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Enhancing Green Energy Investments through Customer-Centric Innovation Strategies

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Abstract. The purpose of this study is to evaluate the significant dimensions of customer-centric innovation in renewable energy projects. We construct a novel fuzzy decision-making model to address this objective. In the first stage, significant indicators are identified using balanced scorecard-based determinants and weighted through the multi-step wise weight assessment ratio analysis (M-SWARA) method integrated with quantum spherical fuzzy sets. In the second stage, the energy efficiency of renewable energy alternatives is assessed for customer-centric innovation performance via technique for order preference by similarity to ideal solution (TOPSIS). We offer priority strategies for green energy investors to enhance customer-centric innovation with more reasonable costs. Methodologically, the proposed model provides important advantages by effectively handling uncertainty through quantum spherical fuzzy structures, incorporating the golden ratio in degree calculations, and capturing interdependencies among criteria through the improved M-SWARA approach. The findings reveal that customization is the most critical indicator for improving customer-centric innovation performance, followed by efficiency, while optimization and innovation have relatively lower importance. The ranking results indicate that solar energy projects demonstrate the highest performance in managing customer-centric innovation, followed by wind and geothermal energy alternatives.

Key words: green energy, energy finance, strategic innovation, performance assessment.

1. Introduction

Energy is becoming increasingly vital as a key resource for modern life. It plays a central role in raising living standards and supporting sustainable economic development. The method of energy production is critical to achieving sustainability goals. Fossil fuel-based energy generation significantly damages natural resources and intensifies environmental degradation (Lorente *et al.*, 2023). Therefore, electricity must be generated through

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cleaner and more environmentally friendly sources. Otherwise, pollution caused by fossil fuels will continue to hinder sustainability objectives. Despite their advantages, renewable energy alternatives also present certain challenges. Energy generation from many renewable sources is highly dependent on climatic conditions, which may lead to fluctuations and interruptions in supply. However, uninterrupted electricity production is essential for economic activities, particularly industrial production (Amin *et al.*, 2022). For this reason, effective measures must be implemented to ensure reliability and stability in energy generation. Effective demand management is another critical issue in this process. Both individual and institutional energy consumption must be carefully analysed. With the acceleration of globalization, energy demand has increased substantially. When this demand is not properly met, consumer dissatisfaction may arise (Lotfabadi *et al.*, 2022). Insufficient electricity supply disrupts production processes and negatively affects national economic performance. Conversely, excessive electricity generation reduces operational efficiency for energy companies. Therefore, accurate planning of customer-centric innovation is crucial for maintaining profitability in renewable energy investments. Difficulties in balancing supply and demand decrease investment efficiency (Abedrabboh *et al.*, 2022). Hence, energy supply-demand analysis should guide strategic decisions and policy formulation in advance.

In this context, the transition toward renewable energy investments does not merely represent a technological shift but also requires a transformation in value creation logic. Green energy companies increasingly operate in competitive and customer-sensitive markets where reliability, flexibility, and responsiveness shape customer satisfaction. Therefore, renewable energy investments must be aligned with customer-centric innovation principles. Rather than focusing solely on energy production capacity, firms must design systems that anticipate demand patterns, integrate smart technologies, and create value through adaptive service models. This perspective establishes a conceptual bridge between sustainability-driven energy investments and customer-oriented innovation strategies. Companies aiming to strengthen customer-centric innovation in clean energy investments must consider several strategic factors. Efficiency is one of the most important dimensions. The use of equipment that completes processes in shorter periods improves overall production performance. In addition, electricity consumption must be optimized through accurate forecasting and timing (Rusu, 2022). Providing the required energy at the right time enhances operational effectiveness. Smart technologies further enable energy systems to respond to customer expectations more precisely. Customer-centric energy generation strategies can significantly improve efficiency. Moreover, advanced technological applications help reduce disruptions in renewable energy investments (Mungai *et al.*, 2022). As a result, production interruptions can be minimized, and customer satisfaction can be enhanced.

However, improving customer-centric innovation requires additional investments. Every strategic improvement increases operational costs. Therefore, it is not optimal for firms to invest equally in all variables affecting performance. Instead, businesses must identify the most critical determinants and allocate their resources efficiently. Conducting a priority analysis becomes essential in this context. The results of such an analysis enable firms to implement the most appropriate strategies to enhance customer-centric innovation performance (Abbasi *et al.*, 2022). Consequently, renewable energy companies can achieve more effective outcomes by using their operating budgets more strategically. Accordingly, this study aims to analyse energy efficiency for customer-centric innovation. In this study, the concept of energy efficiency for customer-centric innovation refers to a dual perspective. First, it involves the efficient generation, storage, and distribution of energy to meet dynamic customer demand with minimal waste and operational loss. Second, it encompasses the efficiency of innovation processes that enhance responsiveness, technological adaptability, and service quality. Therefore, the term does not solely refer to technical energy efficiency but also includes strategic and operational efficiency in delivering customer-oriented energy solutions. This integrated understanding aligns energy performance with innovation capability and customer value creation. First, significant indicators are identified by using Balanced Scorecard (BNSD) determinants. These items are evaluated with M-SWARA method with Quantum Spherical fuzzy sets (QSFNs). Secondly, the energy efficiency of the renewable alternatives is examined for customer-centric innovation. For this purpose, TOPSIS with QSFNs is used to rank five different clean energy alternatives.

