

Minimizing Negative Socio-Economic Impacts of Green Transformation in Industrial Sectors: Policy Prioritization through Behavioral Leadership Fuzzy Decision Modelling

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ABSTRACT

Green transformation in industrial sectors brings with it significant socio-economic problems such as high costs, employment losses, and regional inequalities. While numerous policy proposals exist in the literature to mitigate these problems, there is no consensus on which policies should be prioritized and are more effective. Existing studies emphasize the necessity of such policies but do not sufficiently focus on their comparative prioritization. This creates a significant gap in the literature and leads to uncertainties in policymakers' decision-making processes. The primary objective of this study is to identify the most appropriate policy alternatives to minimize the negative socio-economic impacts of green transformation in industrial sectors. To achieve this objective and address the identified gap in the literature, an original decision-making model is developed. The opinions obtained from 10 experts are evaluated using a novel fuzzy set approach called "behavioral leadership fuzzy sets." This method allows for separate analyses of expert opinions based on leadership types, minimizing the subjectivity problem often encountered in expert evaluations. Then, using the Euclidean weighting technique, different levels of importance are assigned to the experts' opinions based on their demographic characteristics, and the criterion weights are calculated using the method based on removal effects of criteria (MEREC). In the final stage, policy alternatives are ranked using the weighted aggregated sum product assessment (WASPAS) method, and the most appropriate policy is determined. The study contributes to the literature by filling a significant research gap through the development of a holistic decision-making model for prioritizing green transformation policies. The advantages of the model include (1) reducing subjectivity through behavioral leadership fuzzy sets and (2) enabling a more realistic assessment of expert opinions through Euclidean weighting. The key findings indicate that the employment protection criterion is of paramount importance and that compliance with international standards also plays a significant role. Among the policy alternatives, a green skills training and employment program and a special transformation support program for SMEs stand out as the most suitable strategies.

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1. Introduction

In industrial sectors, green transformation means making production processes and business models environmentally friendly, energy efficient, and sustainable. Reducing carbon emissions and minimizing waste are among the policies that can be considered in this process. This process reduces the negative impact of economic growth on the environment. Furthermore, establishing an industrial structure compatible with international climate targets is also possible. However, green transformation can also lead to some negative socio-economic consequences [1]. The financial costs of green transformation processes can be quite high. Adapting industrial facilities to new technologies, modernizing production lines, and renewing energy infrastructure entail significant investment costs. This can increase competitive pressure, especially for small and medium-sized enterprises, and may lead to closures. In addition, green transformation processes can also lead to some employment losses. In other words, workers in fossil fuel-based industries may lose their jobs. Another negative aspect of green transformation is its potential to increase regional inequalities. Some regions may have a high concentration of high-emission industries such as coal and iron and steel [2]. The closure of these enterprises during green transformation processes leads to economic problems in these regions. This may lead to an increase in unemployment rates and an acceleration of migration movements.

Several policies can be implemented in industrial sectors to minimize the negative socio-economic impacts of the green transformation process. The most significant negative impact of this transformation is the change in employment structure. The transition from traditional production methods to low-carbon or digitalized production models can lead to unemployment of unskilled workers. To mitigate this risk, the government and industries should work together to focus on retraining the workforce [3]. Vocational training programs should be designed to focus on green skills, and this training should be tailored to regional needs. This will enable the workforce to be employed in new areas without being negatively impacted by the transformation. From an economic perspective, green transformation investments by industrial enterprises can incur significant costs. This can negatively impact the financial performance of businesses. To address this problem, governments should develop financial incentives. Within this framework, low-interest loans, tax deductions, and government-supported funds should be made easier for businesses to invest in green technologies. From a societal perspective, green transformation has the potential to exacerbate income inequalities. Therefore, policies should be developed that do not ignore the social dimension of the transformation [4]. In this context, social support programs should be offered to low-income segments. Moreover, to reduce regional disparities, green investments should be directed not only to developed industrial regions but also to socio-economically underdeveloped regions.

Many different policies are being considered to mitigate the negative socio-economic impacts of green transformation in industrial sectors. Some of these policies focus on protecting employment, while others aim to reduce the financial burden on businesses or prevent social inequalities. However, implementing all these policies simultaneously is practically impossible. Financial resources are limited, and manpower has limited capacity [5]. Therefore, determining which policies should be prioritized becomes a critical issue. However, literature lacks a clear answer to this question. There is no consensus among researchers and policymakers on the most appropriate policy. This situation creates various uncertainties both in academic debates and in practice. An examination of existing studies reveals that the necessity of policies and their importance in the green transformation process are generally emphasized. However, studies comparing policies with each other and determining their priority are quite limited. This points to a significant gap in literature. The lack of

comparative analyses weakens the hand of decision-makers in policy making and makes the process more uncertain. Therefore, there is a growing need for research that will reveal which policies are more critical and which should be considered secondary. Future studies assessing policy priorities across different sectors and countries will both contribute to the literature and guide practice. This will enable the green transformation process in industrial sectors to be more effectively framed, considering not only environmental benefits but also economic sustainability and social balance.

This study aims to identify the most appropriate policy alternatives to minimize the negative socio-economic impacts that green transformation may have on industrial sectors. The primary motivation for this study is that, despite the increasing inevitability of the green transformation process, there is no consensus in the literature on which policies should be prioritized to mitigate its negative socio-economic impacts. While most existing research emphasizes the necessity of policies, it has not sufficiently focused on determining the priority order or comparative effectiveness of these policies. Based on this motivation, a new decision-making model is developed, combining multi-criteria decision-making methods with a unique approach. Initially, a comprehensive literature review identified 12 criteria and 6 policy alternatives under economic, social, technological, and governance dimensions. Subsequently, opinions on the criteria and policy strategies are obtained from 10 experts, and these opinions are analyzed according to their leadership styles. In this context, a new fuzzy set approach called "behavioral leadership fuzzy sets" is proposed to more accurately reflect the differences in expert assessments. Then, to consider the demographic characteristics of the experts, different importance levels are assigned to the expert opinions using the Euclidean weighting technique, and the criterion weights are calculated using the MEREC method. In the final stage, policy alternatives are ranked using the WASPAS technique, and the most appropriate policy is selected. The study's research questions focus on which policies play a more critical role in mitigating the negative impacts of green transformation in industrial sectors and how these policies should be prioritized.

The contribution of the study to the literature is that it fills an important gap in the literature by developing a holistic decision-making model for the prioritization of green transformation policies in industrial sectors. The model proposed in this study distinguishes itself from previously developed models in the literature in several ways and offers significant advantages. (1) The most critical contribution of the model is the development of new fuzzy sets called "behavioral leadership fuzzy sets." This approach allows for the analysis of experts based on their leadership types, thus minimizing the subjectivity problem frequently encountered in expert opinions. (2) Another significant advantage is the use of the Euclidean weighting technique. This technique assigns different importance levels to experts' opinions based on their demographic characteristics, thus enabling a more realistic and balanced assessment. Many models in the literature do not consider the importance weights of experts; analysis is conducted solely on the average opinions. This leads to the assumption that every expert's opinion is weighted equally, which leads to the disregard of differences among experts. (3) The proposed model also uses the MEREC method to determine criterion weights, considering the information value of each criterion, thereby increasing objectivity in the decision-making process. This feature provides a significant methodological advantage over the subjective assumptions of many models in the literature at the weighting stage. (4) The WASPAS method used in the final stage combines both multiplicative and additive decision-making mechanisms, enabling a more balanced ranking of policy alternatives. This integrated approach allows the model to produce more reliable, consistent, and guiding results for policymakers, not only theoretically but also in practice.

The missing part in the literature is discussed in the next section. The proposed model is explained the results are given in the third and fourth sections. The final section includes the discussions and conclusion.

Economic factors are highly influential in determining the most appropriate policies to be implemented to minimize the negative socio-economic impacts of green transformation in industrial sectors. The green transformation process directly impacts the financial figures of businesses [6]. Significant financial resources are required to undertake the technological investments necessary for the transformation. These costs can be a significant burden for small and medium-sized businesses. Therefore, economic factors play a critical role in determining which policies should be prioritized [7]. Financial incentives also contribute significantly to minimizing these problems. Financial incentives such as tax reductions are highly effective in ensuring cost-effectiveness for businesses. Furthermore, the economic impacts of green transformation policies are significant not only at the business level but also at the macroeconomic level [8]. Regulations such as carbon taxes or emissions trading systems can affect income distribution and regional development in a country. Tan *et al.*, [1] highlighted that considering economic factors in policy formulation is essential to protect social well-being. Low-carbon production systems can contribute to a reduction in the current account deficit by reducing dependence on energy imports. Wu *et al.*, [9] denoted that green transformation has the potential to cause some macroeconomic negative effects in the short and medium term. Especially in developing countries, high-cost technological investments can disrupt budget balances.

Social factors should also be considered in determining the most appropriate policies to minimize the negative socio-economic impacts of green transformation in industrial sectors. Green transformation is not only about its economic and technological dimensions. It is also directly related to areas such as social welfare, employment, income distribution, and social justice [10]. Job losses may occur in some sectors during the green transformation process. This necessitates the retraining and acquisition of new skills by the workforce. Furthermore, the social dimension of green transformation encompasses income inequality and regional disparities [11]. Transformation policies should not focus solely on developed industrial regions. Otherwise, socio-economically disadvantaged regions may fall further behind [12]. Therefore, policies that consider regional balance are critical to maintaining social justice. Lei and Xu [13] demonstrated that low-income groups may be directly affected by the transformation. Social factors also determine the level of public participation and acceptance in the transformation process. Dong *et al.*, [14] underlined that involving the public, civil society organizations, and unions in the process increases the feasibility of policies. A participatory governance approach supports the success of policies by reducing social resistance.

