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Full Length Article

A machine learning and fuzzy logic model for optimizing digital transformation in renewable energy: Insights into industrial information integration

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ABSTRACT

The most essential criteria to improve digital transformation in renewable energy projects should be identified. This situation helps the companies to use limited financial budgets and human resources in the most efficient way. Therefore, a new study is needed to analyze the performance indicators of the digital transformation process in renewable energy projects. Accordingly, this study aims to identify the most significant performance indicators of digital transformation for these projects. A three-stage machine learning and fuzzy logic-based decision-making model has been constructed in this process. The first stage includes the weight calculation of the experts by dimension reduction methodology. Secondly, essential factors of digital transformation in renewable energy projects are examined via Fermatean fuzzy criteria importance through intercriteria correlation (CRITIC). The final part consists of the ranking of emerging seven countries with Fermatean fuzzy weighted aggregated sum product assessment (WASPAS). On the other side, combined compromise solution (CoCoSo) method is also taken into consideration in this process to make a comparative evaluation. The main contribution of this study is the generation of novel machine learning and fuzzy logic integrated decision-making model to make evaluation related to the digital transformation of renewable energy projects. In this model, machine learning technique is used to determine the importance weights of the experts. Similarly, integrating Fermatean fuzzy numbers with CRITIC and WASPAS techniques also contributes to the literature by minimizing the uncertainty and identifying the relationship between the items. The findings demonstrate that employing qualified personnel plays the most critical role in increasing digital transformation in renewable energy projects. Additionally, government support is very critical in the successful implementation of digital transformation processes in renewable energy projects.

1. Introduction

Digital transformation refers to the process of a business transforming its business processes using digital technologies. In other words, efforts are being made to adapt existing business models to new technologies. In this way, it is aimed to increase both the operational efficiency and competitiveness of businesses. Digital transformation can play a critical role in improving the performance of renewable energy projects [1]. Thanks to this transformation, it is possible to analyze energy data more comprehensively. This contributes to the detection of

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possible problems in the process much earlier. Similarly, it may be easier to optimize energy production processes with digital transformation. Thus, renewable energy projects can operate much more efficiently. On the other hand, thanks to smart energy systems, efficiency can also be achieved in energy distribution and storage processes. Thus, it is possible to both reduce costs and increase the amount of energy produced [2]. In summary, digital transformation is of vital importance as it allows solving problems such as operational inefficiency, production and demand imbalance and high costs in renewable energy projects.

Digital transformation must be ensured in renewable energy projects. For this process to be successful, some issues need to be taken into consideration. First, the cost effectiveness of the projects must be ensured. Otherwise, businesses will experience financial problems, and in this case, they will be reluctant to digital transformation. Another important issue in this context is the political stability and adequate legal regulations in the country [3]. These situations increase investors' confidence in the market. On the other hand, government incentives also contribute to reducing the costs of these projects. For example, offering tax deductions helps ensure the cost-effectiveness of digital transformation. Qualified personnel are needed to successfully carry out digital transformation in renewable energy projects. Since there are very comprehensive stages in this process, the staff must be competent to quickly resolve possible problems. Meeting customer expectations is another factor that should be considered in this process [4]. In this process, customers' needs must be clearly determined. Customer satisfaction must be ensured by paying attention to these issues during the digital transformation process.

It is necessary to determine the most important criteria to achieve digital transformation in renewable energy projects. This situation is critical in many respects. Determining important criteria helps determine the factors that should be focused primarily on during the digital transformation process. Renewable energy companies have limited financial budgets and human resources. To use these limited resources in the most efficient way, priority analysis of the criteria must be made. Thus, digital transformation in renewable energy projects can be implemented more successfully [5]. However, there are a limited number of studies in the literature where priority analysis is made for these factors [6,7]. This situation emerges as an important gap in the literature. Therefore, a new study is needed to analyze the performance indicators of the digital transformation process in renewable energy projects [8,9]. With this new study, the priority strategies that businesses need to implement to effectively implement the digital transformation process can be determined. This allows businesses to use their resources more effectively and efficiently during the digital transformation process.

This study aims to identify the most significant performance indicators of digital transformation for renewable energy companies. Taking this into consideration, the research question of this study is to determine which strategies should be prioritized to successfully achieve digital transformation in these projects. To achieve this goal, a three-stage machine learning and fuzzy logic-based decision-making model is developed. The first stage focuses on the weight calculation of the experts via dimension reduction methodology. In the next part, essential factors of digital transformation in renewable energy projects are evaluated by Fermatean fuzzy criteria importance through intercriteria correlation (CRITIC). The final part consists of the ranking of emerging seven countries with Fermatean fuzzy weighted aggregated sum product assessment (WASPAS). On the other side, combined compromise solution (CoCoSo) method is also taken into consideration in this process to make a comparative evaluation. The motivation for this study is the need for a comprehensive analysis to determine priority strategies for the successful implementation of digital transformation in renewable energy projects [10,11]. In such studies in the literature, different approaches such as SWOT (strengths, weaknesses, opportunities, and threats) analysis, PESTEL (i.e., political, economic, social, technological, environmental, and legal), case analysis and balanced scorecard are taken into consideration [12,13]. In addition, decision-making analyzes can also be considered to determine the most important criteria [14,15]. However, it is important to consider the criticisms made against these methods in a new analysis of this process.

