Research Article

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An Evaluation of E7 Countries' Sustainable Energy Investments: A Decision-Making Approach with Spherical Fuzzy Sets

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Abstract: The purpose of this study is to identify important strategies to increase sustainable energy investments in emerging economies. For this situation, first, four different indicators are selected according to the dimensions of the balanced scorecard technique. The weights of these items are computed by using Quantum Spherical fuzzy DEMATEL. In the second phase, emerging seven (E7) countries are ranked regarding the performance of sustainable energy investments. In this process, Quantum Spherical fuzzy TOPSIS is taken into consideration. The main contribution of this study is that prior factors can be defined for emerging economies to increase sustainable energy investments in a more effective way. Furthermore, a novel decision-making model is developed while integrating TOPSIS and DEMATEL with Quantum theory, Spherical fuzzy sets, facial expressions of the experts, and collaborative filtering. It is concluded that competition is the most significant factor for the performance of sustainable energy investments. In addition, the ranking results denote that China and Russia are the most successful emerging economies with respect to sustainable energy investments. It is strongly recommended that emerging countries should mainly consider benchmarking the capacity of energy hubs with the aim of increasing the capacity of ongoing energy plants.

Keywords: quantum spherical fuzzy sets, DEMATEL, TOPSIS, recommender systems, neuro decision-making

1 Introduction

Sustainable energy investments are projects that focus on not harming environmental factors in the energy production process. In this way, natural resources are consumed less in the energy production process. This contributes significantly to the sustainability of energy production. As a result of obtaining energy using fossil fuels, air pollution caused by carbon emissions occurs. Therefore, it is aimed to focus on clean energy alternatives instead of fossil resources in sustainable energy projects. For example, in solar energy projects, energy is produced from sunlight owing to the specially designed panels (Alao et al., 2022). Similarly, it is possible to generate electricity from the blowing wind with the help of turbines. On the other hand, electricity is obtained from the flow rate of water in hydroelectric energy projects. In summary, renewable energy projects have a powerful contribution to the economic improvements of the countries. As can be seen, in these energy projects, natural resources are not consumed unconsciously, and environmental pollution does not occur in energy production. Thus, it is much easier to deal with vital problems such as climate change and global warming.

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In this context, it is more possible for energy investments to be sustainable (Isiksal & Assi, 2022).

Effective financial analysis plays a critical role in improving the performance of sustainable energy investments. Thanks to the comprehensive financial analysis, it is possible to make an effective risk analysis. This is important for early detection of potential problems that may be encountered in the project (Bello & Ch'ng, 2022). Thus, it will be possible to solve the problems that may occur in the energy production process in a very short time. Meeting customer expectations is another issue to be considered in this process. In this context, a very comprehensive examination is required to clearly understand the expectations of the customers. Otherwise, investors do not show interest in projects where customer satisfaction cannot be achieved. This situation causes the lack of financing resources necessary for the execution of the projects. On the other hand, for these projects to be more successful, the organizational effectiveness of the companies should be ensured (Lin et al., 2022). In this context, it is necessary to manage the projects correctly and coordinate the processes effectively. Moreover, effective market benchmarking is necessary to make the best investment choice among different sustainable energy projects. This situation is quite important for the cost-effectiveness of the projects.

Improvements should be made regarding the factors mentioned above for this purpose. The biggest impediment in this process is that all the improvements to be made increase the cost at the same time. For example, a finance department consisting of qualified personnel should be established to carry out effective financial analysis (Zhang, 2022). Since these personnel must be paid high wages, the costs will increase significantly. Similarly, an effective customer solution center should be established to increase customer satisfaction. In this process, it is necessary to use up-to-date technology. Therefore, it is important for enterprises to increase their energy technology investments. These investments cause a significant increase in operating costs. As can be seen, each improvement to be made increases the costs of the enterprise and negatively affects the profitability. Thus, making different improvements together puts the sustainability of the projects at risk, as the costs will increase radically (Lee & Wang, 2022). Therefore, it is financially correct to focus on the variables that are more important when making improvements. Therefore, a priority analysis is needed to determine the important ones among these variables.

Accordingly, in this study, it is aimed to evaluate the indicators of sustainable energy investment for emerging economies. In this context, the main research question of the study is what are the priority issues that developing countries should pay attention to develop their sustainable energy investments effectively. To reach this objective, a new model has been developed which is different from previous decision-making models in the literature. In the first stage, four different indicators are selected by considering the dimensions of the balanced scorecard approach. The weights of these items are calculated by using Quantum Spherical fuzzy DEMATEL. In the second stage, emerging seven (E7) countries are ranked for the performance of sustainable energy investments. Within this context, Quantum Spherical fuzzy TOPSIS methodology is used.

The main contributions of this study are demonstrated as follows.

(i) Prior factors are identified for emerging economies to improve sustainable energy investments in a more effective way. There are main indicators that should be considered for this purpose. However, it is not optimal to improve all of them because these actions lead to an increase in the costs. For the purpose of maintaining profitability, the costs of the investments should not increase very much. Therefore, the companies should mainly take action for the most important indicators. The results of this study pave the way for investors to identify these significant determinants.

(ii) Using DEMATEL technique to weight the criteria provides some benefits. This methodology provides an opportunity to consider causal directions between the factors (Yan et al., 2023). In this study, the main indicators of sustainable energy investments are evaluated. The main issue in this context is that these factors may have an influence on each other. For example, financial effectiveness can contribute to customer expectations. Hence, to reach an appropriate conclusion, the causal relationship between the determinants should be considered in the evaluation process. Because of this issue, it is seen that DEMATEL is the optimal technique for the subject of this study in comparison with other similar methods (Mao et al., 2023).

(iii) Considering TOPSIS to rank the emerging countries regarding sustainable energy investments has also some advantages. The main superiority of TOPSIS by comparing with other similar techniques is that the distances to both positive and negative solutions are taken into consideration in the examination process (Awodi et al., 2023). However, most other techniques consider only the distance to the positive optimal solution. This situation gives information that the TOPSIS technique makes more sensitive evaluations than other ones. Ranking emerging seven countries for sustainable energy investments is a very complex and critical issue. Thus, to make an evaluation for such a critical subject, a more sensitive evaluation should be made. In this scope, it is understood that TOPSIS is the ideal technique for this situation (Hajiaghaei-Keshteli et al., 2023).

(iv) Integrating Quantum theory with Spherical fuzzy sets increases the quality of the proposed model. Quantum theory focuses on different probabilities in the analysis process. Additionally, the main advantage of Spherical fuzzy sets is that membership, non-membership, and hesitancy parameters can be examined (Ali & Garg, 2023). This situation helps to consider a wider data range in the evaluation process. Hence, by integrating these two approaches, more appropriate evaluations can be conducted.
(v) Another important contribution is that facial expressions of the decision-makers and collaborative filtering methodology are taken into consideration. Decision makers may be undecided between two options in some cases while evaluating. In this case, it is important to consider the facial expressions of the decision-makers to obtain more effective results (Jia et al., 2023). On the other hand, thanks to the collaborative filtering approach, decision-makers are offered the opportunity not to answer questions for which they are not very sure of the outcome. This situation contributes to the more accurate results obtained.
(vi) Selecting the determinants according to the balanced scorecard methodology provides some benefits. The main superiority of this approach is that in addition to the financial factors, nonfinancial issues can also be considered in the analysis process, such as customer satisfaction, organizational effectiveness, and learning and growth (Nikkhah et al., 2017). This condition allows us to make an analysis from a broader perspective. Therefore, more effective evaluations can be carried out (Zhang et al., 2023).

The remainder of the article has the following structure. The second section focuses on previous research. The third section identifies the methodology. The results are displayed in the fourth section. The study is concluded in the final section.

2 Literature Review

The clean energy segment is expected to see considerable levels of technological innovation, as well as huge amounts of funding and long periods of capital spending with uncertain returns (Ilbahar et al., 2022). Hence, the first branch of literature concentrated on examining the risk factors associated with renewable energy investment. In this regard, Liu and Zeng (2017) listed the following risks associated with investments in renewable energy technological risk, compliance risk, and market risk. According to Kul et al. (2020), the main investment risk in renewable energy projects is economic and commercial risk, followed by market risk, political and regulatory risk, technical risk, environmental risk, and social risk. Solangi et al. (2021) reinforced that the most significant renewable energy constraint is economic and financial, followed by political and policy, and lastly by the market. Shahnazi and Alimohammadlou (2022) found that complicated authorization regulations and non-renewable energy prices are the highest-ranked concerns. Because of the scale of the decarbonization from conventional fuels to alternative energy sources, markets must be engaged in addition to policy guidance (Silva et al., 2021). Rani et al. (2020) revealed nine essential factors that should be considered when assessing seven renewables, including effectiveness, energy efficiency (rational effectiveness), cost involved, operating costs, water contamination, particulate emission, land necessity, acceptance, and employment generation, using fuzzy TOPSIS.

