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Quantum Spherical Fuzzy Bayesian Network Integrated with Artificial Intelligence Based Decision Analytics for Evaluating Renewable Energy Investment Competencies

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Abstract. This study proposes an integrated AI-driven quantum spherical fuzzy decision framework for multi-criteria evaluation under uncertainty. The model combines AI-based decision-maker weighting, quantum spherical fuzzy Bayesian networks for criteria weighting, and WASPAS for

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ranking. Decision makers are clustered using k-means to reduce bias, while interdependencies and uncertainty are captured probabilistically. The framework is applied to assess renewable energy investment competencies in G7 economies. Results highlight the importance of customer-centric expectations and real-time financial performance. The model offers a flexible, robust, and scalable approach, improving reliability, transparency, and decision quality in complex environments.

Key words: artificial intelligence, fuzzy decision-making, decision support systems, quantum spherical fuzzy, Bayesian networks, WASPAS, renewable energy projects.

1. Introduction

It is important to develop competencies to increase the success of renewable energy projects (REPs). This contributes positively to the long-term sustainability of these projects. By developing competencies, it is possible to plan REPs more successfully. Similarly, developing competencies significantly supports increasing the success of projects. It is possible to reduce costs by making more accurate planning. This allows the profit margin of investments to be increased (Hampl, 2024; Demir, 2026). On the other hand, with the development of competencies, businesses gain a significant competitive advantage. Businesses aiming to improve their competencies focus on innovations in this process. In this way, businesses can improve their technological infrastructure. As a result, it is possible to increase the competitiveness of businesses. Moreover, increasing competencies allows the success of REPs to improve (Mathieu and Valenzuela, 2025). As a result, these projects will be increased, and new employment opportunities will arise.

Many various indicators can influence the success improvements of the renewable energy competencies. Effective cost management of energy projects with data analytics helps to increase the profit margin of these projects. Similarly, taking action to meet customer expectations plays a critical role in this context. By ensuring customer satisfaction, the companies can increase their competitive powers (Kou *et al.*, 2024). Technological improvements have an important influence to improve renewable energy competencies. Owing to using new technologies, cybersecurity in data processing of smart energy can be provided. Similarly, incremental innovations are very helpful to increase the success of new energy services. In addition to them, renewable system integration should be provided to reach energy optimization purposes (Alshareef and Fathy, 2024). This situation positively affects the cost effectiveness of these projects.

Necessary actions need to be taken to increase the competencies of REPs. Within this framework, improvements should be made regarding the variables pertaining to the success of this process. However, there are many variables that relate to success of this process. Considering that each improvement increases costs, it is understood that taking many actions is not financially reasonable (Boukhatem and Oei, 2024). Therefore, it is appropriate to focus on the most important indicators affecting the competencies of these investments. In this way, it will be possible to take the necessary actions without incurring too much cost. In summary, the criteria that are most effective on the competencies of REPs need to be determined. But there are many articles focusing on this topic in literature. Therefore, an original article on this subject is needed.

Existing studies on renewable energy investment evaluation generally rely on conventional fuzzy MCDM techniques that assume either independence among criteria or equal importance of decision makers. However, such assumptions limit the capability of these models to reflect the complex and interdependent nature of renewable energy systems. Moreover, many existing approaches do not adequately capture both probabilistic uncertainty and linguistic ambiguity simultaneously. While some studies incorporate fuzzy logic to address uncertainty, they often lack dynamic structures to model causal relationships among criteria. In addition, the role of decision maker heterogeneity is frequently overlooked, leading to potential biases in the evaluation results. Therefore, there is a clear need for a more advanced and integrated framework that can simultaneously consider interdependencies among criteria, incorporate uncertainty in a more comprehensive manner, and objectively determine decision maker weights. This study addresses these limitations by integrating artificial intelligence with quantum spherical fuzzy Bayesian networks, thereby providing a more robust and adaptive decision-making approach.

This study is motivated by the increasing complexity and uncertainty associated with renewable energy investment decisions in the knowledge economy. Although a growing body of literature has addressed renewable energy evaluation using fuzzy and artificial intelligence-based approaches, existing studies often treat decision makers as homogeneous entities and fail to simultaneously capture both probabilistic uncertainty and linguistic ambiguity. Moreover, the interdependent structure of investment criteria is generally oversimplified, limiting the realism of the decision-making process. These limitations create a significant research gap in developing a comprehensive and integrated framework that can incorporate decision maker heterogeneity, model causal relationships among criteria, and handle multi-dimensional uncertainty in a unified structure. Therefore, this study aims to address these shortcomings by proposing an advanced hybrid decision analytics model that integrates artificial intelligence, quantum spherical fuzzy sets, and Bayesian networks.

Accordingly, the purpose of this article is to identify the most critical criteria for renewable energy investment (REI) competencies in knowledge economy. Thus, the research question of this manuscript is to determine which indicators play the most essential role for the improvements of the competencies of these projects. For this purpose, a new AI-based fuzzy decision-making model has been proposed that has two methods. First, the DMs are prioritized by creating decision matrix with AI methodology. In the following stage, selected REI competencies are weighted by using QSF Bayesian Networks. Finally, G7 economies are ranked with QSF weighted aggregated sum product assessment (WASPAS). The main criticisms on the existing models in the literature are the main motivations of making this article. One of the most important criticisms to these models is that the opinions of the DMs are considered in an equal weight. These DMs should be taken into consideration with different significance weights because they vary based on their qualifications. Thus, this proposed model aims to compute the weight values of the DMs via AI methodology.

The principal contributions of this article are outlined as follows: (i) The utilization of Bayesian Networks in the criteria weighting process offers a dynamic and probabilistic structure that significantly enhances the performance of fuzzy multi-criteria decision-making. While conventional methods such as the Analytical Hierarchy Process (AHP) or entropy weighting typically assume independence among criteria, Bayesian Networks allow the modelling of interdependencies and conditional relationships. This provides a more realistic and flexible representation of decision environments, especially in complex investment contexts like renewable energy. Additionally, Bayesian Networks can be continuously updated as new data becomes available, which supports the development of adaptive decision-making models that evolve with changing market or policy conditions. (ii) The integration of artificial intelligence techniques into the fuzzy decision-making framework is another important contribution. In this study, AI is employed to determine the relative weights of decision makers based on demographic and contextual indicators, rather than relying solely on subjective expert judgments. This approach helps to reduce bias, enhance transparency, and improve the analytical rigour of the model. By embedding AI-driven structure into the early stages of the evaluation, the overall process becomes more data-informed, scalable, and reproducible. (iii) The application of the WASPAS method in the final ranking stage introduces a hybrid computational mechanism that improves the robustness of the evaluation. WASPAS combines the weighted sum model (WSM) and the weighted product model (WPM), effectively capturing both additive and multiplicative preferences. This dual structure increases the sensitivity, reliability, and discriminative power of the model, particularly when dealing with close alternatives. Compared to traditional single-method approaches such as TOPSIS or SAW, WASPAS provides a more balanced output by mitigating the dominance of extreme values or outliers. (iv) While the methodology itself introduces novel integrations, a systematic comparison with other state-of-the-art fuzzy MCDM approaches (e.g. VIKOR, MARCOS, EDAS, or MAIRCA) has not been fully conducted within the scope of this study. This represents a potential direction for future research. Benchmarking the proposed model against other advanced hybrid methods would provide deeper insights into its comparative strengths and limitations. Therefore, this study serves as a foundation for future comparative experimentation in the field of renewable energy investment decision analysis.

The following section gives information about the evaluation of the similar studies. Proposed methodology and analysis results are explained in the next sections. The final parts consist of discussion and conclusion.

2. Literature Review

Effective operating cost management contributes REIs. Effective management of operating costs increases the impact of digital economy on renewable energy innovation. Wang *et al.* (2024a) emphasized in their article that by integrating AI applications and digital technology transformation into renewable energy, production costs will be reduced and energy saving optimization will be achieved. Similarly, Saqib *et al.* (2024) concluded that environmentally friendly information technology applications reduce carbon footprint. In addition, they state that the use of environmentally friendly information technologies contributes to financial development. Yi *et al.* (2024) denoted that the information economy narrows the distances between enterprises and contributes positively to cost management by increasing cooperation and communication between sectors. They also emphasized that the knowledge economy promotes renewable energy through capital and market expansion. In addition to these studies, Al-Madani *et al.* (2024) stated that manufacturing firms need to implement solutions to optimize energy management to maintain their workflows optimally.

Innovative solutions to meet customer expectations are important in increasing REIs. One of the solutions to satisfy customer expectations is the digital finance system (Lin and Zhang, 2024). The green digital finance system offers new financial solutions to investors by combining many modern technologies such as big data and artificial intelligence. In summary, these digital solutions encourage businesses to increase their investments and use resources efficiently to support low-carbon production (Razzaq *et al.*, 2023). For example, Yu *et al.* (2022) emphasized that the use of digital finance applications increases renewable energy consumption in the Chinese economy. It also shows that carbon emissions have a significant relationship with this consumption. However, Sun *et al.* (2024) stated that the way to direct the development of technology in an appropriate way is effective use of digital economy and financial framework. Mignacca *et al.* (2025) proposed financing technologies for inventions and new technologies in the energy sector. Thanks to these financing technologies, new inventions will be integrated more quickly. Finally, Li *et al.* (2024) denoted that digital financing sources used in China accelerate the transition to renewable energy.

The use of innovative technologies in such energy processes is important in increasing the usage of renewable energy. The use of new technologies with the development of technology in renewable energy production will support low-carbon energy production. Jahanger *et al.* (2024) determined that there is an interaction between renewable energy and technological innovation. Similarly, Bergougui (2024) emphasized in their article that increases in technological innovations developed for renewable energy reduce carbon emissions. In a similar study, Oladapo *et al.* (2025) suggested the use of predictive models in the use of renewable energy and reduction of emissions. In this way, the transition to renewable energy will increase with the help of technology. In another study; Zhang *et al.* (2025) stated that increasing geopolitical risk levels increase technological innovation in renewable energy. Movsessian *et al.* (2025) reported that the use of appropriate technology for the transition to renewable energy increases the use of renewable energy. In addition, Sharif *et al.* (2024) underlined that eco-innovations in renewable energy processes, which are important in reducing carbon emissions, will be beneficial for sustainable development. They also think that these innovations will be useful in improving air quality. Finally, Usman *et al.* (2024) demonstrated that investments in the development of energy technologies increase energy security. Finally, Abdelsattar *et al.* (2025) state that the use of machine learning techniques in renewable energy systems will make energy technologies more efficient.