The main contribution of this study is the generation of novel machine learning and fuzzy logic integrated decision-making model to make evaluation related to the digital transformation of renewable energy projects. The proposed model has some significant superiorities as detailed below. (1) A new decision-making model has been established to find the most important factors affecting the digital transformation performance of renewable energy projects. In this model, machine learning technique is used to determine the importance weights of the experts who gave their opinions. This situation contributes to the literature in many ways. Thanks to machine learning, big data can be analyzed effectively. This allows decision-making processes to be more accurate. On the other hand, combining expert opinions with machine learning brings together human knowledge and experience and the power of technology. This situation also contributes to more accurate analysis results. (2) Integrating Fermatean fuzzy numbers with CRITIC technique also contributes to the literature in many ways. Thanks to Fermatean fuzzy numbers, more comprehensive data sets can be examined during the analysis process. This allows the uncertainty experienced in the solution process of decision-making problems to be reduced. The CRITIC method is a technique that objectively evaluates criteria by considering the relationship between factors. Variables affecting digital transformation performance may have a causal relationship with each other. In this context, the use of the CRITIC technique allows more effective results to be obtained in this process. (3) WASPAS is a combination technique of weighted sum and weighted product models. In this way, linear and non-linear weighting situations are examined with different degrees. In this way, it is possible to obtain more accurate results during the ranking of alternatives. This method has some important advantages compared to other popular techniques. For example, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method makes decisions by calculating the distances of the alternatives to the ideal and negative ideal solutions. WASPAS, unlike TOPSIS, combines both the total and multiplication-based approach. As can be understood from here, the WASPAS method is evaluated more comprehensively. Similarly, VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) is a decision-making method that specifically aims to find compromise solutions. WASPAS has a more general structure than VIKOR. In this context, it combines both compromise and definitive performance evaluation. Owing to this issue, both aspects of the decision process can be considered. As a result, a more comprehensive evaluation can be made. (4) Making a comparative examination with CoCoSo to rank the alternatives is also another important contribution of this proposed model. This technique is superior to other ranking methods in many ways. For example, TOPSIS is based only on geometric distance calculation in the analysis process. This situation may cause the performance of the alternatives not to be evaluated sufficiently. Unlike TOPSIS, CoCoSo does not use a distance-based approach only. It allows more effective results to be achieved by performing a more comprehensive analysis. Moreover, MOORA evaluates the performance of the alternatives with ratio analysis. This situation leads to a limited analysis of the performances of the alternatives under some conditions. Unlike MOORA, CoCoSo evaluates the performance of the alternatives with both total and multiplication-based analyses. CoCoSo can analyze the alternatives from a wider perspective. With the help of this situation, the superiority of the alternatives over each other can be determined more accurately.

Literature examination is conducted in the following part. The proposed model is explained in the next section. The results of the proposed model, discussion and conclusion parts are given in the final sections.

2. Literature review

This section includes two different parts that are the evaluation of similar studies and literature review gap.

2.1. Literature on the indicators of digital transformation

Legal qualifications and sanctions are among the factors affecting the success criteria in digital transformation processes. One of the challenges faced by contemporary businesses is to manage and complete the digital transformation process [16]. Hudima et al. [17] stated that one of the main factors in the development of foreign economic policies around digital transformation is the legal framework. Researching the digital transformation processes of logistics service providers, Cichosz et al. [18] revealed that legal sanctions that may arise due to not ensuring data security affect the process as an obstacle. ALsheyab [19] emphasized the necessity of legislative dominance in his study, in which he stated that one of the obstacles to the digitalization of cross-border trade is overcoming legal uncertainty and difficulties. On the other hand, He and Su [20] revealed in their study that digital transformation in business processes positively affects green innovation. They also emphasized that legal regulations positively impact this process. Kamali Saraji et al. [21] showed that the lack of standards and regulations is essential among the external factors affecting digitalization.

Government support is also a driving force in digital transformation processes. China, one of the developing countries, encourages companies in the digital transformation process by offering tax options and loans [22]. In their study on the efficiency of China's energy supply chain in the digital age, Fu et al. [23] revealed that the digital transformation process can be increased by encouraging technology innovation and providing government subsidies. On the other hand, studies have revealed that the digital transformation processes of small and medium enterprises in Greece are negatively affected by the lack of motivation of state officials [24]. Ghobakhloo et al. [25] demonstrated that the most critical factor driving digital transformation is proactive government support and revealed the road map to sustainable industrial transformation. Akhtar et al. [26] stated that the performance of green innovation studies in SMEs is possible with digital transformation and can be increased by providing government support. Moreover, Kamali Saraji et al. [21] also indicated that one of the most critical obstacles to developing clean energy that digital transformation will provide is the lack of government support.

In addition to external factors that affect digital transformation, there are also some internal factors. Among these factors that negatively affect the process of transformation and catching up with the times, resilient leadership stands out [27]. Porfirio et al. [28] revealed the critical role of leadership in companies in the digital transformation process and the importance of its encouragement in the advanced stages of the process. It has been demonstrated that leadership behaviors focused on digital transformation mainly affect the success of the process, and this brings digital resilience [29,30]. Moreover, Benitez et al. [31] concluded that the leadership approach that supports digital transformation also directly affects companies' innovation process. Similarly, Ko et al. [32] also found that management rather than information and communication departments affect the success of digital transformation processes more. Kargas et al. [24] indicated that leaders did not embrace the digital transformation process; therefore, the process could have been more successful.

Among the internal factors, another issue that directly affects or delays the success of the digital transformation process is qualified employees who keep up with change. Wall et al. [33] emphasized the importance of training employees and having the necessary qualifications among the factors affecting the success of the digital transformation process. Moreover, to increase the effectiveness of the process, new collaboration opportunities within the company and the creation of a digital culture among employees also come to the fore [34]. For example, Norveel et al. [35] stated that they have low levels of digital competence, which may affect the success of the process and cause concern. Similarly, Uzule and Verina [36] defined the need for more human resources in the digital transformation process as one of the two most essential obstacles affecting the success of the process. Furthermore, Vuksanovic et al. [37] found that human resources, rather than resistance to change, can be a severe obstacle. Similarly, the research on digital transformation processes in South Korea shows that employees' digital skills are related to digital leadership and corporate performance [38].

2.2. Literature review gap

As a result of the literature review, some important conclusions can be reached. Digital transformation provides vital benefits to renewable energy projects. Thanks to this process, the operational efficiency of projects can be increased, and energy supply-demand balance can be achieved. On the other hand, digital transformation helps reduce the costs and ensure the security of these projects. Due to these issues, digital transformation of renewable energy projects needs to be ensured. On the other hand, the most important factors need to be determined to achieve digital transformation in renewable energy projects. Otherwise, some problems may arise for these projects. Failure to prioritize certain factors can lead to inefficient use of resources. Financial and labor resources are very limited in renewable energy projects. Therefore, to determine the most accurate strategies, it is necessary to determine the factors that most affect the performance of digital transformation. Nevertheless, the number of studies in the literature on this field is quite low. This situation is considered a very important gap in the literature. To eliminate this deficiency, a new model is created in this study.

3. Model

Digitalization of renewable energy projects is important to make the process smoother and more complete. For this reason, the factors effective in digital transformation in renewable energy projects need to be weighted and prioritized and the situations of developing countries should be evaluated. To solve this problem, a hybrid Multi-Criteria Decision Making (MCDM) model is proposed in the article. In the first step of the proposed model, effective criteria are weighted in the digitalization process of renewable energy projects with the help of the CRITIC method. In the second step of the model, the digitalization situations in renewable energy projects of E7 countries are handled with the WASPAS method.