Technological factors play a critical role in determining the most appropriate policies to minimize the negative socio-economic impacts of green transformation in industrial sectors. The green transformation process involves the development of new technologies and their integration into existing production processes [15]. Production technologies used in industrial sectors may be inadequate in terms of energy efficiency, waste management, and emission reduction [16]. This can lead to increased costs for green transformation. Increasing costs, in turn, reduce the financial performance of businesses. Therefore, policy formulation should consider which technologies are more accessible, cost-effective, and readily available [17]. Furthermore, Sun and Chen [18] concluded that technological factors directly impact workforce structure. High-tech production processes can increase the risk of job loss for unskilled workers. Therefore, policies focusing solely on technology investments is not sufficient. Training and skills development programs that enable the workforce to adapt to new technologies should also be supported during this process. Underlying this situation,

employment losses caused by technological transformation can be minimized. Zou *et al.*, [19] identified that the rate of diffusion of technological advancements and regional differences are also decisive factors in policy selection. While developed regions have easier access to green technologies, less developed regions may have difficulties in this process. This can lead to regional disparities. Technology sharing and research support can help reduce these disparities.

Governance factors are highly influential in determining the most appropriate policies to minimize the negative socio-economic impacts of green transformation in industrial sectors. Green transformation is directly related to issues such as transparency in decision-making processes and stakeholder participation [20]. Industrial organizations, labor unions, local governments, and civil society organizations should be included in decision-making processes. Otherwise, transformation policies may encounter social resistance. A participatory governance approach both increases policy acceptability and reduces problems during implementation [21]. Moreover, governance factors are also decisive in terms of regulatory frameworks and institutional capacity. The clarity, enforceability, and adaptability of legal regulations across sectors directly impact the success of policies [22]. Weak institutional structures or inadequate oversight mechanisms can hinder the implementation of even the best-designed policies. Mei and Zhang [23] denoted that governance factors are critical for international cooperation and harmonization. Failure to achieve this harmony can lead to problems in both foreign trade and the ability to attract investment. Similarly, Zhang [2] determined that governance factors are linked to the principles of accountability and justice. The fairness with which decisions made during the transformation process impact different segments of society increases the social acceptance of policies.

The literature review reveals that economic, social, technological, and governance factors play a critical role in determining green transformation policies in industrial sectors. However, despite numerous studies in the literature on the importance of each of these factors, it is noteworthy that comprehensive and comparative analyses for prioritizing the most appropriate policies are limited. This makes it difficult for policymakers to determine which policies are most critical and creates uncertainties. Research generally emphasizes the necessity of policies, but their ranking or the conditions under which they are most effective are not adequately examined. This deficiency constitutes a significant research gap in the literature. This gap creates problems in both theoretical discussions and practice, making it difficult for decision-makers to develop effective policy sets. Therefore, new studies are needed to address this gap, and it is understood that such studies will make valuable contributions to the literature and practice.

2. Methodology

For this manuscript, a fuzzy decision model is constructed to determine the most appropriate strategy. The constructed fuzzy decision model includes a Euclidean distance-based prioritization system for expert weighting. In the second and third steps, criteria are weighted using MEREC, while strategies are ranked using WASPAS, respectively. A fuzzy set, developed to address the leadership qualities of experts and thus predicting more behavioral leadership decision-making, is generated in this manuscript. This minimizes uncertainty in the decision-making process. A diagram depicting the process flow is depicted in Figure 1.

2.1. Behavioral Leadership Fuzzy Sets (BLFSs)

According to the fuzzy logic approach, an object's membership lies between 0 and 1. This approach, particularly in linguistic expressions, performs operations based on these membership values. While experts' behavioral leadership styles can vary, it would be unrealistic to present a single

leadership style. Each leadership style is associated with specific memberships. Sometimes these memberships are balanced, while other times one type may predominate [24]. Therefore, experts' behavioral leadership styles can be defined as a fuzzy set, as in Equation (1).

$$\mathcal{L} = \{\mu(u), \langle \mu_a(\mu(u)), \mu_d(\mu(u)), \mu_t(\mu(u)), \mu_l(\mu(u)), \mu_s(\mu(u)) \rangle | u \in \mathcal{U}\} \quad (1)$$

Wherein $\mathcal{U}$ is a universe of discourse. μ is the base membership of u . μ_a , μ_d , μ_t , μ_l , and μ_s are the membership degrees of authoritarian, democratic, transformational, Laissez-Faire and servant behavioral leadership styles. All memberships are between 0 and 1. The memberships of behavioral leadership styles are calculated with mathematical formulas according to the characteristics of behavioral leadership styles.

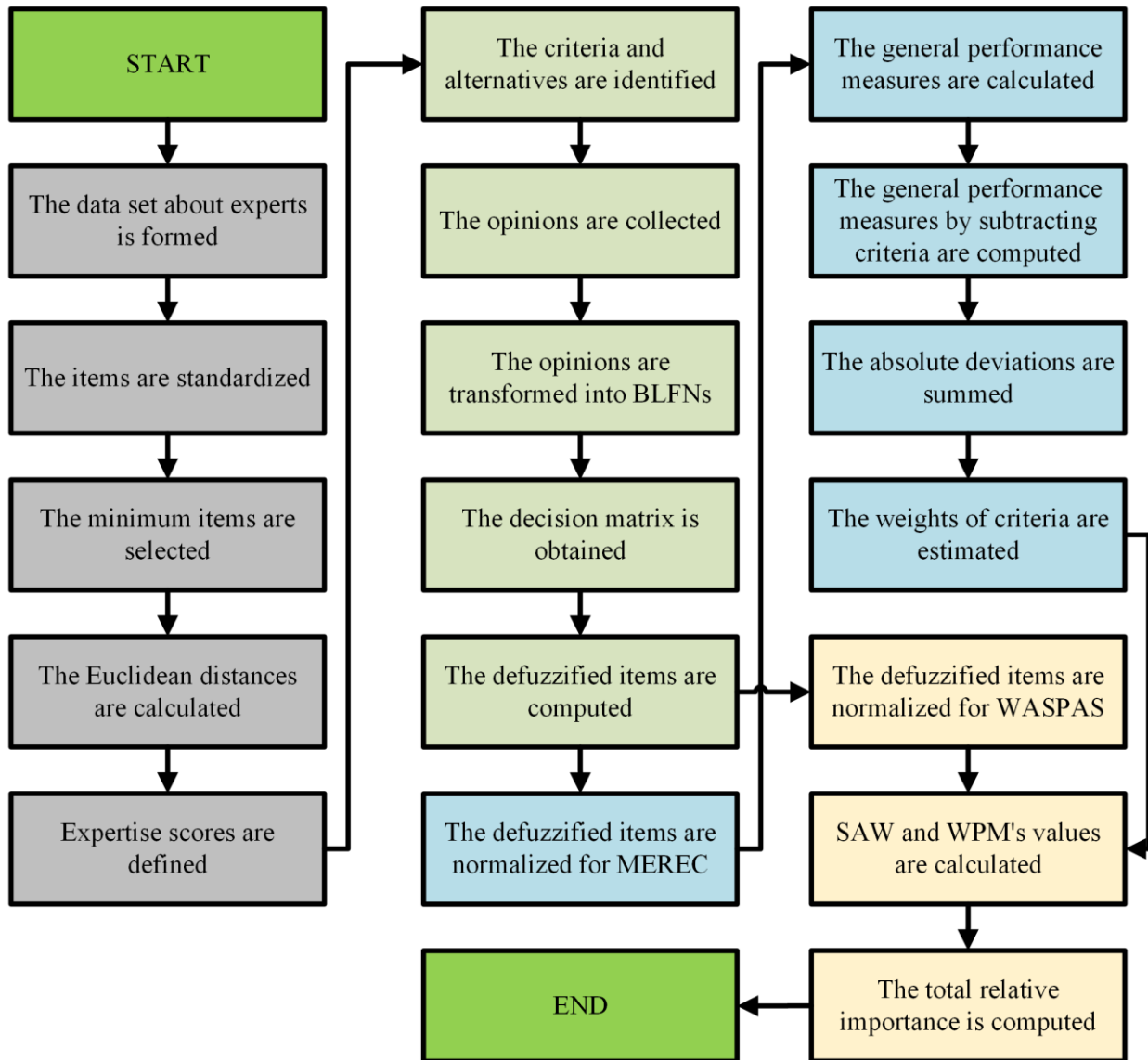


Fig. 1. Diagram Depicting the Process Flow

The authoritarian leadership style characteristic concentrates decision-making authority in situations of crisis or stress. In other words, decisions are made alone in these types of leadership. As the level of crisis or stress increases, participation in decisions increases. Just as the value of the input increases rapidly while the value of the output increases rapidly in exponential functions, the

level of participation in this type of leadership increases very rapidly. In this respect, the membership function of the authoritarian leadership style is defined as in Equation (2).

$$\mu_a(\beta_1, \mu) = \beta_1 e^{\mu-1} \quad (2)$$

Wherein β_1 refers to crisis/stress rate. This parameter is between 0 and 1. The membership function of the authoritarian is shown in Figure 2. As can be seen from Figure 2, the values of the membership function vary between 0 and 1.