The second body of literature centered on the challenges to sustainable energy deployment. By using a novel spherical integrated fuzzy-based multi-criteria decision-making model, Abdul et al. (2023) reported that the most significant barrier is a lack of proper assistance from the government, while the second-ranking issue is a shortage of institutional financing. Pathak et al. (2022) reinforced that policy and political constraints are the most prevalent among the primary group of impediments. In the case of Pakistan, Shah and Longsheng (2022) reinforced that the most substantial impediment is a lack of governmental and regulatory support. Also, Asante et al. (2020) confirmed that political and regulatory hurdles were ranked first among the six categories in Ghana, with corruption and nepotism emerging as the most crucial sub-barrier. Sadat et al. (2021) underlined that the most prominent impediments to the expansion of photovoltaic energy generation in Iran are an unstable economic outlook and ineffective bureaucracy. Similarly, Mostafaeipour et al. (2021) proved, using the fuzzy Best-Worst technique, that the biggest hurdles to solar energy widening are economic factors connected to the adverse influence of volatile circumstances, such as Iran sanctions. According to Asante et al. (2022), the major barriers to the uptake of renewable energy in Ghana include a shortage of infrastructure, inconsistent supply, insufficient technical human capital, a lack of facilities for servicing and maintenance, and initial investment.

Another body of literature was devoted to the criteria for assigning renewable energy sources priority when generating electricity. Land-based wind energy systems were ranked highest in terms of sustainability performance, according to Ghenai et al. (2020), followed by solid oxide fuel cells, phosphoric acid fuel cells, and polycrystalline solar power systems. In the context of Pakistan, Abdul et al. (2022) concluded that the economic condition had the largest weight, followed by the technical factor, while the societal and political elements had the lowest weights. Assadi et al. (2022) suggested for Iran that solar, wind, biomass, hydropower, hydrogen, geothermal, and marine energy resources be ordered in descending order of importance relying on the simultaneous assessment of criteria and alternatives (SECA). Using four MCDM techniques (CRITIC, COPRAS, TOPSIS, and MOORA), Sarkodie et al. (2022) stated that hydro is the most prospective renewable energy for Ghana, and the order of importance is hydro, biomass, solar PV, wind, and solar thermal. Similarly, in the context of China, Li et al. (2020) reiterated that hydropower is the best alternative. Lee and Chang (2018) also showed that hydropower is the proper alternative in Taiwan, followed by solar, wind, biomass, and geothermal. On the other hand, Hashemizadeh et al. (2021) suggested that wind energy has a reduced investment risk in addition to a greater economic reason, followed by hydropower. Also, Al-Barakati et al. (2022) argued that wind energy minimizes the risk of pollution while also advancing human living. Wind energy is the most preferred and dominating form of renewable energy, according to Alghassab (2022). According to Çolak and Kaya (2017), the five top power sources in Turkey are wind energy, solar energy, hydraulic energy, biomass energy, geothermal energy, wave energy, and hydrogen energy. Büyüközkan and Güleryüz (2017), in contrast, stated that electricity generation from geothermal sources is Turkey's best renewable energy source, followed by biogas. Solar energy is the preferable source of energy for Turkey's long-term development, according to Bilgili et al. (2022).

The prior literature on multi-criteria decision-making (MCDM) models for sustainable renewable energy production is outlined in Table 1.

Furthermore, another body of research focused on identifying the most essential aspects of prioritizing renewable energy. Asakereh et al. (2022), for instance, concluded that the most compelling considerations for the spread of renewable power generation systems in Iran, notably in Khuzestan province, are technical and economical. Sitorus and Brito-Parada (2020) revealed that the environmental criteria connected with energy from renewable sources were the most essential feature to consider in the mining industry in the United Kingdom. In the case of Ghana, Agyekum et al. (2021) emphasized that economic factors are the most challenging issue in the field. Kabak and Dağdeviren (2014) exhibited that the economy is the most significant strategic criterion for Turkey, but additional criteria include security, human well-being, technology, and global consequences. Shahnazari et al. (2020) reported that the most relevant criteria for thermochemical waste management systems for energy production from municipal solid waste include environmental, economic, and technical requirements.

3 Methodology

The methods of the proposed model are explained in the following subsections.

3.1 The Importance of Fuzzy Decision-Making Models in Sustainable Energy Projects

In fuzzy multi-criteria decision-making analysis, analysis for many criteria and alternatives is carried out. In other words, it is used to determine the ones that are more important among the many factors that affect the development of a subject (Jing et al., 2023). In this analysis approach, fuzzy logic theory and multi-criteria decision-making techniques are used together (Afzali Behbahani et al., 2022). The most important issue in this process is the uncertainty problem that arises due to the complexity of the problems (Zayat et al., 2023). It is aimed to minimize this problem, especially with the help of fuzzy numbers. In these analyses, first, the criteria and alternative set should be determined (Tsai et al., 2023). In this process, the results of the literature review can be taken into account, or these factors can be selected according to a theory in the literature (Hayati et al., 2023). Then, expert opinions on these factors are provided (El-Morsy, 2023; Sivaprakasam & Angamuthu, 2023). These views are then converted into fuzzy numbers (Li et al., 2023). Next, these numbers are normalized so that the analysis process can be carried out more effectively. In the following phase, the defuzzification process is applied. As a result, factors that are more important are determined (Hasan et al., 2022). To increase the effectiveness and success of these analyses, some issues need to be considered (Jagtap & Karande, 2023; Wang et al., 2023). First, it is important that the experts whose opinions are taken have the necessary knowledge on this subject (Singh & Kumar, 2023). Similarly, current fuzzy numbers should be taken into account in order to minimize the uncertainty in the process (Riaz et al., 2023).

Fuzzy decision-making techniques can be considered to find the critical issues of sustainable energy investments. Prior studies were based on approaches such as AHP (Abdel-Basset et al., 2021; Agyekum et al., 2021; Shahnazari et al., 2020; Solangi et al., 2021), fuzzy AHP (Alghassab, 2022; Asakereh et al., 2022; Karatop et al., 2021; Pavlović et al., 2021;

Table 1: Prior studies on the prioritization of clean energy alternatives using multi-criteria decision-making (MCDM) models

Author(s)	MCDM models	Country	Findings
Abdel-Basset et al. (2021)	AHP-VIKOR-TOPSIS	Egypt	Concentrated solar power is the best alternative, followed by photoelectric power
Ali et al. (2020b)	Analytic hierarchy process (AHP) and combinative distance-based assessment (CODAS)	Bangladesh	The best technology is a solar-wind hybrid energy system
Ali et al. (2020a)	Evaluation based on distance from average solution (EDAS), best-worst method (BWM), integrated determination of objective criteria weights (IDOCRIW)	Bangladesh	Gas power generating technology is the best, whereas wind power generation technology is the worst Solar is the best option among all renewable energy-producing technologies
Alizadeh et al. (2020)	Benefit, opportunity, cost, risk (BOCR) and analytic network process (ANP)	Iran	The optimum source of renewable energy would be solar energy
Alkan and Albayrak (2020)	Fuzzy COPRAS, fuzzy MULTIMOORA	Turkey	Hydropower has been established as a reasonable alternative renewable energy source for the majority of areas
Ding et al. (2023)	DEMATEL	Fujian province, China	Hydropower is the most important source of clean energy, followed by wind energy, solar energy, geothermal energy, and biomass energy
Ecer et al. (2021)	Level-based weight assessment (LBWA) under interval rough number (IRN) to extend the CODAS method	Turkey	Hydropower energy was ranked first, followed by solar energy, geothermal energy, biomass energy, and wind energy
Horasan and Kilic (2022)	Two-phase fuzzy goal programming	Turkey	Solar energy will account for about half of all renewable energy output, with hydroelectric and geothermal energy following
Karaaslan and Gezen (2022)	Integer multi-objective selection problem with interval coefficient (IMOSP-IC)	Turkey	Solar, wind, and geothermal energy are the most appropriate energy alternatives
Karatop et al. (2021)	Fuzzy AHP, EDAS, Fuzzy Failure Mode and Effect Analysis (FMEA)	Turkey	Hydropower is considered first among the renewable energy alternatives wherein investments can be made, with wind energy ranking second
Pavlović et al. (2021)	Fuzzy AHP	Serbia	Hydropower and biomass have the highest potential for producing electricity
Saraswat and Digalwar (2021)	Shannon's entropy method and fuzzy AHP	India	Solar energy was shown to be the best fit, followed by wind and hydro energy sources
Tasri and Susilawati (2014)	Fuzzy AHP	Indonesia	Hydropower is the most efficient renewable energy source, followed by geothermal, solar, wind, and biomass
Wang et al. (2020)	SWOT analysis and Fuzzy AHP	Pakistan	Wind energy is regarded as a desirable renewable resource for generating sustainable electricity
Yazdani et al. (2020)	Shannon Entropy, Evaluation based on distance from average solution (EDAS)	Saudi Arabia	Wind power is chosen as the best energy source
Wu et al. (2018)	Triangular fuzzy numbers (TFNs) and analytic hierarchy process (AHP)	China	Solar PV was selected as the best alternative, followed by hydropower, solar thermal power, wind power, and biomass power

Saraswat & Digalwar, 2021; Tasri & Susilawati, 2014; Wang et al., 2020), AHP-VIKOR (Abdul et al., 2022), AHP and hesitant fuzzy TOPSIS, grey AHP (Shah & Longsheng, 2022), novel spherical fuzzy and Pythagorean fuzzy AHP (Abdul et al., 2023), VIKOR (Abdel-Basset et al., 2021), complex Pythagorean fuzzy VIKOR (Ma et al., 2021), Fermatean CRITIC-VIKOR (Saraj et al., 2023), quantum Pythagorean fuzzy (Gao et al., 2022), CRITIC-TOPSIS (Asante et al., 2022), TOPSIS (Abdel-Basset et al., 2021; An et al., 2023; Shahnazari et al., 2020), fuzzy TOPSIS (Rani et al., 2020; Sadat et al., 2021; Solangi et al., 2021), intuitionistic fuzzy-TOPSIS (Bilgili et al., 2022), DEMATEL (Ding et al., 2023; Shahnazi & Alimohammadlou, 2022), fuzzy DEMATEL (Xu et al., 2020), modified Delphi and AHP (Kul et al., 2020; Pathak et al., 2022), Pythagorean fuzzy set, Pythagorean fuzzy TOPSIS, and complex Pythagorean fuzzy ELECTRE I (Akram et al., 2020). Alike Alizadeh et al. (2020), the designed model can be utilized to make strategic energy policy decisions. In addition, as long as prior articles focused on single countries such as Ghana (Agyekum et al., 2021), India (Saraswat & Digalwar, 2021), Indonesia, Iran (Asakereh et al., 2022; Mostafaeipour et al., 2021; Shahnazi & Alimohammadlou, 2022), Pakistan (Shah & Longsheng, 2022; Solangi et al., 2021), Serbia (Pavlović et al., 2021), Turkey, and United Kingdom (Sitorus & Brito-Parada, 2020).