Realizing global collaborations for potential energy projects is among the important criteria for increasing REIs. These collaborations enable the rapid acquisition of up-to-date technologies for REPs. The transfer of advanced technologies from enterprises with newer technology becomes accessible more quickly. This leads to a significant reduction in the costs of REPs. Thanks to advanced technologies, renewable energy can be obtained more efficiently. For this purpose, Raghavendra *et al.* (2025) investigated the contribution of carbon emission to global co-operation in India. According to the findings of the article, higher carbon emission increases global cooperation in REIs. Similarly, Zhou *et al.* (2024a) indicated that foreign direct investments in REIs reduce environmental pollution in MENA countries. Lin and Ullah (2024) concluded in their article that international co-operation in renewable energy technologies will contribute positively to carbon emissions in Pakistan in the short term.

Some issues stand out in the results obtained from literature. REPs are especially key in the energy transition. Thanks to these projects, the global warming problem can be prevented by reducing carbon emissions. However, these projects also have some disadvantages such as high initial costs. Therefore, to increase the success of projects, the competencies of these investments must be increased. When the articles in literature are searched, there are many criteria that affect the development of the competence of these projects. Nevertheless, the actions taken for the development of these indicators also increase the costs of businesses. In this context, making many improvements can cause businesses to experience financial difficulties. Therefore, focusing on more important variables is important for this process to be more effective and efficient. In summary, it is necessary to find the indicators that have the greatest impact on the competencies of REPs. The most important deficiency in the literature is that there are not enough studies on this subject. In the new AI-based decision-making model developed in this article, priority analysis is applied for indicators affecting the competence of REPs.

The existing literature on renewable energy investment evaluation can be broadly categorized into three main methodological streams. First, fuzzy decision-making approaches have been widely used to handle uncertainty and vagueness in energy-related problems, particularly in multi-criteria evaluation contexts. However, these studies generally focus on static weighting structures and often overlook the interdependencies among criteria. Second, recent studies have incorporated artificial intelligence techniques to enhance decision-making processes, especially in terms of prediction, clustering, and optimization. Despite their advantages, these approaches are often applied independently from fuzzy frameworks, limiting their ability to capture linguistic uncertainty. Third, probabilistic modelling techniques, such as Bayesian networks, provide a dynamic structure to model causal relationships and uncertainty propagation. Nevertheless, their integration with advanced fuzzy environments and AI-based decision-maker prioritization remains limited. Therefore, this study aims to bridge these methodological streams by proposing an integrated framework that combines AI-driven prioritization, quantum spherical fuzzy modelling, and Bayesian network-based analysis in a unified structure.

3. Proposed Model

The aim of this article is to determine REI competencies in the knowledge economy. For this, investment competencies are determined based on literature. Bayesian Network is

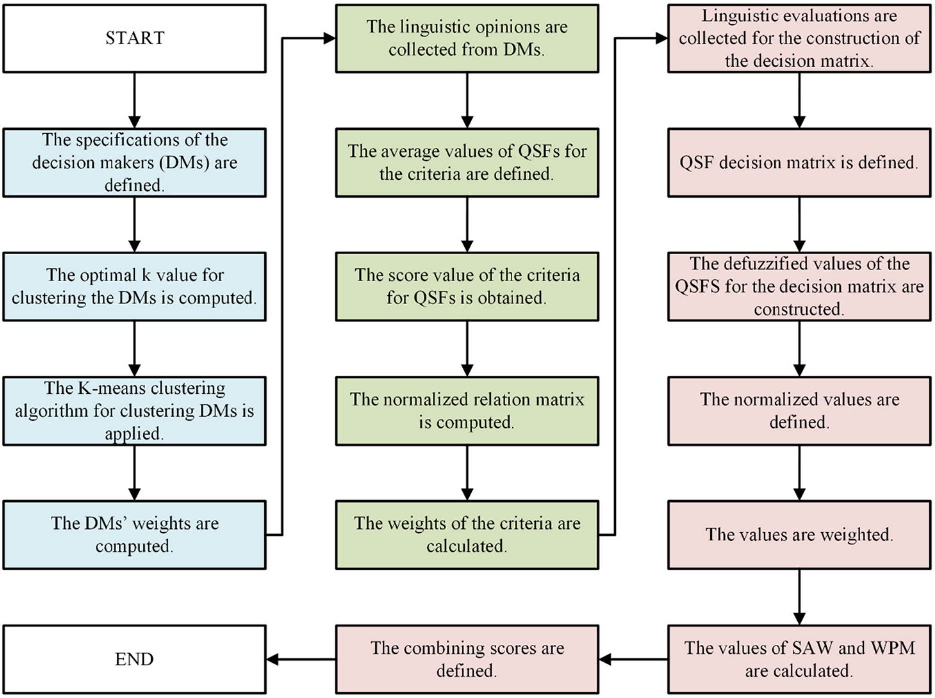

Fig. 1. Flowchart of the proposed model.

used to determine the optimal competence in REIs in the knowledge economy. Since there is an interaction between competencies, the Bayesian Network method is preferred. In this way, weighting of competencies can be achieved by considering the interaction between competencies. However, the Bayesian Network method is an MCDM based on DM opinions. There are two main criticisms of such methods. The first of these is the selection and the assignment of importance weights of DMs. In response to this criticism, the article uses an AI-based DM prioritization method. So, weights and selection of DMs are determined. The second criticism is the inclusion of ambiguity in linguistic expressions into the analysis. In mathematics, fuzzy logic theory is used to measure and evaluate of uncertainty. For this reason, quantum spherical fuzzy (QSF) number set with golden cuts is developed for linguistic uncertainty in DMs' opinions and integrated into the Bayesian Network method (Kurbanova *et al.*, 2025). Finally, country groups are ranked by WASPAS. Formulations of the models used in the analysis phase are shared. Additionally, Fig. 1 shows the flow of the analysis process.

To enhance the clarity and interpretability of the proposed framework, each methodological component is designed to address a specific challenge in renewable energy investment evaluation. The AI-based clustering approach is employed to capture heterogeneity among decision makers and to reduce subjective bias in weighting procedures. The quantum spherical fuzzy structure is integrated to effectively model linguistic ambiguity and complex uncertainty inherent in expert evaluations. In addition, Bayesian networks are utilized to represent interdependencies and causal relationships among criteria, which are often overlooked in traditional approaches. Finally, the WASPAS method is adopted to ensure robust and discriminative ranking by combining additive and multiplicative evaluation mechanisms. This structured integration ensures that each methodological choice directly responds to a limitation identified in the existing literature, thereby improving both analytical rigour and practical relevance.

3.1. *AI-Based Decision-Making*

Weighting DMs' demographic characteristic requires a very complex model. This complex model is created by the k-means clustering method. The k-means clustering algorithm is preferred in this study for determining decision-maker weights due to its ability to objectively group individuals based on multiple demographic and professional characteristics. Unlike traditional weighting approaches such as entropy-based or consistency-based methods, which primarily rely on the structure of the decision matrix or pairwise comparisons, clustering-based prioritization enables the identification of homogeneous subgroups among decision makers. This provides a data-driven mechanism to capture heterogeneity in expertise, experience, and background. In addition, k-means offers computational simplicity and scalability, making it suitable for integration with artificial intelligence-based decision frameworks. Therefore, the use of k-means enhances the objectivity and robustness of the weighting process by reducing subjective bias and reflecting the underlying structure of the expert group more effectively. The k means number of clusters. For determining of optimal value of k, the Within-Cluster Sum of Squares (WCSS) values are found in scope of elbow method. Details of the process are shared below (Dhabe *et al.*, 2023).

In *Step 1*, the characteristic of the decision makers (DMs) is defined. The selection of decision makers (DMs) was conducted with careful consideration of their professional expertise and relevance to renewable energy investment processes. The expert group consists of individuals from both academic and industry backgrounds, including academicians, managers, and sectoral professionals with experience in energy, finance, and production domains. These individuals were selected based on their educational qualifications, years of experience, and domain-specific expertise to ensure a comprehensive and balanced evaluation perspective. Although the number of decision makers is relatively limited, this is consistent with prior studies in fuzzy MCDM literature, where in-depth expert knowledge is prioritized over large sample sizes. Furthermore, the integration of an AI-based weighting mechanism enhances the reliability of the results by accounting for heterogeneity among decision makers and reducing potential bias in expert judgments. In this, a team of DMs is brought together. Sociodemographic information of team members is collected. Data such as education, income, years of experience and age are obtained. *Step 2* covers estimating optimal value to cluster (Wang *et al.*, 2024b). Taking various k values into account, the WS value given in equation (1) is calculated.

$$WS = \sum_{j=1}^{k} \sum_{x_i \in C_j} E(x_i, c_j)^2. \tag{1}$$

In the formulation, the set of x_i in cluster j is symbolized as C_j, and $E(x_i, c_j)$ equals the Euclidean distance between x_i and c_j. Then, a graph is drawn between WS values and k values. In this graph, the turning point of the drawn line is found. This point is called the elbow point and is considered to be equal to the optimal k value. *Step 3* involves applying of the k-means clustering algorithm for clustering DMs. This k is applied to $c_1, c_2, \dots, c_k$ and each x_i is stated to determine the cluster assignments using equation (2).

$$E(x_i, x_j) = \sqrt{\sum_{l=1}^{n} (x_{il} - x_{jl})^2}. \tag{2}$$

Afterwards, cluster centres are updated iteratively with equation (3).