Since the proposed hybrid model is based on MCDM, the weights of expert opinions and uncertainty in linguistic expressions need to be included in the model. For these cases, dimension reduction algorithm, one of the machine learning techniques, and fuzzy set theory in mathematics are integrated into the model. While the weights of the experts are obtained from the demographic information of the experts by the dimension reduction algorithm, the uncertainty in the linguistic expressions is included in the analysis using Fermatean fuzzy numbers. The model is summarized in Fig. 1.

3.1. Dimension reduction algorithm

Models such as data mining, machine learning and artificial intelligence are preferred to solve complex problems. In particular, as nuances such as data diversity, number and volume of data increase, the importance of techniques increases [39]. While weighting experts with different and diverse characteristics is a complex problem, data types also vary [40]. Therefore, with the help of the dimension reduction algorithm, it is aimed to obtain expert weight values from the demographic information data of the experts [41]. The steps of the dimension reduction algorithm are presented in Table 1.

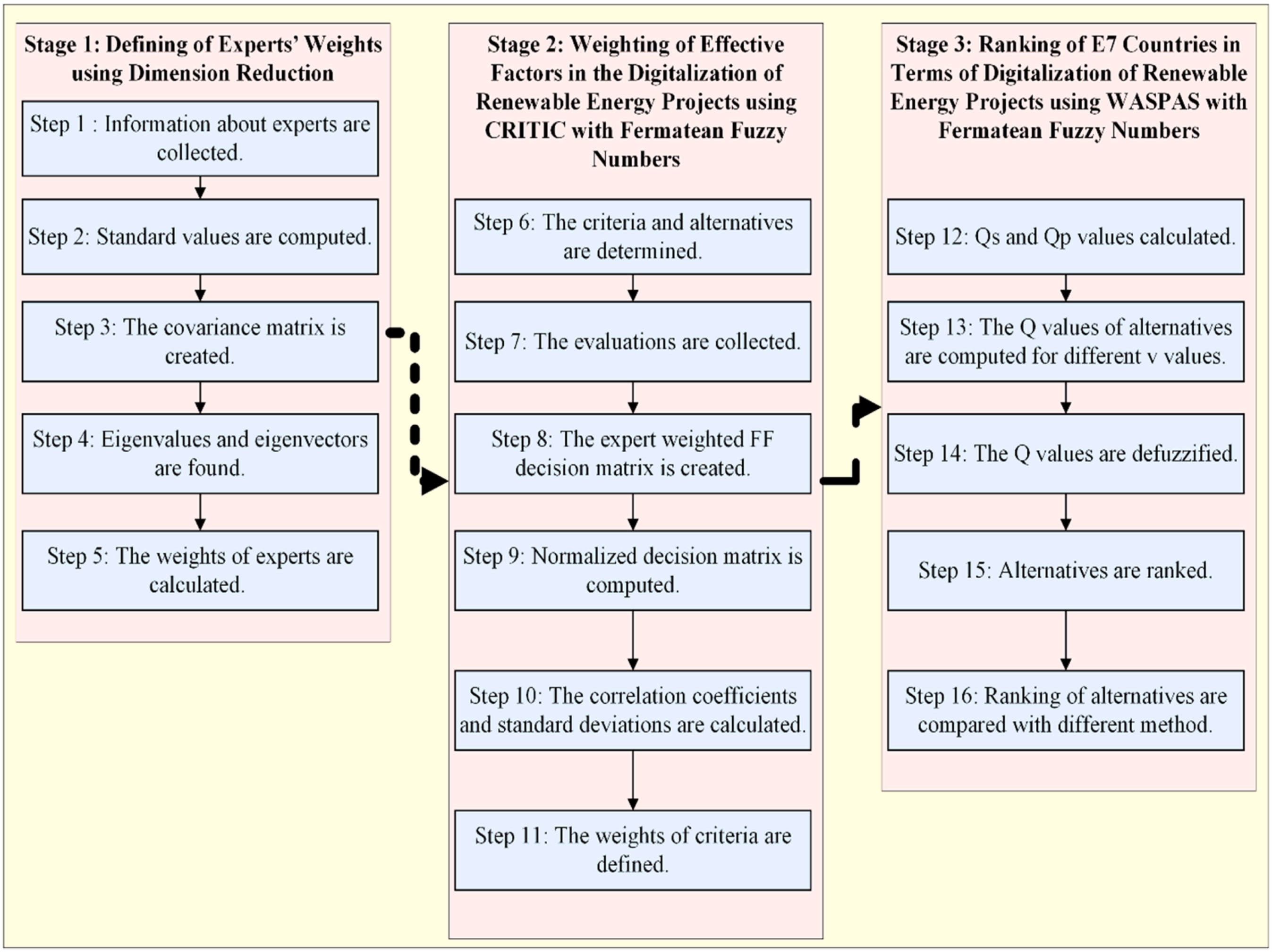

Fig. 1. Flowchart.

Table 1
The pseudo-code of dimension reduction algorithm.

Input: Demographic information $f_{ik}, i \in [1, k], j \in [1, m]$; where k equals number of decision makers, and m equals number of features
Output: Weights of Experts $ew_i, i \in [1, m]$ **Begin** (1) Define a features matrix $F = \left[f_{ij}\right]_{k \times m}$ (2) Compute the standardize values $c_{ij} \leftarrow f_{ij} - \bar{f}_j$ $n_{ij} \leftarrow \frac{c_{ij}}{\sqrt{\sum_{i=1}^{k} c_{ij}^2}}; \forall i \in [1, 2, \ldots, k];\ \forall j \in [1, 2, \ldots, m]$ (3) Found the covariance matrix (CM) (4) Calculate the eigenvalue (λ) of covariance matrix. $Det(CM - \lambda I) = 0$ (5) Compute the eigenvector (v) for the largest eigenvalue (λ_{max}) $(CM - \lambda_{max} I) * v = 0$ (6) Convert matrix to the new space $H \leftarrow$FxV (7) Determine the weights of experts $ew_j \leftarrow \frac{h_j}{\sum_{j=1}^{k} h_j},\ \forall j \in [1, 2, \ldots, k]$ **End**

3.2. CRITIC with Fermatean fuzzy numbers

CRITIC method is an objective multi-criteria decision-making technique that calculates weights using correlation and standard deviation values between criteria. CRITIC, a statistics-based method, is preferred to obtain objective and more accurate results because it calculates criterion weights on data [42,43]. In addition, since it considers the relationship between criteria, it enables more realistic results to be obtained when it comes to concepts related to social fields such as finance and economy [44]. The steps of the CRITIC method are presented in Table 2.