3.2 Quantum Spherical Fuzzy Sets with Golden Cut

Quantum mechanics consider different probabilities in the examination process (Xiao, 2020). Because this issue is appropriate to handle uncertainties, it is integrated with fuzzy decision-making models in this study. The probability of quantum function with the amplitude and the phase angle is demonstrated by Dai and Deng (2020); Gao et al. (2022).

$$Q(|u\rangle) = \varphi e^{j\theta}, \tag{1}$$

$$|\varsigma\rangle = \{|u_1\rangle, |u_2\rangle, \ldots, |u_n\rangle\}, \tag{2}$$

$$\sum_{|u\rangle \subseteq |\varsigma\rangle} |Q(|u\rangle)| = 1. \tag{3}$$

In this scope, ς means collective events and φ^2 refers to the amplitude result. Also, θ^2 indicates the phase angle and $|\varphi_1|^2$ shows the belief degree.

Spherical fuzzy numbers ($\tilde{A}_S$) consider membership, non-membership, and hesitancy degrees as in equations (4) and (5) (Ali & Garg, 2023)

$$\tilde{A}_S = \{\langle u, (\mu_{\tilde{A}_S}(u), v_{\tilde{A}_S}(u), h_{\tilde{A}_S}(u)) | u \in U\}, \tag{4}$$

$$0 \leq \mu^2_{\tilde{A}_S}(u) + v^2_{\tilde{A}_S}(u) + h^2_{\tilde{A}_S}(u) \leq 1, \forall_u \in U. \tag{5}$$

The integration of these two approaches is indicated in equation (6) (Akram et al., 2020; Akram & Naz, 2019; Ma et al., 2021)

$$|\varsigma_{\tilde{A}_S}\rangle = \{\langle u, (\varsigma_{\mu_{\tilde{A}_S}}(u), \varsigma_{v_{\tilde{A}_S}}(u), \varsigma_{h_{\tilde{A}_S}}(u)) | u \in 2^{|\varsigma_{\tilde{A}_S}\rangle}\}. \tag{6}$$

Quantum Spherical fuzzy numbers ς are defined as in equations (7) and (8).

$$\varsigma = [\varsigma_\mu \cdot e^{j2\pi\cdot\alpha}, \varsigma_v \cdot e^{j2\pi\cdot\gamma}, \varsigma_h \cdot e^{j2\pi\cdot\beta}], \tag{7}$$

$$\varphi^2 = |\varsigma_\mu(|u_i\rangle)|. \tag{8}$$

The degrees are computed by golden ratio (G) as detailed in equations (9) and (10).

$$G = \frac{a}{b}, \tag{9}$$

$$G = \frac{1 + \sqrt{5}}{2} = 1.618 \ldots \tag{10}$$

The amplitude of non-membership and hesitancy degrees is determined in equations (11) and (12).

$$\varsigma_v = \frac{\varsigma_\mu}{G}, \tag{11}$$

$$\varsigma_h = 1 - \varsigma_\mu - \varsigma_v. \tag{12}$$

Moreover, equation (13) explains the phase angle.

$$\alpha = |\varsigma_\mu(|u_i\rangle)|. \tag{13}$$

The phase angle of non-member and hesitancy degrees are indicated in equations (14) and (15).

$$\gamma = \frac{\alpha}{G}, \tag{14}$$

$$\beta = 1 - \alpha - \gamma. \tag{15}$$

The operations are detailed in equations (16)–(19).

$$\lambda * \tilde{A}_\varsigma = \left\{ \begin{array}{l} (1-(1-\varsigma_{\mu_{\tilde{A}}}{}^2)^\lambda)^{\frac{1}{2}} e^{j2\pi\cdot\left(1-\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}}, \varsigma_{v_{\tilde{A}}}{}^\lambda e^{j2\pi\cdot\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^\lambda}, ((1-\varsigma_{h_{\tilde{A}}}{}^2)^\lambda - (1-\varsigma_{\mu_{\tilde{A}}}{}^2 - \varsigma_{h_{\tilde{A}}}{}^2)^\lambda)^{\frac{1}{2}} e^{j2\pi\cdot\left(\left(1-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda - \left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2 - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}} \end{array} \right\}, \tag{16}$$

$$\lambda > 0,$$

$$\tilde{A}_\varsigma{}^\lambda = \left\{ \begin{array}{l} \varsigma_{\mu_{\tilde{A}}}{}^\lambda e^{j2\pi\cdot\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^\lambda}, (1-(1-\varsigma_{v_{\tilde{A}}}{}^2)^\lambda)^{\frac{1}{2}} e^{j2\pi\cdot\left(1-\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}}, ((1-\varsigma_{v_{\tilde{A}}}{}^2)^\lambda - (1-\varsigma_{v_{\tilde{A}}}{}^2 - \varsigma_{h_{\tilde{A}}}{}^2)^\lambda)^{\frac{1}{2}} e^{j2\pi\cdot\left(\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda - \left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2 - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}} \end{array} \right\}, \tag{17}$$

$$\lambda > 0,$$

$$\widetilde{A}_\varsigma \oplus \widetilde{B}_\varsigma = \left\{ \begin{array}{l} (\varsigma_{\mu_{\tilde A}}{}^2 + \varsigma_{\mu_{\tilde B}}{}^2 - \varsigma_{\mu_{\tilde A}}{}^2\varsigma_{\mu_{\tilde B}}{}^2)^{\frac12} e^{j2\pi\cdot\left(\left(\frac{\alpha_{\tilde A}}{2\pi}\right)^2+\left(\frac{\alpha_{\tilde B}}{2\pi}\right)^2-\left(\frac{\alpha_{\tilde A}}{2\pi}\right)^2\left(\frac{\alpha_{\tilde B}}{2\pi}\right)^2\right)^{\frac12}}, \varsigma_{v_{\tilde A}}\varsigma_{v_{\tilde B}} e^{j2\pi\cdot\left(\left(\frac{\gamma_{\tilde A}}{2\pi}\right)\left(\frac{\gamma_{\tilde B}}{2\pi}\right)\right)}, ((1-\varsigma_{\mu_{\tilde B}}{}^2)\varsigma_{h_{\tilde A}}{}^2 + (1-\varsigma_{\mu_{\tilde A}}{}^2)\varsigma_{h_{\tilde B}}{}^2 - \varsigma_{h_{\tilde A}}{}^2\varsigma_{h_{\tilde B}}{}^2)^{\frac12} \\ e^{j2\pi\cdot\left(\left(1-\left(\frac{\alpha_{\tilde B}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde A}}{2\pi}\right)^2+\left(1-\left(\frac{\alpha_{\tilde A}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde B}}{2\pi}\right)^2-\left(\frac{\beta_{\tilde A}}{2\pi}\right)^2\left(\frac{\beta_{\tilde B}}{2\pi}\right)^2\right)^{\frac12}} \end{array} \right\}, \tag{18}$$

$$\widetilde{A}_\varsigma \otimes \widetilde{B}_\varsigma = \left\{ \begin{array}{l} \varsigma_{\mu_{\tilde A}}\varsigma_{\mu_{\tilde B}} e^{j2\pi\cdot\left(\frac{\alpha_{\tilde A}}{2\pi}\right)\left(\frac{\alpha_{\tilde B}}{2\pi}\right)}, (\varsigma_{v_{\tilde A}}{}^2 + \varsigma_{v_{\tilde B}}{}^2 - \varsigma_{v_{\tilde A}}{}^2\varsigma_{v_{\tilde B}}{}^2)^{\frac12} e^{j2\pi\cdot\left(\left(\frac{\gamma_{\tilde A}}{2\pi}\right)^2+\left(\frac{\gamma_{\tilde B}}{2\pi}\right)^2-\left(\frac{\gamma_{\tilde A}}{2\pi}\right)^2\left(\frac{\gamma_{\tilde B}}{2\pi}\right)^2\right)^{\frac12}}, ((1-\varsigma_{v_{\tilde B}}{}^2)\varsigma_{h_{\tilde A}}{}^2 + (1-\varsigma_{v_{\tilde A}}{}^2)\varsigma_{h_{\tilde B}}{}^2 - \varsigma_{h_{\tilde A}}{}^2\varsigma_{h_{\tilde B}}{}^2)^{\frac12} \\ e^{j2\pi\cdot\left(\left(1-\left(\frac{\gamma_{\tilde B}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde A}}{2\pi}\right)^2+\left(1-\left(\frac{\gamma_{\tilde A}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde B}}{2\pi}\right)^2-\left(\frac{\beta_{\tilde A}}{2\pi}\right)^2\left(\frac{\beta_{\tilde B}}{2\pi}\right)^2\right)^{\frac12}} \end{array} \right\}. \tag{19}$$

3.3 Spherical Fuzzy DEMATEL

DEMATEL is used to calculate the weights by considering causal directions. In the last decades, the extensions of DEMATEL have been also generated to proceed with the robustness of methodology for the complicated issues of real-world problems (Heravi et al., 2021; Tuncalı Yaman & Akkartal, 2022). The extension with the quantum spherical fuzzy numbers is given later.