$$c_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i. \tag{3}$$

Step 4 covers computing the DMs' weights. In the process, the mean standard deviation is obtained by equations (4)–(6).

$$s_j = \frac{1}{n} \sum_{l=1}^{n} \sigma_{jl}, \tag{4}$$

$$\sigma_{jl} = \sqrt{\frac{1}{|C_j|} \sum_{x_i \in C_j} (x_{il} - \hat{x}_{jl})^2}, \tag{5}$$

$$\hat{x}_{jl} = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_{il}. \tag{6}$$

The cluster weight values w_j are obtained in equation (7):

$$w_j = |C_j| \times s_j. \tag{7}$$

The weight values of the DMs are computed using equation (8):

$$w_{tj} = \frac{1}{|C_j|} \frac{w_j}{\sum_{w_j \in C_j} w_j}. \tag{8}$$

3.2. *QSFS with Golden Cut*

Quantum spherical fuzzy sets provide an advanced framework for representing uncertainty by integrating the advantages of both spherical fuzzy sets and quantum theory. Unlike classical fuzzy sets, which consider only membership degrees, and spherical fuzzy sets, which include membership, non-membership, and hesitation degrees, quantum spherical fuzzy sets additionally incorporate amplitude and phase components derived from quantum mechanics. This structure enables a more flexible and comprehensive representation of uncertainty by capturing both the intensity and the directional characteristics of decision-makers' evaluations. As a result, quantum spherical fuzzy sets can model complex and ambiguous decision environments more effectively, especially when linguistic assessments and probabilistic uncertainty coexist. Therefore, this approach improves the sensitivity and reliability of the decision-making process compared to traditional fuzzy frameworks. Quantum physics deals with the motions and positions of subatomic particles. In other words, quantum mechanics expresses uncertainty in the state of a massless particle as probability (García-Zamora *et al.*, 2025). Specifically, probability equals more efficiently by the quantum theory with the amplitude and the phase angle objects. The probability of quantum mass function is descripted by equations (9)–(11) (Yüksel and Dinçer, 2023).

$$Q\big(|\mathrm{u}\rangle\big) = \varphi e^{j\theta}, \tag{9}$$

$$|\mathbb{C}\rangle = \big\{|\mathrm{u}_1\rangle, |\mathrm{u}_2\rangle, \dots, |\mathrm{u}_n\rangle\big\}, \tag{10}$$

$$\sum_{|\mathrm{u}\rangle\subseteq|\mathbb{C}\rangle} \big|Q\big(|\mathrm{u}\rangle\big)\big| = 1, \tag{11}$$

where φ^2 refers to the amplitude result of probability in quantum. Decision-making problems can be performed with non-numeric data as well as with numerical data. In other words, decision-making problems can be solved by analysing quantitative and qualitative data. For this reason, linguistic ambiguity needs to be considered in the analysis. In mathematics, measurement and analysis of uncertainty is carried out with fuzzy logic. Different types of fuzzy sets are created. One of the developed fuzzy sets is spherical fuzzy sets (SFs). The number of this set has membership (μ), non-membership (ν) and hesitation (h) degrees. The definition of SFs $\tilde{\mathfrak{R}}_S$ is given with equations (12) and (13).

$$\tilde{\mathfrak{R}}_S = \big\{\big\langle u, \big(\mu_{\tilde{\mathfrak{R}}_S}(u), v_{\tilde{\mathfrak{R}}_S}(u), h_{\tilde{\mathfrak{R}}_S}(u)\big)\big| u \in U\big\}, \tag{12}$$

$$0 \leqslant \mu^2_{\tilde{\mathfrak{R}}_S}(u) + v^2_{\tilde{\mathfrak{R}}_S}(u) + h^2_{\tilde{\mathfrak{R}}_S}(u) \leqslant 1, \quad \forall_u \in U. \tag{13}$$

The components amplitude and the phase angles in quantum mechanics are used to evaluate complexity in decision-making problems. This similarity between SFs and quantum mechanics can be shared using equation (14).

$$\big|\mathbb{C}_{\tilde{A}_S}\big\rangle = \big\{\big\langle u, \big(\mathbb{C}_{\mu_{\tilde{\mathfrak{R}}_S}}(u), \mathbb{C}_{v_{\tilde{\mathfrak{R}}_S}}(u), \mathbb{C}_{h_{\tilde{\mathfrak{R}}_S}}(u)\big)\big| u \in 2^{|\mathbb{C}_{\tilde{\mathfrak{R}}_S}\rangle}\big\}. \tag{14}$$

The number of QSFs ($\mathbb{C}$) are determined with the help of equations (15) and (16).

$$\mathbb{C} = \big[\mathbb{C}_\mu . e^{j2\pi.\alpha}, \mathbb{C}_v . e^{j2\pi.\gamma}, \mathbb{C}_h . e^{j2\pi.\beta}\big], \tag{15}$$

$$\varphi^2 = \big|\mathbb{C}_\mu\big(|\mathrm{u}_i\rangle\big)\big|. \tag{16}$$

The golden cut ($\mathcal{G}$) is constructed using the optimal ratio among the scales of SFs. The $\mathcal{G}$ value can be determined with equation (17).

$$\mathcal{G} = \frac{a}{b}. \tag{17}$$

The algebraic form of $\mathcal{G}$ is shown with equation (18).

$$\mathcal{G} = \frac{1+\sqrt{5}}{2} \cong 1.62. \tag{18}$$

The amplitude of v function of the QSFs is identified with $\mathcal{G}$ by equation (19).

$$\mathbb{C}_v = \frac{\mathbb{C}_\mu}{\mathcal{G}}. \tag{19}$$

The amplitude of hesitancy function is determined in equation (20).

$$\mathbb{C}_h = 1 - \mathbb{C}_\mu - \mathbb{C}_v. \tag{20}$$

Afterwards, the phase angle of the QSFs is defined using equation (21).

$$\alpha = \left|\mathbb{C}_\mu\left(|\mathrm{u}_i\rangle\right)\right|. \tag{21}$$

The phase angle of NM function (γ) is estimated by equation (22).

$$\gamma = \frac{\alpha}{\mathcal{G}}. \tag{22}$$

The phase angle of H degrees (β) is created with the help of equation (23).

$$\beta = 1 - \alpha - \gamma. \tag{23}$$

The operations of QSFs are summarized in equations (24)–(27). λ is any positive number.

$$\lambda * \tilde{A}_{\mathbb{C}} = \left\{ \begin{array}{l} (1-(1-\mathbb{C}^2_{\mu_{\tilde{A}}})^\lambda)^{\frac{1}{2}} e^{j2\pi\left(1-\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}}, \mathbb{C}^\lambda_{v_{\tilde{A}}} e^{j2\pi\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^\lambda}, \\ \quad \left((1-\mathbb{C}^2_{h_{\tilde{A}}})^\lambda - (1-\mathbb{C}^2_{\mu_{\tilde{A}}} - \mathbb{C}^2_{h_{\tilde{A}}})^\lambda\right)^{\frac{1}{2}} \\ \quad \times e^{j2\pi\left(\left(1-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda - \left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}} \end{array} \right\}, \tag{24}$$

$$\tilde{A}^\lambda_{\mathbb{C}} = \left\{ \begin{array}{l} \mathbb{C}^\lambda_{\mu_{\tilde{A}}} e^{j2\pi\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^\lambda}, \left(1-\left(1-\varsigma^2_{v_{\tilde{A}}}\right)^\lambda\right)^{\frac{1}{2}} e^{j2\pi\left(1-\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}}, \\ \quad \left((1-\mathbb{C}^2_{v_{\tilde{A}}})^\lambda - (1-\mathbb{C}^2_{v_{\tilde{A}}} - \mathbb{C}^2_{h_{\tilde{A}}})^\lambda\right)^{\frac{1}{2}} \\ \quad \times e^{j2\pi\left(\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda - \left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}} \end{array} \right\}, \tag{25}$$

$$\tilde{A}_{\mathbb{C}} \oplus \tilde{B}_{\mathbb{C}} = \left\{ \begin{array}{l} (\mathbb{C}^2_{\mu_{\tilde{A}}} + \mathbb{C}^2_{\mu_{\tilde{B}}} - \mathbb{C}^2_{\mu_{\tilde{A}}}\mathbb{C}^2_{\mu_{\tilde{B}}})^{\frac{1}{2}} e^{j2\pi\left(\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2 + \left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^2 - \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^2\right)^{\frac{1}{2}}}, \\ \quad \mathbb{C}_{v_{\tilde{A}}} \varsigma v_{\tilde{B}} e^{j2\pi\left(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)\right)}, \\ \quad \left((1 - \mathbb{C}^2_{\mu_{\tilde{B}}})\mathbb{C}^2_{h_{\tilde{A}}} + (1 - \mathbb{C}^2_{\mu_{\tilde{A}}})\mathbb{C}^2_{h_{\tilde{B}}} - \mathbb{C}^2_{h_{\tilde{A}}}\mathbb{C}^2_{h_{\tilde{B}}}\right)^{\frac{1}{2}} \\ \quad \times e^{j2\pi\left(\left(1 - \left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2 + \left(1 - \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^2 - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^2\right)^{\frac{1}{2}}} \end{array} \right\}, \tag{26}$$

$$\tilde{A}_{\mathbb{C}} \otimes \tilde{B}_{\mathbb{C}} = \left\{ \begin{array}{l} \mathbb{C}_{\mu_{\tilde{A}}} \varsigma \mu_{\tilde{B}} e^{j2\pi\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)}, (\mathbb{C}^2_{v_{\tilde{A}}} + \mathbb{C}^2_{v_{\tilde{B}}} - \mathbb{C}^2_{v_{\tilde{A}}}\mathbb{C}^2_{v_{\tilde{B}}})^{\frac{1}{2}} \\ \quad \times e^{j2\pi(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2 + \left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^2 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\left(\frac{\gamma_{\tilde{B}}}{2\pi})^2\right)^{\frac{1}{2}}}, \\ \quad \left((1 - \mathbb{C}^2_{v_{\tilde{B}}})\mathbb{C}^2_{h_{\tilde{A}}} + (1 - \mathbb{C}^2_{v_{\tilde{A}}})\mathbb{C}^2_{h_{\tilde{B}}} - \mathbb{C}^2_{h_{\tilde{A}}}\mathbb{C}^2_{h_{\tilde{B}}}\right)^{\frac{1}{2}} \\ \quad \times e^{j2\pi\left(\left(1 - \left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2 + \left(1 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^2\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^2 - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^2\right)^{\frac{1}{2}}} \end{array} \right\}. \tag{27}$$

3.3. *The Extension of Bayesian Networks-Based Weighting*

In *Step 5*, the linguistic opinions are collected from DMs.