Although fuzzy extensions of SWARA and TOPSIS have been widely applied in sustainability and energy-related decision-making problems, most existing models treat uncertainty and weighting procedures separately and assume limited interaction among criteria. Classical fuzzy SWARA approaches primarily focus on subjective weight determination without explicitly modelling causal interdependencies. Similarly, fuzzy TOPSIS extensions improve ranking robustness under uncertainty but often rely on predetermined weights derived from independent criteria structures. In contrast, the present study integrates an improved M-SWARA model capable of capturing causal relationships among determinants and combines it with quantum spherical fuzzy structures to enhance uncertainty representation. This integrated framework moves beyond incremental fuzzy extensions by simultaneously addressing interdependence, proportional balance, and uncertainty within a unified decision architecture. The main novelties of this study are demonstrated as follows.

(i) Priority strategies will be offered to green energy investors for effective customer-centric innovation. All improvements to be made by green energy companies to further improve customer-centric innovation cause an increase in costs. Therefore, making improvements for many factors creates excessive costs for businesses. In this context, more important issues can be determined with the results of the analysis of this study. In this framework, it will be possible to activate customer-centric innovation with more reasonable costs. In this study, customer-centric innovation refers to the development and implementation of technological, operational, and strategic solutions that prioritize customer needs, demand responsiveness, and value co-creation in energy systems. Drawing from innovation theory and service management literature, customer-centric innovation extends beyond product improvement and emphasizes the design of adaptive systems that enhance customer experience, reliability, and perceived value. In the renewable energy context, this concept involves aligning technological development, demand forecasting, optimization processes, and service flexibility to ensure that energy generation systems respond effectively to dynamic customer expectations.

(ii) The ranking of different renewable energy alternatives according to customer-centric innovation performance is one of the important contributions of the study. In this way, it will be possible to understand which type of green energy is more successful in customer-centric innovation. Thus, improvement strategies will be presented for energy types with low performance. Moreover, investors will be directed to renewable energy alternatives that are determined to be more successful.

(iii) The use of the balanced scorecard technique in criterion selection also provides some advantages. The perspectives in this approach consider both financial and non-financial factors (Mio *et al.*, 2022). In this way, it is possible to analyse with a more comprehensive set of criteria (Elbanna *et al.*, 2022). This also contributes to a more effective priority analysis (Agarwal *et al.*, 2022).

(iv) There are also many methodological advantages in this study. While criterion weights can be calculated in the classical SWARA method, the causality relationship between these factors cannot be determined (Mardani *et al.*, 2017). On the other hand, the factors that determine the effectiveness of customer-centric innovation may have effects on each other. For example, the use of machines that complete their task quickly can both increase efficiency and help the timing of electricity consumption to be done more successfully. In this context, some improvements have been made on the classical SWARA method in this study. Thus, a new technique called M-SWARA has been developed. In this way, both strategies will be produced more accurately, and the methodological originality of the study will be ensured.

(v) Integrating Spherical fuzzy numbers with quantum theory also increases both the originality and effectiveness of the developed model. Thanks to quantum theory, different possibilities can be taken into consideration in the analysis process. In addition, Spherical fuzzy numbers allow different parameters such as hesitancy to be used (Liu and Wang, 2022). To achieve success in the developed decision-making models, it is necessary to integrate the issues that consider complex problems into the model. Otherwise, the developed model will be insufficient to solve decision making problems (Munir *et al.*, 2021). In this context, it will be possible to reach more accurate results thanks to this integration made in this model.

(vi) One of the frequently discussed issues in decision making methods is how the degrees are calculated. In the model developed in this study, golden ratio is used in calculating the degrees of Spherical fuzzy sets. Since this is an original calculation method, it is thought to contribute to the literature. Furthermore, it will be possible to obtain more accurate results in this way.

Literature evaluation is conducted in the next part. The proposed model is explained in the third section. The following section includes analysis results. Discussions and conclusions are provided in the final sections.

2. Literature Review

There are different factors that affect the efficiency of customer-centric innovation of renewable energy enterprises. Businesses should pay attention to productivity-enhancing issues to ensure effective customer-centric innovation. Nair *et al.* (2022) stated that businesses should prefer equipment that completes the process in less time. Owing to this equipment, energy production will be completed in a much shorter time. According to Lankeshwara *et al.* (2022), businesses will be able to produce the required amount of energy on time. This will contribute to meeting energy demands more successfully. Thirunavukkarasu *et al.* (2022) and Ang *et al.* (2022) concluded that materials that will provide more efficiency should be used in the energy production process. It will be possible to produce more energy at the same time. Zahedi *et al.* (2022) and Torkan *et al.* (2022) also identified that it will be possible to obtain the demanded amount of energy more easily. Rajan and Jeevananthan (2022) and Tan *et al.* (2022) underlined that efficiency can be increased with the use of solar panels, which can generate more electricity from sunlight. This will contribute to the successful implementation of customer-centric innovation.

The timing of electricity consumption must be done correctly to manage the customer-centric innovation successfully. In this process, it is important to make the necessary analyses to predict the amount of electricity consumption in advance. According to Cirocco *et al.* (2022) and Elavarasan *et al.* (2021), population growth in the country is a variable that should be taken into consideration in this process. The more the population increases in a country, the more demand for electricity will increase. Moreover, Haq *et al.* (2022) and Hu *et al.* (2022) also concluded that the economic situation of the country is a factor that is directly proportional to the electricity consumption forecast. It is expected to increase its investments in a country with a better economic performance. This will lead to an increase in electricity consumption. Tang *et al.* (2022) discussed that renewable energy enterprises can also make energy consumption forecasts for their customers. Härkönen *et al.* (2022) and Wei *et al.* (2022) identified that considering the energy demands of the customers in the past years, it will be possible to understand how much energy they will need in the future. Thus, it will be possible to manage the customer-centric innovation more successfully.