3.3. WASPAS with Fermatean fuzzy numbers

WASPAS method is a multi-criteria decision-making technique that includes weighted sum and weighted multiplication models with different weights. The advantages of this model, which examines the ranking status of alternatives with the weighted average of these two methods, are sensitivity to changes in the ranking of alternatives, consistency of results and ease of calculation [45]. The algorithm of the WASPAS method are provided in Table 3.

4. Analysis

The results of the analyzes regarding the digitalization processes of renewable energy projects are summarized under this heading. The subheadings include, respectively, the weighting of experts, the weighting of factors effective in the digitalization of renewable energy projects, the ranking of E7 countries in terms of their digitalization in renewable energy, and a comparison of the results. Although analyzed separately according to renewable energy types, the results for wind are presented in detail. The final results for other renewable energy types are summarized.

4.1. Defining of experts' weights using dimension reduction

Invitations are sent via e-mail to experts who work in the digitization of renewable energy projects and have at least 10 years of experience. The demographic information of the three experts who responded positively to the invitation is presented in Table 4.

As can be seen in Table 4, the average age of experts is 42.67. In addition, the number of different E7 countries in which experts work is expressed with the Country variable. The values are standardized to calculate the expert weights with the dimensionality reduction algorithm. This is because the variables have different units. Standard values of experts' demographic information are given in Table 5.

Afterwards, covariance values are calculated among the demographic characteristics of the experts. The covariance matrix containing these values is reported in Table 6.

The polynomial roots, or eigenvalues, of the covariance matrix are computed. The largest of the five eigenvalues is 1.74. The eigenvector corresponding to this eigenvalue is calculated. Finally, the importance levels of experts are determined by normalizing the result of multiplying the eigenvector and the feature matrix. The results of the experts' weights are provided in Table 7.

4.2. Weighting of effective factors in the digitalization of renewable energy projects using CRITIC with Fermatean fuzzy numbers

In the result of the literature research, the criteria that are effective in the digitalization of renewable energy projects are discussed and discussed with experts. As a result of consultation with experts, the determined criteria and their definitions are given in Table 8.

One of the criteria presented in Table 8 is cost efficiency in the process and is included in the analysis as COEFF. Another criterion is political stability, which represents the politics in the country. The supports implemented by the government are examined in the analysis as GOVSUP. Additionally, since qualified personnel are also effective in this process, they are included in the analysis with the QUAEMP code as a criterion. In addition, customer expectations and market conditions are also effective factors in the digitalization process of renewable energy projects. E7 countries are evaluated by experts in terms of eight selected criteria. The scale used by experts for evaluation is shown in Fig. 2.

The opinions of three experts are summarized in Table 9.

The weighted average of the Fermatean fuzzy numbers corresponding to the opinions of the experts is calculated. The weights used in calculating the weighted average are the important levels of the experts. The expert weighted Fermatean fuzzy decision matrix is reported in Table 10.

Afterwards, the values in Table 10 are defuzzified. After that, the results are normalized. The normalized decision matrix is given in Table 11.

Standard deviation values of the criteria are computed. Afterwards, correlation values between the criteria are determined. The calculated statistical values are given in Table 12.

The information quality value is calculated by using the statistical values of the criteria that are effective in the digitalization of renewable energy projects. By normalizing the information quality values of the criteria, the weights of the criteria are computed. The weights of the criteria are shown in Fig. 3.

According to Fig. 3, the two most influential factors in the digitalization of renewable energy projects are qualified personnel and government support. The weights of the criteria are 0.1557 and 0.1511, respectively. According to these results, if the employees in renewable energy projects are qualified, the digitalization process will both accelerate and be error-free. Similarly, having government support encourages project managers and thus accelerates the digitalization of the country's renewable energy projects. In addition, with the importance given to these criteria, obstacles to the digitalization of renewable energy projects are also removed.

Table 2
The pseudo-code of CRITIC.

Input: Values $d_{ij}, i \in [1,m], j \in [1,n]$; where n equals number of criteria; m equals number of alternatives
Output: Weights of criteria $w_i, i \in [1,n]$ **Begin** (1) Create a expert weighted decision matrix $\widetilde{D} = [\widetilde{d}_{ij}]_{m \times n}$ (2) Compute the defizzified values (3) Obtain the normalize values (4) Calculate the correlation values (r) (5) Compute the standard deviations of criteria (σ) (6) Compute of the information quantity $V_j \leftarrow \sigma_j \left(\sum_{i=1}^{m} (1 - r_{ij}) \right)$ (7) Obtain the weights of criteria $w_j \leftarrow \frac{v_j}{\sum_{j=1}^{m} v_j}, \ \forall j \in [1,2,\ldots,n]$ **End**

Table 3
The pseudo-code of WASPAS.

Input: Values $d_{ij}, i \in [1, m], j \in [1, n]$; where n equals number of criteria; m equals number of alternatives; Weights of criteria $w_i, i \in [1, n]$

Output: Ranking of alternatives $A_i, i \in [1, m]$
Begin
(1) Create a matrix
$\widetilde{D} = [\widetilde{d}_{ij}]_{m \times n}$
(2) Compute the normalized matrix ($\widetilde{N}$)
(3) Calculate the $\widetilde{Q_s}$ and $\widetilde{Q_p}$ values.
$\widetilde{Q_{si}} \leftarrow \sum w_j \widetilde{N}_{ij}$
$\widetilde{Q_{pi}} \leftarrow \prod \widetilde{N}_{ij}^{\ w_j}$
(4) Determine the measure of $\widetilde{Q}$
$\widetilde{Q}_i \leftarrow v\widetilde{Q_{si}} + (1 - v)\widetilde{Q_{pi}};\ 0 \le v \le 1$
(5) Determine the defuzzified values of $\widetilde{Q}$
(6) Obtain the ranking of alternatives
End

Table 4
The demographic information of the three experts.

	Age	Experience	Salary	Education	Country	Managerial period	Number of certificates
DM1	40	10	2000	Master	4	3	6
DM2	44	12	2700	PhD	3	4	7
DM3	44	15	2500	PhD	5	4	7

Table 5
The standard values of experts' data.