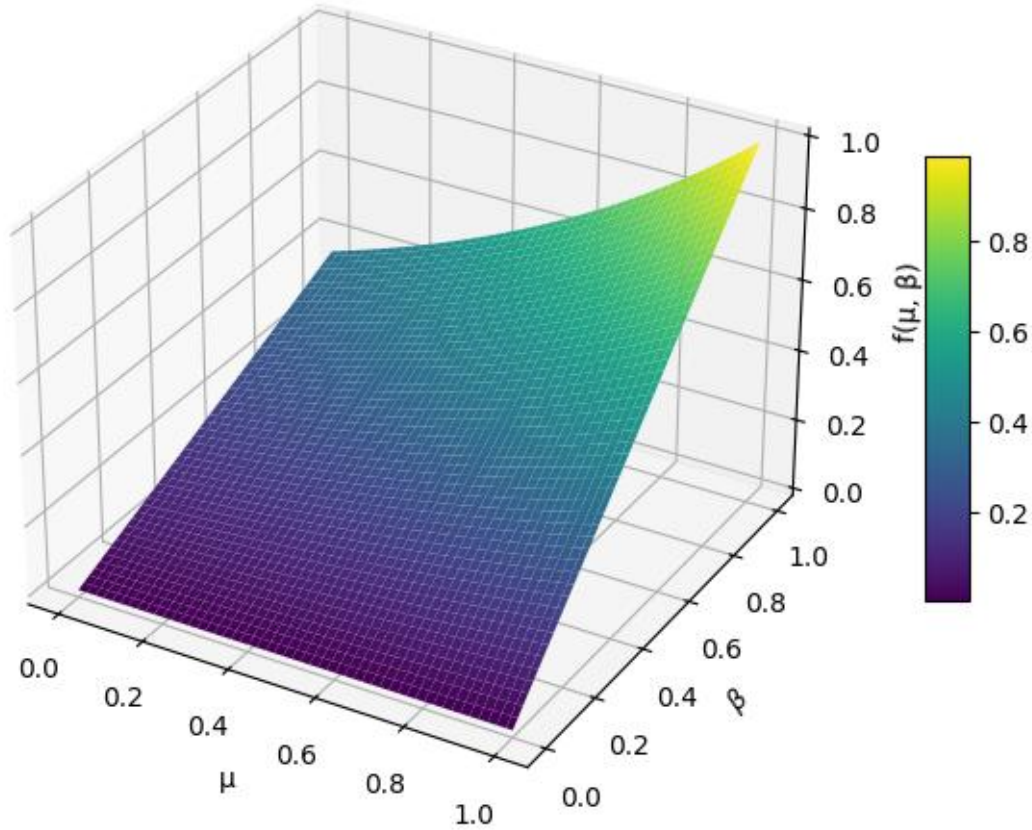


Fig. 2. Membership of Authoritarian

The characteristic of democratic leadership is that decision-making power increases as the process becomes more standardized. However, the increase in participation is gradual and limited. In other words, it presents a gradual and limited increase, as in sigmoid functions. In this respect, the membership function of the democratic leadership style is identified as in Equation (3).

$$\mu_d(\beta_2, \mu) = \frac{1}{1 + e^{-\beta_2(\mu-0.5)}} \quad (3)$$

Wherein β_2 is about the participation of decision of expert. The expert with a big value has bigger participation in decision. This coefficient is between 0 and 10. The membership function of the democratic is shown in Figure 3. As can be seen from Figure 3, the values of the membership function vary between 0 and 1.

A characteristic of the transformational leadership style is that it makes the most effective decisions at optimal levels. In extreme situations, the tendency to make decisions decreases. In other words, similar to a Gaussian function, involvement is high in intermediate situations and less so in extreme situations. The membership function of the transformational leadership style is determined as in Equation (4).

$$\mu_t(\beta_3, \mu) = \beta_3 e^{\frac{-\mu^2}{2\sigma^2}} \quad (4)$$

Wherein β_3 is the rate of increase/decrease in decision process. This value is between 0 and 1. σ is the standard deviation and positive value. The membership function of the transformational is shown in Figure 4. As can be seen from Figure 4, the values of the membership function vary between 0 and 1.

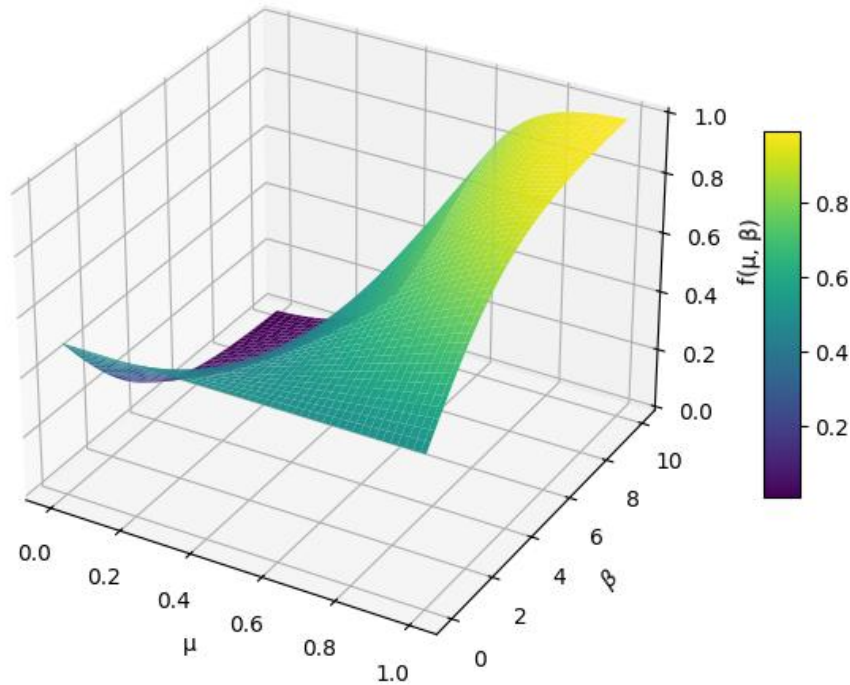


Fig. 3. Membership of Democratic

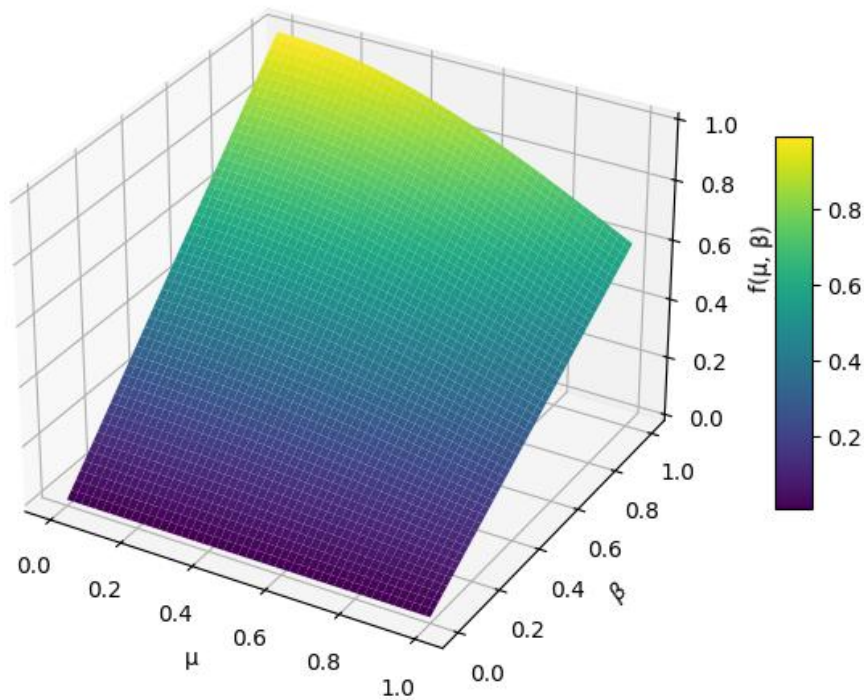


Fig. 4. Transformational Membership

A characteristic of the Laissez-Faire leadership style is the ability to isolate oneself from decisions in routine situations. In other words, as values increase, decision-making decreases. As in the inverse exponential function, increasing values leads to decreasing output. The membership function of the Laissez-Faire leadership style is determined as in Equation (5).

$$\mu_l(\beta_4, \mu) = -\beta_4 e^{-\mu} \quad (5)$$

Wherein β_4 is the ratio of the intervention effect. This parameter is between -1 and 0. The membership function of the Laissez-Faire is shown in Figure 5. As can be seen from Figure 5, the values of the membership function vary between 0 and 1.

