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Research paper

A Machine Learning–Based Multi-Criteria Decision-Making Model for Prioritizing Climate Change Policy Strategies under Spherical Fuzzy Environment

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Abstract

The objective of this study is to identify the most prioritized policy strategies that can be implemented to combat climate change, thereby filling the gap in the literature and providing policymakers with a scientifically based roadmap. The proposed model utilizes the opinions of five experts. A machine learning-based method calculates importance weights based on the experts' demographic characteristics. The criteria importance through intercriteria correlation (CRITIC) is used to determine the criteria weights, and the weighted aggregated sum-product assessment (WASPAS) is considered to rank policy alternatives. Furthermore, spherical fuzzy sets are integrated into the model to more effectively manage uncertainties. The study contributes to the literature by proposing a unique decision-making model where expert weights are objectively calculated using machine learning, CRITIC and WASPAS methods are applied in an integrated manner, and uncertainty is managed more flexibly and reliably through spherical fuzzy sets. This model offers an innovative solution to the long-discussed problem of "assuming equal expert weights" in the literature and provides a more robust methodological framework for policy environments with high uncertainty. Research findings indicate that the most critical criteria are technological feasibility and economic feasibility. Moreover, carbon taxes and renewable energy incentives are the most optimal policy strategies.

Keywords: *machine learning; soft computing; fuzzy decision making; climate change; energy investments*

1. Introduction

Climate change, one of the most significant global environmental problems of the 21st century, profoundly threatens both natural systems and human life. This process, triggered by the increasing accumulation of greenhouse gases in the atmosphere, stems primarily from human activities such as industrialization, fossil fuel consumption, deforestation, and rapid urbanization (Chancel et al., 2025). Rising global average temperatures are leading to rapid glacier melting and rising sea levels. Furthermore, it brings with it environmental consequences such as the intensification of extreme weather events such as droughts and floods, and irreversible disruptions to ecosystems (Verma et al., 2025). Furthermore, climate change has devastating impacts not only ecologically but also economically and socially. These include decreased agricultural productivity, jeopardized food and water security, and the emergence of energy supply vulnerabilities (Horbach and Rammer, 2025). Similarly, this problem could accelerate mass migration and pose serious risks to public health. At the same time, the economic costs of the climate crisis lead to disruptions in production and trade chains, fluctuations in energy prices, and deepening inequalities between countries (Goodell et al., 2025). Considering these multifaceted risks, climate change is not just an environmental problem. It also poses a fundamental threat to sustainable development, social well-being, and global security. Therefore, developing, implementing, and resolutely pursuing science-based, holistic, and long-term policy strategies at the national and international levels to combat this problem is not a choice but a necessity to secure the future (Wu et al., 2025).

Achieving successful results in combating climate change is possible not only by identifying the problem but also by implementing effective and implementable policies. Renewable energy incentives aim to diversify energy supply and reduce emissions by reducing fossil fuel use, while also supporting long-term energy security (Levy et al., 2025). Carbon taxes and emissions trading mechanisms, on the other hand, integrate environmental costs into the economic system, guiding industrial enterprises toward cleaner production methods (Li, 2025). Green building programs reduce the environmental pressure of urbanization and promote sustainable urbanization through energy-efficient buildings. Electric vehicle investments reduce greenhouse gas emissions from fossil fuels in the transportation sector and improve the quality of life in society (Shobanke et al., 2025). However, the performance of these policy alternatives depends not only on their design but also on critical criteria such as emission reduction, economic feasibility, technological feasibility, social acceptance, and political stability (Mills-Novoa and Mikulewicz, 2025). While emission reduction measures environmental effectiveness, economic feasibility determines the cost-benefit balance of policies; technological feasibility reflects the existence of the necessary infrastructure and the capacity for innovation (Singer et al., 2025). Furthermore, while social acceptance involves public support and behavioral changes, political stability ensures long-term continuity and effective oversight mechanisms. Therefore, these criteria play a decisive role in decision-making processes regarding which strategies should be prioritized in combating climate change and provide an indispensable framework for evaluating the effectiveness of policy alternatives (Barr et al., 2025).