	Age	Experience	Salary	Education	Country	Managerial period	Number of certificates
DM1	-0.816	-0.656	-0.784	-0.816	0	-0.816	-0.816
DM2	0.408	-0.094	0.588	0.408	-0.707	0.408	0.408
DM3	0.408	0.749	0.196	0.408	0.707	0.408	0.408

Table 6
The covariance matrix.

	Age	Experience	Salary	Education	Country	Managerial period	Number of certificates
Age	0.333	0.33	0.161	0.235	0.236	0.235	0.235
Experience	0.33	0.333	0.202	0.268	0.199	0.268	0.268
Salary	0.161	0.202	0.333	0.32	-0.092	0.32	0.32
Education	0.235	0.268	0.32	0.333	0	0.333	0.333
Country	0.236	0.199	-0.092	0	0.333	0	0
Managerial period	0.235	0.268	0.32	0.333	0	0.333	0.333
Number of certificates	0.235	0.268	0.32	0.333	0	0.333	0.333

Table 7
The experts' weights.

	Values
DM1	0.278
DM2	0.373
DM3	0.349

Table 8
The selected criteria for digitalization of renewable energy projects.

Codes	Definitions
COEFF	Cost effectiveness
POLSTA	Political stability
LEGEFF	Legal effectiveness
GOVSUP	Government support
RESLEA	Resilient leadership
QUAEMP	Qualified employee
MARCON	Market conditions
CUSEXP	Customer expectations

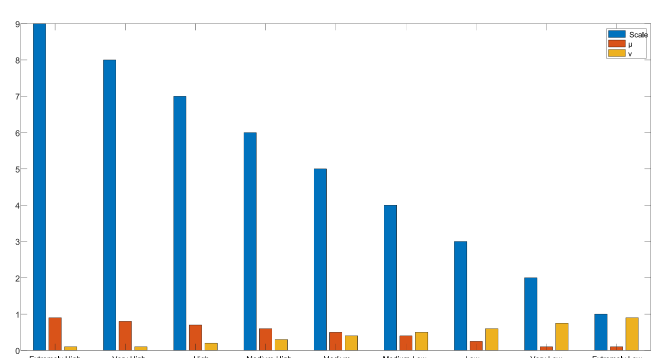

Fig. 2. Scale of evaluations.

4.3. Ranking of E7 countries in terms of digitalization of renewable energy projects using WASPAS with Fermatean fuzzy numbers

The expert weighted Fermatean fuzzy decision matrix is normalized.

Table 9
The opinions of three experts.

DM1	COEFF	POLSTA	LEGEFF	GOVSUP	RESLEA	QUAEMP	MARCON	CUSEXP
E1	7	7	6	3	4	4	5	4
E2	9	9	8	8	9	8	9	8
E3	6	7	5	7	6	6	5	5
E4	9	6	7	6	5	6	8	6
E5	9	8	7	3	9	2	8	1
E6	8	8	8	8	9	8	8	8
E7	4	5	6	5	6	4	7	4
DM2	**COEFF**	**POLSTA**	**LEGEFF**	**GOVSUP**	**RESLEA**	**QUAEMP**	**MARCON**	**CUSEXP**
E1	4	7	5	8	3	4	2	5
E2	8	8	9	9	9	8	7	8
E3	5	6	6	5	5	5	8	4
E4	7	7	6	8	6	7	5	8
E5	8	8	2	9	8	1	2	6
E6	7	9	8	9	8	7	9	7
E7	8	5	5	3	7	3	6	5
DM3	**COEFF**	**POLSTA**	**LEGEFF**	**GOVSUP**	**RESLEA**	**QUAEMP**	**MARCON**	**CUSEXP**
E1	4	7	5	7	5	6	4	5
E2	8	9	9	8	8	7	9	9
E3	7	8	5	7	6	5	4	6
E4	5	6	7	8	5	7	7	5
E5	3	7	2	9	8	6	9	2
E6	7	8	7	7	8	8	7	7
E7	6	5	5	5	6	7	6	4

Table 10
The expert-weighted fermatean fuzzy decision matrix.

	COEFF		POLSTA		LEGEFF		GOVSUP		RESLEA		QUAEMP		MARCON		CUSEXP	
E1	0.533	0.388	0.700	0.200	0.533	0.369	0.699	0.209	0.409	0.495	0.493	0.419	0.389	0.547	0.477	0.426
E2	0.837	0.100	0.872	0.100	0.880	0.100	0.847	0.100	0.874	0.100	0.771	0.127	0.854	0.130	0.845	0.100
E3	0.614	0.290	0.716	0.183	0.543	0.359	0.645	0.259	0.568	0.334	0.533	0.369	0.654	0.257	0.515	0.393
E4	0.756	0.210	0.643	0.258	0.668	0.233	0.762	0.136	0.543	0.359	0.677	0.224	0.689	0.214	0.682	0.220
E5	0.778	0.187	0.771	0.127	0.480	0.519	0.849	0.165	0.837	0.100	0.434	0.584	0.783	0.212	0.444	0.560
E6	0.734	0.165	0.847	0.100	0.771	0.127	0.827	0.127	0.837	0.100	0.769	0.130	0.827	0.127	0.734	0.165
E7	0.677	0.229	0.500	0.400	0.533	0.369	0.441	0.465	0.643	0.258	0.539	0.389	0.633	0.268	0.444	0.460

Table 11
The normalized decision matrix.

	COEFF	POLSTA	LEGEFF	GOVSUP	RESLEA	QUAEMP	MARCON	CUSEXP
E1	0.0000	0.4068	0.1032	0.4965	0.0000	0.1668	0.0000	0.0834
E2	1,0000	1,0000	1,0000	0.9939	1,0000	1,0000	1,0000	1,0000
E3	0.1927	0.4505	0.1190	0.3615	0.2105	0.2529	0.4182	0.1391
E4	0.6440	0.2671	0.3523	0.6829	0.1718	0.6422	0.4971	0.4778
E5	0.7326	0.6177	0.0000	1,0000	0.8622	0.0000	0.7520	0.0000
E6	0.5625	0.8965	0.6188	0.9119	0.8622	0.9898	0.9008	0.6178
E7	0.3705	0.0000	0.1032	0.0000	0.3460	0.2597	0.3748	0.0373

Table 12
The statistical values.

