the weighted accuracy by adopting Equation (8) to obtain a matrix of $H \times G$.

Step 3: Determine the weighted sum vector and weighted product vector by adopting Equations (13) and (14) by considering the weighted accuracy matrix from Step 2. The weighted accuracy value from Step 2 and the criteria weight vector from the previous section are considered for calculating the parameters associated with the algorithm.

$$SM_i = \sum_{j=1}^{G} W_j \times WA_{ij} \tag{13}$$

$$PT_i = \prod_{j=1}^{G} \left(WA_{ij}\right)^{W_j} \tag{14}$$

where SM_i is the weighted sum of alternative i and PT_i is a weighted product of alternative i, W_j is the weight of criterion j.

Step 4: Adopt a linear combination mechanism by considering parameters from Equations (13) and (14) to determine the final ranking of barriers. Equation (15) is applied to calculate the barriers' final rank vector. A vector of $1 \times H$ is obtained as the rank vector used to select suitable barriers.

$$\gamma_i = \beta \times SM_i + (1 - \beta) \times PT_i \tag{15}$$

where β is the strategic value in the unit interval, and γ_i is the final rank value associated with barrier i.

From the formulation, the following inferences can be gained: (i) two parameters, viz., weighted sum and weighted product, are determined for each alternative, which follows the aggregation function for arithmetic and geometric zones; (ii) final rank is determined by considering linear combination mechanism of both the parameters, which is supported by a strategy factor β to understand the effect of decision behavior of experts on the ordering of barriers; and (iii) finally, the algorithm considers personal choices of experts in the form of a choice vector on alternatives (barriers), which is embedded in the formulation to gain a rational ranking of barriers that hinder IoT adoption in the clean energy sector.

Figure 1 shows the working model of the proposed framework that provides a clear understanding of how the model can be implemented for barrier ranking of IoT adoption in the clean energy sector. The procedure begins with data collection from experts for different barriers and CE criteria, which are shortlisted by the expert committee based on detailed discussion and voting mechanisms. The collected data are a Likert-scale rating further transformed to FFN based on the tabular values. The collected data are put in the form of matrices for determining the criteria weights and the rank values of barriers. These matrices are given as input to the methods proposed in Section 3. Opinion vectors from experts on each criterion are fed as input to the Fermatean fuzzy (FF) regret measure algorithm that determines the weights of criteria by considering the importance of each expert along with the opinion vectors. Based on the Von Neumann measure, regret measure, and utility factor, the weight vector is obtained that is later provided as input to the ranking algorithm (FF-WAPAS) along with the preference matrix from the committee. The weighted sum and the weighted product are calculated for each barrier, and finally, rank values are determined based on different strategy values. Based on these rank values, finally, barriers are ordered, and the top barrier is identified by the organization/stakeholders for effective strategic planning to circumvent the challenge/barrier. The model developed in this paper is elegant and attempts to minimize human intervention, thereby reducing subjectivity and biases. It must be noted that methodical determination of decision parameters, such as weights of criteria and rank values of alternatives (barriers here), reduces subjectivity and inaccuracies.

From Tables 1 and 2, the authors identify some research gaps that are circumvented by the research contributions presented in this research. We use the FFS as preference information that is capable of representing membership as well as non-membership grades. Fuzzy sets and their interval variants cannot represent these grades explicitly, but IFS and PFS can do so. Even though PFS and IFS can represent two grades explicitly, the level of broadness in choice expression is not high, and as a result, values such as (0.95, 0.10), (0.80, 0.70), etc. cannot be accepted by IFS and PFS but is acceptable in FFS. This feature motivated the authors to use FFS in this study.

Further, experts' weights are methodically calculated to reduce subjectivity and inaccuracies. Further, the regret measure can consider criteria type and hesitation of experts in the weight calculation process, which needs to be improved in extant barrier ranking models (kindly refer to Table 2). Finally, choice-driven ranking is presented in this work, which allows consideration of personal choices during rank estimation to get a sense of personalization in the prioritization process, which is also not explored in extant barrier ranking models (kindly refer to Table 2).

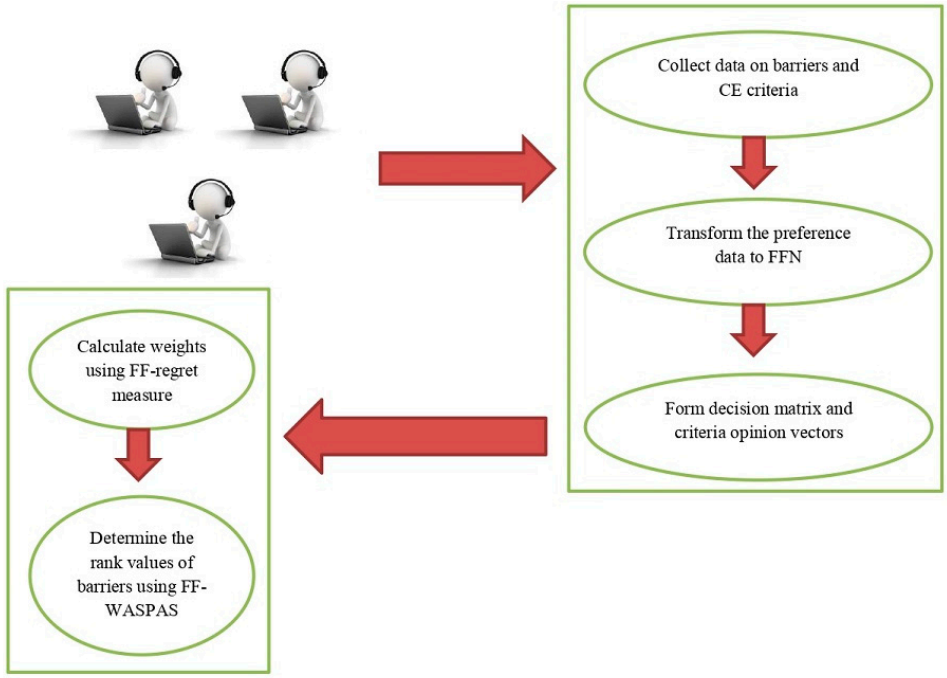

Figure 1. Integrated Fermatean fuzzy model for barrier ranking.

4. Case Example of Barrier Ranking in the Clean Energy Sector

This section puts forward an example to express the usefulness of the model developed by the authors. For this purpose, the clean energy sector of India is considered. Based on the discussion with personnel from the respective sector, it is evident that there is an urge for digital technology to provide a consistent and rational solution to the problems associated with the sector, such as production, distribution, and maintenance. The initiative 'Digital India' has triggered different sectors to investigate the possibilities for adopting technologies in their work to mitigate issues and promote sustainability effectively. Specifically, in the clean energy sector, the professionals mentioned the importance of IoT technology that could effectively promote interactions among various devices and objects and aid in increased communication among entities, thereby improving production, maintenance, and distribution to meet the nation's demand. The discussion also clarified that direct adoption of technologies is not possible owing to diverse barriers involved in extending technology-based solutions.