Step 6 is about defining the average values of QSFs for the criteria. $\mathbb{C}_{\mu_{\tilde{A}}}$ $\mathbb{C} = [\mathbb{C}_{ij}]_{n\times n}$ in the Eq. (28) means the relationship degrees between criteria (Sathyan *et al.*, 2023).

$$\mathbb{C}_k = \begin{bmatrix} 0 & \mathbb{C}_{12} & \cdots & \cdots & \mathbb{C}_{1n} \\ \mathbb{C}_{21} & 0 & \cdots & \cdots & \mathbb{C}_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbb{C}_{n1} & \mathbb{C}_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{28}$$

$\mathbb{C}$ is known as the QSF direct relation matrix. The aggregated value ($\mathbb{C}$) of the DM is computed with equation (29).

$$\mathbb{C} = \left\{ \begin{array}{l} [1 - \prod_{i=1}^k (1 - \mathbb{C}^2_{\mu_i})^{\frac{1}{k}}]^{\frac{1}{2}} e^{2\pi.\left[1 - \prod_{i=1}^k \left(1 - \left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}}, \prod_{i=1}^k \mathbb{C}^{\frac{1}{k}}_{v_i} e^{2\pi.\prod_{i=1}^k \left(\frac{\gamma_i}{2\pi}\right)^{\frac{1}{k}}}, \\ \quad [\prod_{i=1}^k (1 - \mathbb{C}^2_{\mu_i})^{\frac{1}{k}} - \prod_{i=1}^k (1 - \mathbb{C}^2_{\mu_i} - \mathbb{C}^2_{h_i})^{\frac{1}{k}}]^{\frac{1}{2}} \\ \quad \times e^{2\pi\left[\prod_{i=1}^k \left(1 - \left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac{1}{k}} - \prod_{i=1}^k \left(1 - \left(\frac{\alpha_i}{2\pi}\right)^2 - \left(\frac{\beta_i}{2\pi}\right)^2\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}} \end{array} \right\}. \tag{29}$$

Step 7 involves obtaining of the score value of the criteria for QSFs. The defuzzified ($Def\mathbb{C}$) QSFs are obtained by the score function with Eq. (30).

$$Def\mathbb{C}_i = \mathbb{C}_{\mu_i} + \mathbb{C}_{h_i}\left(\frac{\mathbb{C}_{\mu_i}}{\mathbb{C}_{\mu_i} + \mathbb{C}_{v_i}}\right) + \left(\frac{\alpha_i}{2\pi}\right) + \left(\frac{\gamma_i}{2\pi}\right)\left(\frac{(\frac{\alpha_i}{2\pi})}{(\frac{\alpha_i}{2\pi}) + (\frac{\beta_i}{2\pi})}\right). \tag{30}$$

Step 8 is about calculating the normalized relation matrix. The normalized direct relation matrix ($\mathcal{B} = [b_{ij}]_{n\times n}$) is shared in Eqs. (31) and (32).

$$\mathcal{B} = \frac{\mathbb{C}}{\max_{1\leqslant i\leqslant n}\sum_{j=1}^{n}\mathbb{C}_{ij}}, \tag{31}$$

$$0 \leqslant b_{ij} \leqslant 1. \tag{32}$$

Step 9 is about the entropy results by computing equations (33) and (34):

$$E(C_i) = -\sum PR(C_i)In\big(PR(C_i)\big), \tag{33}$$

$$E(C_i|C_j) = -\sum PR(C_j).PR(C_i|C_j)In\big(PR(C_i|C_j)\big), \tag{34}$$

where $E(C_i)$ refers to the entropy results for each criterion. $E(C_i|C_j)$ means the conditional entropy indicating the remaining uncertainty about ith criterion after knowing jth criterion. $PR(C_i)$ is the prior probability of the criteria and assumed that each criterion has equal value as $\frac{1}{n}$ in the criteria. $PR(C_i|C_j)$ is the conditional probability of ith criterion given jth criterion.

Step 10 is about calculating the weights of the criteria in equations (35) and (36):

$$\mathcal{IG}(C_i) = E(C_i) - E(C_i \mid C_j), \tag{35}$$

$$W(C_i) = \frac{\mathcal{IG}(C_i)}{\sum_{k=1}^{n}\mathcal{IG}(C_k)}, \tag{36}$$

where $\mathcal{IG}(C_i)$ is the value of the reduction in uncertainty of ith criterion when other criteria are known. $W(C_i)$ is the weight of ith criterion.

3.4. *The Extension of WASPAS*

In *Step 11*, linguistic assessments are collected to the construction of the decision matrix. *Step 12* is about defining of QSF decision matrix by considering the linguistic assessments of DMs. The decision matrix ($\mathcal{X} = [x_{ij}]_{n\times m}$) is given in equation (37) (Zavadskas *et al.*, 2025).

$$\mathcal{X}_k = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & \cdots & x_{nm} \end{bmatrix}, \tag{37}$$

where x_{ij} references value on the ith alternative with respect to jth criterion. $x_{ij} = (x_{\mu_{ij}}e^{2\pi.\alpha_{ij}}, x_{v_{ij}}e^{2\pi.\gamma_{ij}}, x_{h_{ij}}e^{2\pi.\beta_{ij}})$ and the number of DMs is symbolized by k. After that, the aggregated elements of DMs are obtained using equation (29). *Step 13* involves constructing the crisped values of the QSFS for the decision matrix according to the score degree with the equation (30). *Step 14* covers defining the normalize elements using the vector normalization as per equation (38).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}. \tag{38}$$

Step 15 includes weighting of the values with the help of equation (39).

$$v_{ij} = w_j \times r_{ij}, \tag{39}$$

wherein w_j is $W(C_i)$ in equation (36). *Step 16* calculates the values of SAW $\mathfrak{Q}_i^{SAW}$ and WPM $\mathfrak{Q}_i^{WPM}$ as

$$\mathfrak{Q}_i^{SAW} = \sum_{j=1}^{m} v_{ij}, \tag{40}$$

$$\mathfrak{Q}_i^{WPM} = \prod_{j=1}^{m} r_{ij}^{w_{ij}}. \tag{41}$$

Step 17 defines the combining scores $\mathfrak{Q}_i$ to rank the alternatives by using the equation (42).

$$\mathfrak{Q}_i = \gamma \mathfrak{Q}_i^{SAW} + (1-\gamma)\mathfrak{Q}_i^{WPM}, \tag{42}$$

where γ is the combination parameters that define the weights of the results among the simple additive weighting (SAW) and the weighted product model (WPM). The highest $\mathfrak{Q}_i$ is chosen as the best choice in the alternatives. The γ has range 0 to 1. if $\gamma = 0$, the synergistic effects of the criteria are in forefront. In the case of the criteria interdependence, the combined effects of the criteria are more meaningful than the individual causes. In $\gamma = 1$, the individual contributions of the criteria together with the total effects are more important than the combined actions of the items (Zavadskas *et al.*, 2012).

To improve the clarity and transparency of the proposed methodology, the overall decision-making process is summarized as a structured sequence of steps. First, decision makers are evaluated and weighted using an AI-based clustering approach to reflect their heterogeneity. Second, linguistic evaluations are collected and transformed into quantum spherical fuzzy numbers to capture uncertainty and ambiguity. Third, the interdependencies among criteria are modelled through a Bayesian network structure, and the corresponding weights are derived based on entropy and information gain measures. Finally, the alternatives are evaluated and ranked using the WASPAS method, which integrates both additive and multiplicative aggregation mechanisms. This stepwise procedure provides a comprehensive view of the modelling framework and facilitates a clearer understanding of how the proposed methods are integrated throughout the analysis.

Table 1
Specifications of the DMs.

DMs	Education	Experience	Expertise	Position
DM1	3 (PhD)	19	2 (Energy)	1 (Academician)
DM2	3 (PhD)	16	3 (Production)	1 (Academician)
DM3	2 (Master)	20	2 (Energy)	2 (Manager)
DM4	2 (Master)	18	3 (Production)	2 (Manager)
DM5	2 (Master)	22	2 (Energy)	2 (Manager)
DM6	1 (Bachelor)	24	1 (Finance)	3 (Shareholder)

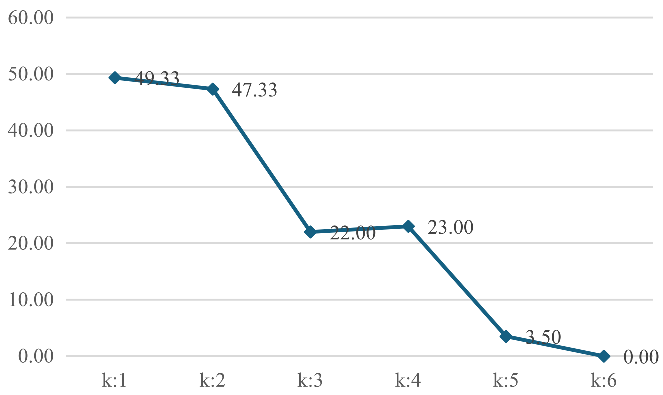

Fig. 2. Elbow method.

4. Analysis

The outputs of the analysis conducted to evaluate the competencies of REIs in the information economy are shared with subheadings.

4.1. *Computing the Priorities of the DMs*

In process of *Step 1*, the characteristic of the DMs is defined. The results are presented in Table 1.