One of the fundamental conditions for achieving successful outcomes in combating climate change is the systematic identification of the most important and prioritized alternatives among existing policy options. Given limited financial resources, technological capabilities, and political implementation capacities on a global scale, not every policy can be implemented to the same extent (Kumler et al., 2025). Therefore, accurately determining strategic priorities becomes essential. Failure to identify the most appropriate and effective policies can lead to serious problems such as the misdirection of resources, inadequate greenhouse gas emission reductions, increased economic losses, decreased social support and trust, and, in the long run, further exacerbation of the climate crisis (Heikonen et al., 2025). In this context, comparatively evaluating the performance of alternatives such as renewable energy incentives, carbon tax implementations, green building programs and electric vehicle investments is a critical need, both from a scientific perspective and for policymakers' decision-making processes (Malik and Ford, 2025). However, a review of the existing literature reveals that studies based on systematic methods, such as multi-criteria decision-making techniques, that quantify the importance of such policy alternatives are quite limited (Glavina et al., 2025; Dyderski et al., 2025). This situation fails to provide a clear framework for determining which strategies should be prioritized in climate policy implementation, creating a clear research gap in the literature. This research gap creates uncertainty for decision-makers in strategic planning processes and highlights the lack of holistic, comparative, and interdisciplinary approaches in scientific knowledge generation. Therefore, filling this gap will not only contribute to the academic literature but also significantly contribute to the design of more effective, applicable, and sustainable climate policies at the national and international levels.

The aim of this study is to identify the most prioritized policy alternatives that can be implemented to combat climate change, thus filling a significant research gap in the literature and providing policymakers with a scientifically based roadmap. The motivation for this study stems from the difficulties decision-makers face in determining strategic priorities due to the multitude and uncertainty of existing policy options. In this context, five evaluation criteria and five policy strategies are identified following a comprehensive literature review, and a novel decision-making model is developed to identify the most important of these criteria and alternatives. In the proposed model, opinions are obtained from five different subject-matter experts, and importance weights are calculated based on their demographic characteristics using a machine learning-based approach. The CRITIC method is used to determine the criteria weights, and the WASPAS technique is used to prioritize policy strategies. Furthermore, to manage uncertainties more effectively, spherical fuzzy sets are incorporated into the model, aiming to yield more flexible, reliable, and realistic results. The fundamental research questions sought in this study are formulated as follows: (1) Which policy strategies should be prioritized in combating climate change? (2) Which criteria play a more dominant role in determining the importance levels of these strategies? (3) How do the demographic characteristics of the experts affect the importance weights in the decision-making process? (4) What kind of advantages does the integration of CRITIC and WASPAS methods with Spherical fuzzy sets provide in the prioritization of policy alternatives? (5) In what ways does this novel decision-making model offer innovative contributions compared to existing approaches in the literature?

This study fills the gap in the literature on prioritizing policy alternatives to combat climate change and offers an original contribution to the literature by proposing an innovative machine learning-based decision-making model. The proposed model offers significant advantages over traditional multi-criteria decision-making approaches in the literature. (1) First, integrating machine learning techniques into the multi-criteria decision-making process increases the model's originality and methodological power. Many studies in the literature assign equal weight to expert opinions, leading to individuals with different demographic characteristics, knowledge, experience levels, and areas of expertise being evaluated with the same impact. However, such an approach fails to reflect the real decision-making environment and reduces the reliability of the results. In this study, importance weights are objectively calculated using a machine learning-based method, taking into consideration the demographic characteristics of experts. This ensures that expert differences are realistically reflected in the decision-making process. This not only allows for a more accurate assessment of expert opinions but also provides an innovative solution to the long-discussed "equality of expert weights" problem in the literature. (2) Secondly, the spherical fuzzy sets used in the model offer significant advantages over other fuzzy set approaches in complex decision-making environments such as climate policy, where uncertainty is highly felt. While traditional approaches such as triangular fuzzy sets, type-2 fuzzy sets, or q-ROF sets offer a certain degree of flexibility, they are limited in representing membership, non-membership, and degrees of uncertainty in a comprehensive and balanced manner. Spherical fuzzy sets, on the other hand, offer decision-makers a broader range of expressive power by simultaneously evaluating these three dimensions. Thus, they enable more realistic modeling of environmental, economic, and social criteria, particularly those with high levels of uncertainty. In this respect, the proposed model provides a more robust, reliable, and flexible decision-making framework than existing models in the literature, both in terms of weighting expert opinions and managing uncertainty and offers a methodologically innovative contribution to the prioritization of climate change policies.