Evaluations are taken. Next, the relation matrix is with equation (20).

$$\varsigma_k = \begin{bmatrix} 0 & \varsigma_{12} & \cdots & \cdots & \varsigma_{1n} \\ \varsigma_{21} & 0 & \cdots & \cdots & \varsigma_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{20}$$

Aggregated values are identified in equation (21).

$$\varsigma = \left\{ \begin{array}{l} \left[1-\prod_{i=1}^{k}(1-\varsigma_{\mu_i}{}^2)^{\frac1k}\right]^{\frac12} e^{2\pi\cdot\left[1-\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac1k}\right]^{\frac12}} \\ , \prod_{i=1}^{k}\varsigma_{v_i}{}^{\frac1k} e^{2\pi\cdot\prod_{i=1}^{k}\left(\frac{\gamma_i}{2\pi}\right)^{\frac1k}}, \left[\prod_{i=1}^{k}(1-\varsigma_{\mu_i}{}^2)^{\frac1k} - \prod_{i=1}^{k}(1-\varsigma_{\mu_i}{}^2-\varsigma_{h_i}{}^2)^{\frac1k}\right]^{\frac12} \\ e^{2\pi\cdot\left[\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac1k}-\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2-\left(\frac{\beta_i}{2\pi}\right)^2\right)^{\frac1k}\right]^{\frac12}} \end{array} \right\}. \tag{21}$$

Equation (22) is used to compute defuzzified values.

$$\mathrm{Def}\varsigma_i = \varsigma_{\mu_i} + \varsigma_{h_i}\left(\frac{\varsigma_{\mu_i}}{\varsigma_{\mu_i}+\varsigma_{v_i}}\right) + \left(\frac{\alpha_i}{2\pi}\right) + \left(\frac{\gamma_i}{2\pi}\right)\left(\frac{\left(\frac{\alpha_i}{2\pi}\right)}{\left(\frac{\alpha_i}{2\pi}\right)+\left(\frac{\beta_i}{2\pi}\right)}\right). \tag{22}$$

With equations (23) and (24), normalized values are computed.

$$B = \frac{\varsigma}{\max_{1\le i\le n}\sum_{j=1}^{n}\varsigma_{ij}}, \tag{23}$$

$$0 \le b_{ij} \le 1. \tag{24}$$

Total relation matrix is created by equation (25).

$$\lim_{k\to\infty}(B + B^2 + \ldots + B^k) = B(I-B)^{-1}. \tag{25}$$

Causal directions are identified. In this scope, the cause factors D are computed by the sums of rows whereas the effect factors E are identified in the sums of columns with equations (26) and (27).

$$D = \left[\sum_{j=1}^{n} e_{ij}\right]_{nx1}, \tag{26}$$

$$E = \left[\sum_{i=1}^{n} e_{ij}\right]_{1xn}. \tag{27}$$

The values of (D + E) are used for weight calculation while the values of (D-E) are considered for causal directions. Threshold value α is used for computing causality relationship as in equation (28)

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[e_{ij}]}{N}. \tag{28}$$

3.4 Quantum Spherical Fuzzy TOPSIS

TOPSIS is considered to rank alternatives (Hwang & Yoon, 1981). In this study, we propose an extension of TOPSIS based on Quantum Spherical fuzzy sets. First, evaluations are obtained (Tutak & Brodny, 2022). Later, the decision matrix is generated by equation (29).

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{29}$$

The values are normalized by equation (30).

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} \quad . \tag{30}$$

Equation (31) is used for computing weighted values.

$$v_{ij} = w_{ij} \times r_{ij}. \tag{31}$$

The positive (A^+) and negative (A^-) ideal solutions are calculated as in equations (32) and (33).

$$A^+ = \{v_{1j}, v_{2j}, \ldots, v_{mj}\} = \{\max v_{1j} \quad \text{for} \quad \forall j \in n\}, \tag{32}$$

$$A^- = \{v_{1j}, v_{2j}, \ldots, v_{mj}\} = \{\min v_{1j} \quad \text{for} \quad \forall j \in n\}. \tag{33}$$

The distances to the best (D_i^+) and worst alternatives (D_i^-) are calculated by equations (34) and (35).

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}, \tag{34}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2}, \tag{35}$$

Relative closeness (RC_i) is defined by equation (36).

$$\mathrm{RC}_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{36}$$

3.5 Quantum Spherical Fuzzy VIKOR

VIKOR technique is used to rank different alternatives regarding their significance. In this proposed model, this method is used with Quantum Spherical fuzzy sets. The first three steps in TOPSIS are similar to VIKOR. Next, the best $\tilde{f}_J^*$ and worst $\tilde{f}_j^-$ values are defined with equation (37) (Akram et al., 2021).

$$\tilde{f}_J^* = \max_i \tilde{x}_{ij}, \quad \text{and} \quad \tilde{f}_j^- = \min_i \tilde{x}_{ij}. \tag{37}$$

Equations (38) and (39) are considered to compute mean group utility and maximal regret.

$$\tilde{S}_i = \sum_{i=1}^{n} \tilde{w}_j \frac{(|\tilde{f}_j^* - \tilde{x}_{ij}|)}{(|\tilde{f}_j^* - \tilde{f}_j^-|)}, \tag{38}$$

$$\tilde{R}_i = \max_j \left[\tilde{w}_j \frac{(|\tilde{f}_j^* - \tilde{x}_{ij}|)}{(|\tilde{f}_j^* - \tilde{f}_j^-|)} \right]. \tag{39}$$

Equation (40) is used to compute $\tilde{Q}_i$ so that the alternative rankings can be calculated.

$$\tilde{Q}_i = v(\tilde{S}_i - \tilde{S}^*)/(\tilde{S}^- - \tilde{S}^*) + (1 - v)(\tilde{R}_i - \tilde{R}^*) /(\tilde{R}^- - \tilde{R}^*). \tag{40}$$

3.6 Collaborative Filtering

Collaborative filtering technique provides an opportunity for the decision-makers to leave the answers to some questions blank. With the help of this situation, decision-makers do not have to give answers when they are not sure. Collaborative filtering methodology includes a mathematical calculation to determine the value of the blank question. In this process, similarity, $\mathrm{sim}(u, v)$, and prediction indices, $p_{u,i}$, are taken into consideration. Equations (41) and (42) explain the details of this process (Kaya & Kaleli, 2022).

$$\mathrm{sim}(u, v) = \frac{\sum_{i \in I} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{i \in I} (r_{v,i} - \bar{r}_v)^2}}, \tag{41}$$

$$p_{u,i} = \frac{\sum_{j \in S} \mathrm{sim}(u, v) r_{u,j}}{\sum_{j \in S} |\mathrm{sim}(u, v)|}. \tag{42}$$

3.7 Facial Action Coding System

The Facial Action Coding System (FACS) takes people's facial expressions into account in the analysis process. In this context, facial expressions are classified according to different emotions. In this way, it is aimed to determine the emotional expressions of people more clearly. One of the most important issues in decision-making processes is the uncertainty that arises due to the complexity of the problem. In order to achieve more accurate results, this problem must be successfully managed. There are many factors that cause the increase in uncertainty in this process. One of these issues is the indecision experienced by experts while answering some questions. The FACS approach