These professional claims motivated the present work and induced the authors to search literature studies for diverse barriers. Studies such as Mardani et al. [10], Cui et al. [11], and Hu et al. [56] are reviewed to choose the initial set of 22 barriers that contribute to the problem of adoption of digital technologies such as IoT. Based on these barriers, 15 are shortlisted for the present study. The professionals from the clean energy sector claimed that there is an urge to order/rank these barriers so that strategic plans could be made to resolve the most crucial barrier that would impede IoT adoption in the sector. The core objective of utilizing digital technology such as IoT is to promote sustainability within the sector and contribute to the green mission of the nation. As a result, these 15 barriers are rated based on nine CE criteria [12]. Out of seven professionals, four professionals formed a team to proceed further with the decision process. These personnel have ten years of experience in technology-related solutions and networking concepts. Additionally, this personnel had certification in IoT implementation and management, which supported the study toward rational decision making. Experts considered for this study are from the sustainability/circular economy, financial, and IoT design and engineering domains. Names and other personal details are kept anonymous for ethical reasons. These experts formed a panel to rate 15 barriers based on nine criteria. The barriers and criteria considered for the study are strategy insufficiency to combine Industry 4.0 and CE, labor/workforce skill insufficiency, and funding problems. Investment risk, an ineffective framework for performance, insufficient legislation and control, ineffective waste management, technology divide, improper or overutilization of resources, insufficient government policies/initiatives, lack of attitude to adapt to change, short-term goals, ineffective management, lack of time for training and skill practice, lack of demand knowledge, and lack of awareness of technology drive, which is rated qualitatively by adopting Likert scales based on waste reduction and pollution control, cost cutting via a reuse scheme, emission control, resource circularity, green logistics, resource/energy efficiency, green product design, green purchase, and scaling profit with green habits.

All criteria are of benefit type from the list above, and the barriers are rated based on these CE criteria. The clean energy sector intends to identify the ordering of these diverse barriers based on the CE criteria so that it becomes viable for the sector to plan its strategies appropriately to address or tackle barriers that hinder IoT adoption. In order to achieve the goal, the clean energy sector adopts the proposed decision framework, which identifies rank values for each barrier that hinders the adoption of IoT. Based on these values, the barriers are ordered to determine the most effective and least influential barriers. This would help in efficient strategy planning and management. With this notion, the procedure for ranking barriers is presented below:

Step 1: Expert team rates 15 barriers based on nine CE criteria in a qualitative manner by adopting a Likert scale rating. As a result, a decision matrix of order 15×9 is formed.

Table 3 gives the conversion values of qualitative terms in terms of FFNs. Table 4 provides the decision matrix that represents the preference information given by the panel for rating barriers that hinder IoT adoption in the clean energy sector based on CE criteria. This is rating information in the qualitative form, which is converted to FFN based on tabular values from Table 3.

Table 3. Qualitative rating with Fermatean fuzzy values.

Likert Scale	FIN	Likert Scale	FIN
Extremely low (EL)	(0.10,0.95)	Very highly preferred (VHP)	(0.95, 0.10)
Very low (VL)	(0.60,0.90)	Highly preferred (HP)	(0.80, 0.60)
Moderately low (ML)	(0.70,0.80)	Moderately preferred (MP)	(0.80, 0.65)
Low (L)	(0.60,0.70)	Preferred (P)	(0.75, 0.60)
Moderate (M)	(0.50,0.50)	Neutral (N)	(0.50, 0.50)
High (H)	(0.75,0.60)	Slightly preferred (SP)	(0.60, 0.70)
Moderately high (MH)	(0.80,0.65)	Less preferred (LP)	(0.70, 0.80)
Very high (VH)	(0.80,0.60)	Very less preferred (VLP)	(0.60, 0.90)
Extremely high (EH)	(0.95,0.10)	Not preferred (NP)	(0.10, 0.95)

Table 4. Preference data rating barriers based on criteria.

X	CE Criteria								
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
X_1	M	M	VH	ML	L	L	L	MH	ML
X_2	MH	MH	VH	ML	H	MH	VL	MH	MH
X_3	MH	MH	H	VH	L	L	M	VL	H
X_4	MH	MH	VH	H	L	L	H	ML	VH
X_5	VL	M	MH	MH	L	MH	ML	ML	L
X_6	VH	MH	L	L	MH	H	VL	MH	H

Table 4. *Cont.*

X	CE Criteria								
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
X_7	H	H	ML	MH	VL	M	MH	L	MH
X_8	L	M	H	ML	M	M	MH	H	VH
X_9	MH	M	M	VL	MH	M	L	M	VL
X_{10}	MH	VH	H	L	H	M	H	MH	VH
X_{11}	M	ML	H	ML	H	M	M	MH	H
X_{12}	VH	M	L	L	M	VH	M	VH	VH
X_{13}	H	L	MH	MH	L	H	H	MH	MH
X_{14}	ML	VL	ML	L	L	M	L	M	M
X_{15}	ML	L	VH	VL	M	VL	VL	VH	M

Values in Table 4 deal with the impact/influence a specific barrier would pose for a CE criterion. The first two columns of Table 3 are utilized for converting Table 4 values to their respective FFN.

Step 2: Construct a weight calculation matrix of 4×9 order where each expert from the panel provides her/his choice of each CE criterion. This eventually results in forming four vectors, each of 1×9 order. These vectors are qualitative that shares experts' views on CE criteria.

The values in Table 5 are converted to FFN by adopting Table 3 (the last two columns). Section 3.2 further utilizes these to determine the weights/importance of CE criteria.

$$Von\ Neuman = \begin{pmatrix} 0.5 & 0.8 & 0.93 & 0.89 & 0.8 & 0.75 & 0.8 & 0.89 & 0.5 \\ 0.5 & 0.8 & 0.5 & 0.75 & 0.89 & 0.5 & 0.5 & 0.75 & 0.890 \\ 0.97 & 0.8 & 0.8 & 0.75 & 0.5 & 0.8 & 0.8 & 0.5 & 0.89 \\ 0.5 & 0.8 & 0.97 & 0.75 & 0.8 & 0.97 & 0.93 & 0.8 & 0.8 \end{pmatrix}$$

$$Regret = \begin{pmatrix} 0.22 & 0.33 & 0.37 & 0.36 & 0.33 & 0.31 & 0.33 & 0.36 & 0.22 \\ 0.22 & 0.33 & 0.22 & 0.31 & 0.36 & 0.22 & 0.22 & 0.31 & 0.36 \\ 0.38 & 0.33 & 0.33 & 0.31 & 0.22 & 0.33 & 0.33 & 0.22 & 0.36 \\ 0.22 & 0.33 & 0.38 & 0.31 & 0.33 & 0.38 & 0.37 & 0.33 & 0.33 \end{pmatrix}$$

Based on Table 5 and Equations (9) and (10), Von Neumann and regret measures are calculated, which are further fed to Equation (11) for generating the utility vector of criteria. It is finally normalized to determine the weights of criteria (Equation (12)), a vector of 1×9 order, and it is given by 0.06, 0.21, 0.10, 0.14, 0.11, 0.06, 0.09, 0.10, and 0.13, respectively.

Step 3: The decision matrix from Step 1 and the criteria weight vector from Step 2 are considered to determine the personalized ranks by adopting the procedure presented in Section 3.3.