In the continuation of this study, the methodology of the proposed model is presented in detail in the second section, the findings are presented in the third section, these findings are discussed by comparing them with the literature in the fourth section, and the general conclusions of the study and recommendations for policy makers and future research are presented in the last section.

2. Methods

This section is about the definition of SFSs, machine learning, CRITIC, and WASPAS. SFSs are used for measuring the uncertainty and machine learning is used for obtaining the important of experts' evaluations. Then, the weights of criteria are computed using CRITIC and the alternatives are ranked by WASPAS.

2.1 Spherical Fuzzy Sets (SFSs)

Let a set D be a universe of discourse. A SFS (S) is an object having the form in Equation (1) (Rahim et al., 2025).

$$S = \{a, (s_S(a), t_S(a), r_S(a)) | a \in D\} \tag{1}$$

Wherein the function $s_S(a), t_S(a), r_S(a)$ and $0 \leq (s_S(a))^2 + (t_S(a))^2 + (r_S(a))^2 \leq 1$ are the functions of membership, non-membership and hesitancy of a to S, respectively. The refusal function is identified in Equation (2)

$$\delta_S(a) = \sqrt{1 - \left(s_S(a)\right)^2 - \left(t_S(a)\right)^2 - \left(r_S(a)\right)^2} \tag{2}$$

2.2 Machine Learning

A dataset $\left(X = [x_{ij}]\right)$ is constructed. The dataset contains professional indicators of experts such as age, global and teaching experiences, etc. Next, the items of dataset are standardized using Equations (3) – (5) (Kalra, 2025).

$$\bar{x}_j = \frac{\sum_{i=1}^{e} x_{ij}}{e} \tag{3}$$

$$c_{ij} = x_{ij} - \bar{x}_j \tag{4}$$

$$n_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{d} \left(c_{ij}\right)^2}} \tag{5}$$

Wherein is the number of experts. Later, the covariance coefficients are computed with Equation (6).

$$cov_{jk} = \frac{\sum_{i=1}^{e} (n_{ij} - \bar{n}_j)(n_{ik} - \bar{n}_k)}{e} \tag{6}$$

Afterwards, the eigenvalues (λ) of the covariance matrix (A), which accepts the covariance coefficients as elements, are obtained by solving Equation (7).

$$\det(A - I\lambda) = 0 \tag{7}$$

Wherein I is identity matrix. Later, the eigenvector regarding maximum eigenvalue is obtained by solving Equation (8).

$$(A - I \max \lambda)V = 0 \tag{8}$$

Finally, the dataset is multiplied by eigenvector using Equation (9). Next, the items of this one-dimensional matrix are normalized via Equation (10).

$$P = XV \tag{9}$$

$$\xi_i = \frac{p_i}{\sum_{i=1}^{e} p_i} \tag{10}$$

2.3 Critic

The alternatives and criteria are defined. Next, the evaluations are collected from each expert, and these evaluations are converted to SFNs. The evaluation matrix for k^{th} expert is created as Equation (11) (Rasool et al., 2025).

$$D^k = \left[d_{ij}^k\right] \tag{11}$$

Wherein d_{ij}^k is the SFNs and equals to evaluation of j^{th} criterion of i^{th} alternative for k^{th} expert. After that, the expert-weighted average of SFNs is calculated using Equation (12).