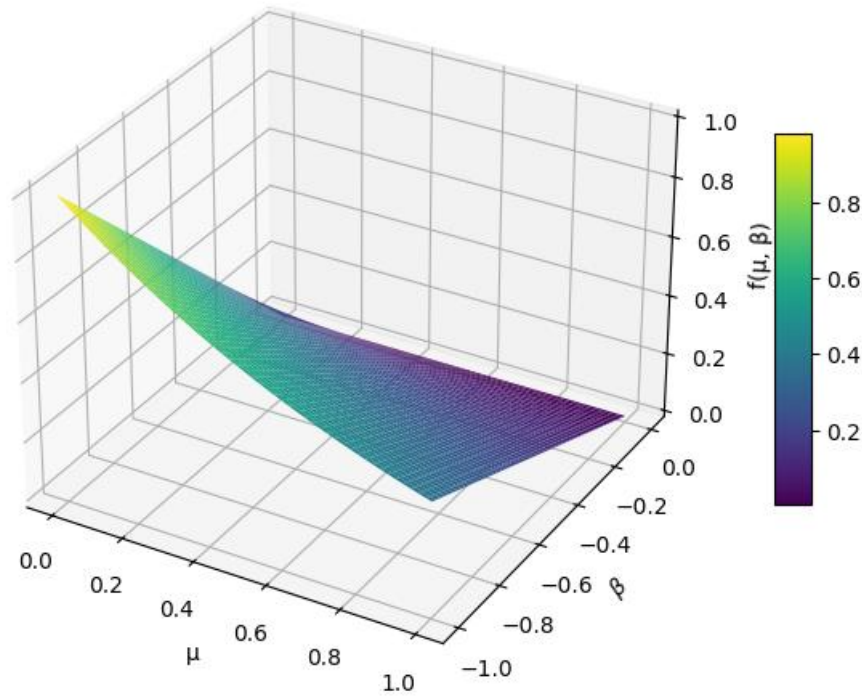


Fig. 5. Membership of Laissez-Faire

Servant leadership traits tend to avoid decision-making when situations are stable. However, as uncertainty in the process increases, they take on a balancing role. Similar to an inverse Gaussian function, they become active at extreme values. The membership function of the Servant leadership style is obtained as in Equation (6).

$$\mu_s(\beta_5, \mu) = -\beta_5 e^{\frac{-\mu^2}{2\sigma^2}} + 1 \quad (6)$$

Wherein β_5 represents the ratio of intervention and impact. This parameter is between 0 and 1. The membership function of the servant is shown in Figure 6. As can be seen from Figure 6, the values of the membership function vary between 0 and 1.

Accordingly, the behavioral leadership fuzzy set is identified in Equation (7).

$$\mathcal{L} = \left\{ \mu(u), \langle \beta_1 e^{\mu-1}, \frac{1}{1+e^{-\beta_2(\mu-0.5)}}, \beta_3 e^{\frac{-\mu^2}{2\sigma^2}}, -\beta_4 e^{-\mu}, -\beta_5 e^{\frac{-\mu^2}{2\sigma^2}} + 1 \rangle | u \in \mathcal{U} \right\} \quad (7)$$

Let A and B be any two BLFSs. Then, basic operators are determined by Equations (8) and (9).

$$A \cup B = \{ \max\{\mu_{A_d}, \mu_{B_d}\}, \max\{\mu_{A_d}, \mu_{B_d}\}, \min\{\mu_{A_t}, \mu_{B_t}\}, \min\{\mu_{A_l}, \mu_{B_l}\}, \max\{\mu_{A_s}, \mu_{B_s}\} \} \quad (8)$$

$$A \cap B = \{ \min\{\mu_{A_d}, \mu_{B_d}\}, \min\{\mu_{A_d}, \mu_{B_d}\}, \max\{\mu_{A_t}, \mu_{B_t}\}, \max\{\mu_{A_l}, \mu_{B_l}\}, \min\{\mu_{A_s}, \mu_{B_s}\} \} \quad (9)$$

Assume A and B be any two BLFNs. Then, basic mathematical operators are computed using Equations (10) and (13).

$$A + B = \{\mu_{A_a} + \mu_{B_a} - \mu_{A_a}\mu_{B_a}, \mu_{A_d} + \mu_{B_d} - \mu_{A_d}\mu_{B_d}, \mu_{A_t} + \mu_{B_t} - \mu_{A_t}\mu_{B_t}, \mu_{A_l} + \mu_{B_l} - \mu_{A_l}\mu_{B_l}, \mu_{A_s} + \mu_{B_s} - \mu_{A_s}\mu_{B_s}\} \quad (10)$$

$$A \times B = \{\mu_{A_a}\mu_{B_a}, \mu_{A_d}\mu_{B_d}, \mu_{A_t}\mu_{B_t}, \mu_{A_l}\mu_{B_l}, \mu_{A_s}\mu_{B_s}\} \quad (11)$$

$$\lambda A = \{1 - (1 - \mu_{A_a})^\lambda, 1 - (1 - \mu_{A_d})^\lambda, \mu_{A_t}^\lambda, \mu_{A_l}^\lambda, 1 - (1 - \mu_{A_s})^\lambda\} \quad (12)$$

$$A^\lambda = \{\mu_{A_a}^\lambda, \mu_{A_d}^\lambda, 1 - (1 - \mu_{A_t})^\lambda, 1 - (1 - \mu_{A_l})^\lambda, \mu_{A_s}^\lambda\} \quad (13)$$

Let A be a BLFN. Then, Equation (14) is estimated as score function.

$$\text{score}(A) = \mu_{A_a} + \mu_{A_d} - \mu_{A_t} - \mu_{A_l} + \mu_{A_s} \quad (14)$$

Next, the accuracy function is defined as Equation (15).

$$\text{acc}(A) = \frac{\mu_{A_a} + \mu_{A_d} + \mu_{A_t} + \mu_{A_l} + \mu_{A_s}}{5} \quad (15)$$

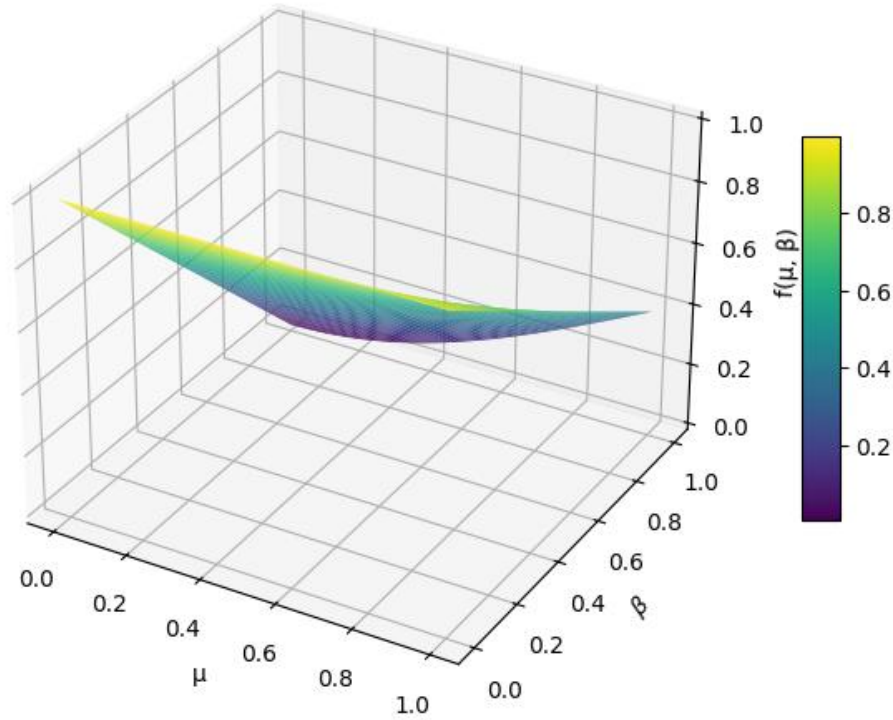


Fig. 6. Membership of Servant

2.2. Euclidean Distance based Expert Prioritization

In decision models, the creation of a decision matrix by averaging expert opinions has been criticized. The primary reason for this is the varying levels of expertise among experts. Despite this criticism, experts' professional knowledge is analyzed to calculate their expertise scores. The Euclidean distance-based expert prioritization model is introduced below [25]. Firstly, the data set including the professional information of experts is formed as Equation (16).

$$\mathcal{X} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{e1} & \cdots & x_{ep} \end{bmatrix} \quad (16)$$

Wherein e and p refer to numbers of experts and professional information of experts. Next, the items of data set are standardized using Equations (17) – (19). Because the types of professional information in the data set are different from each other.

$$\bar{x}_j = \frac{\sum_{i=1}^e x_{ij}}{e} \quad (17)$$

$$sd_j = \sqrt{\frac{\sum_{i=1}^e (x_{ij} - \bar{x}_j)^2}{e}} \quad (18)$$

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{sd_j} \quad (19)$$

Standardized items are unitless. Thus, unit size problems do not occur in metric calculations. Later, the minimum item of standardized items for each professional information is selected via Equation (20).

$$\min_j = \min_i z_{ij} \quad (20)$$

Afterwards, the Euclidean distance of each expert to these minimum items is calculated with Equation (21).

$$\mathcal{D}_i = \sqrt{\sum_{j=1}^p (z_{ij} - \min_j)^2} \quad (21)$$

Finally, the Euclidean distances are normalized using Equation (22). These normalized Euclidean distances are defined as expertise score of experts.

$$p_i = \frac{\mathcal{D}_i}{\sum_{t=1}^e \mathcal{D}_t} \quad (22)$$

2.3. MEREC

MEREC is an objective weighting method. According to the method, the greater the change in performance of alternatives caused by a criterion's absence, the higher the criterion's weight. The biggest advantage of MEREC is that it calculates the criteria weights based on the impact of the data on the decision matrix. Calculation details of the MEREC method with behavioural leadership fuzzy numbers are given below [26].