Innovative implementations can also increase the performance of customer-centric innovation of green energy companies. Especially thanks to data mining-style applications, it is possible to perform customer-centric innovation more successfully. Bedi *et al.* (2022) discussed that demand in energy markets can be very volatile. This situation can cause green energy companies to have difficulties in managing this variable demand. Siddiqui *et al.* (2022) and Mellouk *et al.* (2019) determined that unexpected and instantaneous power plant failures may occur. This situation can cause problems in energy demand management, and businesses should take the necessary measures to solve such problems quickly. Gunarathna *et al.* (2022) and Aragón *et al.* (2022) stated that unpredictable changes in the amount of consumption that customers can create may also cause imbalances on the demand side. Owing to smart technologies, these imbalances can be controlled instantly.

New technologies can also increase the success of renewable energy companies in customer-centric innovation. Being affected by climate differences is a drawback of green energy projects. Oliinyk *et al.* (2022) defined that in some cases, while excess energy is produced, sometimes the amount of energy produced cannot meet the need and will adversely affect the success of renewable energy companies in customer-centric innovation. Mojumder *et al.* (2022) and Benmouna *et al.* (2021) determined that new technologies can solve these problems. Energy storage applications are vital in this process. Owing to this new technology, excess energy will be stored, and this will contribute to the more successful demand management of renewable energy projects (Härkönen *et al.*, 2022). Cheekatamarla *et al.* (2022) concluded that the energy storage systems may have high costs. New research studies are needed to overcome this problem (Piano and Smith, 2022). Mostafa *et al.* (2022) also concluded that owing to the new systems to be developed, it will be possible to reduce the high cost in this process.

From a theoretical perspective, customer-centric innovation in renewable energy can be framed within innovation theory and service-dominant logic. Innovation theory emphasizes the role of technological advancement, knowledge diffusion, and value creation in shaping competitive advantage. In the renewable energy context, innovation is not limited to technical efficiency but also includes process optimization and service integration. In parallel, service-dominant logic highlights value co-creation between firms and customers, suggesting that energy companies must design systems that respond dynamically to customer needs rather than merely supplying electricity as a standardized product. Accordingly, customer-centric innovation in green energy represents a shift from product-oriented energy provision to value-oriented service ecosystems. This theoretical positioning strengthens the conceptual foundation of the present study. Although prior studies provide valuable insights into renewable energy efficiency, demand management, and technological innovation, several limitations remain. First, many studies examine these dimensions separately rather than within an integrated decision-making framework. As a result, the interdependencies among productivity, optimization, innovation, and customer-oriented factors are often overlooked. Second, existing models frequently rely on traditional weighting techniques that assume criteria independence and deterministic evaluations, which may not adequately reflect uncertainty and expert hesitancy in complex energy investment decisions. Third, while customer satisfaction and demand responsiveness are discussed in the literature, few studies explicitly frame these issues within a customer-centric innovation perspective linked to strategic prioritization. Therefore, there is a clear need for a comprehensive model that simultaneously captures uncertainty, interrelationships among criteria, and strategic prioritization in renewable energy investments.

The literature demonstrates that effective customer-centric innovation plays a crucial role in improving the performance of renewable energy projects. Prior studies highlight the importance of productivity-enhancing mechanisms, electricity consumption timing, innovative applications, and emerging technologies. However, most of this research examines these factors in isolation rather than within an integrated strategic framework. Furthermore, although the cost implications of improving customer-centric innovation are widely acknowledged, limited attention has been given to systematically prioritizing these determinants under conditions of uncertainty. Existing models generally do not capture interdependencies among criteria, nor do they provide a structured approach to identifying which factors should be strategically emphasized when resources are limited. Therefore, a clear research gap exists in developing a comprehensive decision-making model that simultaneously evaluates uncertainty, interrelationships among determinants, and strategic prioritization in renewable energy investments.

In response to this gap, the present study seeks to answer the following research questions: Which factors are most critical for enhancing customer-centric innovation performance in renewable energy projects? How can these determinants be prioritized under uncertainty and interdependent conditions? And which renewable energy alternatives perform best within this integrated customer-centric innovation framework? To address these questions, this study evaluates energy efficiency for customer-centric innovation and proposes a structured prioritization model for renewable energy companies.

3. Proposed Model

In this study, an original model is created to evaluate energy efficiency for customer-centric innovation. First, significant indicators are identified by using BNSD determinants. These items are evaluated with M-SWARA method with QSFNs. Quantum theory considers different probabilities in the analysis process. In this framework, amplitude and the phase angle factors are considered with the aim of decreasing uncertainty. Equations (1)–(3) explain these items where it shows collective events, denotes the amplitude result, demonstrates the phase angle and u refers to the event (Aksoy *et al.*, 2022).

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

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

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

The integration of quantum theory into the spherical fuzzy framework is not solely a mathematical extension but provides a deeper theoretical contribution to uncertainty modelling. Classical fuzzy approaches represent uncertainty through degrees of membership and non-membership; however, they generally assume static and deterministic evaluation structures. Quantum theory introduces the concepts of superposition and probability amplitude, allowing multiple potential evaluation states to coexist before final aggregation. In complex renewable energy investment decisions, expert judgments often reflect overlapping, hesitant, and probabilistic assessments rather than fixed evaluations. By incorporating quantum principles, the model captures dynamic uncertainty structures and interaction effects more effectively than conventional fuzzy methods. Therefore, quantum integration enhances both the flexibility and realism of the decision-making framework. Spherical fuzzy sets were introduced to manage uncertainty problems by considering hesitancy issues (Ashraf *et al.*, 2019). Equations (4) and (5) indicate these sets in which μ, ν, and π represent membership, non-membership and hesitancy parameters (Kutlu

Gündoğdu and Kahraman, 2020).

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

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

In this model, these sets are integrated with Quantum theory with equations (6)–(8).

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

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

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

Additionally, in this model, golden ratio (G) is used to compute these degrees by equations (9)–(15) (Xu *et al.*, 2023).