$$d_{ij} = \left\{ \left[1 - \prod_{k=1}^{d} \left(1 - s_{d_{ij}^k}^2\right)^{\xi_k}\right]^{\frac{1}{2}}, \prod_{k=1}^{d} t_{d_{ij}^k}{}^{\xi_k}, \left[\prod_{k=1}^{d} \left(1 - s_{d_{ij}^k}^2\right)^{\xi_k} - \prod_{k=1}^{d} \left(1 - s_{d_{ij}^k}^2 - r_{d_{ij}^k}^2\right)^{\xi_k}\right]^{\frac{1}{2}} \right\} \tag{12}$$

Afterwards, the decision matrix is normalized. For this, Equation (13) is used for beneficial criterion and Equation (14) is used for cost criterion.

$$\pi_{ij} = \frac{1 - \frac{s_{ij}^2 \mathrm{X} s_-^2 + t_{ij}^2 \mathrm{X} t_-^2 + r_{ij}^2 \mathrm{X} r_-^2}{s_{ij}^2 \mathrm{V} s_-^2 + t_{ij}^2 \mathrm{V} t_-^2 + r_{ij}^2 \mathrm{V} r_-^2}}{1 - \frac{s_-^2 \mathrm{X} s_+^2 + t_-^2 \mathrm{X} t_+^2 + r_-^2 \mathrm{X} r_+^2}{s_-^2 \mathrm{V} s_+^2 + t_-^2 \mathrm{V} t_+^2 + r_-^2 \mathrm{V} r_+^2}} \tag{13}$$

$$\pi_{ij} = \frac{1 - \frac{s_{ij}^2 \mathrm{X} s_+^2 + t_{ij}^2 \mathrm{X} t_+^2 + r_{ij}^2 \mathrm{X} r_+^2}{s_{ij}^2 \mathrm{V} s_+^2 + t_{ij}^2 \mathrm{V} t_+^2 + r_{ij}^2 \mathrm{V} r_+^2}}{1 - \frac{s_-^2 \mathrm{X} s_+^2 + t_-^2 \mathrm{X} t_+^2 + r_-^2 \mathrm{X} r_+^2}{s_-^2 \mathrm{V} s_+^2 + t_-^2 \mathrm{V} t_+^2 + r_-^2 \mathrm{V} r_+^2}} \tag{14}$$

Wherein (s_-, t_-, r_-) and (s_+, t_+, r_+) are the minimum and maximum optimal values. Next, the correlation coefficient is estimated by Equation (15).

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (\pi_{ij} - \bar{\pi}_j)(\pi_{ik} - \bar{\pi}_k)}{\sqrt{\sum_{i=1}^{m} \left(\pi_{ij} - \bar{\pi}_j\right)^2 \sum_{i=1}^{m} (\pi_{ik} - \bar{\pi}_k)^2}} \tag{15}$$

At the same time, the standard deviation is obtained via Equation (16).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(\text{π}_{ij}-\bar{\text{π}}_j)^2}{m-1}} \tag{16}$$

Finally, the weights of criteria are defined with Equations (17) and (18).

$$\mathfrak{C}_j = \sigma_j \sum_{k=1}^{n}(1-\rho_{jk}) \tag{17}$$

$$w_j = \frac{\mathfrak{C}_j}{\sum_{j=1}^{n}\mathfrak{C}_j} \tag{18}$$

2.4 WASPAS

The decision matrix in Equation (19) is constructed by calculating the expert-weighted average of the SFNs of the evaluations of alternatives with Equation (12) (Rasheed et al., 2025).

$$D = [d_{ij}] \tag{19}$$

Afterwards, the weighted sum model is computed using Equation (20).

$$Q_i^1 = \sum_{j=1}^{n} w_j d_{ij} \tag{20}$$

While the multiplication of a scalar and SFN is defined in Equation (21), the sum of two SFNs is expressed in Equation (22).