	COEFF	POLSTA	LEGEFF	GOVSUP	RESLEA	QUAEMP	MARCON	CUSEXP
COEFF	1,0000	0.5554	0.6602	0.6892	0.8141	0.5562	0.8869	0.6775
POLSTA	0.5554	1,0000	0.7238	0.8479	0.7695	0.6111	0.7489	0.7032
LEGEFF	0.6602	0.7238	1,0000	0.5338	0.5945	0.9375	0.7005	0.9881
GOVSUP	0.6892	0.8479	0.5338	1,0000	0.7098	0.4466	0.7130	0.5691
RESLEA	0.8141	0.7695	0.5945	0.7098	1,0000	0.4826	0.9348	0.5448
QUAEMP	0.5562	0.6111	0.9375	0.4466	0.4826	1,0000	0.6523	0.9458
MARCON	0.8869	0.7489	0.7005	0.7130	0.9348	0.6523	1,0000	0.6923
CUSEXP	0.6775	0.7032	0.9881	0.5691	0.5448	0.9458	0.6923	1,0000
St. Dev.	0.3140	0.3238	0.3357	0.3460	0.3737	0.3751	0.3204	0.3475

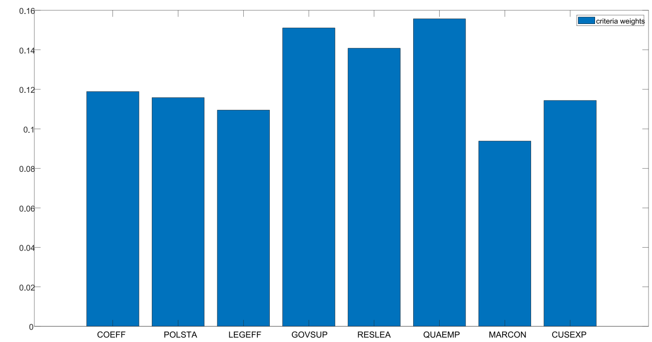

Fig. 3. The weights of criteria.

Then, Qs and Qp values are calculated. Qs and Qp values of E7 countries are displayed in Fig. 4.

Finally, with the help of Qs and Qp values, Q measurements of E7 countries are computed for different v values between 0 and 1. Then the Q values are defuzzified. The calculation results for $V = 0.5$ are reported in Table 13.

The calculation results of E7 countries with different v values are visualized in Fig. 5.

As can be seen from Fig. 5, the rankings are generally similar for different values of v. At all v values, the first two E7 countries are the same, and E2 and E6 countries stand out in their digitalization in renewable energy projects.

4.4. Comparative ranking of E7 countries and sensitivity analysis

In multi-criteria decision-making techniques, the results are compared with a second different method for the validity of the ranking results. For this purpose, analyzes with the CoCoSo method are carried out using Fermatean fuzzy numbers. The advantage of the CoCoso method is the simplicity of calculation, easy to understand and suit the ranking set, low computational complexity, high efficiency. It is based on weighted sum and weighted multiplication models. The fact that these two models have results obtained with different weights constitutes the limitation of the model. Although the WASPAS model has a similar calculation, it is simpler and more understandable in terms of calculation practice. The ranking of E7 countries as a result of WASPAS

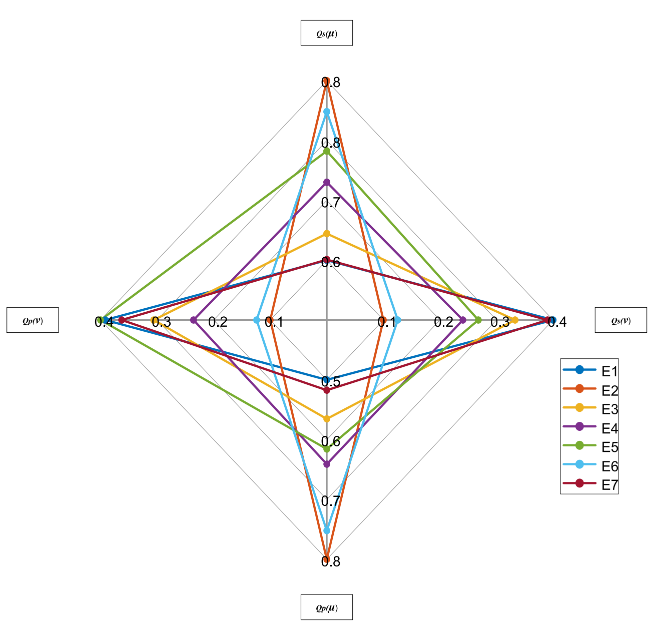

Fig. 4. The Qs and Qp values of E7 countries.

Table 13
The Q values of E7 countries.

	$\tilde{Q}$		Q
E1	0.5446	0.3818	0.5530
E2	0.8463	0.1074	0.8024
E3	0.5997	0.3105	0.5928
E4	0.6809	0.2355	0.6513
E5	0.6971	0.3207	0.6529
E6	0.7961	0.1304	0.7512
E7	0.5536	0.3634	0.5609

for $V = 0.5$ and CoCoSo are shown in Fig. 6.

According to Fig. 6, the results of the two methods are the same. Spearman Rank Correlation coefficient is calculated for the similarity of the good method result. Since the correlation coefficient is 0.964, it can be stated that the results are similar. In other words, the rankings of digitalization of renewable energy projects in E7 countries are valid.

Using different weight values, E7 countries are re-ranked with WASPAS analysis. Different scenarios of weights are created by changing the current criteria weights between 1 % and 5 %. The method is repeated with the new scenario weights and the ranking results are compared. Thus, the sensitivity of the results to changes in the criteria weights is tested. In other words, it is seen whether minimal changes in the criteria weights create a difference in the ranking results. For this purpose, the rankings obtained for ten different scenarios are shown in Fig. 7.

It can be seen that the ranking of E7 countries does not change in ten different scenarios with different criterion weights. In other words, the ranking results appear to be unaffected by minimal changes in weights.

4.5. Reanalysis for 3 different types of renewable energy

The same methodology is applied for solar and hydroelectric projects, except for the wind energy type. Evaluations are collected from decision makers for these energy types and the analysis is repeated. The criteria weighting results for three different energy types are reported in Table 14.

Although there are changes in the order of the criteria in the three different energy types, the order of the first two and the last two criteria has not changed. This shows that the first two criteria are the most important in all cases. Similarly, E7 countries are ranked in three different renewable energy types. The analysis is repeated with the collected decision maker evaluations. The results are presented in Table 15.

Similarly, although there are changes in the ranking of E7 in the three different energy types, the order of the first and the last country has not changed. This shows that the first country is the best county for three different renewable energy types.