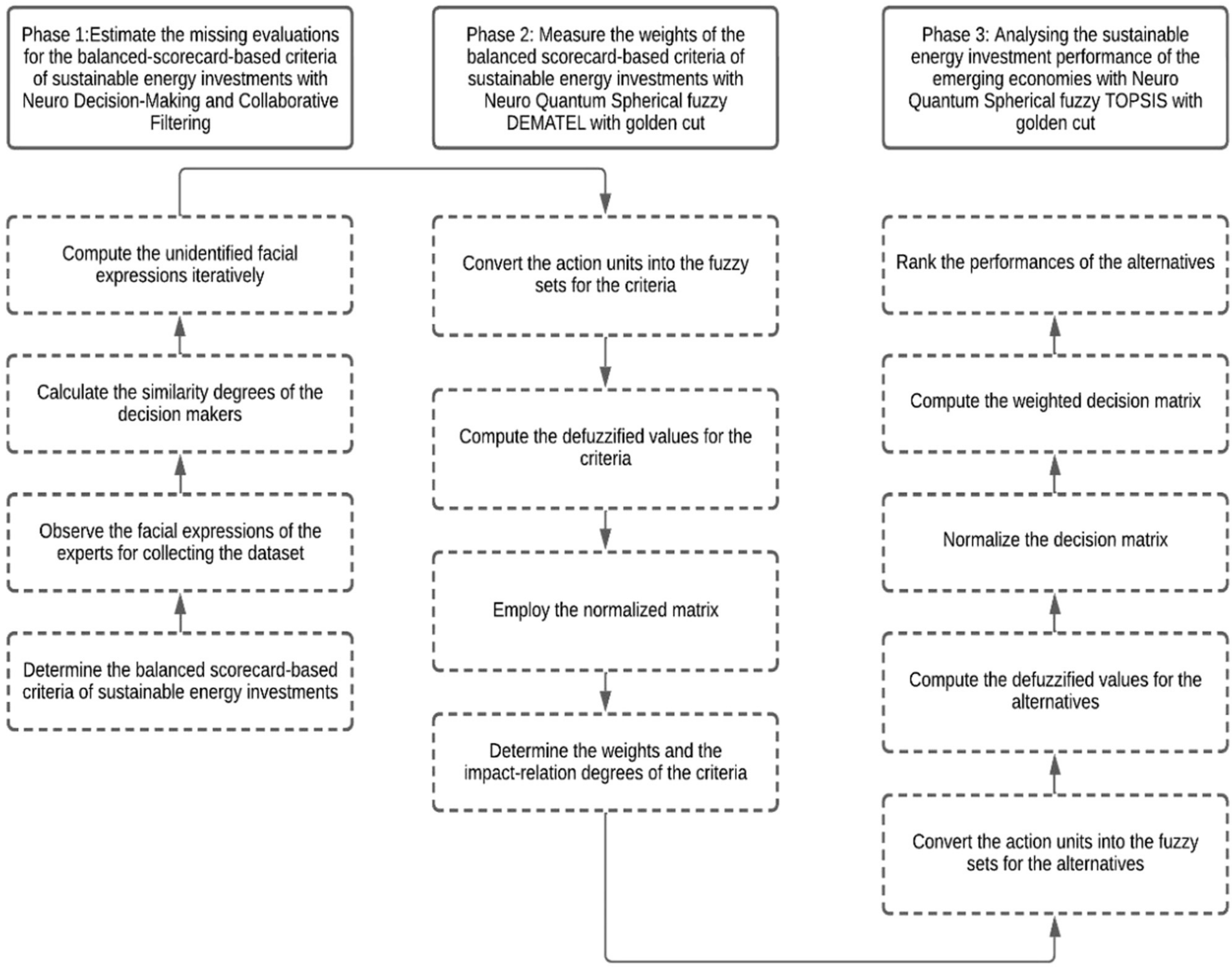

Figure 1: The flowchart of the novel decision-making approach.

contributes to a more effective management of uncertainty in this process. In this context, thanks to FACS, the facial expressions of the people who answered the questions can also be included in the analysis process. Thus, the different emotions experienced by the experts while answering the questions can be taken into account. This allows for more realistic results to be achieved (Cen et al., 2022).

4 Analysis Results

To solve this complex problem, the decision-making methodology with three phases is proposed, and the flowchart and the details are given as follows (Figure 1).

A new neuro-based decision-making approach is considered with the facial expressions of the decision makers for constructing the linguistic evaluations of the relation and decision matrices. The agents' views diverge in scope and complexity (Kwangsun, 1980). Accordingly, the emotional expressions of the decision-makers are determined by using the action units of the facial acting coding system. The most prominent two facial expressions of the decision-makers in the action units are noted by the observer who is the expert on the facial acting coding system as the relation of the criteria and the performance of the alternatives are asked to the decision-makers.

The proposed model includes three phases, respectively, for measuring the balanced scorecard-based criteria of sustainable energy investments for emerging economies. In the first phase, collaborative filtering with the expert-expert recommendation system is applied for estimating the unpredicted values of the facial expressions for the relation matrix of the criteria. In the second phase, the weighted values of the balanced scorecard-based criteria are computed. In the final phase, E7 economies are ranked. The computation process and analysis results are illustrated in detail later:

4.1 Phase 1: Estimate the missing evaluations for the balanced-scorecard-based criteria of sustainable energy investments

Step 1: Determine the balanced scorecard-based criteria of sustainable energy investments.

In the first step, the balanced scorecard-based criteria of sustainable energy investments are defined with the supported literature in Table 2.

As seen in Table 2, the prominent factors of sustainable energy investments can be listed in terms of balanced scorecard perspectives with the supported literature. In other words, different balanced scorecard perspectives are used to select the criteria which are finance, customer, organizational effectiveness, and learning and growth. Balanced scorecard technique has some significant advantages. With the help of this approach, both financial and nonfinancial factors can be taken into consideration. This situation has a positive contribution to make more appropriate and effective evaluation. Hence, by integrating the perspectives of this technique with literature review results, a comprehensive criterion set can be generated. The outstanding studies demonstrate that financial factors have a great impact on renewable energy and green projects with the use of new financial tools and reducing costs (Dahiru et al., 2021; Dinçer et al., 2022; Vásquez-Ordóñez et al., 2023; Wang et al., 2023). Customer expectations is another important factor of the sustainable energy projects. Customization of the energy services in demand management including the new service and product development process should be considered strictly to get successful business results of sustainable energies for both commercial and non-commercial users (Gonçalves & Patrício, 2022; Li et al., 2021; Zhu & Zhang, 2023). Additionally, the internal process based on the organizational skills and competencies remains one of the most important investment priorities for the decision of the renewable energy project. Furthermore, the assignment of qualified employees together with the right policies of human resources is among the criteria for sustainable energy investments in terms of the organizational perspective as well (Rasool et al., 2022). The last criterion but not least is named as the competitional items of the energy projects. In this scope, the benchmarking activities are processed to evaluate the project performance of the energy plants. The comparative results of the renewable alternatives are investigated to understand the best practices and the efficient outcomes of the sustainable energy markets (Andrews & Jain, 2022; Cai et al., 2022).

Step 2: Observe the facial expressions of the experts for collecting the dataset.

In the following step, the set of emotions, selected action units with their pair combinations, as well as the linguistic scales, and possibility degrees are provided with QSFNs as seen in Table 3.

It is aimed to measure the sustainable energy investment performances of the E7 economies. For this purpose, the alternative list is selected as China (CHN), Mexico (MXC), Turkey (TRK), Brazil (BRZ), Indonesia (INS), Russia (RSS), and India (IND) for the decision matrix. Six decision-makers are appointed to evaluate the relation among the criteria and decision matrix of the emerging economies with respect to the balanced scorecard-based criteria of sustainable energy investments. Four of these people are academicians who make lots of publications related to sustainable energy investments. They have more than 25 years of working experience. Furthermore, two experts are the chief financial officers in solar energy companies. These people have also more than 20 years of managerial experience in the industry. The observer who is the expert in the facial action coding system detected the emotions of the decision makers by considering the facial expressions with the action units in Table 3. Table A1 shows the observations of the most apparent pair action units for the decision makers. In some cases, the decision makers couldn't declare any expressions to define the relation of some

Table 2: Balanced-scorecard-based criteria of sustainable energy investments

Criteria	Definition	Supported Literature
Financial (FNCL)	Considering the financial leverage and cost efficiency for long-term energy projects	Dahiru et al. (2021), Vásquez-Ordóñez et al. (2023), Wang et al. (2023)
Consumer-based (CNSR)	Customizing the energy services with rigorous demand management	Dahiru et al. (2021), Gonçalves and Patrício (2022), Li et al. (2021), Zhu and Zhang (2023)
Organizational (ORGN)	Gathering the human resources and other internal facilities for the energy project planning	Rasool et al. (2022)
Competitional (CMPT)	Benchmarking the capacity of energy hubs to increase the capacity of ongoing energy plants	Andrews and Jain (2022); Cai et al. (2022)

criteria and these items are defined as n/a. After that, the missing evaluations are completed by using the collaborative filtering iteratively. Observations are denoted in Table A2.

Step 3: Calculate the similarity degrees of the decision makers.

In the third step of the first phase, Table A3 declares that the similarity degrees of the decision makers are computed for the balanced scorecard-based criteria by the formula (37).

Step 4: Compute the unidentified facial expressions iteratively.

The missing values are iteratively computed in the following step by using the prediction index in the equation (38). For the first iteration, the prediction's similarity index value is chosen based on the highest value of normalized similarity degrees for each decision maker. If the missing values are not filled in the first iteration, the second iteration is used to complete the process. The second greatest value of normalized similarity degrees is selected for the prediction similarity index value in the second iteration. If the missing expert evaluations still exist, the third iteration with the greatest third value among the normalized similarity degrees for each decision maker is used. Table A4 summarizes the findings. According to the results in Table A4, the missing facial expressions are completed into 2 iterations. The predicted values are computed by considering the preference values 1 to 5.

4.2 Phase 2: Measure the weights of the balanced scorecard-based criteria of sustainable energy investments

Step 1: Convert the action units into the fuzzy sets for the criteria.

Completed expert evaluations with preference numbers are converted into the fuzzy sets and the overall evaluations of the decision makers are given in Table A5. The overall quantum spherical fuzzy set results are obtained by using the aggregated values of the fuzzy sets using the equation (21).

Step 2: Compute the defuzzified values for the criteria.

The score function is used for the defuzzified values of the relation matrix via the formula (22) as given in Table A6.

Step 3: Employ the normalized matrix.

In this step, Table A7 presents the results of the normalization procedure using equations (23) and (24).

Step 4: Determine the weights and the impact-relation degrees of the criteria.

In Table 4, the results of the total relation matrix and the values of D and E as well as the weights and directions are given by processing equations (25)–(28).