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

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

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

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

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

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

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

The integration of the golden ratio is not merely a mathematical preference but serves a conceptual purpose in the decision-making structure. The golden ratio is widely associated with proportional balance and optimal distribution in complex systems. In the context of fuzzy decision modelling, its use helps achieve a more balanced scaling of membership, non-membership, and hesitancy degrees. This proportional adjustment supports numerical stability and prevents extreme dominance of any single parameter. Therefore, incorporating the golden ratio enhances the interpretability and structural consistency of the weighting process, particularly for readers who may not specialize in advanced fuzzy mathematics. The operations are detailed in equations (16)–(19).

$$\begin{aligned}\lambda * \tilde{A}_\varsigma = \Big\{ & \big(1 - (1 - \varsigma^2_{\mu_{\tilde{A}}})^\lambda\big)^{\frac{1}{2}} e^{j2\pi\left(1-\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}}, \varsigma^\lambda_{v_{\tilde{A}}} e^{j2\pi\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^\lambda}, \big((1 - \varsigma^2_{h_{\tilde{A}}})^\lambda \\ & - (1 - \varsigma^2_{\mu_{\tilde{A}}} - \varsigma^2_{h_{\tilde{A}}})^\lambda\big)^{\frac{1}{2}} e^{j2\pi\left(\left(1-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda - \left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^2-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^2\right)^\lambda\right)^{\frac{1}{2}}} \Big\}, \quad \lambda > 0,\end{aligned} \tag{16}$$

$$\tilde{A}_{\varsigma}^{\lambda} = \Big\{ \varsigma_{\mu_{\tilde{A}}}^{\lambda} e^{j2\pi \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{\lambda}}, \left(1 - \left(1 - \varsigma_{v_{\tilde{A}}}^{2}\right)^{\lambda}\right)^{\frac{1}{2}} e^{j2\pi \left(1 - \left(1 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}}, \left(\left(1 - \varsigma_{v_{\tilde{A}}}^{2}\right)^{\lambda} - \left(1 - \varsigma_{v_{\tilde{A}}}^{2} - \varsigma_{h_{\tilde{A}}}^{2}\right)^{\lambda}\right)^{\frac{1}{2}} e^{j2\pi \left(\left(1 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda} - \left(1 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2} - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}} \Big\}, \quad \lambda > 0, \tag{17}$$

$$\tilde{A}_{\varsigma} \oplus \tilde{B}_{\varsigma} = \Big\{ \left(\varsigma_{\mu_{\tilde{A}}}^{2} + \varsigma_{\mu_{\tilde{B}}}^{2} - \varsigma_{\mu_{\tilde{A}}}^{2} \varsigma_{\mu_{\tilde{B}}}^{2}\right)^{\frac{1}{2}} e^{j2\pi \left(\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2} + \left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2} - \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}}, \varsigma_{v_{\tilde{A}}} \varsigma_{v_{\tilde{B}}} e^{j2\pi \left(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)\right)}, \left(\left(1 - \varsigma_{\mu_{\tilde{B}}}^{2}\right)\varsigma_{h_{\tilde{A}}}^{2} + \left(1 - \varsigma_{\mu_{\tilde{A}}}^{2}\right)\varsigma_{h_{\tilde{B}}}^{2} - \varsigma_{h_{\tilde{A}}}^{2} \varsigma_{h_{\tilde{B}}}^{2}\right)^{\frac{1}{2}} \times e^{j2\pi \left(\left(1 - \left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2} + \left(1 - \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2} - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}} \Big\}, \tag{18}$$

$$\tilde{A}_{\varsigma} \otimes \tilde{B}_{\varsigma} = \Big\{ \varsigma_{\mu_{\tilde{A}}} \varsigma_{\mu_{\tilde{B}}} e^{j2\pi \left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)}, \left(\varsigma_{v_{\tilde{A}}}^{2} + \varsigma_{v_{\tilde{B}}}^{2} - \varsigma_{v_{\tilde{A}}}^{2} \varsigma_{v_{\tilde{B}}}^{2}\right)^{\frac{1}{2}} \times e^{j2\pi \left(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2} + \left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2} - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}}, \left(\left(1 - \varsigma_{v_{\tilde{B}}}^{2}\right)\varsigma_{h_{\tilde{A}}}^{2} + \left(1 - \varsigma_{v_{\tilde{A}}}^{2}\right)\varsigma_{h_{\tilde{B}}}^{2} - \varsigma_{h_{\tilde{A}}}^{2} \varsigma_{h_{\tilde{B}}}^{2}\right)^{\frac{1}{2}} e^{j2\pi \left(\left(1 - \left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2} + \left(1 - \left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2} - \left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}} \Big\}. \tag{19}$$

Some improvements are adopted to the SWARA, and a new model called M-SWARA is generated. While criterion weights can be calculated in the classical SWARA method, the causality relationship between these factors cannot be determined (Xu *et al.*, 2023). However, the criteria to increase the performance of customer-centric innovation may have impacts on each other. Therefore, the classical SWARA technique is insufficient to answer the research question of this study (Xu *et al.*, 2023). Evaluations are firstly obtained, and relation matrix is generated by equation (20).