Table 5. Criteria opinion vectors from experts.

Y	CE Criteria								
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
Y_1	N	P	LP	MP	P	SP	P	MP	N
Y_2	N	P	N	SP	MP	N	N	SP	MP
Y_3	VLP	P	P	SP	N	P	P	N	MP
Y_4	N	P	VLP	SP	P	VLP	LP	P	P

Values from Table 6 aid in determining the ranking order of barriers. The rank vector in the last column of Table 4 is utilized for determining the ordering of barriers. As it can be seen from the formulation in Section 3.3, along with the decision matrix and weight vector, a personal choice vector is also considered as input, and it is given as 0.35, 0.40, 0.45, 0.30, 0.35, 0.65, 0.55, 0.60, 0.60, 0.70, 0.50, 0.45, 0.55, 0.40, and 0.60, respectively. Based on the γ_i Vector, the ordering of barriers, is given by $X_2 \succ X_4 \succ X_7 \succ X_5 \succ X_{13} \succ X_6 \succ X_3 \succ X_1 \succ X_{14} \succ X_{11} \succ X_{15} \succ X_{10} \succ X_{12} \succ X_9 \succ X_8$. It can be seen that barrier X_2 is considered more crucial per the preference data and must be strategically resolved to help the clean energy sector better utilize IoT technology for their global expansion and sustainable market.

Table 6. Parameters of the ranking algorithm.

X	SM_i	PT_I	γ_i
X_1	0.749	0.732	0.741
X_2	0.849	0.847	0.848
X_3	0.754	0.742	0.748
X_4	0.837	0.835	0.836
X_5	0.780	0.764	0.772
X_6	0.751	0.746	0.749
X_7	0.769	0.754	0.761
X_8	0.609	0.574	0.591
X_9	0.627	0.573	0.600
X_{10}	0.680	0.669	0.674
X_{11}	0.717	0.692	0.705
X_{12}	0.626	0.607	0.616
X_{13}	0.749	0.747	0.748
X_{14}	0.750	0.725	0.738
X_{15}	0.711	0.671	0.691

Sensitivity Analysis

In this section, the inter/intra-sensitivity analysis is performed. In the intra-sensitivity analysis, the strategy values are altered systematically with step size one to form nine strategy values from 0.1 to 0.9. For each value, the ordering of barriers is observed graphically from Figure 2. Eventually, nine lines, each representing a strategy value, are obtained in the line graph. Later, we extend the line graph to different criteria weight sets. This is done via rotation of weight values, and as a result, nine sets of weight vectors are obtained, and for each set, such line graphs are obtained as shown below in Figure 2a–i.

This is a comprehensive sensitivity analysis of the criteria weights and strategy values depicted as intra- and inter-cases. By this, we understand the effect of strategy values and CE criteria weights on the ordering of barriers. From Figure 2a–i, it is evident that the proposed model is robust against alterations to strategy values indicating that the developed integrated approach can effectively counter the changes in the experts' strategy values by retaining the rank ordering intact even though there are changes in rank values owing to the change in strategy values. On the other hand, in terms of weight alteration of criteria, we could infer the competition between barriers via the change in order. The proposed model reveals the competition among barriers and shows that the top-ranked barrier, X2, remains on top of the order list even after adequate changes are made to criteria weights through the shift operation. As a result, it is inferred that X_2 (labor/workforce skill insufficiency) is a crucial barrier that an organization should focus on for effectively facilitating IoT adoption in the clean energy sector.

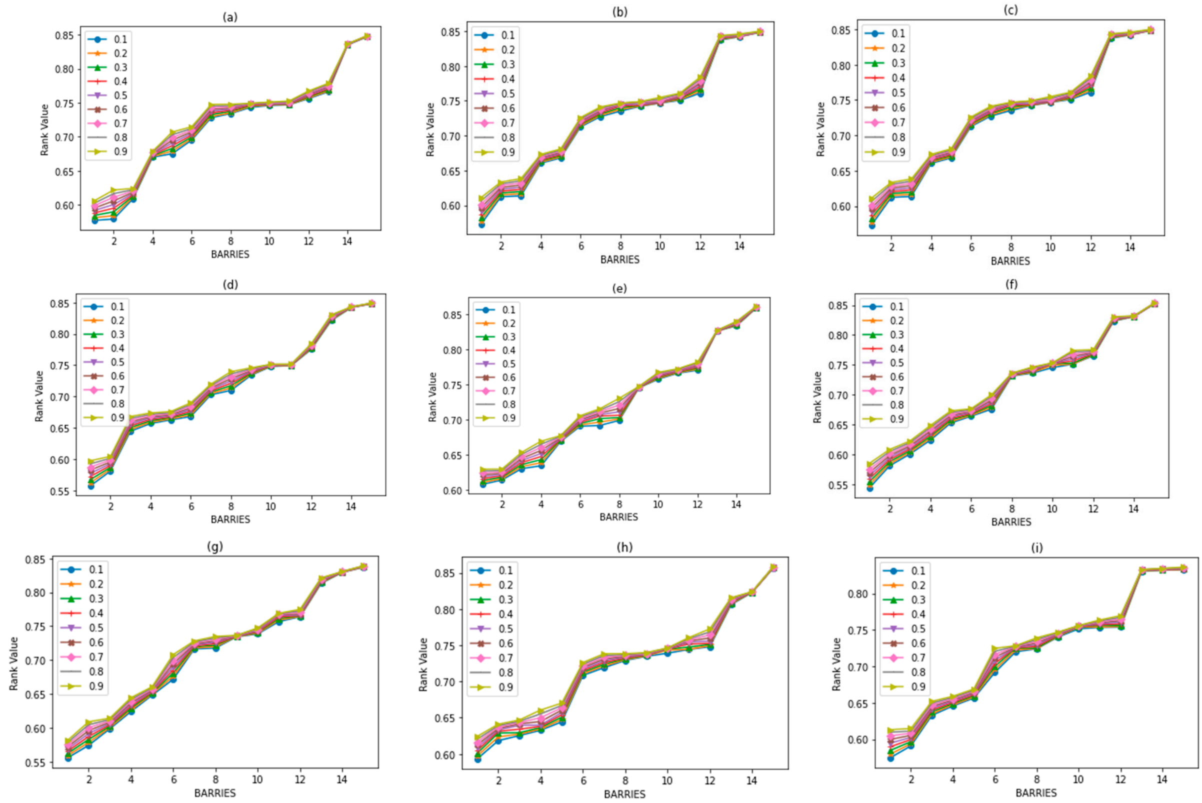

Figure 2. Sensitivity analysis (**a**–**i**) denotes nine sets of criteria weight vectors obtained via rotation.

5. Comparative Analysis of the Proposed Model vs. Other Models

The efficacy of the proposed Fermatean fuzzy framework is realized in this section from both the application and method-driven perspectives. Regarding the application perspective, barrier selection is considered the theme for comparison with extant models. In terms of method, Fermatean fuzzy-based decision models are compared with the proposed work in terms of consistency and discrimination ability. For this purpose, extant models such as Cui et al. [11], Kumar et al. [12], Mardani et al. [10], and Rahman et al. [16] are compared with the proposed model under the application context. Table 7 describes the proposed model's and extant models' characteristics, which infers the proposal's efficacy.