$$w_j d_{ij} = \left(\left(1-\left(1-s_{d_{ij}}^2\right)^{w_j}\right)^{0.5}, t_{d_{ij}}^{w_j}, \left(\left(\left(1-s_{d_{ij}}^2\right)^{w_j}\right)-\left(1-s_{d_{ij}}^2-r_{d_{ij}}^2\right)^{w_j}\right)^{0.5}\right) \tag{21}$$

$$d_i + d_k = \left(\left(s_{d_i}^2+s_{d_k}^2-s_{d_i}^2 s_{d_k}^2\right)^{0.5}, t_{d_i}t_{d_k}, \left(\left(1-s_{d_i}^2\right)r_{d_k}^2+\left(1-s_{d_k}^2\right)r_{d_i}^2-r_{d_i}^2 r_{d_k}^2\right)^{0.5}\right) \tag{22}$$

At the same time, the weighted product model is calculated with the help of Equation (23).

$$Q_i^2 = \prod_{j=1}^{n} d_{ij}{}^{w_j} \tag{23}$$

While the exponential of SFN is identified in Equation (24), the multiplication of two SFNs is determined in Equation (25).

$$d_{ij}{}^{w_j} = \left(s_{d_{ij}}^{w_j}, \left(1-\left(1-t_{d_{ij}}^2\right)^{w_j}\right)^{0.5}, \left(\left(1-t_{d_{ij}}^2\right)^{w_j}-\left(1-t_{d_{ij}}^2-r_{d_{ij}}^2\right)^{w_j}\right)^{0.5}\right) \tag{24}$$

$$d_i d_k = \left(s_{d_i}s_{d_k}, \left(t_{d_i}^2+t_{d_k}^2-t_{d_i}^2 t_{d_k}^2\right)^{0.5}, \left(\left(1-t_{d_i}^2\right)r_{d_k}^2+\left(1-t_{d_k}^2\right)r_{d_i}^2-r_{d_i}^2 r_{d_k}^2\right)^{0.5}\right) \tag{25}$$

Finally, the Q value is estimated via Equation (26). Then, the score values of Q values are defined with the help of Equation (27). According to score values, alternatives are ranked.

$$Q_i = \mathcal{T} Q_i^1 + (1-\mathcal{T})Q_i^2 \tag{26}$$

$$q_i = \left(s_{Q_i} - r_{Q_i}\right)^2 - \left(t_{Q_i} - r_{Q_i}\right)^2 \tag{27}$$

3. Results

The results of the ranking of policy alternatives in combating climate change are presented in this section.

3.1 Obtaining the experts' weights

The professional indicators of five experts are collected, and the dataset is constructed. The dataset is shown in Table 1.

Table 1: Professional Indicators

	Age	Global Experience	Manager Experience	Teaching Experience
Expert1	40	20	10	4
Expert2	45	24	12	5
Expert3	50	28	15	5
Expert4	53	33	16	6
Expert5	38	15	5	2

Afterwards, the items in Table 1 are standardized using Equations (3) – (5). Because both the value range and units of the indicators are not equal. The standardized items are given in Table 2.

Table 2: Standardized Indicators

	Age	Global Experience	Manager Experience	Teaching Experience
Expert1	-.408	-.287	-.182	-.132
Expert2	-.016	.000	.046	.198
Expert3	.376	.287	.387	.198
Expert4	.611	.646	.501	.528
Expert5	-.564	-.646	-.751	-.791

Using the standardized items in Table 2, the covariance coefficients between the standardized indicators are computed with Equation (6). The covariance matrix accepts the covariance coefficients as elements is created. Covariance matrix is presented in Table 3.

Table 3: Covariance Matrix

	Age	Global Experience	Manager Experience	Teaching Experience
Age	.200	.197	.190	.179
Global Experience	.197	.200	.194	.189
Manager Experience	.190	.194	.200	.194
Teaching Experience	.179	.189	.194	.200

Afterwards, the eigenvalues are obtained. The results of Equation (7) are equal to .772, .023, .001, and .004, respectively. The maximum eigenvalue is .772. Thus, Equation (8) is solved to estimate the eigenvector. The items of this eigenvector are .496, .506, .504, and .494, respectively. Finally, the professional indicators of experts are multiplied by the items of this eigenvector using Equation (9) and normalized via Equation (10). The results are summarized in Table 4.