Firstly, the criteria and alternative sets are identified. Then, the alternatives are evaluated by experts regarding to criteria. Next, the memberships of evaluations are defined. These memberships are multiplied by the expertise score for each expert with Equation (12) and then summed by Equation (10). Thus, expert weighted-decision items are obtained. The decision matrix is shown in Equation (23).

$$\mathcal{S} = \begin{bmatrix} s_{11} & \cdots & s_{1n} \\ \vdots & \ddots & \vdots \\ s_{m1} & \cdots & s_{mn} \end{bmatrix} \quad (23)$$

Wherein the numbers of alternatives and criteria are symbolized as m and n, respectively. After creating the decision matrix, the defuzzified items are computed via Equation (24).

$$y_{ij} = \text{score}(s_{ij}) \quad (24)$$

Afterwards, the defuzzified items are normalized using Equation (25) and (26).

$$n_{ij} = \frac{\min_i y_{ij}}{y_{ij}}; \text{ for Useful} \quad (25)$$

$$n_{ij} = \frac{y_{ij}}{\max_i y_{ij}}; \text{ for Useless} \quad (26)$$

In next step, the general performance measures of alternatives are calculated with the help of Equation (27).

$$\mathfrak{S}_i = \ln \left(1 + \left(\frac{1}{n} \sum_{j=1}^n |\ln(n_{ij})| \right) \right) \quad (27)$$

Similarly, the general performance measures of the alternatives by subtracting the value of each criterion are computed by Equation (28).

$$\mathfrak{S}_{ij} = \ln \left(1 + \left(\frac{1}{n} \sum_{j=1, j \neq i}^n |\ln(n_{ij})| \right) \right) \quad (28)$$

After obtaining the general performance measures, the absolute deviations are summed with Equation (29).

$$\mathfrak{E}_j = \sum_{i=1}^m |\mathfrak{S}_{ij} - \mathfrak{S}_i| \quad (29)$$

Finally, the total absolute deviations are normalized using Equation (30).

$$w_j = \frac{\mathfrak{E}_j}{\sum_{j=1}^n \mathfrak{E}_j} \quad (30)$$

2.4. WASPAS

WASPAS is a hybrid ranking method. It combines SAW and WPM, thus offering the advantages of both methods. The parameters that balance the two methods provide flexibility in the results. Calculation details of the WASPAS method with behavioural leadership fuzzy numbers are given below [27].

As MEREC, the criteria and alternative sets are identified. Then, the alternatives are evaluated by experts regarding to criteria. Next, the memberships of evaluations are defined. These memberships are multiplied by the expertise score for each expert with Equation (12) and then summed by Equation (10). Thus, expert weighted-decision items are obtained. The decision matrix is shown in Equation (23). After creating the decision matrix, the defuzzified items are computed via Equation (24). Then, the defuzzified items are normalized using Equations (31) and (32).

$$\mathfrak{h}_{ij} = \frac{\min_i y_{ij}}{y_{ij}}; \text{for Useless} \quad (31)$$

$$\mathfrak{h}_{ij} = \frac{y_{ij}}{\max_i y_{ij}}; \text{for Useful} \quad (32)$$

Afterwards, SAW and WPM's values are calculated with the help of Equations (33) and (34).

$$Q_i^{SAW} = \sum_{j=1}^n \mathfrak{h}_{ij} w_j \quad (33)$$

$$Q_i^{WPM} = \prod_{j=1}^n \mathfrak{h}_{ij}^{w_j} \quad (34)$$

Finally, the total relative importance of alternatives is computed by Equation (35).

$$Q_i = \varphi Q_i^{SAW} + (1 - \varphi) Q_i^{WPM} \quad (35)$$

Wherein φ is the adjustment coefficient between the SAW and WPM. This coefficient is between 0 and 1.

3. Results

The result of analysis is presented in this section with figures and tables.

3.1 Expert Prioritization

Firstly, the experts are selected according to according to their suitability for their profession and managerial experience. To be included in the analysis, experts are required to have at least 25 years of experience in industry. Ten experts who meet this requirement are identified. Their professional information such as age, experience, management experience and number of certificates, patents, etc. is shared in Table 1.

According to information in Table 1, the average age, experience, managerial experience and certificate and patent numbers of the experts are 54.1, 33.4, 15.7 and 2.80, respectively. The other descriptive statistics are summarized in Table 2.

The measurement units of these four professional information variables are not the same. Therefore, professional information is standardized using Equations (17) - (19). For this, the mean and standard deviation for each professional information in Table 2 are used. The standardized items are illustrated in Table 3.

Table 1
Professional Information

Expert	Age	Experience (Years)	Management Experience (Years)	Number of Certificates, Patents etc.
Expert1	45	25	7	2
Expert2	53	31	13	3
Expert3	59	40	22	4
Expert4	59	39	20	4
Expert5	60	38	23	3
Expert6	54	33	17	3
Expert7	50	29	9	1
Expert8	61	39	21	4
Expert9	48	29	13	2
Expert10	52	31	12	2

Table 2
Descriptive Statistics

	Age	Experience (Years)	Management Experience (Years)	Number of Certificates, Patents etc.
Mean	54.100	33.400	15.700	2.800
Stand. Dev.	5.224	4.984	5.386	.980
Min	45.000	25.000	7.000	1.000
Max	61.000	40.000	23.000	4.000

Table 3
Standard Items

Expert	Age	Experience (Years)	Management Experience (Years)	Number of Certificates, Patents etc.
Expert1	-1.742	-1.685	-1.615	-.816
Expert2	-.211	-.482	-.501	.204
Expert3	.938	1.324	1.170	1.225
Expert4	.938	1.124	.798	1.225
Expert5	1.129	.923	1.355	.204
Expert6	-.019	-.080	.241	.204
Expert7	-.785	-.883	-1.244	-1.837
Expert8	1.321	1.124	.984	1.225
Expert9	-1.168	-.883	-.501	-.816
Expert10	-.402	-.482	-.687	-.816

Later, the minimum item of standardized items for each professional information is selected via Equation (20). The minimum items of professional information are -1.742, -1.685, -1.615, and -1.837, respectively. Then Euclidean distances are computed using Equation (21). Finally, the distances are normalized by Equation (22) and the expertise scores of experts are obtained. The distances and expertise scores of experts are exhibited in Table 4.

As can be seen expertise scores in Table 4, the experts with the most important opinion are Expert 3 and Expert 8. These experts' coefficients are .1631 and .1632, respectively. When the professional information of these experts is examined, their experience, age, management experience, and number of certificates, patents etc. are similar to each other and generally higher than others.

Table 4
Distance and Expertise Scores

Expert	Distance	Expertise Score
Expert1	1.021	0.029
Expert2	3.033	0.086
Expert3	5.777	0.163
Expert4	5.502	0.155
Expert5	5.295	0.150
Expert6	3.627	0.102
Expert7	1.303	0.037
Expert8	5.779	0.163
Expert9	1.805	0.051
Expert10	2.269	0.064

3.2. Weighting of Criteria

The strategies are selected as green transformation incentive package (GTNIP), green skills training and employment program (GSKTP), special transformation support program for SMEs (SPTFS), green technology R&D and domestic production incentive (GRTDP), regional green transformation development plan (RGTD), and transfer of carbon tax revenue to the social support fund (TCTXS). These strategies are assessment according to criteria in Figure 7.