Table 7. Summarized view of different characteristics of proposed and extant barrier prioritization models.

Characteristics	Proposed	Mardani et al. (2021) [10]	Cui et al. (2021) [11]	Rahman et al. (2021) [16]	Kumar et al. (2021) [12]
Data	FFN	HFS	PFS	Fuzzy set	Fuzzy set
Criteria weights	Considered	Considered	Considered	Considered	Considered
Flexibility	High	Moderate	Moderate	Low	Low
Uncertainty	Modeled in three ways	Modeled in one way	Modeled in three ways	Modeled in one way	Modeled in one way
Hesitation	Considered	Not considered	Not considered	Not considered	Not considered
Criteria nature (weight calculation)	Considered	Not considered	Not considered	Not considered	Not considered
Experts' importance	Considered	Not considered	Not considered	Not considered	Not considered
Complexity	Moderate	Moderate	Moderate	High	High
Personal choices	Considered	Not considered	Not considered	Not considered	Not considered

Note: FFN—Fermatean fuzzy number, HFS—hesitant fuzzy set, and PFS—Pythagorean fuzzy set.

From Table 7, it is clear that the proposed model mitigates human intervention by methodically determining parameters and specific novel innovations are:

- FFN is used as the preferred structure that could not only model uncertainty from three dimensions, viz., membership, non-membership, and hesitation but also allow flexible elicitation of preferences by providing a broader window for preference expression, which is lacking in the extant barrier ranking models considered for comparison. As evidence to the claim, readers can refer to the work in [13], which is the inception of FFNs, where the authors clarify the flexibility that FFNs offer to experts during the preference elicitation process by extending the window of expression, which is lacking in classical fuzzy sets and PFS.
- Furthermore, it can be observed that the weights are methodically determined by considering the nature of the criteria and experts' hesitation. Unlike the extant models, in the proposed method, criteria type is considered that intuitively aids in the rationality of weight calculation. Precisely, when experts provide similar opinions or ratings to a particular criterion, at that time, the effect of the risk component measured via the Von Neumann measure becomes subtle owing to the criteria type factor of the Von Neumann measure in the utility function that suppresses the risk component. As a result, there is only a regret component, and the risk component is either negligible or zero, indicating that the particular criterion is less important than others and that experts exhibit a higher level of hesitation towards that criterion. On the other hand, if both the risk and regret components are involved, and their aversion values a and b, respectively, are chosen close to the complete aversion that unity, the risk and regret values become negligible or close to zero, with high rejoice and as a result, the criterion gets high importance with less hesitation from the experts' viewpoint. The hesitation of experts is mapped onto the consideration of risk and regret components. When a particular component is suppressed (either by considering less aversion of risk/regret or less variability in the preference distribution), the hesitancy level of experts is high, and the net utility value is small for the criterion indicating less importance. In other words, if risk and regret are high, hesitation is high, and utility value is low, eventually leading to less weight for the criterion.
- Further, the importance of experts is considered during the criteria weight determination, as the experts are crucial owing to their choice sharing for each criterion. Unlike other models, in the proposed model, consideration is given to the weights of experts that can be intuitively observed as potential information in the decision process. Moreover, the complexity of the proposed model is moderate. At the same time, some approaches have high complexity owing to their pairwise comparison formulation that adds overhead to the model and increases the computational complexity.
- Finally, the personal choices of experts on each barrier are collected in the form of a vector and utilized in the formulation for determining rank values of barriers with a sense of personalization intuitively; the process provides rationality in the rank estimation and gives a feel of the customizable ordering of barriers. Such a feature needs to be improved in the extant barrier ranking models compared to the proposed model.

From Figure 2a–i, it is clear that though there is a change in rank order in the inter-analysis case, the rank order remains intact in the intra-case, where strategy values are altered systematically. Personal choices were considered during the analysis process. However, in Figure 3, we determined the rank values of each barrier without the choice vector and with criteria weights calculated from Section 3.2. It is evident from the figure that the ordering for a change in strategy values remains intact here. However, there is a change in rank values. This shows that the proposed model is stable even after adequate alterations are introduced in the strategy values in both the choice and no-choice cases. Further, the analysis depicts the importance of criteria weights and their substantial role in influencing rank orders of barriers in the study.

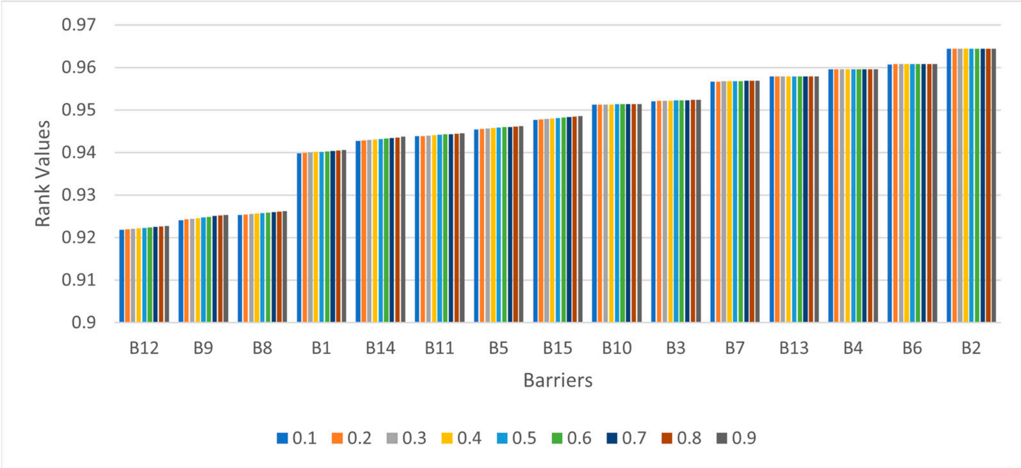

Figure 3. Sensitivity analysis of strategy values with equal choices.

Apart from realizing efficacy from the application's perspective, let us also investigate the efficacy from the method's perspective. For this purpose, we consider extant models such as Sahoo et al. [31]—TOPSIS, Krishankumar et al. [44]—COPRAS, and Gul et al. [37]—VIKOR that are compared with the proposed work in terms of rank uniqueness and Spearman correlation is adopted on the rank orders obtained from each model based on the preference data from the previous section.

From Figure 4, it is inferred that the proposed model yields a unique rank order for barriers that can be intuitively explained by the ability of the proposed model to consider not only personal choices but also determine rank order based on choice vectors from experts. Such formulation provides rationality in the rank determination process with the support of personalization that induces a sense of lack of loss of information from experts. Furthermore, the rank algorithm proposed in this research considers both the importance of experts and criteria during rank value estimation.