Table 4: Experts' Weights

	1D Matrix	Normalized
Expert1	36.982	.174
Expert2	42.989	.202
Expert3	49.006	.230
Expert4	54.022	.254
Expert5	29.952	.141

3.2 Computing the weights of criteria

The policy alternatives in combating climate change are renewable energy incentives (RNINC), carbon tax (CRBNT), green building program (GRBPM), electric vehicle investments (EVINV), and afforestation (AFFST). Similarly, the criteria are determined as emission reduction (EMRDC), economic feasibility (ECFSB), technological feasibility (TCFSB), social acceptance (SCACC), and political effectiveness (PLEFF). All criteria are beneficial. Next, the evaluation numbers are collected from five experts. The evaluation numbers are shared in Table 5.

Table 5: Evaluation Numbers

	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	6	8	8	6	8
CRBNT	9	8	8	8	9
GRBPM	3	8	2	3	9
EVINV	1	5	2	1	3
AFFST	1	2	3	5	3
	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	6	7	6	7	7
CRBNT	7	8	7	9	7
GRBPM	4	3	6	8	3
EVINV	3	6	3	5	5
AFFST	3	5	3	6	1
	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	7	8	8	6	7
CRBNT	8	8	8	9	7
GRBPM	9	7	5	4	5
EVINV	5	1	6	1	3
AFFST	4	4	2	2	1
	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	6	8	7	5	6
CRBNT	9	7	7	9	8
GRBPM	8	7	6	3	6
EVINV	1	2	6	6	3
AFFST	5	5	6	2	3
	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	6	7	7	7	8
CRBNT	7	7	7	8	7
GRBPM	4	8	9	6	2
EVINV	5	1	3	3	6
AFFST	1	2	6	2	4

Afterwards, these evaluation numbers are converted to SFNs. Next, the expert weighted average of SFNs is calculated using Equation (12). The decision matrix is illustrated in Table 6.

Table 6: Decision Matrix

	EMRDC			ECFSB			SCACC			TCFSB			PLTEFF		
RNINC	.627	.374	.377	.771	.238	.233	.732	.278	.278	.619	.370	.391	.718	.280	.292
CRBNT	.831	.188	.184	.766	.233	.238	.746	.258	.258	.876	.124	.129	.779	.237	.234
GRBPM	.716	.325	.246	.697	.327	.269	.632	.365	.357	.543	.446	.320	.624	.450	.335
EVINV	.349	.666	.376	.378	.659	.338	.475	.560	.359	.415	.630	.363	.409	.583	.380
AFFST	.356	.683	.375	.410	.604	.426	.445	.585	.347	.391	.628	.349	.259	.770	.266

After constructing the decision matrix, the decision matrix is normalized. Since all criteria are of a beneficial type, Equation (13) is used. The normalized decision matrix is displayed in Table 7.

Table 7: Normalized Decision Matrix

	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
RNINC	.538	.000	.060	.630	.175
CRBNT	.000	.016	.000	.000	.000
GRBPM	.318	.243	.445	.765	.447
EVINV	1.000	1.000	.934	.978	.835
AFFST	.999	.946	1.000	1.000	1.000

Using values in Table 7, the correlation coefficients between the normalized decision criteria are estimated by Equation (15). Next, the correlation matrix accepted the correlation coefficients as elements is obtained. Correlation matrix is expressed in Table 8.

Table 8: Correlation Matrix

	EMRDC	ECFSB	SCACC	TCFSB	PLTEFF
EMRDC	1.000	.884	.872	.893	.903
ECFSB	.884	1.000	.979	.771	.959
SCACC	.872	.979	1.000	.844	.991
TCFSB	.893	.771	.844	1.000	.884
PLTEFF	.903	.959	.991	.884	1.000

At the same time, the standard deviations of normalized decision criteria are computed via Equation (16). These standard deviations equal to .389, .443, .420, .364, and .380, respectively. Finally, the weights of criteria are defined with Equations (17) and (18). The results are exhibited in Table 9.