5. Discussion

It is extremely important to employ qualified personnel in increasing digital transformation in renewable energy projects. Advanced technology is needed to successfully develop digital transformation processes. To develop these technologies correctly, qualified personnel must be employed. Moreover, another issue required for the digital transformation process to be successful is big data analysis. Zhong et al. [46] defined that qualified personnel are needed to implement this process successfully. Thanks to these personnel, the data collection and analysis process can be carried out more successfully. According to Yu et al. [47], qualified personnel can quickly adapt to new technologies and methods. This situation allows innovative solutions to be offered to the business. Similarly, Wang et al. [48] indicated that it is possible to quickly resolve possible disruptions that may occur during the digital transformation process. In addition to them, El Zein and Gebresenbet

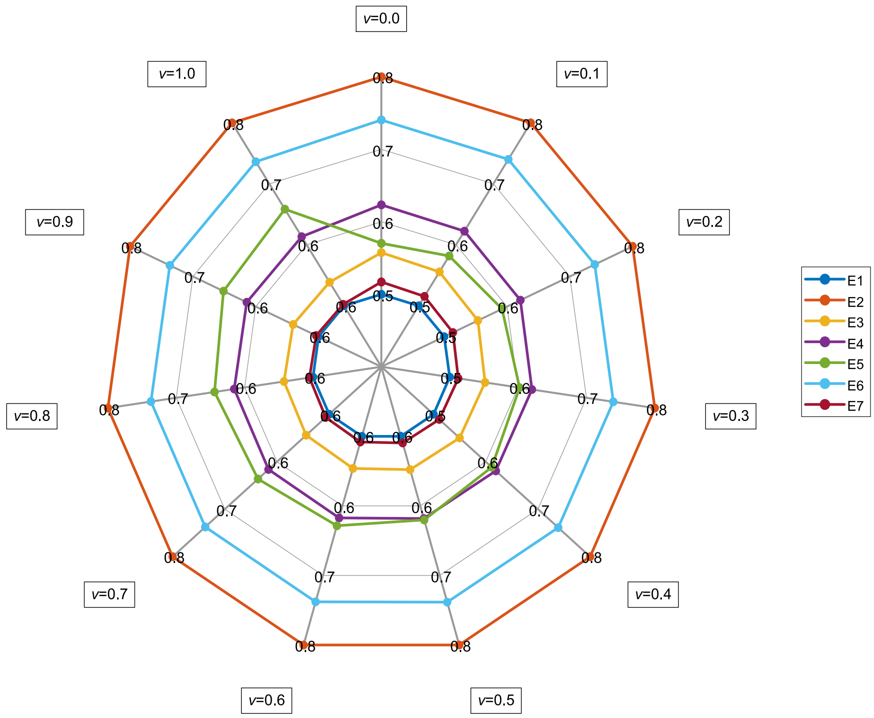

Fig. 5. The results of WASPAS with different v values.

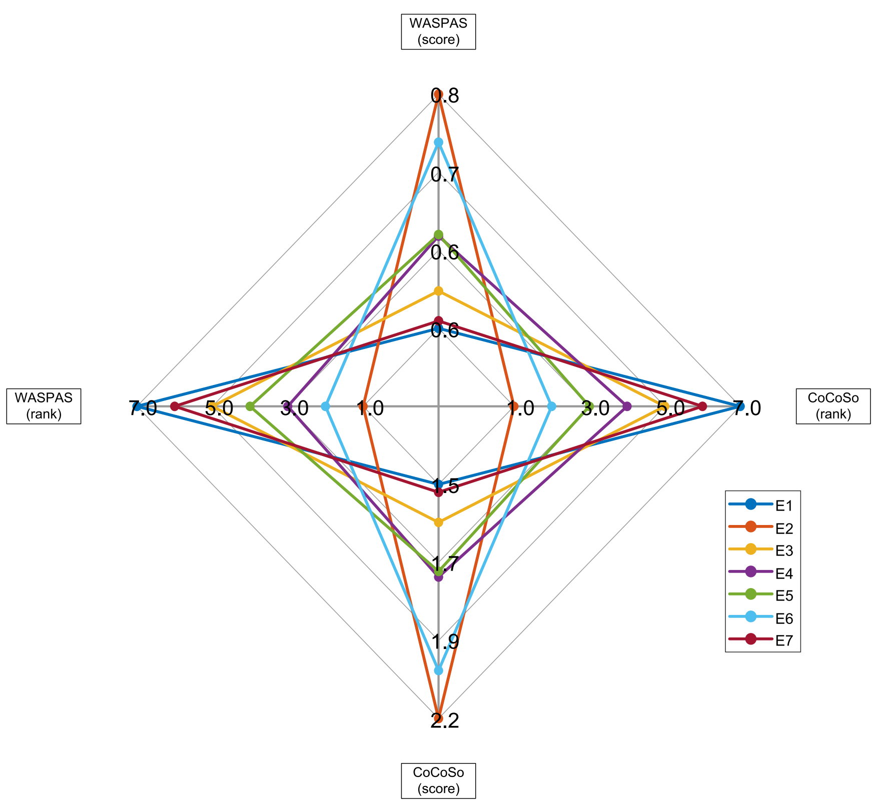

Fig. 6. The results of two methods.

[49] and Hassan et al. [50] also identified that qualified personnel also support the achievement of sustainability goals. The main reason for this is that qualified personnel can easily implement the necessary technological and operational changes to increase energy efficiency.

Government support is very critical in the successful implementation of digital transformation processes in renewable energy projects. Tax deductions may be provided to companies investing in renewable energy projects. This supports the financial sustainability of the projects. Another contribution of this situation to projects is that it reduces costs. The role of governments is also very important in creating legal