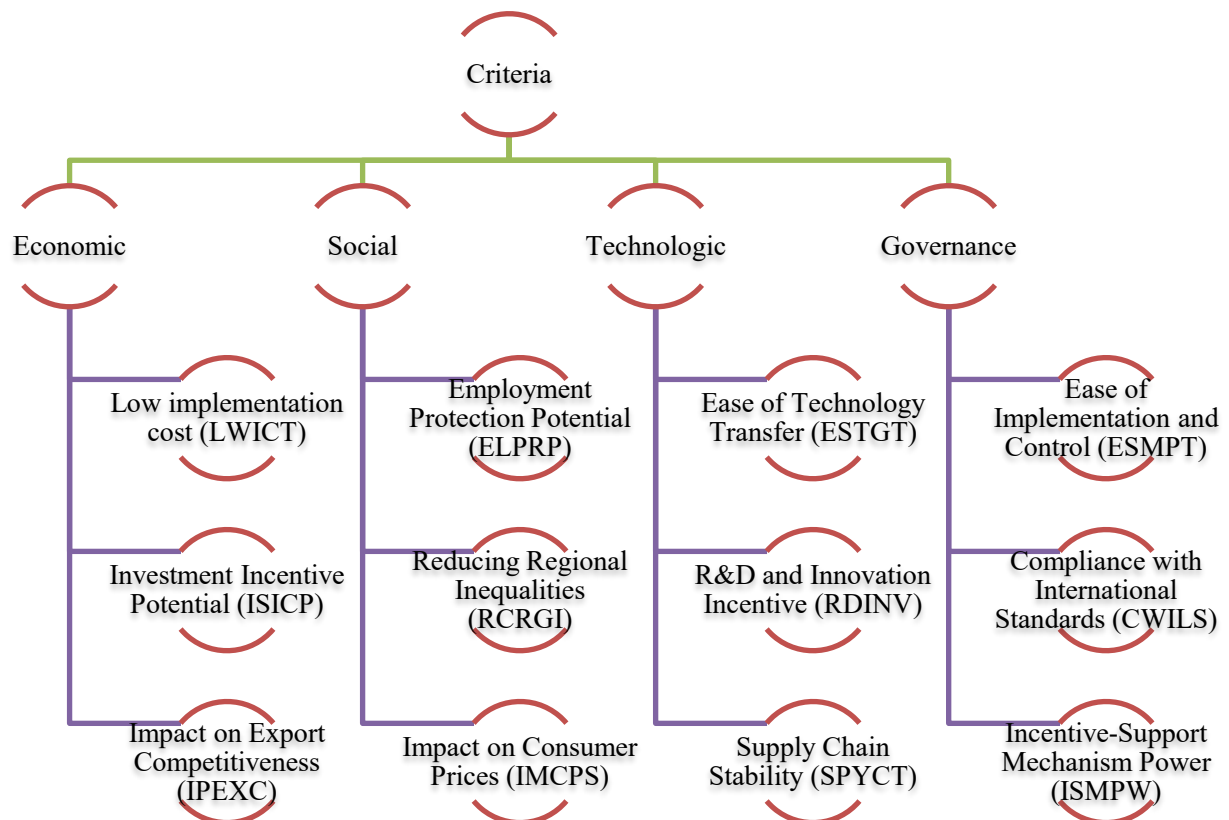


Fig. 7. Criteria

As can be seen in Figure 7, there are 4 dimensions, each consisting of 3 sub-dimensions. In other words, 12 criteria are determined for analysis. After defining the strategies and criteria, ten experts evaluate the alternatives regarding criteria. The opinions are collected with assessment numbers in Figure 8.

The opinions of ten experts are displayed in Table 5. Table 5 contains each expert's opinions of each alternative according to each criterion. In other words, each matrix belongs to the experts respectively and the total number of matrices is 10.

Afterwards, the assessment numbers are transformed into BLFNs in Figure 8. Then, BLFNs are multiplied by the prioritization of experts in Table 4. Next, by summing, the expert weighted-decision items are obtained. The decision matrix is illustrated in Table 6.

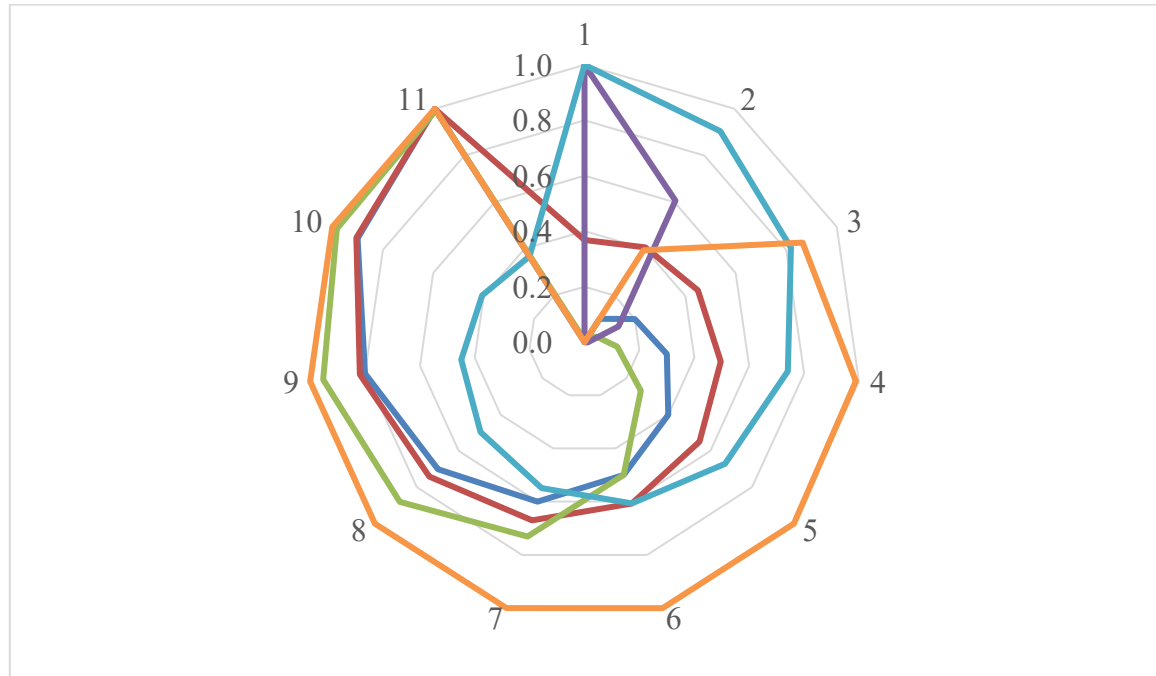


Fig. 8. BLFNs

Table 5
Opinions

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	7	4	5	8	6	2	4	7	4	4	9	3
GSKTP	9	9	8	9	9	10	7	9	10	7	7	8
SPTFS	9	9	10	10	10	8	7	7	8	8	8	8
GRTDP	3	3	4	7	6	2	6	1	6	4	6	5
RGTDP	3	2	6	9	7	6	1	7	5	4	8	6
TCTXS	6	6	5	9	4	1	2	3	6	6	7	7
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	6	4	6	8	7	3	7	6	4	3	9	1
GSKTP	7	10	9	8	10	8	9	10	9	7	10	10
SPTFS	7	9	10	8	8	8	10	7	10	9	8	8
GRTDP	3	5	2	8	1	2	4	4	4	7	8	5
RGTDP	7	4	5	9	1	2	5	5	1	5	6	5
TCTXS	7	5	1	7	6	3	1	6	4	5	8	1
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	7	1	2	8	4	5	7	4	6	5	6	4
GSKTP	7	10	9	10	10	7	9	10	10	8	7	7
SPTFS	8	7	8	9	9	10	8	7	10	9	7	7
GRTDP	1	5	1	8	1	4	2	6	6	5	7	2
RGTDP	3	3	4	8	3	6	5	1	4	6	6	5
TCTXS	4	2	5	8	5	1	5	6	1	3	8	2

Table 5

Continued

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	2	7	4	8	4	1	1	3	1	3	9	6
GSKTP	10	10	10	9	9	7	7	8	8	9	8	7
SPTFS	9	8	8	7	10	8	9	7	10	8	9	10
GRTDP	7	1	4	9	5	6	2	7	2	2	6	2
RGTD	6	2	2	7	6	2	1	5	6	6	7	4
TCTXS	3	5	7	7	6	5	2	6	7	5	9	4
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	5	2	7	7	1	4	1	6	4	4	8	3
GSKTP	8	8	8	8	9	7	8	10	7	10	7	8
SPTFS	10	9	7	9	8	7	10	7	10	7	8	9
GRTDP	1	7	5	9	4	6	6	6	6	2	7	7
RGTD	3	5	1	8	1	7	2	6	3	7	9	1
TCTXS	5	2	4	9	7	1	4	5	3	2	9	5
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	3	2	1	8	3	4	4	2	6	3	6	1
GSKTP	9	7	10	8	7	9	7	7	10	7	10	7
SPTFS	8	8	7	7	8	9	8	9	7	9	8	9
GRTDP	4	3	1	9	4	1	4	6	7	5	7	7
RGTD	6	2	1	9	2	1	5	7	7	2	9	3
TCTXS	1	3	3	7	7	6	3	1	5	6	7	7
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	2	2	2	7	5	7	5	5	6	3	6	5
GSKTP	7	8	10	8	9	9	7	10	8	7	9	10
SPTFS	8	10	8	7	9	9	7	8	8	7	9	7
GRTDP	4	7	3	9	3	2	4	7	4	7	9	3
RGTD	7	2	3	9	1	4	7	5	7	1	7	7
TCTXS	1	1	6	7	2	6	7	6	4	6	6	2
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	2	3	7	7	1	3	5	1	5	7	7	2
GSKTP	10	10	7	9	7	7	7	8	9	8	10	8
SPTFS	7	9	9	10	10	7	9	8	8	8	8	9
GRTDP	5	7	3	9	6	6	4	5	7	4	9	5
RGTD	6	6	1	8	7	7	2	5	4	5	7	2
TCTXS	2	5	4	9	6	6	2	1	5	2	8	7
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	4	2	4	7	5	5	4	1	1	5	9	5
GSKTP	9	8	10	10	7	8	9	7	7	9	10	7
SPTFS	7	8	7	8	7	9	8	8	8	7	8	7
GRTDP	4	6	5	7	5	5	4	3	7	6	7	7
RGTD	2	1	6	8	2	4	3	3	2	4	7	4
TCTXS	4	2	4	7	5	2	3	5	7	3	8	2
	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	3	3	5	9	5	3	2	2	1	7	9	3
GSKTP	9	9	8	9	8	9	7	10	8	8	10	7
SPTFS	10	8	7	9	8	8	10	9	8	9	8	10
GRTDP	7	5	1	9	6	7	1	5	3	2	6	1
RGTD	3	4	2	7	3	4	1	2	2	2	7	6
TCTXS	6	2	3	7	3	4	4	2	3	7	6	1