As a result of *Step 2*, the k is computed for k-means algorithm. Using equation (1), the values of the WS are obtained. For numbers of cluster between 1 to 6, WS values are computed and shared in Table A1. Afterwards, the elbow point is obtained, and this point equals k. In summary, the plot is drawn in Fig. 2.

When Fig. 2 is examined, k equals 3. As a part of *Step 3*, the clustering algorithm is applied using equations (2) and (3). This k is applied for obtaining the clusters of DMs. The iterative results are shared in Table A2. At the end of this step, first and fourth DMs are stated in the first cluster. Cluster 2 has only DM, DM2. Third, fifth and sixth DMs are elements of 3th of clusters. *Step 4* covers computing the weights of the DMs using equations (4)–(8). The weight values of the DMs are shared in Table A3. Normalized DM weights are identified by the Pareto rule. The normalized weights are presented in Table 2.

Table 2
The DMs' weights.

	Weight	Normalized weight
DM1	.15	.10
DM2	.00	.00
DM3	.23	.27
DM4	.15	.10
DM5	.23	.27
DM6	.23	.27

Table 3
Selected criteria for REI competencies in knowledge economy.

Codes of criteria	Definitions of criteria
CSTMNG	Cost management of energy projects with data analytics
RTFINMEA	Real time financial measurements of ongoing energy plants
GLINSCO	Global investment cooperations for the potential energy projects
CUSEXP	Customer-centric expectations of local renewables
CYBSEC	Cybersecurity in data processing of smart energy
CLOTECH	Cloud technology for tailmade renewable energy services
TECHDIV	Technology diversification with several renewable alternatives
RENSYSINT	Renewable system integration for energy optimization
DECDATAMNG	Decentralized data management for grid projects
INCINN	Incremental innovations for new energy services
AUTOSUPP	Automation supports for constant energy supply
KNOWTRNSF	Knowledge transfer in competitive energy market

In Table 2, third, fifth and sixth DMs are important DMs with the value of .23. The normalization of values is computed with the Pareto principle. According to normalization value in Table 2, first, third, fourth, fifth and sixth DMs are the best in the group. In other words, the opinions of five DMs except second DM are gathered.

4.2. *Weighting the REI Competencies in Knowledge Economy With QSF-Bayesian Networks*

As a result of *Step 5*, the linguistic opinions about criteria are taken from DMs. For this, linguistic scales and golden cut based QSFs in Table A4 are used. The values in Table A4 were calculated using the equations in the second subheading of the third section. In other words, these values are calculated by equations (9)–(27). Competency criteria in REIs in the knowledge economy are obtained through literature review. The definition and coding of the twelve criteria are summarized in Table 3.

The results of the evaluation of the criteria in Table 3 by DMs are displayed in Table A5. *Step 6* is about determining the average values of QSFs for the criteria with equations (28) and (29). These average values are illustrated in Table A6. As a part of *Step 7*, the score value of the criteria for QSFs is computed with equation (30). The results are shown in Table A7. At the end of *Step 8*, the normalized relation matrix is found with equations (31)

Table 4
Entropy and information gain values, the weights.

	$E(C_i)$	$E(C_i \mid C_j)$	$IG(C_i)$	Weights	Ranks
CSTMNG	2.485	−2.938	5.423	0.0817	11
RTFINMEA		−3.145	5.630	0.0849	2
GLINSCO		-3.046	5.531	0.0834	7
CUSEXP		−3.177	5.661	0.0853	1
CYBSEC		−2.995	5.480	0.0826	8
CLOTECH		−2.929	5.414	0.0816	12
TECHDIV		−3.135	5.620	0.0847	3
RENSYSINT		−3.064	5.549	0.0836	5
DECDATAMNG		−3.092	5.577	0.0841	4
INCINN		−2.970	5.455	0.0822	9
AUTOSUPP		−3.063	5.548	0.0836	6
KNOWTRNSF		−2.969	5.454	0.0822	10

and (32) and displayed in Table A8. In *Step 9 and 10*, the entropy and information gain values, as well as the weights of the criteria, are defined in Table 4.

According to Table 4, the most effective criterion for the competence of REIs in the knowledge economy has been determined as "Customer-centric expectations of local renewables". The importance weight is .0853. According to the result, customer feedback should be considered to ensure high competence of REIs. If customer expectations are met, the competence of REIs in the knowledge economy will increase. Similarly, the "Real time financial measurements of ongoing energy plants" criterion ranks second in importance with a weight value of 0.0849. It has become extremely important to take advantage of technology and up-to-date software to make real-time financial measurements. Thus, instant financial monitoring can play an important role in renewable energy competence with new decisions and strategies to be taken.

4.3. *Ranking the REI Competencies with QSF-WASPAS*

As a part of *Step 11*, DM opinions are collected for the G7 economies. DM opinions are presented in Table 5.

As a result of *Step 12*, the average fuzzy values for G7 economies shown in equation (37) is computed. The output of this matrix is exhibited in Table A9. Using equation (30), at the end of *Step 13*, the crisped values shared in Table A10 are calculated. In *Step 14*, the normalized values are obtained by equation (38) and are presented in Table A11. The process of *Step 15* finds the weighted values using equation (39) by considering the weights of the criteria. The weighted values for the decision matrix are shared in Table A12.

In *Step 16 and 17*, equations (40)–(42) define the values of SAW, WPN, and combining scores for ranking alternatives. γ is determined .5 for balanced result. The results are given in Table 6.

According to Table 6, Italy is the most successful developed country in this framework. On the other side, Germany is in the last place because it has the lowest RCI value. However, the rankings with different combination parameters are also summarized in Table 7.

Table 5
Linguistic evaluations for G7 economies.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
Decision Maker 1												
Germany	B	F	G	B	B	G	F	P	P	F	P	P
U.S.	G	F	P	P	F	P	F	F	P	F	P	P
U.K.	G	B	P	F	F	P	F	B	G	B	G	P
Italy	P	F	B	B	F	P	P	F	P	B	G	P
France	F	B	G	F	B	G	B	F	P	F	P	F
Japan	F	F	B	F	F	B	F	P	F	F	P	F
Canada	F	G	G	F	B	G	P	B	G	B	G	P
Decision Maker 3												
Germany	B	F	G	B	B	G	F	B	B	F	B	B
U.S.	B	B	B	F	F	F	F	B	B	F	F	F
U.K.	F	F	P	F	F	P	F	B	G	B	G	P
Italy	F	F	P	F	F	P	P	F	P	B	F	F
France	B	F	F	F	F	G	B	F	F	F	B	B
Japan	F	F	B	F	F	B	F	F	F	F	F	F
Canada	F	B	B	B	B	B	B	B	G	B	B	B
Decision Maker 4												
Germany	F	B	G	B	B	G	G	F	F	B	F	B
U.S.	G	F	F	G	F	F	G	F	P	F	G	F
U.K.	G	F	P	F	F	F	F	G	G	F	G	F
Italy	F	G	F	B	F	F	B	F	F	G	F	G
France	F	B	G	F	B	G	F	F	F	G	F	B
Japan	F	F	B	F	F	F	F	B	F	F	P	F
Canada	F	G	G	F	B	G	P	B	G	B	F	G
Decision Maker 5												
Germany	F	B	G	B	B	G	F	P	G	F	G	F
U.S.	G	F	P	F	G	P	F	F	F	G	F	G
U.K.	G	F	P	F	F	P	F	B	F	G	F	G
Italy	F	G	B	F	B	P	P	F	F	B	F	B
France	F	B	G	G	F	G	B	F	G	F	G	F
Japan	F	F	B	F	F	B	F	P	F	B	F	B
Canada	F	G	G	F	B	G	P	B	G	B	G	P
Decision Maker 6												
Germany	B	G	F	B	B	G	F	P	G	F	G	F
U.S.	G	F	F	G	F	F	G	F	F	G	F	G
U.K.	F	B	G	F	F	P	F	B	F	G	F	G
Italy	G	F	F	B	F	F	B	F	F	B	F	B
France	F	G	G	F	B	G	F	F	G	F	G	F
Japan	F	F	B	F	F	B	F	P	F	B	F	B
Canada	F	G	G	F	B	G	P	B	G	B	G	P

In Table 7, the ranking results are same with different combination parameters.

Table 6
Ranking results for alternatives.

	SAW	WPN	CS (γ : 0.5)
Germany	0.377	0.377	0.3773
U.S.	0.379	0.379	0.3787
U.K.	0.377	0.377	0.3774
Italy	0.379	0.379	0.3789
France	0.378	0.378	0.3782
Japan	0.378	0.378	0.3782
Canada	0.377	0.377	0.3768

Table 7
Ranking results with different combination parameters.

Alternatives	$\gamma = 0$	$\gamma = 0.1$	$\gamma = 0.2$	$\gamma = 0.3$	$\gamma = 0.4$	$\gamma = 0.5$	$\gamma = 0.6$	$\gamma = 0.7$	$\gamma = 0.8$	$\gamma = 0.9$	$\gamma = 1$
Germany	6	6	6	6	6	6	6	6	6	6	6
U.S.	2	2	2	2	2	2	2	2	2	2	2
U.K.	5	5	5	5	5	5	5	5	5	5	5
Italy	1	1	1	1	1	1	1	1	1	1	1
France	3	3	3	3	3	3	3	3	3	3	3
Japan	4	4	4	4	4	4	4	4	4	4	4
Canada	7	7	7	7	7	7	7	7	7	7	7

4.4. *Comparative Ranking Results and Sensitivity Analysis*

In multi-criteria decision-making methods, comparative and sensitivity analysis are performed to validate the ranking of alternatives. The outputs obtained from the WASPAS are compared with the VIKOR and RATGOS methods. Additionally, analyses are performed for 12 different cases and the sensitivity of the results is tested. Comparative ranking outputs are summarized in Table 8.

Table 8 denotes that the three methods provided similar results. In this framework, the Italy ranked first in every condition. Similarly, alternative Canada ranks seventh in all cases. Since the ranking of the other alternatives is similar in all conditions, we can say that the analysis results are consistent.