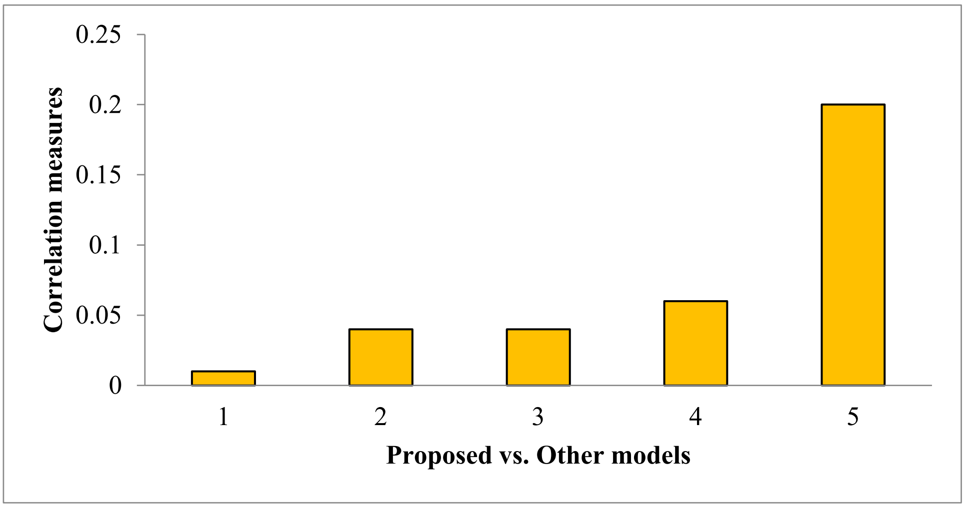

Figure 4. Uniqueness measure of proposed model (X-axis 1—equal choices or no choice, 2—Sahoo et al. [31], 3—Gul et al. [37], 4—Krishankumar et al. [44], and 5—choice with equal weights).

Figure 5 shows the broadness measure of the proposed framework to infer its superiority in effectively discriminating alternatives (barriers in this case) for proper backup management and planning in crucial situations. Specifically, 400 matrices of 15×9 are randomly generated as a part of the simulation experiment. These matrices are fed as input to the proposed framework along with the criteria weight vector and choice vector utilized from Section 4. The matrices are given as input with and without the choice vectors, and rank vectors are determined for all 400 matrices. Therefore, two matrices of 400×15 are formed, one for a framework with choice vectors and the other for a framework without choice vectors. Variance is calculated for each rank vector and plotted in Figure 5, which clearly shows that the proposed framework, with the inclusion of choice vector, produces broader rank vectors compared to its counterpart. Typically, this allows effective discrimination of alternatives (barriers in this case), and approximately, the choice-based variant of the proposed model produces rank values that are ten times broader than its counterpart, indicating that personal choices play a significant role in rational rank estimation and provides ease of selection and backup management at critical situations. Though the stability of the framework is unaffected by the presence or absence of choice vector, criteria weights play a crucial role in stability determination. In that line of thought, choice vectors play a substantial role in determining the framework's discrimination ability, and it can be inferred intuitively from Figure 5.

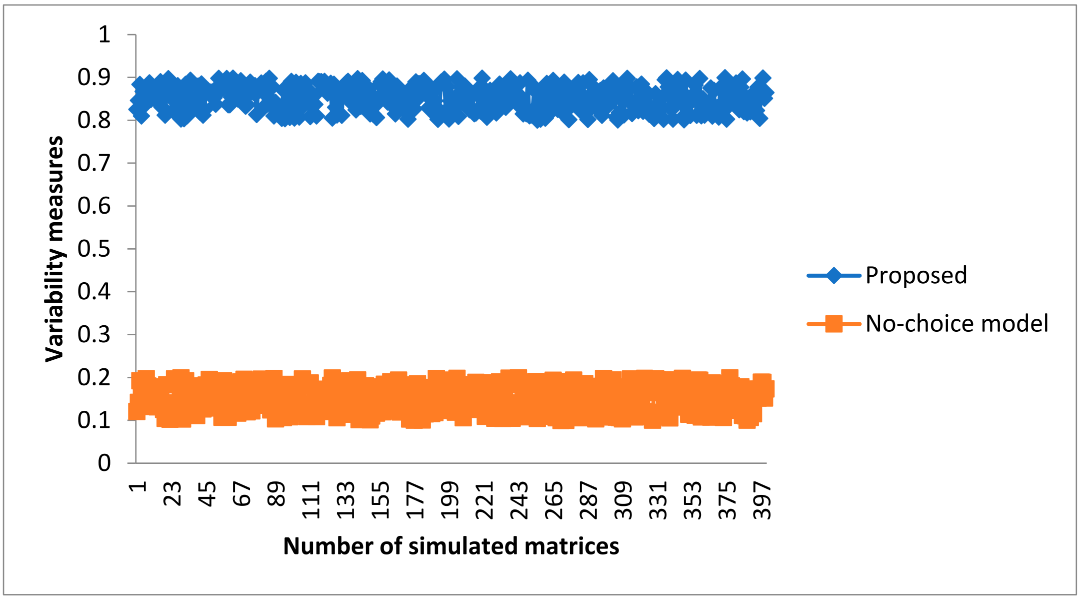

Figure 5. Investigation on discrimination ability of FFS-based WAPAS method.

6. Conclusions

The present work adds value to the field of barrier assessment, particularly in the technology adoption context in the clean energy sector. As the world is moving towards clean energy and non-conventional alternatives, integrating technology into the sector is substantial. However, as discussed above, it needs to be more direct, and hence, the challenges/barriers must be identified and ranked to support organizations/stakeholders in planning their strategic line of action. In that train of thought, the present work proposes a novel integrated decision approach that determines values methodically for criteria weights and barrier ranks. Hesitation during preference elicitation from experts is carefully captured by the proposed formulation, along with the choice vectors from experts to offer rational ordering of barriers.

From the sensitivity analysis, it is inferred that the proposed model is stable when adequate changes are made to strategy values. From the comparative investigation, it is clear that the proposed model is novel in terms of the application's perspective and yields unique rank orders of barriers when compared to its counterparts, along with overall rank values for effective discrimination of different barriers involved in the hindrance of IoT adoption in the clean energy sector. Specifically, the proposed work shows that criteria weights are crucial during rank value estimation, and choice vectors are crucial in understanding the experts' cognitive thought on each alternative and effectively driving the approach's discrimination ability for ease of backup management and planning at critical times.

Though the proposed approach is innovative and attempts to reduce human intervention, some limitations are worth pointing out, such as: (i) weights of experts are not methodically determined, (ii) partial information on entities is not considered, and (iii) subjective weights are not integrated into the decision process. Further, some implications of the work are: (i) the developed integrated approach is a ready-to-use model that organizations/stakeholders could use for properly planning their strategies on the crucial barriers, (ii) the developed approach minimizes subjective randomness and biases in the decision process, (iii) the integrated approach also reduces human intervention by rationally calculating values of weights and ranks by considering criteria type and choice vectors, (iv) model can be flexibly extended to other decision problems as well based on appropriate preference information, and (v) finally, some training is required for experts and stakeholders to utilize the full potential of the developed approach.