Table 6
Decision Matrix

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS
GTNIP	(.58,.49,0,.67,1)	(.52,.34,0,.74,1)	(.61,.6,0,.04,1)	(1,.94,0,.02,1)	(.99,.98,0,.02,1)	(.53,.97,0,.03,1)
GSKTP	(1,.97,0,.42,1)	(1,.98,0,.4,1)	(1,.98,0,.01,1)	(1,.98,0,.01,1)	(1,1,0,.01,1)	(1,1,0,.01,1)
SPTFS	(1,.97,0,.44,1)	(1,.97,0,.43,1)	(1,.95,0,.02,1)	(1,.97,0,.01,1)	(1,1,0,.01,1)	(1,1,0,.01,1)
GRTDP	(.57,.48,0,.69,1)	(.62,.65,0,.61,1)	(.5,.19,0,.04,1)	(1,.97,0,.02,1)	(.99,.98,0,.02,1)	(.6,.98,0,.03,1)
RGTD	(.61,.58,0,.62,1)	(.53,.33,0,.7,1)	(.49,.19,0,.03,1)	(1,.95,0,.01,1)	(.98,.92,0,.03,1)	(.61,.98,0,.04,1)
TCTXS	(.55,.4,0,.69,1)	(.52,.3,0,.71,1)	(.58,.47,0,.04,1)	(1,.95,0,.02,1)	(.99,.99,0,.02,1)	(.55,.92,0,.06,1)
	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPPW
GTNIP	(.58,.52,0,.68,1)	(.54,.38,0,.71,1)	(.57,.45,0,.08,1)	(.99,.52,0,.03,1)	(1,1,0,.01,1)	(.53,.97,0,.03,1)
GSKTP	(.82,.94,0,.46,1)	(1,.98,0,.41,1)	(1,.97,0,.02,1)	(1,.96,0,.01,1)	(1,1,0,.01,1)	(1,1,0,.02,1)
SPTFS	(1,.98,0,.41,1)	(.79,.93,0,.47,1)	(1,.98,0,.01,1)	(1,.96,0,.02,1)	(1,1,0,.01,1)	(1,1,0,.02,1)
GRTDP	(.54,.32,0,.7,1)	(.64,.68,0,.58,1)	(.65,.68,0,.02,1)	(.99,.45,0,.03,1)	(1,1,0,.01,1)	(.6,1,0,.02,1)
RGTD	(.52,.29,0,.74,1)	(.59,.55,0,.64,1)	(.58,.48,0,.06,1)	(.99,.61,0,.03,1)	(1,1,0,.01,1)	(.55,.96,0,.04,1)
TCTXS	(.52,.26,0,.73,1)	(.57,.52,0,.66,1)	(.59,.49,0,.02,1)	(.98,.43,0,.05,1)	(1,1,0,.01,1)	(.59,.93,0,.06,1)

After constructing the decision matrix, the fuzzy items are defuzzified using Equation (24). For this, score function is used. This function is identified in Equation (14). Defuzzified items are expressed in Table 7.

Table 7
Defuzzified Items

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPPW
GTNIP	1.401	1.123	2.172	2.916	2.945	2.473	1.422	1.210	1.941	2.480	2.992	2.463
GSKTP	2.551	2.583	2.965	2.969	2.991	2.985	2.298	2.568	2.959	2.951	2.994	2.983
SPTFS	2.530	2.532	2.936	2.957	2.991	2.988	2.567	2.254	2.968	2.942	2.990	2.985
GRTDP	1.366	1.654	1.660	2.956	2.950	2.559	1.155	1.750	2.302	2.409	2.986	2.574
RGTD	1.565	1.160	1.646	2.939	2.873	2.554	1.070	1.501	1.999	2.564	2.986	2.467
TCTXS	1.258	1.108	2.021	2.927	2.965	2.407	1.041	1.430	2.060	2.371	2.990	2.467

Twelve criteria are useful. For this reason, Equation (25) is used in normalization process. In other words, the minimum values for each criterion are divided by the values. The results are given in Table 8.

Table 8
Normalization Results for MEREC

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPPW
GTNIP	0.898	0.987	0.758	1.000	0.975	0.973	0.732	1.000	1.000	0.956	0.998	1.000
GSKTP	0.493	0.429	0.555	0.982	0.960	0.806	0.453	0.471	0.656	0.803	0.997	0.826
SPTFS	0.497	0.438	0.560	0.986	0.960	0.806	0.406	0.537	0.654	0.806	0.999	0.825
GRTDP	0.921	0.670	0.992	0.986	0.974	0.941	0.901	0.692	0.843	0.984	1.000	0.957
RGTD	0.804	0.956	1.000	0.992	1.000	0.942	0.973	0.806	0.971	0.925	1.000	0.998
TCTXS	1.000	1.000	0.814	0.996	0.969	1.000	1.000	0.846	0.943	1.000	0.999	0.998

Using the normalized items, the general performance measures are calculated with the help of Equation (27). The general performance measures equal to .0065, .336, .333, .103, .055, and .038, respectively. Next, the general performance measures of the alternatives by subtracting the value of each criterion are computed by Equation (28). Table 9 shows the results of the general performance measures of the alternatives by subtracting the value of each criterion.

Table 9

General Performance Measures by Subtracting

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	0.057	0.064	0.043	0.065	0.063	0.063	0.041	0.065	0.065	0.062	0.065	0.065
GSKTP	0.293	0.284	0.300	0.335	0.334	0.323	0.288	0.290	0.311	0.323	0.336	0.325
SPTFS	0.290	0.282	0.297	0.332	0.330	0.320	0.277	0.295	0.307	0.320	0.332	0.321
GRTDP	0.096	0.072	0.102	0.102	0.101	0.098	0.095	0.074	0.090	0.101	0.103	0.099
RGTDP	0.038	0.052	0.055	0.055	0.055	0.051	0.053	0.038	0.053	0.049	0.055	0.055
TCTXS	0.038	0.038	0.022	0.038	0.036	0.038	0.038	0.025	0.034	0.038	0.038	0.038

After that, the absolute deviations are summed with Equation (29). In other words, difference between $\mathfrak{S}_i$ and Table 9 are estimated. Finally, the total absolute deviations are normalized using Equation (30). The weights of criteria are visualized in Figure 9.

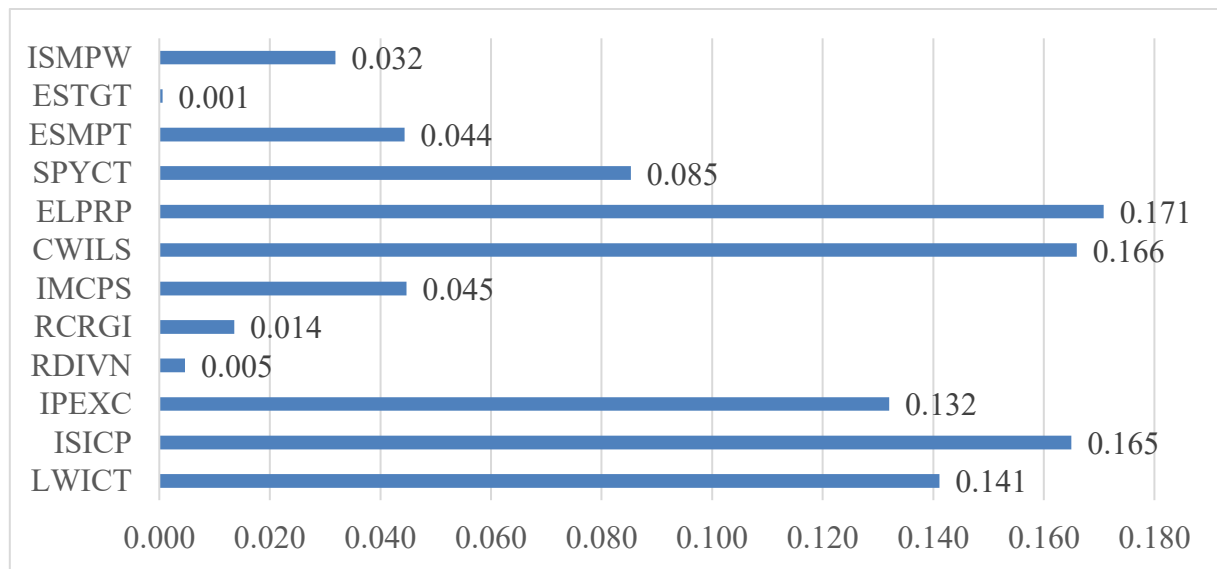


Fig. 9. Weights of Criteria

According to weights in Figure 9, the most important criteria for this manuscript are employment protection potential and compliance with international standards with .171 and .166, respectively. In other words, the two criteria with the largest criterion weights are found as these criteria because of the analysis.

3.3. Ranking of Strategies

In the last step of the constructed fuzzy decision model, the six strategies determined are ranked using the criteria weights. At this stage, the defuzzified items in Table 7 are used. In other words, the stage continues with the defuzzified version of the fuzzy weighted average of the opinions. After this stage, the items are normalized using Equation (31). The main reason for choosing Equation (31) is that the entire criterion is useful. The normalized matrix for WASPAS is illustrated in Table 10.

Afterwards, using Equations (33) and (34), the SAW and WPM's values are calculated. The values in Figure 9 are used as the weight parameters of Q_i^{SAW} and Q_i^{WPM} . Thus, the weighted sum and product values are obtained. The results are expressed in Table 11.

Finally, the total relative importance of strategies is computed by Equation (35). For the importance of SAW and WPM to be equal, the calculation is made by φ parameter as 0.5. The Q values of strategies are shown in Figure 10.