5. Discussion

Meeting customer expectations is of great importance in developing the competencies of REPs. In this way, the basic needs of the renewable energy market can be met. Customers may have very important expectations from renewable energy investors. In this context, these expectations must first be clearly understood. This allows projects to be more successful. In this context, customer feedback should be provided periodically. In this way, it is possible to clearly understand the flaws in the process. Bolonio *et al.* (2024) and Zhou *et al.* (2024b) identified that it will make it easier to take the necessary actions to solve the problems in a timely manner. These actions contribute to significantly increasing the competitiveness of businesses. Tiwari and Menegaki (2024) concluded that projects that better

Table 8
Comparative ranking outputs.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
						WASPAS						
Germany	6	6	6	6	6	6	6	6	6	6	6	6
U.S.	2	2	2	2	2	2	2	2	2	2	2	2
U.K.	5	5	5	5	5	4	4	4	4	4	4	4
Italy	1	1	1	1	1	1	1	1	1	1	1	1
France	3	3	3	3	3	3	3	3	3	3	3	3
Japan	4	4	4	4	4	5	5	5	5	5	5	5
Canada	7	7	7	7	7	7	7	7	7	7	7	7
						Extended VIKOR						
Germany	6	6	6	6	6	6	6	6	6	6	6	6
U.S.	2	2	2	2	2	2	2	2	2	2	2	2
U.K.	5	5	5	5	5	4	4	4	4	4	4	4
Italy	1	1	1	1	1	1	1	1	1	1	1	1
France	3	3	3	3	3	3	3	3	3	3	3	3
Japan	4	4	4	4	4	5	5	5	5	5	5	5
Canada	7	7	7	7	7	7	7	7	7	7	7	7
						Extended RATGOS						
Germany	6	6	6	6	6	6	6	6	6	6	6	6
U.S.	2	2	2	2	2	2	2	2	2	2	2	2
U.K.	5	5	5	5	5	4	4	4	4	4	4	4
Italy	1	1	1	1	1	1	1	1	1	1	1	1
France	3	3	3	3	3	3	3	3	3	3	3	3
Japan	4	4	4	4	4	5	5	5	5	5	5	5
Canada	7	7	7	7	7	7	7	7	7	7	7	7

meet customer expectations are preferred over their competitors because they can satisfy customers. On the other hand, Joof *et al.* (2024) and Sandri *et al.* (2024) highlighted that customer feedback also supports the creation of innovative solutions on account of REPs. This can seriously help the development of the technological infrastructure of businesses.

The prominence of customer-centric expectations and real-time financial measurements can be explained by the increasing role of knowledge-based dynamics in renewable energy systems. In knowledge-driven energy markets, consumers are no longer passive users but active participants who influence investment decisions through their preferences, feedback, and demand for sustainable solutions. Therefore, aligning renewable energy projects with customer expectations enhances market acceptance and long-term project viability. In addition, real-time financial measurement systems enable continuous monitoring of project performance, allowing investors to respond quickly to market fluctuations, operational inefficiencies, and risk factors. This is particularly critical in renewable energy investments, which are characterized by high initial costs and uncertain returns. These findings are consistent with the broader energy economics literature, which emphasizes the importance of digitalization, financial transparency, and consumer-oriented strategies in improving energy efficiency and investment performance. Hence, the results highlight that both market responsiveness and financial adaptability are key drivers of competency in knowledge-based renewable energy systems.

The financial success analysis of the projects must be carried out comprehensively to improve the competencies of REPs. For businesses to focus on REPs, these investments must be financially successful. In this context, financial analysis helps businesses manage costs and increase financial efficiency. This contributes significantly to increasing the profitability of projects. Uyar *et al.* (2024), Abdelsattar *et al.* (2024a), Abdelsattar *et al.* (2024b) and Kwilinski *et al.* (2024) underlined that effective risk management also supports increasing the financial success of projects. In this framework, the main risks of the projects are clearly determined. Thanks to this analysis, it is possible to implement effective measures against these risks in a timely manner. Rizki and Suprapto (2024), Hafez and Elbaset (2023) and Muslu and Isik (2024) concluded that this enables minimizing financial problems arising from not being able to manage risks. High financial success of projects also helps establish healthier relationships with investors. Abdelsattar *et al.* (2022) stated that maximizing net savings is a way to minimize costs. Willys *et al.* (2025) defined that the biggest problem of these projects is that the beginning investment amount is very big. Considering this situation, high financial success for businesses allows this problem to be solved more successfully.

5.1. *Managerial Implications*

The findings of this study provide several important managerial implications for decision makers and practitioners in the renewable energy sector. First, the results highlight the critical role of customer-centric expectations and real-time financial monitoring in enhancing investment competencies, suggesting that managers should prioritize digital tools and feedback mechanisms to better align projects with market needs. Second, the proposed integrated framework enables decision makers to systematically evaluate complex and interdependent criteria, thereby supporting more informed and data-driven investment strategies. Third, the incorporation of artificial intelligence in weighting decision makers reduces subjective bias and improves the reliability of strategic evaluations. Finally, the model offers a flexible decision-support tool that can be adapted to different organizational and national contexts, assisting policymakers and investors in optimizing renewable energy project performance under uncertainty.

6. Conclusion

This study evaluates REI competencies by proposing a new AI-based fuzzy decision-making model that has two models. In the first stage, the DMs are prioritized by creating decision matrix with AI methodology. In the following stage, selected REI competencies are weighted by using QSF Bayesian Network. Finally, G7 economies are ranked with QSF WASPAS. According to the results, meeting customer expectations is of great importance in developing the competencies of REPs. In this way, the basic needs of the renewable energy market can be met. Similarly, it is also found that the financial success analysis of the projects must be carried out comprehensively to improve the competencies of REPs.

For businesses to focus on REPs, these investments must be financially successful. In this context, financial analysis helps businesses manage costs and increase financial efficiency.

Although the proposed framework is demonstrated using G7 economies, it has a flexible and adaptable structure that allows its application to different contexts. The integrated use of artificial intelligence, quantum spherical fuzzy sets, and Bayesian networks enables the model to handle various types of uncertainty, making it suitable for developing economies where data limitations and higher uncertainty levels are more prevalent. In addition, the framework can be extended to different sectors beyond renewable energy, such as sustainable finance, smart infrastructure, and circular economy investments. The methodology can also be adapted to evaluate other sustainability-related decision problems that require the integration of expert judgment and complex criteria structures. Therefore, the proposed model has significant potential to contribute to broader decision science applications and policy analysis in both developed and developing contexts.

The weights of the DMs can be determined based on their demographic indicators. This condition has a benefit contribution to the accuracy and effectiveness of the analysis results. Moreover, considering Bayesian network methodology provides few advantages to the proposed model. Therefore, the impact relation map should be considered to define the most important criteria. The limitation of the article is that only criteria weighting is conducted in the analysis process. In this context, there is no alternative ranking process in the model. Hence, regarding the future research direction, a country group can be evaluated based on the success of renewable energy competencies. There are also some limitations of the proposed model. Bayesian Network methodology is taken into consideration in the evaluation process. Nevertheless, this approach is criticized because of some reasons in the literature. Thus, some improvements can be made for this technique in the following studies to overcome these criticisms.

Abbreviations

AI – Artificial Intelligence
BN – Bayesian Network
QSF – Quantum Spherical Fuzzy
QSFS – Quantum Spherical Fuzzy Sets
MCDM – Multi-Criteria Decision Making
DM – Decision Maker
REI – Renewable Energy Investment
REP – Renewable Energy Project
WASPAS – Weighted Aggregated Sum Product Assessment
SAW – Simple Additive Weighting
WPM – Weighted Product Model
WCSS – Within-Cluster Sum of Squares
K-means – K-means Clustering Algorithm
QSFN – Quantum Spherical Fuzzy Number
IG – Information Gain
SD – Standard Deviation

A. Appendix

Table A1
The WS.

K:1		K:2		K:3		K:4		K:5		K:6	
First cluster	Values	First cluster	Values	First cluster	Values	First cluster	Values	First cluster	Values	First cluster	Values
DM1	2.11	DM1	3.78	DM1	8.50	DM1	0	DM1	0	DM1	0
DM2	16.78	DM4	6.44	DM6	8.50	Second cluster	Values	Second cluster	Values	Second cluster	Values
DM3	.11	DM6	16.44	Second cluster	Values	DM2	0	DM2	0	DM2	0
DM4	4.11	Second cluster	Values	DM2	1.50	Third cluster	Values	Third cluster	Values	Third cluster	Values
DM5	4.78	DM2	12.44	DM4	1.50	DM3	1.00	DM3	0	DM3	0
DM6	21.44	DM3	.78	Third cluster	Values	DM5	1.00	Fourth cluster	Values	Fourth cluster	Values
		DM5	7.44	DM3	1.00	Fourth cluster	Values	DM4	0	DM4	0
				DM5	1.00	DM4	1.50	Fifth cluster	Values	Fifth cluster	Values
						DM6	1.50	DM5	1.75	DM5	0
								DM6	1.75	Sixth cluster	Values
Sum	49.33	Sum	47.33	Sum	22.00	Sum	23.00	Sum	3.50	DM6	0

Table A2
The results of clustering.

DMs	C1	C2	C3	Cluster assignment
		Initial Cluster Centers (Distances)		
DM1	.00	3.16	1.73	1
DM2	3.16	.00	4.36	2
DM3	1.73	4.36	.00	3
DM4	2.00	2.45	2.24	1
DM5	3.32	6.24	2.00	3
DM6	5.83	8.72	4.36	3
		Average of Data Points (Distances)		
DM1	1.00	3.16	3.56	1
DM2	2.65	.00	6.43	2
DM3	1.73	4.36	2.08	3
DM4	1.00	2.45	4.24	1
DM5	3.61	6.24	.58	3
DM6	6.08	8.72	2.31	3

Iteration (First Decision Maker is in the First Cluster; Second Decision Maker is in the Second Cluster; last Decision Maker is in another cluster).

Table A3
The weights and standard deviations.