In the future, plans are made to address the limitations of the proposed work. Further, we use more straightforward representations of uncertainty to see if the output changes for the present decision problem and many other decision problems to provide inferences on the decision process comprehensively. Additionally, plans are made to utilize a neutrosophic fuzzy set for developing a decision model to address the problem of barrier prioritization and other decision applications. Further, the approach presented in this article can be extended for other decision problems in the clean energy sector, such as location assessment for installation of power plants, storage location evaluation, storage method evaluation, raw material selection, etc.; and/or sustainability domain such as waste treatment assessment, alternative transport mode evaluation, green material selection, and alike, and/or other domains viz., education, health as well. Notably, with a broad scope for experimentation on the application side, and methodically, the authors have plans to explore group aspects of decision making along with different fuzzy variants such as neuromorphic sets and hesitant fuzzy sets. Finally, we also plan to introduce recommendation and machine learning paradigms with decision approaches for performing large-scale decision making.

Author Contributions: N.S.S.R.—prototyping, modeling, code implementation, writing—original draft, and presentation. R.K.—data curation, formulation, modeling, supervision, writing—original draft, and editing draft. S.S.P.—supervision, formulation, presentation, editing code, and language editing. F.C.—prototyping, supervision, writing—original draft, language editing, and presentation. A.M.—data curation, modeling, supervision, presentation, and language editing. K.S.R.—data curation, formulation, modeling, supervision, presentation. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Symbols used in the equations are presented in Table A1, along with their meaning.

Table A1. Symbols and meaning.

Symbol	Meaning
μ	Degree of membership or membership grade
υ	Degree of non-membership or non-membership grade
π	Degree of hesitancy or hesitancy grade
FF_i	Fermatean fuzzy number

Table A1. *Cont.*

Symbol	Meaning
ρ	Any scalar value greater than 0
R	Number of experts
G	Number of criteria
NU_{lj}	von-Neumann value of expert l rating criterion j
TY_{lj}	Regret value of expert l rating criterion j
l	Index of expert
j	Index of criterion
a	Parameter reflecting risk aversion coefficients
b	Parameter reflecting regret aversion coefficient
TI_j	The utility value of criterion j
W_j	Weight of criterion j
H	Number of barriers
h_i	The choice value associated with barrier i
i	Index of barrier
WA_{ij}	Weighted accuracy value associated with barrier i rated over criterion j
SM_i	The weighted sum of barrier i
PT_I	Weighted product of barrier i
γ_i	The final rank value of barrier i
β	Strategy value
$S(*)$	The score value of *
$A(*)$	Accuracy value of *

Appendix B

The correlation values of the proposed versus other approaches are depicted in Figure A1, which indicates the complete correlation set of 6 × 6 order. Proposed model, no choice model, model in [31], model in [37], model in [44], and choice with equal weights model are compared with each other. The proposed Model is presented in this article that utilizes criteria weights methodically determined by the procedure in Section 3.2 and the choice vector of experts. Other models are self-explanatory.

Table A2. Correlation matrix.

Correlation	Proposed	No Choice Mode	[31]	[37]	[44]	Choice with Equal Weights
Proposed	1	0.01	0.04	0.04	0.055	0.2
No choice model	0.01	1	0.5	0.5	0.6	0.03
[31]	0.04	0.5	1	0.5	0.4	0.04
[37]	0.04	0.5	0.5	1	0.4	0.04
[44]	0.055	0.6	0.4	0.4	1	0.05
Choice with equal weights	0.2	0.03	0.04	0.04	0.05	1

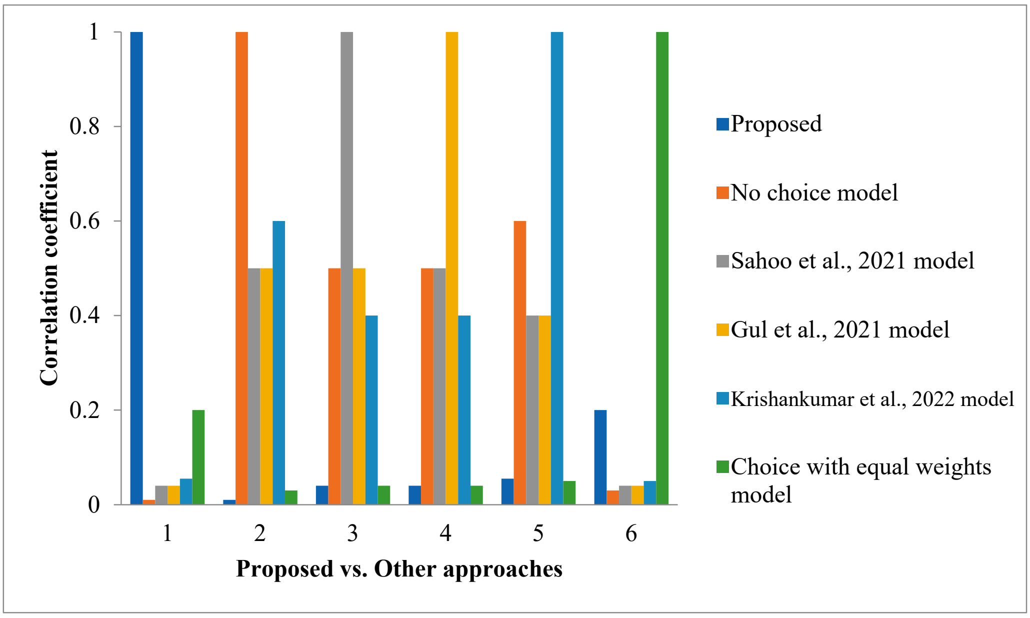

Figure A1. Correlation values for different decision approaches.

Since the formulation of the proposed ranking method differs from the extant approaches, the ranking order determined by the proposed method is unique. Intuitively, both the methodical determination of criteria weights and choice vectors influence the ordering of barriers. Since the proposed model considers these two parameters, unlike the other models the ordering obtained by the proposed model can be justified.

From Figure 2, it can be seen that the ordering for the different strategy values remains unchanged for barriers. The ordering of barriers changes for new weight sets obtained via rotation of criteria weights. As a result, a particular barrier takes different rank places, as depicted in Table A3. From Table A3, it is clear that there is competition among barriers for different rank places, and we can infer that criteria weights play a crucial role in rank order determination.

Table A3. Rank of barriers with respect to sensitivity analysis of criteria.

Barriers	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
X_1	8	10	7	7	6	5	6	4	5
X_2	1	1	1	2	1	1	1	1	2
X_3	7	5	8	4	10	7	9	8	7
X_4	2	2	2	1	3	2	2	2	3
X_5	4	3	3	3	2	3	3	3	1
X_6	6	7	5	5	5	8	4	7	9
X_7	3	9	6	9	4	9	5	0	4
X_8	15	14	15	14	13	14	15	15	14
X_9	14	15	14	15	12	15	14	13	15
X_{10}	12	11	10	12	11	13	11	14	12
X_{11}	10	13	13	13	15	12	12	11	13
X_{12}	13	12	12	11	13	10	13	12	11
X_{13}	5	6	4	6	7	6	7	6	6
X_{14}	9	8	9	10	8	11	8	10	8
X_{15}	11	4	11	8	9	4	10	5	10

From Table A3, it can be seen that barriers take different rank positions, and this happens due to a change in weight values for criteria in each set owing to the rotation of criteria. Specifically, this shows the competition among barriers, supported by Figure 2. Table A3 depicts the rank orders of barriers for different sets of weights at a strategy value of 0.50.