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

Also, equations (21) and (22) demonstrate the aggregated and defuzzified values.

$$\varsigma = \Bigg\{ \left[1 - \prod_{i=1}^{k}\left(1 - \varsigma_{\mu_i}^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}} e^{2\pi \left[1 - \prod_{i=1}^{k}\left(1 - \left(\frac{\alpha_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}}, \prod_{i=1}^{k} \varsigma_{v_i}^{\frac{1}{k}} e^{2\pi \prod_{i=1}^{k}\left(\frac{\gamma_i}{2\pi}\right)^{\frac{1}{k}}}, \left[\prod_{i=1}^{k}\left(1 - \varsigma_{\mu_i}^{2}\right)^{\frac{1}{k}} - \prod_{i=1}^{k}\left(1 - \varsigma_{\mu_i}^{2} - \varsigma_{h_i}^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}} \times e^{2\pi \left[\prod_{i=1}^{k}\left(1 - \left(\frac{\alpha_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}} - \prod_{i=1}^{k}\left(1 - \left(\frac{\alpha_i}{2\pi}\right)^{2} - \left(\frac{\beta_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}} \Bigg\}, \tag{21}$$

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

By using equations (23)–(25), critical items are computed where significance ratio is denoted, coefficient is represented, recalculated weight is indicated and the weights are showed.

$$k_j = \begin{cases} 1, & j = 1, \\ s_j + 1, & j > 1, \end{cases} \tag{23}$$

$$q_j = \begin{cases} 1, & j = 1, \\ \frac{q_{j-1}}{k_j}, & j > 1, \end{cases} \tag{24}$$

$$\text{If } s_{j-1} = s_j, \quad q_{j-1} = q_j, \qquad \text{If } s_j = 0, \quad k_{j-1} = k_j,$$

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k}. \tag{25}$$

Finally, by limiting and transposing the matrix, the weights and causal degrees of the determinants can be computed (Kafka *et al.*, 2024).

Secondly, the energy efficiency of the renewable alternatives is examined for customer-centric innovation. For this purpose, TOPSIS with QSFNs is taken into consideration to rank five different green energy alternatives (Dinçer and Yüksel, 2018).

Firstly, evaluations are collected. Secondly, decision matrix is generated with equation (26).

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{26}$$

Thirdly, defuzzification is made with equation (22). Normalized and weighted values are identified by equations (27) and (28).

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}, \tag{27}$$

$$v_{ij} = w_{ij} \times r_{ij}. \tag{28}$$

Also, equations (29) and (30) include positive and negative ideal results.

$$A^+ = \{v_{1j}, v_{2j}, \ldots, v_{mj}\} = \{\max v_{1j}, \ \text{for } \forall j \in n\}, \tag{29}$$

$$A^- = \{v_{1j}, v_{2j}, \ldots, v_{mj}\} = \{\min v_{1j}, \ \text{for } \forall j \in n\}. \tag{30}$$

After that, the distances are computed by

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^+\right)^2}, \tag{31}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2}. \tag{32}$$

Finally, relative closeness is calculated by equation (33).

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{33}$$

The overall structure of the proposed methodology, including the two-stage evaluation process and the integration of M-SWARA and TOPSIS with quantum spherical fuzzy theory, is illustrated in Fig. 1.

As shown in Fig. 1, the analysis consists of two main stages. The first stage focuses on determining the weights and causal relationships of the BNSD-based criteria, while the second stage evaluates and ranks renewable energy alternatives based on customer-centric innovation performance.

4. Analysis Results

The proposed model consists of two different stages so that analysis results are presented in two subtitles as follows.

4.1. *Weighting the BNSD-Criteria of Energy Efficiency for Customer-Centric Innovation (Stage 1)*

The Balanced Scorecard framework is particularly suitable for evaluating customer-centric innovation in green energy investments because it integrates financial and non-financial performance dimensions within a strategic perspective. Renewable energy projects operate in environments where technological efficiency, customer responsiveness, internal processes, and financial sustainability are simultaneously critical. The Balanced Scorecard allows these interrelated dimensions to be evaluated holistically rather than in isolation. Moreover, customer-centric innovation inherently requires alignment between learning capabilities, process optimization, financial viability, and customer value creation. Therefore, the BNSD structure provides a comprehensive and strategically consistent basis for identifying and prioritizing the determinants of customer-centric innovation in renewable energy contexts. In accordance with the first stage presented in Fig. 1, the BNSD-based criteria are weighted using the M-SWARA approach. *Step 1* is related to the selection of the BNSD-criteria of energy efficiency for customer-centric innovation. Four perspectives