Centers	Number of members	Edu	Exp	Expertise	Position	SD	W
C1	2	.50	.50	.50	.50	.50	1.00
C2	1	.00	.00	.00	.00	.00	.00
C3	3	.47	1.63	.47	.47	.76	2.29

Table A4
Linguistic variable and QSFNs.

Linguistic variables		Degrees	Scale	QSFNs
No (n)	Worst (W)	.40	1	$\left[\sqrt{.16}e^{j2\pi..4}, \sqrt{.10}e^{j2\pi..25}, \sqrt{.74}e^{j2\pi..35}\right]$
Somewhat (s)	Poor (P)	.45	2	$\left[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}\right]$
Medium (m)	Fair (F)	.50	3	$\left[\sqrt{.25}e^{j2\pi..50}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..19}\right]$
High (h)	Good (G)	.55	4	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
Very high (vh)	Best (B)	.60	5	$\left[\sqrt{.36}e^{j2\pi..6}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$

Table A5
Opinions of DMs.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
						Decision Maker 1						
CSTMNG		N	VH	H	S	H	H	H	VH	M	VH	M
RTFINMEA	H		S	N	H	S	S	VH	M	N	M	H
GLINSCO	VH	S		S	M	H	S	H	S	S	H	M
CUSEXP	M	H	S		VH	M	VH	H	VH	VH	M	H
CYBSEC	M	VH	S	VH		H	H	M	H	M	M	M
CLOTECH	H	M	H	H	H		H	H	H	H	H	M
TECHDIV	VH	M	VH	VH	H	VH		VH	VH	M	M	H
RENSYSINT	M	H	H	M	VH	M	M		VH	H	H	M
DECDATAMNG	H	VH	VH	M	M	H	VH	H		H	M	H
INCINN	H	H	M	M	M	M	M	M	M		H	H
AUTOSUPP	VH	VH	M	M	H	H	H	VH	H	M		H
KNOWTRNSF	H	M	M	S	S	M	M	M	M	H	H	
						Decision Maker 3						
CSTMNG		N	VH	M	VH	H	H	H	VH	M	VH	M
RTFINMEA	H		S	H	M	S	S	M	VH	H	M	H
GLINSCO	VH	S		VH	M	H	S	H	M	VH	M	M
CUSEXP	M	H	S		VH	M	VH	VH	M	M	VH	H
CYBSEC	M	VH	S	VH		H	H	M	H	H	M	M
CLOTECH	H	M	H	H	H		H	H	H	VH	M	VH
TECHDIV	VH	M	VH	VH	H	VH		VH	VH	M	M	VH
RENSYSINT	M	VH	M	VH	VH	M	M		VH	H	H	M

(*continued on next page*)

Table A5
(*continued*)

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
DECDATAMNG	H	M	H	M	M	H	VH	H		H	VH	M
INCINN	VH	M	VH	M	M	M	M	M	M		H	H
AUTOSUPP	VH	VH	M	M	H	H	H	VH	H	M		H
KNOWTRNSF	H	M	M	S	S	M	M	M	M	H	H	
Decision Maker 4												
CSTMNG		S	VH	H	M	M	H	H	M	M	H	M
RTFINMEA	H		S	N	M	M	M	M	M	M	M	H
GLINSCO	VH	S		S	M	H	H	M	M	H	H	M
CUSEXP	M	H	S		S	S	M	M	S	S	M	H
CYBSEC	M	VH	S	VH		H	H	M	M	M	M	H
CLOTECH	M	M	H	H	H		H	M	H	H	M	M
TECHDIV	M	M	M	VH	H	VH		S	S	M	H	H
RENSYSINT	M	H	H	M	VH	M	M		VH	S	S	M
DECDATAMNG	S	S	M	M	M	H	VH	H		H	M	H
INCINN	H	H	M	M	M	M	M	M	M		H	H
AUTOSUPP	VH	VH	M	M	H	H	H	VH	H	M		H
KNOWTRNSF	H	M	M	S	S	M	M	M	M	H	H	
Decision Maker 5												
CSTMNG		S	VH	H	M	VH	H	H	M	M	VH	H
RTFINMEA	H		S	N	H	S	VH	M	M	H	S	VH
GLINSCO	VH	S		S	VH	S	M	M	M	VH	S	M
CUSEXP	M	H	S		M	H	M	M	S	M	H	M
CYBSEC	M	VH	S	VH		H	H	M	M	M	M	H
CLOTECH	M	M	H	H	H		H	M	H	M	VH	H
TECHDIV	M	M	M	VH	H	VH		S	S	H	M	VH
RENSYSINT	M	M	H	S	VH	M	M		VH	VH	H	S
DECDATAMNG	S	M	VH	S	M	H	VH	H		M	VH	S
INCINN	H	M	M	H	M	M	M	M	M		M	H
AUTOSUPP	VH	M	M	M	H	H	H	VH	H	M		H
KNOWTRNSF	H	M	H	H	S	M	M	M	M	H	H	
Decision Maker 6												
CSTMNG		S	VH	M	M	VH	VH	H	M	M	M	VH
RTFINMEA	H		S	M	S	M	M	M	M	M	S	M
GLINSCO	VH	S		M	M	M	M	M	M	M	M	M
CUSEXP	M	H	S		M	H	M	M	S	M	H	M
CYBSEC	S	M	H	VH		H	H	M	M	M	M	H
CLOTECH	M	M	M	H	H		H	M	H	S	M	H
TECHDIV	M	S	M	H	H	VH		S	S	M	M	M
RENSYSINT	S	M	H	M	VH	M	M		VH	S	M	H
DECDATAMNG	M	M	M	M	H	H	VH	H		M	M	M
INCINN	S	M	H	M	M	M	M	M	M		M	H
AUTOSUPP	M	M	M	M	S	M	H	S	M	H		H
KNOWTRNSF	H	M	H	H	M	M	M	M	M	M	H	

Table A6
Average matrix.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH
CSTMNG		$\left[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}\right]$	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
RTFINMEA	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$		$\left[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}\right]$	$\left[\sqrt{.22}e^{j2\pi..47}, \sqrt{.14}e^{j2\pi..29}, \sqrt{.64}e^{j2\pi..24}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.22}e^{j2\pi..47}, \sqrt{.14}e^{j2\pi..29}, \sqrt{.64}e^{j2\pi..24}\right]$
GLINSCO	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$	$\left[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}\right]$		$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$
CUSEXP	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}\right]$		$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$
CYBSEC	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.46}e^{j2\pi..09}\right]$	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$		$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
CLOTECH	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	
TECHDIV	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.46}e^{j2\pi..09}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$
RENSYSINT	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$
DECDATAMNG	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
INCINN	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$
AUTOSUPP	$\left[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.46}e^{j2\pi..09}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$
KNOWTRNSF	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.22}e^{j2\pi..47}, \sqrt{.14}e^{j2\pi..29}, \sqrt{.64}e^{j2\pi..24}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$

	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
CSTMNG	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.46}e^{j2\pi..09}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$
RTFINMEA	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
GLINSCO	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$

(continued on next page)

Table A6
(*continued*)

	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
CUSEXP	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$
CYBSEC	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$
CLOTECH	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.27}e^{j2\pi..51}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..22}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
TECHDIV		$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
RENSYSINT	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$		$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$
DECDATAMNG	$\left[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$		$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$
INCINN	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$		$\left[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
AUTOSUPP	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	$\left[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.46}e^{j2\pi..09}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$		$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$
KNOWTRNSF	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.26}e^{j2\pi..50}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..23}\right]$	$\left[\sqrt{.29}e^{j2\pi..54}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..15}\right]$	$\left[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}\right]$	

Table A7
Defuzzification values.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
CSTMNG	.000	1.243	1.236	1.244	1.266	1.257	1.242	1.236	1.268	1.118	1.261	1.257
RTFINMEA	1.236	.000	1.236	1.284	1.253	1.243	1.273	1.257	1.257	1.271	1.243	1.250
GLINSCO	1.236	1.236	.000	1.278	1.257	1.256	1.253	1.244	1.241	1.280	1.253	1.236
CUSEXP	1.236	1.236	1.236	.000	1.282	1.253	1.268	1.257	1.278	1.266	1.255	1.244
CYBSEC	1.241	1.263	1.256	1.236	.000	1.236	1.236	1.236	1.244	1.241	1.236	1.244
CLOTECH	1.244	1.236	1.241	1.236	1.236	.000	1.236	1.244	1.236	1.269	1.257	1.255
TECHDIV	1.268	1.241	1.268	1.245	1.236	1.236	.000	1.301	1.301	1.241	1.241	1.257
RENSYSINT	1.241	1.255	1.241	1.266	1.236	1.236	1.236	.000	1.236	1.280	1.256	1.248
DECDATAMNG	1.260	1.266	1.264	1.241	1.241	1.236	1.236	1.236	.000	1.244	1.268	1.253
INCINN	1.267	1.244	1.257	1.241	1.236	1.236	1.236	1.236	1.236	.000	1.244	1.236
AUTOSUPP	1.263	1.271	1.236	1.236	1.256	1.241	1.236	1.288	1.241	1.241	.000	1.236
KNOWTRNSF	1.236	1.236	1.244	1.265	1.241	1.236	1.236	1.236	1.236	1.241	1.236	.000

Table A8
Normalization values.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
CSTMNG	.000	.090	.089	.090	.092	.091	.090	.089	.092	.081	.091	.091
RTFINMEA	.089	.000	.089	.093	.091	.090	.092	.091	.091	.092	.090	.090
GLINSCO	.089	.089	.000	.092	.091	.091	.091	.090	.090	.093	.091	.089
CUSEXP	.089	.089	.089	.000	.093	.091	.092	.091	.092	.092	.091	.090
CYBSEC	.090	.091	.091	.089	.000	.089	.089	.089	.090	.090	.089	.090
CLOTECH	.090	.089	.090	.089	.089	.000	.089	.090	.089	.092	.091	.091
TECHDIV	.092	.090	.092	.090	.089	.089	.000	.094	.094	.090	.090	.091
RENSYSINT	.090	.091	.090	.092	.089	.089	.089	.000	.089	.093	.091	.090
DECDATAMNG	.091	.092	.091	.090	.090	.089	.089	.089	.000	.090	.092	.091
INCINN	.092	.090	.091	.090	.089	.089	.089	.089	.089	.000	.090	.089
AUTOSUPP	.091	.092	.089	.089	.091	.090	.089	.093	.090	.090	.000	.089
KNOWTRNSF	.089	.089	.090	.091	.090	.089	.089	.089	.089	.090	.089	.000