References

1. Tollefson, J.; Weiss, K.R. Nations adopt historic global climate accord: Agreement commits the world to holding warming well below'2 [degrees] C. *Nature* **2015**, *582*, 315–317. [CrossRef]
2. Vaishnavi, V.; Suresh, M. Assessment of readiness level for implementing lean six sigma in healthcare organization using fuzzy logic approach. *Int. J. Lean Six Sigma* **2021**, *12*, 175–209. [CrossRef]
3. Goswami, H. Opportunities and challenges of digital India programme. *Int. Educ. Res. J.* **2016**, *2*, 78–79.
4. Ganchev, I.; Ji, Z.; O'Droma, M. A generic IoT architecture for smart cities. In Proceedings of the 25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communications Technologies (ISSC 2014/CIICT 2014), Limerick, Ireland, 26–27 June 2014; pp. 196–199.
5. Sehrawat, D.; Gill, N.S. Smart sensors: Analysis of different types of IoT sensors. In Proceedings of the 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 23–25 April 2019; pp. 523–528.
6. Chen, S.; Xu, H.; Liu, D.; Hu, B.; Wang, H. A Vision of IoT: Applications, Challenges, and Opportunities With China Perspective. *IEEE Internet Things J.* **2014**, *1*, 349–359. [CrossRef]
7. Motlagh, N.H.; Mohammadrezaei, M.; Hunt, J.; Zakeri, B. Internet of Things (IoT) and the Energy Sector. *Energies* **2020**, *13*, 494. [CrossRef]
8. Mahajan, P.; Naik, C. Development of Integrated IoT and Machine Learning based data collection and analysis system for the effective prediction of agricultural residue/biomass availability to regenerate clean energy. In Proceedings of the 2019 9th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP-19), Nagpur, India, 1–2 November 2019; pp. 1–5.
9. Smith, R.M.; Pathak, P. Urban sustainability in India: Green buildings, AMRUT yojana, and smart cities. In *Metropolitan Governance in Asia and the Pacific Rim*; Springer: Singapore, 2018; pp. 163–190.
10. Mardani, A.; Saraji, M.K.; Mishra, A.R.; Rani, P. A novel extended approach under hesitant fuzzy sets to design a framework for assessing the key challenges of digital health interventions adoption during the COVID-19 outbreak. *Appl. Soft Comput.* **2020**, *96*, 106613. [CrossRef]
11. Cui, Y.; Liu, W.; Rani, P.; Alrasheedi, M. Internet of Things (IoT) adoption barriers for the circular economy using Pythagorean fuzzy SWARA-CoCoSo decision-making approach in the manufacturing sector. *Technol. Forecast. Soc. Change* **2021**, *171*, 120951. [CrossRef]
12. Kumar, P.; Singh, R.K.; Kumar, V. Managing supply chains for sustainable operations in the era of industry 4.0 and circular economy: Analysis of barriers. *Resour. Conserv. Recycl.* **2020**, *164*, 105215. [CrossRef]
13. Senapati, T.; Yager, R.R. Fermatean fuzzy sets. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 663–674. [CrossRef]
14. Zhenmin, L.; Espinosa, P. Tackling climate change to accelerate sustainable development. *Nat. Clim. Chang.* **2019**, *9*, 494–496. [CrossRef]
15. Krishankumar, R.; Amritha, P.P.; Ravichandran, K.S. An integrated fuzzy decision model for prioritization of barriers affecting sustainability adoption within supply chains under unknown weight context. *Oper. Manag. Res.* **2022**, *15*, 1010–1027. [CrossRef]
16. Rahman, H.U.; Raza, M.; Afsar, P.; Alharbi, A.; Ahmad, S.; Alyami, H. Multi-Criteria Decision Making Model for Application Maintenance Offshoring Using Analytic Hierarchy Process. *Appl. Sci.* **2021**, *11*, 8550. [CrossRef]
17. Roy, S.; Paul, A.; Paul, A.; Kashyap, S.; Jana, A. Ranking Barriers of Supply Chain Management by MCDM Method during Disaster Management: A Case Study of India. *Int. J. Syst. Dyn. Appl.* **2021**, *10*, 1–16. [CrossRef]
18. Chowdhury, N.M.; Reshad, A.I.; Rahman, M.M. Identifying Barriers of Implementing IoT in Manufacturing Industry using Analytical Hierarchy Process (AHP): A Bangladeshi Perspective. Available online: https://www.kuet.ac.bd/icmiee2022/Technical_and_Keynote_papers/All_Paper/ICMIEE20-006.pdf (accessed on 9 February 2023).
19. Torkabadi, A.M.; Pourjavad, E.; Mayorga, R.V. An integrated fuzzy MCDM approach to improve sustainable consumption and production trends in supply chain. *Sustain. Prod. Consum.* **2018**, *16*, 99–109. [CrossRef]
20. Kumar, V.; Vrat, P.; Shankar, R. Prioritization of strategies to overcome the barriers in Industry 4.0: A hybrid MCDM approach. *Opsearch* **2021**, *58*, 711–750. [CrossRef]
21. Mishra, A.R.; Rani, P.; Saha, A.; Hezam, I.M.; Pamucar, D.; Marinovic, M.; Pandey, K. Assessing the Adaptation of Internet of Things (IoT) Barriers for Smart Cities' Waste Management Using Fermatean Fuzzy Combined Compromise Solution Approach. *IEEE Access* **2022**, *10*, 37109–37130. [CrossRef]
22. Schitea, D.; Deveci, M.; Iordache, M.; Bilgili, K.; Akyurt, I.Z.; Iordache, I. Hydrogen mobility roll-up site selection using intuitionistic fuzzy sets based WASPAS, COPRAS and EDAS. *Int. J. Hydrogen Energy* **2019**, *44*, 8585–8600. [CrossRef]
23. Erol, I.; Ar, I.M.; Peker, I.; Searcy, C. Alleviating the Impact of the Barriers to Circular Economy Adoption Through Blockchain: An Investigation Using an Integrated MCDM-based QFD With Hesitant Fuzzy Linguistic Term Sets. *Comput. Ind. Eng.* **2022**, *165*, 107962. [CrossRef]