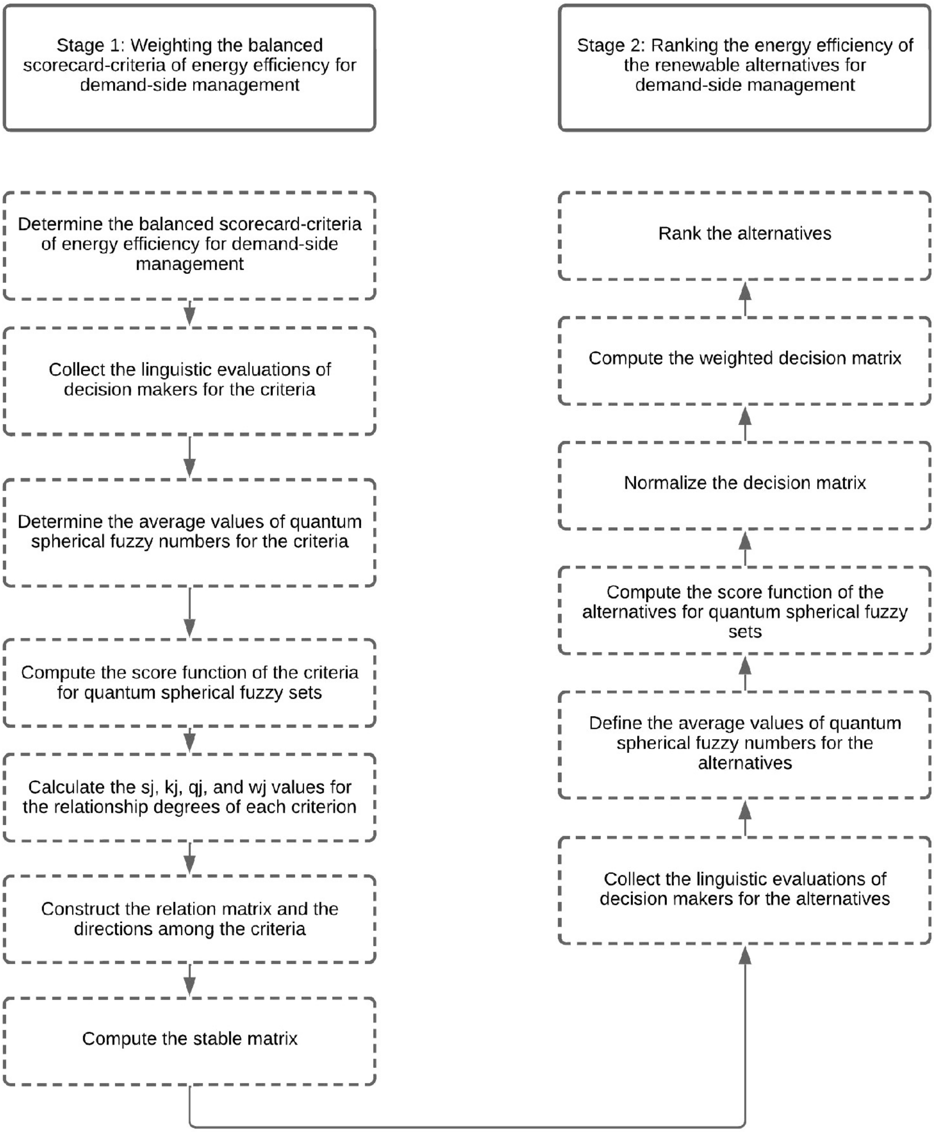

Fig. 1. Flowchart.

of this technique are taken into consideration. Additionally, while making literature evaluations, a criteria list can be created that is relevant to the BNSD methodology. Considering this technique in criterion selection provides some benefits (Kaplan and Norton, 2007). Both financial and non-financial factors can be examined in this process. Hence, it is possible to analyse with a more comprehensive set of criteria (Kaplan and Norton, 2015). This also contributes to a more effective priority analysis. Selected criteria of the energy efficiency for customer-centric innovation are denoted in Table 1.

Table 1
Determinants of the energy efficiency for customer-centric innovation.

BNSD perspectives	Criteria	Literature
Learning and growth	customization	(Härkönen *et al.*, 2022; Cheekatamarla *et al.*, 2022; Piano and Smith, 2022)
Finance	efficiency	(Wei *et al.*, 2022; Nair *et al.*, 2022); (Tang *et al.*, 2022)
Consumer	optimization	(Zahedi *et al.*, 2022; Lorente *et al.*, 2023; Rusu, 2022)
Internal process	innovation	(Bedi *et al.*, 2022; Siddiqui *et al.*, 2022)

The selection of the four criteria is grounded in both theoretical relevance and practical significance identified in the literature. Although various determinants influence renewable energy performance, customization, efficiency, optimization, and innovation consistently emerge as core dimensions linking technological capability with customer responsiveness. Customization captures the adaptability of energy systems to heterogeneous customer needs. Efficiency reflects operational and resource performance. Optimization represents demand forecasting and timing mechanisms. Innovation addresses smart technologies and adaptive infrastructure. While other factors such as regulatory conditions, financial incentives, or macroeconomic variables may also affect renewable energy investments, these are typically external or contextual variables rather than firm-level strategic determinants. Therefore, this study focuses on the four criteria that directly reflect managerial decision-making and customer-centric value creation within renewable energy firms.

Customization states the use of modular technologies in energy generation. This will help green energy projects to gain competitive advantage. This is also very important for the success of customer-centric innovation. An efficient energy storage system is required for uninterrupted electricity production. On the other hand, it is vital to follow the technological developments to maintain this process with reasonable costs. Efficiency means the use of less load-intensive equipment. Within this context, materials that will provide more efficiency should be taken into consideration in the energy production process. With the help of this issue, more energy can be produced at the same time. Therefore, the demanded amount of energy can be provided more easily. Optimization gives information about the timing of electricity consumption. In this process, it is necessary to determine the important factors that affect the energy demand. This analysis will help to predict energy demand more successfully in the future. Innovation refers to the smart control on load demand. Energy demand can increase or decrease very quickly. This situation makes it difficult to ensure a successful demand management. Thanks to innovative solutions, this process can be carried out much easier. Thanks to applications such as smart grid systems, customer-centric innovation can be monitored instantly.

In *Step 2*, evaluations are provided from three experts (LPOL). They work as top managers who have more than 30-year work experience about the strategy generation, energy investment decisions and customer-centric innovation. This team considers the scales in Table 2.

Moreover, evaluations are demonstrated in Table 3.

Step 3 includes the average of the created values (Table 4).

Table 2
Scales and fuzzy numbers.

Scales of indicators	Scales of energy types	Possibility degrees	QSFNs
No (NO)	worst (SRT)	.40	$[\sqrt{.16}e^{j2\pi..4}, \sqrt{.10}e^{j2\pi..25}, \sqrt{.74}e^{j2\pi..35}]$
Some (MOE)	unsuccessful (UCS)	.45	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$
Normal (NML)	standard (NDD)	.50	$[\sqrt{.25}e^{j2\pi..50}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..19}]$
Influential (FLN)	successful (SCS)	.55	$[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}]$
Magnificent (MGC)	perfect (RFT)	.60	$[\sqrt{.36}e^{j2\pi..6}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}]$

Table 3
Evaluations for indicators.