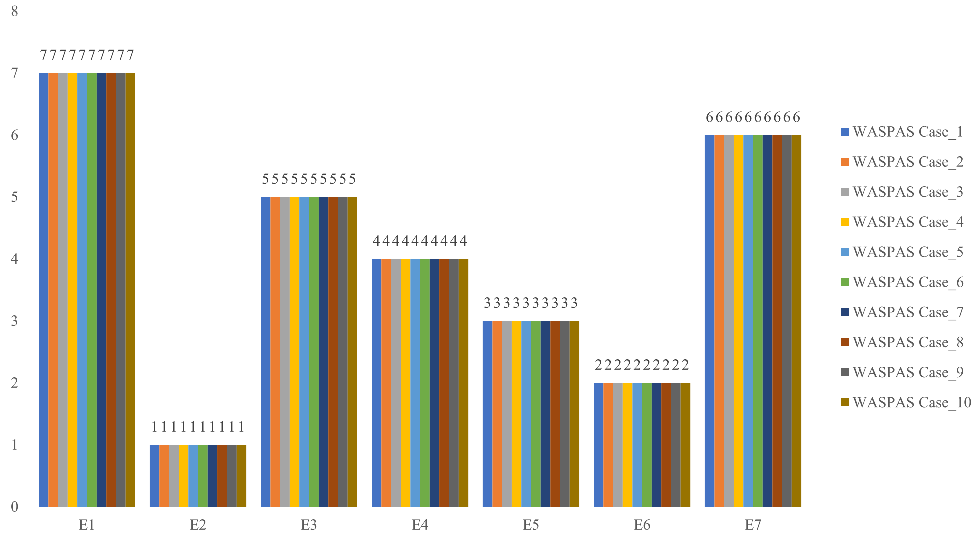

Fig. 7. The results of sensitivity analysis.

Table 14
Weighting results for three renewable energy type.

	Wind	Solar	Hydroelectric
COEFF	4	3	5
POLSTA	5	5	4
LEGEFF	7	7	7
GOVSUP	2	2	2
RESLEA	3	4	3
QUAEMP	1	1	1
MARCON	8	8	8
CUSEXP	6	6	6

Table 15
Ranking results of E7 for three renewable energy type.

	Wind	Solar	Hydroelectric
E1	7	7	7
E2	1	1	1
E3	5	4	4
E4	4	3	6
E5	3	5	3
E6	2	2	2
E7	6	6	5

regulations that encourage the adoption of renewable energy and digital transformation technologies. Jiao et al. [51] and Bie et al. [52] explained that by establishing these regulations effectively, investors' confidence in the sector increases. On the other hand, Kanabar and Cosoreanu [53] and Chen et al. [54] concluded that governments can fund research projects to develop innovative solutions in the field of renewable energy and digital transformation. Thanks to these research works, it can be easier to achieve digital transformation in renewable energy projects [55]. In addition to them, Sun et al. [56] determined that states also have an important role in developing the energy infrastructure in countries. For example, it is possible to increase the efficiency of renewable energy projects with infrastructure works for energy storage processes.

There are practical applications in many countries on this subject. These applications are generally parallel to the findings of the study. Germany is implementing very important applications in digital transformation in the renewable energy sector. This situation plays a critical role for energy grid optimizations. Germany attaches great importance to developing qualified personnel in this process. Similarly, Germany implements state incentives and policies to support digital transformation in the renewable energy sector. To achieve this goal, Germany's state-owned development bank KfW offers low-interest loans for energy efficiency and digital energy solutions. The smart energy showcases - digital agenda for the energy transition (SINTEG) program is also an important digital energy transformation strategy in Germany [57,58]. Similarly, there are some applications in the USA for the successful implementation of digital transformation in solar energy projects. There are various policies in the USA to encourage digital transformation for solar energy projects. For instance, significant state support is provided for solar energy projects with the investment tax credit (ITC) application [59]. In this context, businesses can receive tax credits up to 30 % of the project cost. Within the scope of the California Solar Initiative (CSI), a number of incentives are offered for the development of energy storage and digital grid technologies in solar projects [60].

6. Conclusion

In this study, it is aimed to identify the most significant performance indicators of digital transformation for these projects. A three-stage machine learning and fuzzy logic-based decision-making model has been constructed in this process. The first stage includes the weight calculation of the experts by dimension reduction methodology. Secondly, essential factors of digital transformation in renewable energy projects are examined via Fermatean fuzzy CRITIC. The final part consists of the ranking of emerging seven countries with Fermatean fuzzy WASPAS. On the other side, CoCoSo method is also taken into consideration in this process to make a comparative evaluation. It is concluded that employing qualified personnel plays the most critical role in increasing digital transformation in renewable energy projects. Moreover, government support is also found as a critical issue in the successful implementation of digital transformation processes in renewable energy projects. According to these results, if the employees in renewable energy projects are qualified, the digitalization process can be implemented more effectively. It is also determined that Brazil and China are the most successful emerging countries with respect to the digitalization performance in renewable energy projects.

Various policies and strategies can be applied to employ qualified personnel to increase digital transformation in renewable energy projects. First, training and development programs also enable this goal to be achieved. In this way, staff can become more knowledgeable on issues such as big data analysis and artificial intelligence. Moreover, university and industry collaborations also contribute to the training of more qualified personnel. In addition to them, offering competitive salaries and career opportunities can also increase the work motivation of qualified personnel. On the other hand, effective policies can be implemented to provide government support to increase digital transformation in renewable energy projects. Some grants may be provided by states for projects that develop digital transformation and renewable energy technologies. This helps reduce the costs of projects. Similarly, innovation centers can be established for start-ups developing renewable energy and digital transformation technologies.

The main contribution of this study is the generation of novel machine learning and fuzzy logic integrated decision-making model to make evaluation related to the digital transformation of renewable energy projects. In this model, machine learning technique is used to determine the importance weights of the experts. Similarly, integrating Fermatean fuzzy numbers with CRITIC and WASPAS techniques also contributes to the literature by minimizing the uncertainty and identifying the relationship between the items. The main theoretical limitation in this study is that renewable energy types are not specifically analyzed. Due to this situation, a new evaluation can be conducted in the following studies by comparing the conditions of solar and wind energy projects. On the other hand, there are also some limitations related to the proposed model. In this framework, limited number of dimensions are taken into consideration to compute the weights of the experts by machine learning technique. Hence, in the future evaluations, a much more comprehensive analysis can be performed by using more variables. Moreover, in this study, WASPAS and CoCoSo models are taken into consideration to rank the alternatives. However, these methods are also criticized in the literature because of some issues. Thus, a new ranking technique can be introduced in the following studies for the purpose of overcoming these criticisms.

CRediT authorship contribution statement

Serkan Eti: Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Serhat Yüksel:** Writing – original draft, Validation, Software, Methodology, Investigation. **Hasan Dinçer:** Writing – original draft, Validation, Software, Methodology, Investigation. **Dragan Pamucar:** Writing – review & editing, Visualization, Validation, Supervision, Software. **Muhammet Deveci:** Writing – review & editing, Validation, Supervision, Investigation. **Gabriela Oana Olaru:** Writing – review & editing, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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