24. Nimawat, D.; Gidwani, B.D. Prioritization of barriers for Industry 4.0 adoption in the context of Indian manufacturing industries using AHP and ANP analysis. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 1139–1161. [CrossRef]
25. Kumar, V.; Kalita, K.; Chatterjee, P.; Zavadskas, E.K.; Chakraborty, S. A SWARA-CoCoSo-based approach for spray painting robot selection. *Informatica* **2022**, *33*, 35–54. [CrossRef]
26. Jena, R.; Dwivedi, Y. Prioritizing the barriers to tourism growth in rural India: An integrated multi-criteria decision making (MCDM) approach. *J. Tour. Futur.* **2021**, *ahead-of-print*. [CrossRef]
27. Khan, S.; Haleem, A. Investigation of circular economy practices in the context of emerging economies: A CoCoSo approach. *Int. J. Sustain. Eng.* **2021**, *14*, 357–367. [CrossRef]
28. Atanassov, K. Review and New Results on Intuitionistic Fuzzy Sets. *Prepr. Im-MFAIS-1-88 Sofia* **1988**, *5*. Available online: http://www.biomed.bas.bg/bioautomation/2016/vol_20.s1/files/20.s1_03.pdf (accessed on 9 February 2023).
29. Yager, R.R. Pythagorean Membership Grades in Multicriteria Decision Making. *IEEE Trans. Fuzzy Syst.* **2013**, *22*, 958–965. [CrossRef]
30. Keshavarz-Ghorabaee, M.; Amiri, M.; Hashemi-Tabatabaei, M.; Zavadskas, E.K.; Kaklauskas, A. A New Decision-Making Approach Based on Fermatean Fuzzy Sets and WASPAS for Green Construction Supplier Evaluation. *Mathematics* **2020**, *8*, 2202. [CrossRef]
31. Sahoo, L. Some Score Functions on Fermatean Fuzzy Sets and Its Application to Bride Selection Based on TOPSIS Method. *Int. J. Fuzzy Syst. Appl.* **2021**, *10*, 18–29. [CrossRef]
32. Senapati, T.; Yager, R.R. Some New Operations Over Fermatean Fuzzy Numbers and Application of Fermatean Fuzzy WPM in Multiple Criteria Decision Making. *Informatica* **2019**, *30*, 391–412. [CrossRef]
33. Senapati, T.; Yager, R.R. Fermatean fuzzy weighted averaging/geometric operators and its application in multi-criteria decision-making methods. *Eng. Appl. Artif. Intell.* **2019**, *85*, 112–121. [CrossRef]
34. Xu, C.; Shen, J. Multi-criteria decision making and pattern recognition based on similarity measures for Fermatean fuzzy sets. *J. Intell. Fuzzy Syst.* **2021**, *41*, 5847–5863. [CrossRef]
35. Akram, M.; Shahzadi, G.; Ahmadini, A.A.H. Decision-Making Framework for an Effective Sanitizer to Reduce COVID-19 under Fermatean Fuzzy Environment. *J. Math.* **2020**, *2020*, 3263407. [CrossRef]
36. Silambarasan, I. New operators for Fermatean fuzzy sets. *Ann. Commun. Math* **2020**, *3*, 116.
37. Gül, S. Fermatean fuzzy set extensions of SAW, ARAS, and VIKOR with applications in COVID-19 testing laboratory selection problem. *Expert Syst.* **2021**, *38*, e12769. [CrossRef]
38. Aydin, S. A Novel Multi-Expert Mabac Method Based on Fermatean Fuzzy Sets. *J. Mult. Valued Log. Soft Comput.* **2021**, *37*, 533–552.
39. Deng, Z.; Wang, J. New distance measure for Fermatean fuzzy sets and its application. *Int. J. Intell. Syst.* **2022**, *37*, 1903–1930. [CrossRef]
40. Jeevaraj, S. Ordering of interval-valued Fermatean fuzzy sets and its applications. *Expert Syst. Appl.* **2021**, *185*, 115613. [CrossRef]
41. Krishankumar, R.; Mishra, A.R.; Cavallaro, F.; Zavadskas, E.K.; Antuchevičienė, J.; Ravichandran, K.S. A New Approach to the Viable Ranking of Zero-Carbon Construction Materials with Generalized Fuzzy Information. *Sustainability* **2022**, *14*, 7691. [CrossRef]
42. Mishra, A.R.; Liu, P.; Rani, P. COPRAS method based on interval-valued hesitant Fermatean fuzzy sets and its application in selecting desalination technology. *Appl. Soft Comput.* **2022**, *119*, 108570. [CrossRef]
43. Hadi, A.; Khan, W.; Khan, A. A novel approach to MADM problems using Fermatean fuzzy Hamacher aggregation operators. *Int. J. Intell. Syst.* **2021**, *36*, 3464–3499. [CrossRef]
44. Krishankumar, R.; Ecer, F.; Mishra, A.R.; Ravichandran, K.S.; Gandomi, A.H.; Kar, S. A SWOT-Based Framework for Personalized Ranking of IoT Service Providers With Generalized Fuzzy Data for Sustainable Transport in Urban Regions. *IEEE Trans. Eng. Manag.* **2022**, 1–14. [CrossRef]
45. Kirişci, M. Fermatean Hesitant Fuzzy Sets with Medical Decision Making Application. *Mapp. Intimacies* **2022**. Available online: https://www.researchsquare.com/article/rs-1151389/latest.pdf (accessed on 9 February 2023). [CrossRef]
46. Sindhu, M.S.; Siddique, I.; Ahsan, M.; Jarad, F.; Altunok, T. An Approach of Decision-Making under the Framework of Fermatean Fuzzy Sets. *Math. Probl. Eng.* **2022**, *2022*, 8442123. [CrossRef]
47. Ali, G.; Ansari, M.N. Multiattribute decision-making under Fermatean fuzzy bipolar soft framework. *Granul. Comput.* **2022**, *7*, 337–352. [CrossRef]
48. Atanassov, K. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [CrossRef]
49. Yager, R.R. Generalized Orthopair Fuzzy Sets. *IEEE Trans. Fuzzy Syst.* **2016**, *25*, 1222–1230. [CrossRef]
50. Anbuudayasankar, S.; Srikanthan, R.; Karthik, M.; Nair, P.R.; Sivakarthik, N.; Indukumar, P. Cloud-based technology for small and medium scale enterprises: A decision-making paradigm using IPA, AHP and fuzzy-AHP techniques. *Int. J. Integr. Supply Manag.* **2020**, *13*, 335. [CrossRef]
51. Liu, L.; Wu, J.; Wei, G.; Wei, C.; Wang, J.; Wei, Y. Entropy-Based GLDS Method for Social Capital Selection of a PPP Project with q-Rung Orthopair Fuzzy Information. *Entropy* **2020**, *22*, 414. [CrossRef]
52. Rani, P.; Ali, J.; Krishankumar, R.; Mishra, A.R.; Cavallaro, F.; Ravichandran, K.S. An Integrated Single-Valued Neutrosophic Combined Compromise Solution Methodology for Renewable Energy Resource Selection Problem. *Energies* **2021**, *14*, 4594. [CrossRef]

53. Ghoushchi, S.J.; Dorosti, S.; Khazaeili, M.; Mardani, A. Extended approach by using best–worst method on the basis of importance–necessity concept and its application. *Appl. Intell.* **2021**, *51*, 8030–8044. [CrossRef]
54. Sivagami, R.; Krishankumar, R.; Sangeetha, V.; Ravichandran, K.S.; Kar, S.; Gandomi, A.H. Assessment of cloud vendors using interval-valued probabilistic linguistic information and unknown weights. *Int. J. Intell. Syst.* **2021**, *36*, 3813–3851. [CrossRef]
55. Krishankumar, R.; Ravichandran, K.S.; Saeid, A.B. A new extension to PROMETHEE under intuitionistic fuzzy environment for solving supplier selection problem with linguistic preferences. *Appl. Soft Comput.* **2017**, *60*, 564–576. [CrossRef]
56. Hu, Y.; Al-Barakati, A.; Rani, P. Investigating the Internet-of-Things (IoT) risks for supply chain management using q-rung orthopair fuzzy-SWARA-ARAS framewor. *Technol. Econ. Dev. Econ.* **2022**, 1–26. [CrossRef]