	LPOL 1				LPOL 2				LPOL 3			
	CC	EE	OO	II	CC	EE	OO	II	CC	EE	OO	II
Customization		MOE	NML	MOE		MOE	MOE	MOE		MOE	NML	MOE
Efficiency	MGC		MOE	MOE	MGC		MOE	MOE	MGC		MOE	MOE
Optimization	NML	NML		NML	NML	NML		NML	FLN	NML		FLN
Innovation	NML	NML	MGC		MOE	MOE	VH		FLN	VH	FLN	
LPOL: experts												

CC – Customization; EE – Efficiency; OO – Optimization; II – Innovation.

Table 4
Average values for the indicators.

	Customization	Efficiency
Customization		$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$
Efficiency	$[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}]$	
Optimization	$[\sqrt{.27}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.57}e^{j2\pi..17}]$	$[\sqrt{.25}e^{j2\pi..50}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..19}]$
Innovation	$[\sqrt{.26}e^{j2\pi..50}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..20}]$	$[\sqrt{.28}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.58}e^{j2\pi..19}]$
	Optimization	**Innovation**
Customization	$[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}]$	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$
Efficiency	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$
Optimization		$[\sqrt{.27}e^{j2\pi..52}, \sqrt{.16}e^{j2\pi..32}, \sqrt{.57}e^{j2\pi..17}]$
Innovation	$[\sqrt{.34}e^{j2\pi..58}, \sqrt{.21}e^{j2\pi..36}, \sqrt{.45}e^{j2\pi..07}]$	

Score values (Table 5) are presented in *Step 4*, and critical values (Table 6) are computed in *Step 5*.

Causal directions are calculated in *Step 6*, and the results are stated in Table 7.

These causal directions indicate the influence structure among the criteria. When a criterion is identified as affecting another, it implies that improvements in the former are likely to generate positive changes in the latter. In practical terms, this helps decision-makers prioritize root factors that trigger broader performance improvements. For instance, if optimization influences customization and innovation, focusing on optimization strategies may indirectly enhance technological development and innovative capacity.

Table 5
Score values.

	Customization	Efficiency	Optimization	Innovation
Customization	.000	1.236	1.243	1.236
Efficiency	1.236	.000	1.236	1.236
Optimization	1.243	1.236	.000	1.243
Innovation	1.256	1.284	1.247	.000

Table 6
Critical values.

Customization	Sj	kj	qj	wj	Efficiency	Sj	Kj	qj	Wj
Optimization	.335	1.000	1.000	.400	customization	.333	1.000	1.000	.333
Innovation	.333	1.333	.750	.300	optimization	.333	1.333	1.000	.333
Efficiency	.333	1.333	.750	.300	innovation	.333	1.333	1.000	.333
Optimization	Sj	kj	qj	wj	Innovation	Sj	Kj	qj	Wj
Customization	.334	1.000	1.000	.364	efficiency	.339	1.000	1.000	.432
Innovation	.334	1.334	1.000	.364	customization	.332	1.332	.751	.324
Efficiency	.332	1.332	.751	.273	optimization	.329	1.329	.565	.244

Table 7
Causal directions.

	Customization	Efficiency	Optimization	Innovation	Impact directions
Customization		.300	.400	.300	customization → optimization
Efficiency	.333		.333	.333	–
Optimization	.364	.273		.364	optimization → customization, optimization → innovation
Innovation	.324	.432	.244		innovation → efficiency

Therefore, the causal analysis provides strategic guidance by identifying leverage points that create multiplier effects within the system. It is found that customization has an impact on the optimization. This situation shows that when there is technological development, timing of the energy consumption can be made more effectively. Moreover, it is also seen that innovation affects the efficiency significantly. This issue gives information that considering smart grid systems has a contribution to the use of less load-intensive equipment. Finally, optimization has an influence on both customization and innovation. With the help of considering smart grid systems, the companies can increase both technological power and innovation performance. *Step 7* states the construction of the stable matrix (Table 8) which gives information about the weights of the indicator.

It is identified that customization is the most essential indicator for green energy companies to increase the performance of the customer-centric innovation. Efficiency has the second greatest weight in this regard. Optimization and innovation have lower importance than the others. It is understood that green energy companies should prioritize technological development to activate customer-centric innovation. This will help minimize some of the disadvantages of these projects. For example, generating less electricity in certain

Table 8
Stable matrix.

	Customization	Efficiency	Optimization	Innovation
Customization	.254	.254	.254	.254
Efficiency	.251	.251	.251	.251
Optimization	.246	.246	.246	.246
Innovation	.249	.249	.249	.249

Table 9
Evaluations for green energy types.

	LPOL 1				LPOL 2				LPOL 3			
	CC	EE	OO	II	CC	EE	OO	II	CC	EE	OO	II
Bioenergy	UCS	SCS	SRT	SRT	UCS	SCS	UCS	UCS	NDD	SCS	SRT	SRT
Wind	UCS	RFT	UCS	RFT	UCS	RFT	UCS	RFT	UCS	RFT	NDD	NDD
Geothermal	UCS	SCS	RFT	NDD	UCS	SCS	RFT	RFT	NDD	SCS	RFT	NDD
Hydropower	NDD	NDD	SRT	SRT	NDD	UCS	SRT	SRT	NDD	NDD	SRT	NDD
Solar	UCS	SRT	SCS	SRT	UCS	UCS	RFT	UCS	UCS	NDD	NDD	SRT

CC – Customization; EE – Efficiency; OO – Optimization; II – Innovation.

climatic conditions is an important disadvantage of renewable energy projects. Along with technological developments, it will be possible to eliminate this negativity thanks to new applications such as energy storage systems.

4.2. *Ranking the Energy Efficiency of the Renewable Alternatives for Customer-Centric Innovation (Stage 2)*

As indicated in the second stage of Fig. 1, the renewable energy alternatives are evaluated and ranked through the TOPSIS method integrated with quantum spherical fuzzy sets. *Step 8* focuses on the collection of the evaluations regarding the green energy types. Within this context, five renewable energy types are selected as alternatives that are bioenergy, wind, geothermal, hydropower and solar. Evaluations are demonstrated in Table 9.