Table 9: Weights of Criteria

	$\mathfrak{C}$	w
EMRDC	.174	.216
ECFSB	.180	.223
SCACC	.132	.163
TCFSB	.221	.274
PLTEFF	.100	.124

As can be seen from the weights in Table 9, the most important criterion for determining the policy alternatives in combating climate change is technological feasibility with .274. The second important criterion is economic feasibility with .216.

3.3 Calculating the ranking value of policy alternatives in combating climate change

The values in Table 6 are used for WASPAS. In addition, the weight values in Table 9 are used for weight parameters of WASPAS. Next, the weighted sum and product models are obtained with the help of Equations (20) – (25). The results are summarized in Table 10.

Table 10: Weighted Sum and Product Models

		Q^1			Q^2	
RNINC	.694	.310	.321	.682	.322	.333
CRBNT	.817	.191	.197	.807	.205	.207
GRBPM	.648	.377	.301	.636	.386	.306
EVINV	.404	.626	.362	.399	.630	.363
AFFST	.385	.643	.367	.376	.652	.362

Afterwards, the Q values of alternatives are estimated via Equation (26). Then, the score value for each alternative is defined with the help of Equation (27). The Q values with .5 are shared in Table 11.

Table 11: Q Values ($\mathcal{T}$ =.5)

		Q		score(q)
RNINC	.688	.316	.327	.130
CRBNT	.812	.198	.202	.372
GRBPM	.642	.382	.303	.108
EVINV	.402	.628	.363	-.069
AFFST	.380	.647	.365	-.080

When the score(q) values in Table 11 are examined, the most suitable policy alternatives in combating climate changes are carbon tax and renewable energy incentives with .372 and .130, respectively. The other $\mathcal{T}$ values are used to comparative results. In other words, WASPAS is repeated using values between 0 and 1. The comparative results are presented in Table 12.

Table 12: Comparative Results

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
RNINC	2	2	2	2	2	2	2	2	2	2
CRBNT	1	1	1	1	1	1	1	1	1	1
GRBPM	3	3	3	3	3	3	3	3	3	3
EVINV	4	4	4	4	4	4	4	4	4	4
AFFST	5	5	5	5	5	5	5	5	5	5

The ranking of policy alternatives in combating climate changes does not change for different values between 0 and 1. This confirms the sensitivity and validity of the results.

4. Discussion

The findings of this study clearly demonstrate that a carbon tax is one of the top policy options for combating climate change. By enabling the integration of environmental costs into the economic system, a carbon tax directly reduces the cost of polluting activities. Cuni-Sanchez et al. (2025) defined that this creates a shift toward cleaner, lower-carbon choices at both the producer and consumer levels. When designed correctly, this mechanism can be a powerful tool for reducing greenhouse gas emissions. Furthermore, Guesmi et al. (2025) identified that by channeling tax revenues into renewable energy investments, energy efficiency projects, sustainable transportation infrastructure, or social support programs, it can also finance a more inclusive and long-term transformation. However, several factors must be considered to increase the effectiveness of a carbon tax (Lu et al., 2025). Primarily, it is crucial to set tax rates at levels that truly reduce environmental impacts, ensure a fair and applicable distribution across sectors, and increase public support for this policy (Peng et al., 2025). To strengthen social acceptance, it is crucial to use tax revenues transparently, develop compensation mechanisms for low-income groups with respect for income equity, and maintain education and information activities to raise environmental awareness (Karagiannakis et al., 2025). Furthermore, Lang et al. (2025) identified that while a carbon tax is a powerful policy tool, it alone is insufficient to address the climate crisis. Therefore, its implementation alongside complementary strategies, such as renewable energy incentives, green building programs, and electric vehicle investments, frequently emphasized in the literature, is crucial. Yang et al. (2025) mentioned that renewable energy incentives strengthen energy supply security and reduce fossil fuel dependency. Furthermore, green building practices minimize the environmental pressures of urbanization, and electric vehicle investments reduce transportation emissions, reinforcing the impact of the carbon tax (Yi et al., 2025; Puig et al., 2025). Therefore, the integrated implementation of the carbon tax, identified as the top priority policy in this study, with other complementary strategies will enable more holistic, lasting, and sustainable success in combating climate change (Duan et al., 2025).