Table A9
Average fuzzy values for alternatives.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH
Germany	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.29}e^{j2\pi..54},\\ \sqrt{.18}e^{j2\pi..33},\\ \sqrt{.54}e^{j2\pi..15}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.36}e^{j2\pi..60},\\ \sqrt{.22}e^{j2\pi..37},\\ \sqrt{.42}e^{j2\pi..03}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.36}e^{j2\pi..60},\\ \sqrt{.22}e^{j2\pi..37},\\ \sqrt{.42}e^{j2\pi..03}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.24}e^{j2\pi..48},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..22}\end{bmatrix}$
U.S.	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.24}e^{j2\pi..48},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..22}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.24}e^{j2\pi..48},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..22}\end{bmatrix}$
U.K.	$\begin{bmatrix}\sqrt{.28}e^{j2\pi..52},\\ \sqrt{.16}e^{j2\pi..32},\\ \sqrt{.58}e^{j2\pi..19}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.24}e^{j2\pi..48},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..22}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.20}e^{j2\pi..45},\\ \sqrt{.13}e^{j2\pi..28},\\ \sqrt{.67}e^{j2\pi..27}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.22}e^{j2\pi..47},\\ \sqrt{.14}e^{j2\pi..29},\\ \sqrt{.64}e^{j2\pi..24}\end{bmatrix}$
Italy	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.27}e^{j2\pi..51},\\ \sqrt{.15}e^{j2\pi..31},\\ \sqrt{.60}e^{j2\pi..22}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.29}e^{j2\pi..54},\\ \sqrt{.18}e^{j2\pi..33},\\ \sqrt{.54}e^{j2\pi..15}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.28}e^{j2\pi..52},\\ \sqrt{.16}e^{j2\pi..32},\\ \sqrt{.58}e^{j2\pi..19}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.22}e^{j2\pi..47},\\ \sqrt{.14}e^{j2\pi..29},\\ \sqrt{.64}e^{j2\pi..24}\end{bmatrix}$
France	$\begin{bmatrix}\sqrt{.28}e^{j2\pi..52},\\ \sqrt{.16}e^{j2\pi..32},\\ \sqrt{.58}e^{j2\pi..19}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.34}e^{j2\pi..58},\\ \sqrt{.21}e^{j2\pi..36},\\ \sqrt{.46}e^{j2\pi..09}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.22}e^{j2\pi..47},\\ \sqrt{.14}e^{j2\pi..29},\\ \sqrt{.64}e^{j2\pi..24}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$
Japan	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.36}e^{j2\pi..60},\\ \sqrt{.22}e^{j2\pi..37},\\ \sqrt{.42}e^{j2\pi..03}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.26}e^{j2\pi..50},\\ \sqrt{.14}e^{j2\pi..30},\\ \sqrt{.62}e^{j2\pi..23}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.34}e^{j2\pi..58},\\ \sqrt{.21}e^{j2\pi..36},\\ \sqrt{.46}e^{j2\pi..09}\end{bmatrix}$
Canada	$\begin{bmatrix}\sqrt{.20}e^{j2\pi..45},\\ \sqrt{.13}e^{j2\pi..28},\\ \sqrt{.67}e^{j2\pi..27}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.28}e^{j2\pi..52},\\ \sqrt{.16}e^{j2\pi..32},\\ \sqrt{.58}e^{j2\pi..19}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.36}e^{j2\pi..60},\\ \sqrt{.22}e^{j2\pi..37},\\ \sqrt{.42}e^{j2\pi..03}\end{bmatrix}$	$\begin{bmatrix}\sqrt{.30}e^{j2\pi..55},\\ \sqrt{.19}e^{j2\pi..34},\\ \sqrt{.51}e^{j2\pi..11}\end{bmatrix}$

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Table A9
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	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
Germany	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.28}e^{j2\pi..52}, \\ \sqrt{.16}e^{j2\pi..32}, \\ \sqrt{.58}e^{j2\pi..19} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.29}e^{j2\pi..54}, \\ \sqrt{.18}e^{j2\pi..33}, \\ \sqrt{.54}e^{j2\pi..15} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.29}e^{j2\pi..54}, \\ \sqrt{.18}e^{j2\pi..33}, \\ \sqrt{.54}e^{j2\pi..15} \end{bmatrix}$
U.S.	$\begin{bmatrix} \sqrt{.27}e^{j2\pi..51}, \\ \sqrt{.15}e^{j2\pi..31}, \\ \sqrt{.60}e^{j2\pi..22} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.28}e^{j2\pi..52}, \\ \sqrt{.16}e^{j2\pi..32}, \\ \sqrt{.58}e^{j2\pi..19} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.27}e^{j2\pi..51}, \\ \sqrt{.15}e^{j2\pi..31}, \\ \sqrt{.60}e^{j2\pi..22} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$
U.K.	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.36}e^{j2\pi..60}, \\ \sqrt{.22}e^{j2\pi..37}, \\ \sqrt{.42}e^{j2\pi..03} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.28}e^{j2\pi..52}, \\ \sqrt{.16}e^{j2\pi..32}, \\ \sqrt{.58}e^{j2\pi..19} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.28}e^{j2\pi..52}, \\ \sqrt{.16}e^{j2\pi..32}, \\ \sqrt{.58}e^{j2\pi..19} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$
Italy	$\begin{bmatrix} \sqrt{.28}e^{j2\pi..52}, \\ \sqrt{.16}e^{j2\pi..32}, \\ \sqrt{.58}e^{j2\pi..19} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.24}e^{j2\pi..48}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..22} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.36}e^{j2\pi..60}, \\ \sqrt{.22}e^{j2\pi..37}, \\ \sqrt{.42}e^{j2\pi..03} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$
France	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.29}e^{j2\pi..54}, \\ \sqrt{.18}e^{j2\pi..33}, \\ \sqrt{.54}e^{j2\pi..15} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$
Japan	$\begin{bmatrix} \sqrt{.20}e^{j2\pi..45}, \\ \sqrt{.13}e^{j2\pi..28}, \\ \sqrt{.67}e^{j2\pi..27} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.24}e^{j2\pi..48}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..22} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$
Canada	$\begin{bmatrix} \sqrt{.24}e^{j2\pi..48}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..22} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.36}e^{j2\pi..60}, \\ \sqrt{.22}e^{j2\pi..37}, \\ \sqrt{.42}e^{j2\pi..03} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.36}e^{j2\pi..60}, \\ \sqrt{.22}e^{j2\pi..37}, \\ \sqrt{.42}e^{j2\pi..03} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.30}e^{j2\pi..55}, \\ \sqrt{.19}e^{j2\pi..34}, \\ \sqrt{.51}e^{j2\pi..11} \end{bmatrix}$	$\begin{bmatrix} \sqrt{.26}e^{j2\pi..50}, \\ \sqrt{.14}e^{j2\pi..30}, \\ \sqrt{.62}e^{j2\pi..23} \end{bmatrix}$

Table A10
Defuzzification values for decision matrix.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
Germany	1.271	1.264	1.241	1.236	1.236	1.186	1.241	1.278	1.269	1.299	1.269	1.282
U.S.	1.242	1.231	1.273	1.253	1.241	1.243	1.244	1.257	1.273	1.282	1.248	1.253
U.K.	1.244	1.268	1.256	1.236	1.239	1.241	1.236	1.245	1.244	1.298	1.244	1.260
Italy	1.248	1.244	1.282	1.203	1.257	1.243	1.301	1.236	1.243	1.264	1.241	1.280
France	1.257	1.261	1.210	1.241	1.271	1.236	1.271	1.236	1.253	1.287	1.269	1.268
Japan	1.236	1.236	1.236	1.236	1.236	1.263	1.239	1.278	1.236	1.298	1.243	1.268
Canada	1.239	1.242	1.242	1.257	1.236	1.242	1.281	1.236	1.236	1.236	1.250	1.285

Table A11
Normalized values for decision matrix.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
Germany	.385	.382	.376	.377	.375	.362	.373	.386	.383	.383	.383	.381
U.S.	.376	.372	.385	.383	.377	.380	.373	.379	.385	.378	.377	.373
U.K.	.377	.384	.380	.377	.376	.379	.371	.376	.376	.383	.375	.375
Italy	.378	.376	.388	.367	.382	.380	.391	.373	.376	.373	.375	.381
France	.381	.381	.366	.379	.386	.378	.381	.373	.379	.380	.383	.377
Japan	.374	.374	.374	.377	.375	.386	.372	.386	.374	.383	.375	.377
Canada	.375	.376	.376	.384	.375	.380	.385	.373	.374	.365	.377	.382

Table A12
Weighted values for decision matrix.

	CSTMNG	RTFINMEA	GLINSCO	CUSEXP	CYBSEC	CLOTECH	TECHDIV	RENSYSINT	DECDATAMNG	INCINN	AUTOSUPP	KNOWTRNSF
Germany	.032	.032	.031	.031	.031	.030	.031	.032	.032	.032	.032	.032
U.S.	.031	.031	.032	.032	.031	.032	.031	.032	.032	.032	.031	.031
U.K.	.031	.032	.032	.031	.031	.032	.031	.031	.031	.032	.031	.031
Italy	.031	.031	.032	.031	.032	.032	.033	.031	.031	.031	.031	.032
France	.032	.032	.031	.032	.032	.031	.032	.031	.032	.032	.032	.031
Japan	.031	.031	.031	.031	.031	.032	.031	.032	.031	.032	.031	.031
Canada	.031	.031	.031	.032	.031	.032	.032	.031	.031	.030	.031	.032

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