In Table 4, it is seen that the criterion of Competition (CMPT) has the highest degree of importance among the criteria set as the criterion of Consumer (CNSR) is relatively the weakest one by the values of (D + E). However, the criterion of organization (ORGN) is affected by the other criteria mostly while the criterion of finance (FNCL) is the

Table 3: Scales

Emotions	AUs	Pair combinations	Scales for criteria	Scales for alternatives	Degrees	Fuzzy Sets
Contempt (Disdain)	7-10-14-15	(7-10)-(7-14)-(7-15)-(10-14)-(10-15)-(14-15)	No (n)	Weakest (w)	0.40	$\begin{bmatrix}\sqrt{0.16}\,e^{j2\pi\cdot 0.4},\\ \sqrt{0.10}\,e^{j2\pi\cdot 0.25},\\ \sqrt{0.74}\,e^{j2\pi\cdot 0.35}\end{bmatrix}$
Intermediate	1 AU of Contempt + 1 AU of Surprise	(7-1)-(7-2)-(7-5)-(7-27)- (10-1)-(10-2)-(10-5)-(10-27)-(14-1)-(14-2)-(14-5)-(14-27)- (15-1)-(15-2)-(15-5)-(15-27)	Some (s)	Poor (p)	0.45	$\begin{bmatrix}\sqrt{0.20}\,e^{j2\pi\cdot 0.45},\\ \sqrt{0.13}\,e^{j2\pi\cdot 0.28},\\ \sqrt{0.67}\,e^{j2\pi\cdot 0.27}\end{bmatrix}$
Surprise	1-2-5-27 1 AU of Contempt + 1 AU of Happy	(1-2)-(1-5)-(1-27)-(2-5)-(2-27)-(5-27)(7-6)-(7-12)-(7-25)-(7-26)-(10-6)-(10-12)-(10-25)-(10-26)-(14-6)-(14-12)-(14-25)-(14-26)-(15-6)-(15-12)-(15-25)-(15-26)	Medium (m)	Fair (f)	0.50	$\begin{bmatrix}\sqrt{0.25}\,e^{j2\pi\cdot 0.50},\\ \sqrt{0.15}\,e^{j2\pi\cdot 0.31},\\ \sqrt{0.60}\,e^{j2\pi\cdot 0.19}\end{bmatrix}$
Intermediate	1 AU of Surprise + 1 AU of Happy	(1-6)-(1-12)-(1-25)-(1-26)-(2-6)-(2-12)-(2-25)-(2-26)-(5-6)-(5-12)-(5-25)-(5-26)-(27-6)-(27-12)-(27-25)-(27-26)	High (h)	Good (g)	0.55	$\begin{bmatrix}\sqrt{0.30}\,e^{j2\pi\cdot 0.55},\\ \sqrt{0.19}\,e^{j2\pi\cdot 0.34},\\ \sqrt{0.51}\,e^{j2\pi\cdot 0.11}\end{bmatrix}$
Happiness	6-12-25-26	(6-12)-(6-25)-(6-26)-(12-25)-(12-26)-(25-26)	Very high (vh)	Best (b)	0.60	$\begin{bmatrix}\sqrt{0.36}\,e^{j2\pi\cdot 0.6},\\ \sqrt{0.22}\,e^{j2\pi\cdot 0.37},\\ \sqrt{0.42}\,e^{j2\pi\cdot 0.03}\end{bmatrix}$

Table 4: Weights and the impact-relation degrees

	FNCL	CNSR	ORGN	CMPT	D	E	D + E	D − E	Weights	Directions
FNCL	112.118	111.811	112.466	112.732	449.1	449.0	898.1	0.166	0.2501	FNCL → ORGN, FNCL → CMPT
CNSR	112.143	111.339	112.242	112.505	448.2	446.7	895.0	1.493	0.2492	CNSR → CMPT
ORGN	112.209	111.653	112.058	112.572	448.5	449.4	897.8	−0.863	0.2500	ORGN → CMPT
CMPT	112.491	111.933	112.590	112.604	449.6	450.4	900.0	−0.796	0.2506	CMPT → FNCL, CMPT → ORGN

most influencing one among the others according to the values of (D–E). The directions of the criteria are illustrated by using the threshold value stated in the formula (28). The weights of the criteria are also presented in Figure 2.

It is concluded that competitional issues have the highest weight (0.2506) for the effectiveness of sustainable energy investments. Moreover, financial evaluation and organizational effectiveness are also critical for this situation. Nonetheless, consumer-based factors have lower significance in this respect.

4.3 Phase 3: Analyzing the sustainable energy investment performance of the emerging economies

In the final phase, the sustainable energy investment performance of the emerging economies is computed. The results are provided step by step as follows:

Step 1: Convert the action units into the fuzzy sets for the alternatives.

The emotions of the decision makers in terms of facial acting coding system are figured out by the observer and the decision matrix is constructed by converting the action units into the fuzzy sets. The aggregated values of the fuzzy decision sets are given by the formula (21) and the overall values are examined in Table A8.

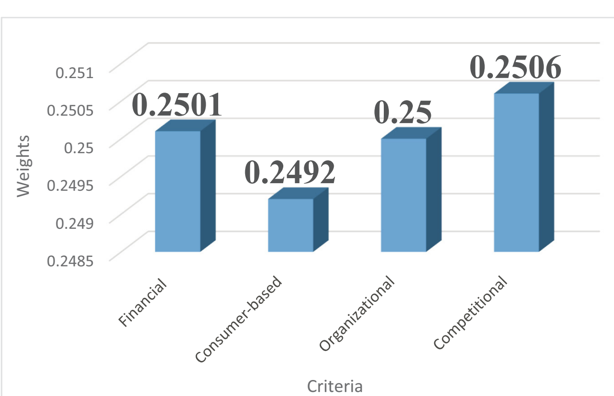

Figure 2: Weights of the criteria.

Step 2: Compute the defuzzified values for the alternatives.

The defuzzification procedure is defined with the formula (22) and the defuzzified decision matrix is constructed in Table A9.

Step 3: Normalize the decision matrix.

The normalization procedure of the TOPSIS is defined in formula (30) and the normalized matrix is stated in Table A10.

Step 4: Compute the weighted decision matrix.

The weighted decision matrix is given in Table A11 by using equation (31).

Step 5: Rank the performances of the alternatives.

The last step is constructed with the help of formulas (32)–(36). The ranking results are illustrated in Table 5.

The ranking results show that China (CHN) has the best sustainable energy investment performance in the E7 economies whereas Mexico is listed at the last rank of the E7 economies. The general ranking results are presented as China, Russia, Turkey, Indonesia, India, Brazil, and Mexico respectively. Moreover, E7 economies are also ranked by using Quantum Spherical fuzzy VIKOR. Comparative analysis results are demonstrated in Figure 3.

Figure 3 demonstrates that the ranking results are the same in two different evaluations. This situation gives information about the coherency of the proposed model.

5 Discussion

Competitional issues should be mainly taken into consideration for the improvements of sustainable energy

Table 5: Performance results of the alternatives

Priorities	D+	D−	RCi	Ranking
CHN	0.001	0.002	0.661	1
MXC	0.002	0.000	0.187	7
TRK	0.002	0.001	0.399	3
BRZ	0.002	0.000	0.224	6
INS	0.002	0.001	0.397	4
RSS	0.001	0.001	0.424	2
IND	0.002	0.001	0.333	5

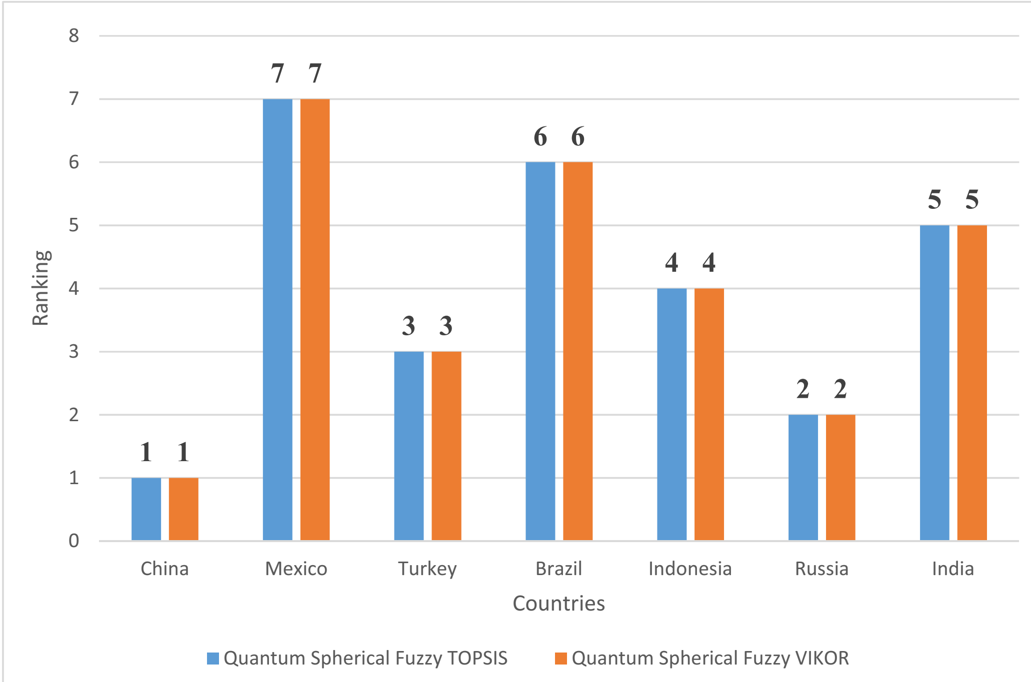

Figure 3: Comparative ranking results.

investments. Within this context, market conditions should be evaluated in a detailed way (Karatop et al., 2021). Similarly, a benchmarking analysis should be carried out to evaluate the conditions (Ghenai et al., 2020). Zhang et al. (2022) argued that reducing risk and maximizing profit may be achieved at the same time if both conventional fossil fuels and renewable energy are jointly incorporated into the power generation portfolio. This strategy can optimize risk reduction if the income is assured or can achieve the greatest return at a specific degree of risk. Effective competition among nations is essential for survival and market expansion. According to Wu (2023) and Xu et al. (2020), a nation's ability to compete in the market is influenced by the efficacy of its economy, which is defined by how well all of its economic operations are managed internally.