The findings of this study reveal that the most critical criteria for combating climate change are technological feasibility and economic feasibility. For any policy strategy to be successful, it is essential to have adequate technical infrastructure and achieve a sustainable cost-benefit balance. Technological feasibility is directly related to establishing the necessary energy infrastructure, developing innovative technologies, and scaling climate-friendly solutions (Eyitayo et al., 2025). Similarly, economic feasibility determines both the short-term viability of strategies such as carbon taxes, renewable energy incentives, or electric vehicle investments, as well as their long-term impact on economic stability. Therefore, policymakers must prioritize research investments, support the dissemination of low-cost and efficient technologies, and strengthen financing mechanisms for the success of climate policies (Ogier et al., 2025). However, the literature frequently emphasizes factors such as social acceptance and political stability, in addition to technological and economic factors (Bagdadee et al., 2025). Because social acceptance involves public support and behavioral changes, it directly impacts the feasibility of policies. Political stability, on the other hand, plays a critical role in ensuring long-term sustainability, establishing effective oversight mechanisms, and protecting environmental objectives independent of political volatility (Olim et al., 2025). Therefore, although technological applicability and economic feasibility have emerged as the most important criteria in this study, social acceptance and political stability must also be considered to achieve lasting success in combating climate change (Tank et al., 2025).

5. Conclusion

This study aims to identify the top priority strategies among policy alternatives that can be implemented to combat climate change and, in this regard, aims to fill a significant gap in the literature. To this end, five criteria and five policy alternatives are identified following a comprehensive literature review, and a machine learning-based approach is developed based on expert opinions. The CRITIC method is used to determine criteria weights, and the WASPAS technique is used to rank policy strategies. Spherical fuzzy sets are also integrated into the model to more effectively manage uncertainties. The research findings indicate that the most critical criteria are technological feasibility and economic feasibility, while the top priority policy alternatives are carbon taxes and renewable energy incentives. These results provide decision-makers with a concrete roadmap for the design and prioritization of climate policies. Furthermore, they contribute to the literature with a unique decision-making model that objectively calculates expert weights using machine learning and manages uncertainties more comprehensively. However, the study's limitations should not be overlooked. First, the limited number of experts to five may prevent diversity across different geographical and sectoral contexts. Furthermore, focusing on only five criteria and five policy alternatives limits the comprehensive representation of the multidimensional nature of climate change policies. Future studies with larger expert groups, data from diverse geographic regions, and a wider range of criteria and policy alternatives would enhance the validity and generalizability of the proposed model.

In conclusion, this study presents an innovative methodological framework for policy prioritization on climate change and makes significant contributions to both the academic literature and practical policymakers. The reliance on five experts from a single institution limits the diversity of perspectives, which may restrict the generalizability of the findings. Future research should include experts from diverse geographical regions and industrial sectors to provide a broader validation of the model. This study is limited to five criteria and five alternatives selected from the most commonly discussed strategies in the literature. Expanding the scope to include additional aspects such as environmental justice, global scalability, carbon capture technologies, and circular economy initiatives could provide a more comprehensive evaluation framework. Beyond the limited number of experts, additional limitations should be noted. First, the applicability of the proposed model to different economic, political, or cultural contexts may be restricted, as the experts consulted were embedded in a specific institutional setting. Second, the integration of machine learning techniques with spherical fuzzy sets increases computational complexity, which may pose challenges for replication and practical application without advanced technical resources. Third, the analysis included only five criteria and five alternatives, which may not capture the full multidimensionality of climate policy design. Future studies should address these limitations by expanding the scope of criteria and alternatives, involving experts from diverse contexts, and testing simplified computational procedures to enhance model usability.

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