Table 10

Normalized Matrix for WASPAS

	LWICT	ISICP	IPEXC	RDIVN	RCRGI	IMCPS	CWILS	ELPRP	SPYCT	ESMPT	ESTGT	ISMPW
GTNIP	0.549	0.435	0.732	0.982	0.984	0.828	0.554	0.471	0.654	0.840	0.999	0.825
GSKTP	10.000	10.000	10.000	10.000	10.000	0.999	0.895	10.000	0.997	10.000	10.000	0.999
SPTFS	0.992	0.980	0.990	0.996	10.000	10.000	10.000	0.878	10.000	0.997	0.999	10.000
GRTDP	0.535	0.640	0.560	0.996	0.986	0.856	0.450	0.681	0.776	0.816	0.997	0.862
RGTDP	0.614	0.449	0.555	0.990	0.960	0.855	0.417	0.584	0.673	0.869	0.997	0.827
TCTXS	0.493	0.429	0.682	0.986	0.991	0.806	0.406	0.557	0.694	0.803	0.999	0.827

Table 11

Q_i^{SAW} and Q_i^{WPM}

	Q_i^{SAW}	Q_i^{WPM}
GTNIP	0.593	0.578
GSKTP	0.982	0.982
SPTFS	0.973	0.972
GRTDP	0.633	0.619
RGTDP	0.582	0.566
TCTXS	0.569	0.551

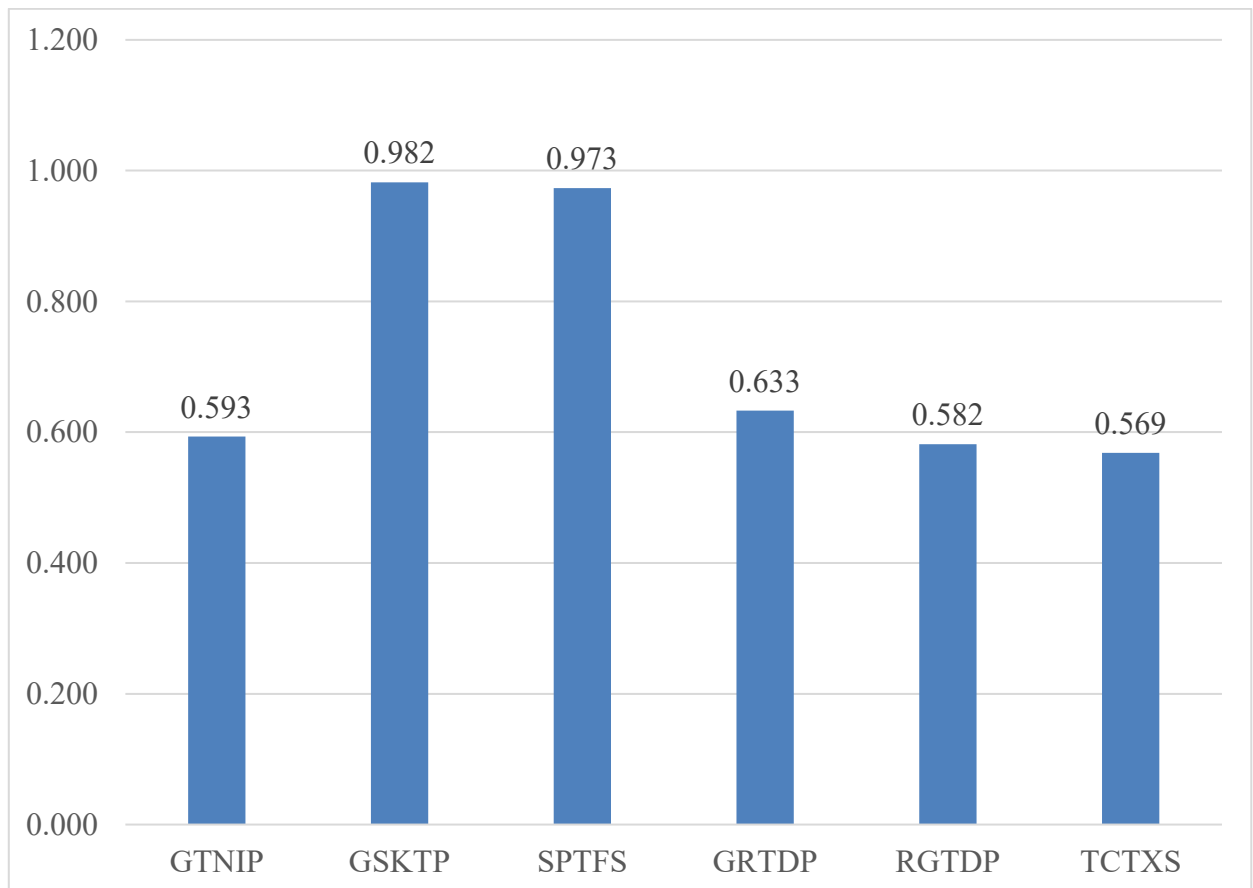


Fig. 10. Q Values

According to Q values in Figure 10, the most suitable strategies are green skills training and employment program and special transformation support program for SMEs with .982 and .973, respectively. For the other φ values, the ranks of the strategies are shared in Table 12.

Table 12
Sensitivity Analysis

φ	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
GTNIP	4	4	4	4	4	4	4	4	4	4	4
GSKTP	1	1	1	1	1	1	1	1	1	1	1
SPTFS	2	2	2	2	2	2	2	2	2	2	2
GRTDP	3	3	3	3	3	3	3	3	3	3	3
RGTDP	5	5	5	5	5	5	5	5	5	5	5
TCTXS	6	6	6	6	6	6	6	6	6	6	6

As can be seen ranks in Table 12, ranks for each φ values are the same. In other words, the ranking of strategies does not change according to the different priorities of SAW and WPM, which shows that the results are consistent.

4. Conclusions

The primary objective of this study is to identify the most appropriate policy alternatives to minimize the negative socio-economic impacts of green transformation in industrial sectors. To this end, a unique model combining multi-criteria decision-making methods and new approaches was developed. Within the scope of the methodology, 12 criteria and six policy alternatives were identified, encompassing economic, social, technological, and governance dimensions. Opinions from 10 experts were analyzed using the behavioral leadership fuzzy sets approach. Furthermore, the Euclidean weighting technique was used to consider the demographic characteristics of the experts, the criteria weights were calculated using the MEREC method, and the most appropriate policy was selected using the WASPAS method. The study's key findings indicate that employment protection is the most critical criterion, and compliance with international standards also plays a significant role. Among the policy alternatives, a green skills training and employment program, and a special transformation support program for SMEs were highlighted. The study's contribution to the literature is its proposal of a holistic model for prioritizing green transformation policies and its filling of a significant gap in the literature. The advantages of the proposed model include reducing subjectivity in expert opinions, taking demographic differences into account, determining objective criteria weights, and obtaining more balanced results in policy ranking.

The results of this study indicate that preserving employment is the most critical criterion in the green transformation process in industrial sectors, and that compliance with international standards also plays a significant role. This finding demonstrates that the social dimension and global competitiveness cannot be ignored in the transformation process [28]. Similarly, numerous studies in the literature emphasize the potential impacts on the labor market and the importance of preserving employment [29, 30]. Furthermore, various studies indicate that compliance with international climate targets is decisive for economic sustainability [31, 32]. However, the results do not indicate that other criteria are unimportant. On the contrary, economic costs, technological suitability, and governance are also frequently highlighted and considered important factors in the literature [6, 33]. Some studies indicate that financial incentives play a key role in businesses' adaptation to the transformation, while others demonstrate that technological innovation is essential for long-term success [34, 35]. Therefore, the findings of this study demonstrate that certain

criteria are more prominent, while confirming that other criteria should also be considered for the success of the transformation process.

The findings offer important lessons for policymakers. Maintaining employment and equipping the workforce with new skills should be among the priority objectives of the green transformation process. Within this framework, green skills training, re-employment programs, and lifelong learning strategies should be implemented [36]. Furthermore, special support mechanisms should be developed to prevent small and medium-sized enterprises from being negatively impacted by the transformation due to high costs [37]. Providing low-interest loans, tax breaks, and transformation-focused funds will be effective in this context. To prevent regional inequalities, investments should be directed not only to developed industrial regions but also to regions with lower socio-economic status [38]. Furthermore, a transparent and participatory governance model should be adopted, and labor unions, local governments, and civil society organizations should be included in the process. Finally, policies aligned with international standards should be developed and global collaborations strengthened [39]. These strategies will ensure not only environmental but also economic sustainability and social justice aspects of the green transformation process.

This study has several theoretical and methodological limitations. First, the analysis is based on the opinions of only 10 experts. The limited number of experts limits the generalizability of the results. Including experts from a wider range of disciplines could have enriched the model with diverse perspectives. Moreover, this study evaluated only 12 criteria and 6 policy alternatives. It is possible that more criteria or different policy options may be more salient in different sectors or different country contexts. Therefore, it is important to test the model in different contexts. Third, the study utilizes specific multi-criteria decision-making methods. Using different methods or hybrid approaches can increase the robustness and comparative validity of the results. Future studies could focus on addressing these limitations. More reliable results could be obtained with larger expert panels or Delphi studies. The model's international validity could be tested by including different sectors and countries in comparative analyses. Furthermore, the consistency of the results could be tested using alternative criteria weighting and ranking techniques.

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Conflicts of 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.

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