It is possible to evaluate the performance of similar projects by making comparisons with the market. This helps to determine the right strategies to increase the performance of sustainable renewable energy projects (Horasan & Kilic, 2022). When the details of similar projects are examined, it can be easier to improve the performance of current investments (Qiu et al., 2023; Sıcakyüz, 2023). Furthermore, Zhang et al. (2022) and Nishitani and Kokubu (2020) identified that making comparisons in the market helps to understand what kind of risk profile similar projects have. This situation helps investors to manage the risks that their investments may face more effectively (Shinwari et al., 2022). Similarly, Bercu and Botezatu (2021) and Giudici et al. (2022) stated that market benchmarking also provides information on different technologies. This situation allows businesses to make the right technology investment (Karatop et al., 2021).

However, different conclusions were also reached in some other studies. For instance, some scholars also underlined that technological innovations should be prioritized. Hailemariam et al. (2022) established that investment in renewable energy R&D had a substantial effect on reducing levels of major air pollutants and greenhouse gases. For rural areas, Saraj et al. (2023) reinforced that the most major impediment to the adoption of renewable energy technology is community commitment. According to An et al. (2023), the Americas and Oceania have the largest rate of renewable energy potential, followed by Europe, and Asia and Africa have the poorest. Moreover, the importance of government support was also highlighted in many different studies. Shinwari et al. (2022) and Ibrahim and Ayomoh (2022) proved that investment in renewable energy, institutional governance, and fiscal decentralization greatly enhanced ecological sustainability. Also, Liu et al. (2022) supported that decentralization of fiscal authority and investments in clean energy reduce emissions.

6 Conclusion

This study examines important strategies to increase sustainable energy investments in emerging economies. First, four different indicators are defined regarding the dimensions of the balanced scorecard. Quantum Spherical fuzzy DEMATEL is considered to weigh these items. Second, E7 countries are ranked according to the performance of sustainable energy investments. For this purpose, Quantum Spherical fuzzy TOPSIS is considered. The findings denote that competition is the most important factor for the performance of sustainable energy investments. Furthermore, the ranking results show that China and Russia are the most successful emerging economies with respect to sustainable energy investments. A comparative examination is also made with Quantum Spherical fuzzy VIKOR. It is identified that the ranking results are quite similar. This condition gives information that the proposed model provides coherent and reliable findings.

The main contribution of this study is that prior factors can be defined for emerging economies to increase sustainable energy investments in a more effective way. Additionally, a novel decision-making model is created by integrating TOPSIS and DEMATEL with Quantum theory, Spherical fuzzy sets, facial expressions of the experts, and collaborative filtering. The main limitation is that the analysis is performed for only developing economies. Nevertheless, sustainable energy investments also play a critical role for developed countries. Hence, in the following studies, a group of seven (G7) countries can be evaluated regarding this situation. Similarly, the proposed model has also some limitations. The validity of the results is not checked with a sensitivity analysis. Thus, for future research direction, a sensitivity analysis can be applied by considering different cases. Owing to this condition, the validity of the findings can be measured.

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Appendix

Table A1: Observations

	DMKR 1	DMKR 2	DMKR 3	DMKR 4	DMKR 5	DMKR 6
FNCL–CNSR	(1,12)	n/a	(2,6)	(6,12)	(5,12)	n/a
FNCL–ORGN	n/a	(5,26)	(5,26)	n/a	n/a	(6,12)
FNCL–CMPT	(15,2)	(1,5)	n/a	(10,12)	(25,26)	n/a
CNSR–FNCL	(15,26)	n/a	(27,25)	(5,6)	(10,12)	(2,6)
CNSR–ORGN	(6,25)	(1,5)	(27,25)	(5,12)	n/a	(5,25)
CNSR–CMPT	(6,25)	(6,25)	n/a	(1,12)	n/a	(5,25)
ORGN–FNCL	n/a	(6,25)	(5,6)	n/a	(1,12)	(5,6)
ORGN–CNSR	n/a	(10,6)	n/a	(14,12)	(10,6)	(7,5)
ORGN–CMPT	(2,12)	(5,27)	(27,12)	(7,5)	n/a	(5,26)
CMPT–FNCL	(5,25)	(10,27)	(5,27)	n/a	(2,26)	(14,12)
CMPT–CNSR	n/a	(10,6)	n/a	(10,6)	(10,27)	n/a
CMPT–ORGN	(27,12)	n/a	(6,25)	(14,12)	(27,12)	n/a

Table A2: Observations of pair action units

	DMKR 1	DMKR 2	DMKR 3	DMKR 4	DMKR 5	DMKR 6
FNCL–CHN	(1,2)	(14,25)	(14,6)	(7,2)	(7,1)	(27,26)
FNCL–MXC	(14,25)	(27,26)	(2,25)	(27,26)	(2,6)	(5,6)
FNCL–TRK	(5,26)	(5,26)	(2,25)	(2,6)	(2,6)	(5,6)
FNCL–BRZ	(14,6)	(14,6)	(14,6)	(14,6)	(14,6)	(10,6)
FNCL–INS	(2,27)	(14,25)	(2,27)	(2,27)	(10,6)	(14,12)
FNCL–RSS	(1,27)	(10,26)	(14,5)	(7,2)	(15,27)	(14,12)
FNCL–IND	(1,2)	(10,26)	(10,6)	(10,26)	(14,12)	(1,2)
CNSR–CHN	(7,2)	(1,2)	(15,27)	(7,2)	(7,2)	(1,2)
CNSR–MXC	(1,27)	(2,27)	(2,25)	(1,27)	(14,25)	(1,27)
CNSR–TRK	(5,26)	(5,26)	(5,6)	(5,6)	(5,6)	(27,26)
CNSR–BRZ	(5,27)	(7,26)	(10,25)	(7,26)	(10,25)	(27,26)
CNSR–INS	(5,27)	(7,26)	(15,27)	(7,26)	(14,5)	(27,12)
CNSR–RSS	(14,5)	(15,27)	(14,5)	(15,27)	(14,5)	(7,26)
CNSR–IND	(10,25)	(5,27)	(5,27)	(1,27)	(10,25)	(7,26)
ORGN–CHN	(10,25)	(15,6)	(7,2)	(1,27)	(7,26)	(7,26)
ORGN–MXC	(10,25)	(10,25)	(1,26)	(1,27)	(7,26)	(1,26)
ORGN–TRK	(1,26)	(1,26)	(12,25)	(1,26)	(7,26)	(27,12)
ORGN–BRZ	(15,6)	(5,27)	(15,6)	(10,25)	(15,27)	(5,27)
ORGN–INS	(14,5)	(5,27)	(14,5)	(7,2)	(14,5)	(7,2)
ORGN–RSS	(15,27)	(5,27)	(14,5)	(7,2)	(15,27)	(10,25)
ORGN–IND	(15,6)	(15,6)	(27,12)	(15,6)	(15,6)	(27,12)
CMPT–CHN	(7,6)	(14,12)	(15,27)	(7,6)	(15,27)	(27,12)
CMPT–MXC	(14,12)	(7,6)	(14,12)	(7,6)	(14,12)	(10,25)
CMPT–TRK	(12,25)	(12,25)	(6,12)	(27,12)	(27,12)	(6,12)
CMPT–BRZ	(14,12)	(14,12)	(15,6)	(14,12)	(14,12)	(27,12)
CMPT–INS	(15,6)	(15,6)	(15,6)	(14,12)	(7,6)	(15,6)
CMPT–RSS	(14,5)	(14,12)	(14,5)	(7,2)	(15,27)	(15,6)
CMPT–IND	(7,6)	(14,12)	(27,12)	(7,2)	(7,6)	(15,6)

Table A3: Similarity index matrix

	DMKR 1	DMKR 2	DMKR 3	DMKR 4	DMKR 5	DMKR 6
DMKR 1	1.00	0.25	0.00	0.24	−0.30	0.05
DMKR 2	0.25	1.00	0.36	0.26	0.06	0.46
DMKR 3	0.00	0.36	1.00	−0.13	0.00	0.23
DMKR 4	0.24	0.26	−0.13	1.00	0.08	0.14
DMKR 5	−0.30	0.06	0.00	0.08	1.00	0.13
DMKR 6	0.05	0.46	0.23	0.14	0.13	1.00

Table A4: Iterative completion

	DMKR 1	DMKR 2	DMKR 3	DMKR 4	DMKR 5	DMKR 6
FNCL–CNSR	4	4 (Iteration 2)	4	5	4	4 (Iteration 2)
FNCL–ORGN	4 (Iteration 1)	4	4	4 (Iteration 1)	5 (Iteration 1)	5
FNCL–CMPT	2	3	3 (Iteration 1)	3	5	3 (Iteration 1)
CNSR–FNCL	3	4 (Iteration 1)	4	4	3	4
CNSR–ORGN	5	3	4	4	4 (Iteration 1)	4
CNSR–CMPT	5	5	5 (Iteration 1)	4	4 (Iteration 1)	4
ORGN–FNCL	5 (Iteration 1)	5	4	5 (Iteration 1)	4	4
ORGN–CNSR	3 (Iteration 1)	3	3 (Iteration 1)	3	3	2
ORGN–CMPT	4	3	4	2	4 (Iteration 1)	4
CMPT–FNCL	4	2	3	2 (Iteration 1)	4	3
CMPT–CNSR	3 (Iteration 1)	3	3 (Iteration 1)	3	2	3 (Iteration 1)
CMPT–ORGN	4	5 (Iteration 2)	5	3	4	5 (Iteration 2)

Table A5: Overall quantum spherical fuzzy numbers for the criteria

	FNCL	CNSR
FNCL		$[\sqrt{0.31}\,e^{j2\pi\cdot 0.56}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.50}\,e^{j2\pi\cdot 0.10}]$
CNSR	$[\sqrt{0.29}\,e^{j2\pi\cdot 0.54}, \sqrt{0.18}\,e^{j2\pi\cdot 0.33}, \sqrt{0.53}\,e^{j2\pi\cdot 0.13}]$	
ORGN	$[\sqrt{0.33}\,e^{j2\pi\cdot 0.57}, \sqrt{0.20}\,e^{j2\pi\cdot 0.35}, \sqrt{0.49}\,e^{j2\pi\cdot 0.12}]$	$[\sqrt{0.24}\,e^{j2\pi\cdot 0.48}, \sqrt{0.14}\,e^{j2\pi\cdot 0.30}, \sqrt{0.62}\,e^{j2\pi\cdot 0.22}]$
CMPT	$[\sqrt{0.26}\,e^{j2\pi\cdot 0.51}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.61}\,e^{j2\pi\cdot 0.22}]$	$[\sqrt{0.24}\,e^{j2\pi\cdot 0.48}, \sqrt{0.14}\,e^{j2\pi\cdot 0.30}, \sqrt{0.62}\,e^{j2\pi\cdot 0.22}]$
	ORGN	CMPT
FNCL	$[\sqrt{0.32}\,e^{j2\pi\cdot 0.56}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.50}\,e^{j2\pi\cdot 0.11}]$	$[\sqrt{0.27}\,e^{j2\pi\cdot 0.51}, \sqrt{0.16}\,e^{j2\pi\cdot 0.31}, \sqrt{0.59}\,e^{j2\pi\cdot 0.20}]$
CNSR	$[\sqrt{0.31}\,e^{j2\pi\cdot 0.56}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.50}\,e^{j2\pi\cdot 0.10}]$	$[\sqrt{0.33}\,e^{j2\pi\cdot 0.57}, \sqrt{0.20}\,e^{j2\pi\cdot 0.35}, \sqrt{0.49}\,e^{j2\pi\cdot 0.12}]$
ORGN		$[\sqrt{0.28}\,e^{j2\pi\cdot 0.53}, \sqrt{0.17}\,e^{j2\pi\cdot 0.32}, \sqrt{0.56}\,e^{j2\pi\cdot 0.15}]$
CMPT	$[\sqrt{0.33}\,e^{j2\pi\cdot 0.57}, \sqrt{0.20}\,e^{j2\pi\cdot 0.35}, \sqrt{0.49}\,e^{j2\pi\cdot 0.12}]$	

Table A6: Defuzzified relation matrix

	FNCL	CNSR	ORGN	CMPT
FNCL	0.000	1.242	1.245	1.262
CNSR	1.243	0.000	1.248	1.247
ORGN	1.247	1.240	0.000	1.254
CMPT	1.256	1.240	1.258	0.000

Table A7: Normalized direct relation matrix

	FNCL	CNSR	ORGN	CMPT
FNCL	0.000	0.331	0.332	0.336
CNSR	0.331	0.000	0.332	0.332
ORGN	0.332	0.330	0.000	0.334
CMPT	0.335	0.330	0.335	0.000

Table A8: Overall quantum spherical fuzzy numbers for the alternatives

	FNCL	CNSR
CHN	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$	$[\sqrt{0.22}\,e^{j2\pi\cdot 0.47}, \sqrt{0.13}\,e^{j2\pi\cdot 0.29}, \sqrt{0.65}\,e^{j2\pi\cdot 0.25}]$
MXC	$[\sqrt{0.29}\,e^{j2\pi\cdot 0.53}, \sqrt{0.18}\,e^{j2\pi\cdot 0.33}, \sqrt{0.54}\,e^{j2\pi\cdot 0.14}]$	$[\sqrt{0.26}\,e^{j2\pi\cdot 0.51}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.61}\,e^{j2\pi\cdot 0.22}]$
TRK	$[\sqrt{0.30}\,e^{j2\pi\cdot 0.55}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.51}\,e^{j2\pi\cdot 0.11}]$	$[\sqrt{0.30}\,e^{j2\pi\cdot 0.55}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.51}\,e^{j2\pi\cdot 0.11}]$
BRZ	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$	$[\sqrt{0.26}\,e^{j2\pi\cdot 0.51}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.61}\,e^{j2\pi\cdot 0.22}]$
INS	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$
RSS	$[\sqrt{0.23}\,e^{j2\pi\cdot 0.48}, \sqrt{0.14}\,e^{j2\pi\cdot 0.29}, \sqrt{0.64}\,e^{j2\pi\cdot 0.24}]$	$[\sqrt{0.21}\,e^{j2\pi\cdot 0.45}, \sqrt{0.12}\,e^{j2\pi\cdot 0.28}, \sqrt{0.68}\,e^{j2\pi\cdot 0.28}]$
IND	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$
	ORGN	**CMPT**
CHN	$[\sqrt{0.24}\,e^{j2\pi\cdot 0.48}, \sqrt{0.14}\,e^{j2\pi\cdot 0.30}, \sqrt{0.62}\,e^{j2\pi\cdot 0.22}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$
MXC	$[\sqrt{0.27}\,e^{j2\pi\cdot 0.51}, \sqrt{0.16}\,e^{j2\pi\cdot 0.31}, \sqrt{0.59}\,e^{j2\pi\cdot 0.20}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$
TRK	$[\sqrt{0.31}\,e^{j2\pi\cdot 0.56}, \sqrt{0.19}\,e^{j2\pi\cdot 0.34}, \sqrt{0.50}\,e^{j2\pi\cdot 0.10}]$	$[\sqrt{0.34}\,e^{j2\pi\cdot 0.58}, \sqrt{0.20}\,e^{j2\pi\cdot 0.35}, \sqrt{0.47}\,e^{j2\pi\cdot 0.11}]$
BRZ	$[\sqrt{0.24}\,e^{j2\pi\cdot 0.48}, \sqrt{0.14}\,e^{j2\pi\cdot 0.30}, \sqrt{0.62}\,e^{j2\pi\cdot 0.22}]$	$[\sqrt{0.26}\,e^{j2\pi\cdot 0.51}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.61}\,e^{j2\pi\cdot 0.22}]$
INS	$[\sqrt{0.21}\,e^{j2\pi\cdot 0.45}, \sqrt{0.12}\,e^{j2\pi\cdot 0.28}, \sqrt{0.68}\,e^{j2\pi\cdot 0.28}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$
RSS	$[\sqrt{0.22}\,e^{j2\pi\cdot 0.47}, \sqrt{0.13}\,e^{j2\pi\cdot 0.29}, \sqrt{0.65}\,e^{j2\pi\cdot 0.25}]$	$[\sqrt{0.22}\,e^{j2\pi\cdot 0.47}, \sqrt{0.13}\,e^{j2\pi\cdot 0.29}, \sqrt{0.65}\,e^{j2\pi\cdot 0.25}]$
IND	$[\sqrt{0.27}\,e^{j2\pi\cdot 0.51}, \sqrt{0.16}\,e^{j2\pi\cdot 0.31}, \sqrt{0.59}\,e^{j2\pi\cdot 0.20}]$	$[\sqrt{0.25}\,e^{j2\pi\cdot 0.50}, \sqrt{0.15}\,e^{j2\pi\cdot 0.31}, \sqrt{0.60}\,e^{j2\pi\cdot 0.19}]$

Table A9: Defuzzified decision matrix

	FNCL	CNSR	ORGN	CMPT
CHN	1.250	1.243	1.240	1.250
MXC	1.241	1.240	1.243	1.236
TRK	1.236	1.236	1.248	1.247
BRZ	1.236	1.240	1.240	1.240
INS	1.236	1.250	1.240	1.236
RSS	1.243	1.240	1.243	1.243
IND	1.236	1.236	1.243	1.246

Table A10: Normalized decision matrix

	FNCL	CNSR	ORGN	CMPT
CHN	0.381	0.379	0.377	0.380
MXC	0.377	0.378	0.378	0.376
TRK	0.377	0.376	0.380	0.379
BRZ	0.377	0.378	0.377	0.377
INS	0.377	0.381	0.377	0.376
RSS	0.379	0.378	0.378	0.378
IND	0.377	0.376	0.378	0.379

Table A11: Weighted decision matrix

	FNCL	CNSR	ORGN	CMPT
CHN	0.095	0.094	0.094	0.095
MXC	0.094	0.094	0.095	0.094
TRK	0.094	0.094	0.095	0.095
BRZ	0.094	0.094	0.094	0.095
INS	0.094	0.095	0.094	0.094
RSS	0.095	0.094	0.095	0.095
IND	0.094	0.094	0.095	0.095