Average values for the energy types (Table 10) are shown in *Step 9*.

Additionally, *Step 10* is related to the score values (Table 11), and *Step 11* includes normalization procedure (Table 12).

Weighted values (Table 13) are demonstrated in *Step 12*.

Finally, the weights of the green energy alternatives (Table 14) are computed in *Step 13*.

The ranking results demonstrate that solar energy projects are the most successful type of investment in the effective management of customer-centric innovation. Wind and geothermal energy projects have also high performance for this issue. Hydropower and bioenergy take place on the last ranks. It is understood that focusing on solar panels help to manage electricity demands more successfully. The main reason is that technology for solar energy projects is developing very rapidly. For instance, new solar panel types have been developed that allow to obtain more electricity from solar energy. Hence, the efficiency of the projects can be increased.

Table 10
Average values for the green energy types.

	Customization	Efficiency
Bioenergy	$[\sqrt{.22}e^{j2\pi..47}, \sqrt{.13}e^{j2\pi..29}, \sqrt{.65}e^{j2\pi..25}]$	$[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}]$
Wind	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$	$[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}]$
Geothermal	$[\sqrt{.22}e^{j2\pi..47}, \sqrt{.13}e^{j2\pi..29}, \sqrt{.65}e^{j2\pi..25}]$	$[\sqrt{.30}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..11}]$
Hydropower	$[\sqrt{.25}e^{j2\pi..50}, \sqrt{.15}e^{j2\pi..31}, \sqrt{.60}e^{j2\pi..19}]$	$[\sqrt{.24}e^{j2\pi..48}, \sqrt{.14}e^{j2\pi..30}, \sqrt{.62}e^{j2\pi..22}]$
Solar	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$	$[\sqrt{.21}e^{j2\pi..45}, \sqrt{.12}e^{j2\pi..28}, \sqrt{.68}e^{j2\pi..28}]$
	Optimization	Innovation
Bioenergy	$[\sqrt{.18}e^{j2\pi..42}, \sqrt{.11}e^{j2\pi..26}, \sqrt{.72}e^{j2\pi..33}]$	$[\sqrt{.18}e^{j2\pi..42}, \sqrt{.11}e^{j2\pi..26}, \sqrt{.72}e^{j2\pi..33}]$
Wind	$[\sqrt{.22}e^{j2\pi..47}, \sqrt{.13}e^{j2\pi..29}, \sqrt{.65}e^{j2\pi..25}]$	$[\sqrt{.33}e^{j2\pi..57}, \sqrt{.20}e^{j2\pi..35}, \sqrt{.49}e^{j2\pi..11}]$
Geothermal	$[\sqrt{.36}e^{j2\pi..60}, \sqrt{.22}e^{j2\pi..37}, \sqrt{.42}e^{j2\pi..03}]$	$[\sqrt{.29}e^{j2\pi..53}, \sqrt{.18}e^{j2\pi..33}, \sqrt{.54}e^{j2\pi..14}]$
Hydropower	$[\sqrt{.16}e^{j2\pi..40}, \sqrt{.10}e^{j2\pi..25}, \sqrt{.74}e^{j2\pi..35}]$	$[\sqrt{.20}e^{j2\pi..45}, \sqrt{.13}e^{j2\pi..28}, \sqrt{.67}e^{j2\pi..27}]$
Solar	$[\sqrt{.31}e^{j2\pi..55}, \sqrt{.19}e^{j2\pi..34}, \sqrt{.51}e^{j2\pi..13}]$	$[\sqrt{.18}e^{j2\pi..42}, \sqrt{.11}e^{j2\pi..26}, \sqrt{.72}e^{j2\pi..33}]$

Table 11
Score values for energy types.

	Customization	Efficiency	Optimization	Innovation
Bioenergy	1.243	1.236	1.243	1.243
Wind	1.236	1.236	1.243	1.269
Geothermal	1.243	1.236	1.236	1.266
Hydropower	1.236	1.243	1.236	1.263
Solar	1.236	1.256	1.259	1.243

Table 12
Normalized matrix.

	Customization	Efficiency	Optimization	Innovation
Bioenergy	.449	.445	.447	.442
Wind	.446	.445	.447	.452
Geothermal	.449	.445	.445	.450
Hydropower	.446	.448	.445	.450
Solar	.446	.452	.453	.442

5. Discussions

Renewable energy projects are inherently exposed to climatic variability, which may lead to fluctuations in electricity generation and consequently affect demand responsiveness. This structural characteristic directly influences the effectiveness of customer-centric innovation in the energy industry. The findings of this study indicate that technological development functions as a central leverage mechanism in mitigating these instabilities. In line with sustainability and energy transition literature, technological advancement enhances system flexibility and operational resilience. Energy storage technologies, in particular, represent a strategic response to production volatility. However, the high initial investment costs of storage systems remain a critical barrier, limiting the competitiveness

Table 13
Weighted values.

	Customization	Efficiency	Optimization	Innovation
Bioenergy	.114	.112	.110	.110
Wind	.113	.112	.110	.113
Geothermal	.114	.112	.109	.112
Hydropower	.113	.112	.109	.112
Solar	.113	.114	.111	.110

Table 14
Ranking results of the green energy types.

Green energy types	Ranking
Bioenergy	5
Wind	2
Geothermal	3
Hydropower	4
Solar	1

of renewable energy projects compared to fossil fuel alternatives. This tension between technological necessity and cost pressure highlights the strategic importance of innovation efficiency. As suggested by Suman (2021) and Timilsina (2021), technological progress not only improves operational performance but also plays a decisive role in enhancing cost effectiveness and long-term sustainability in renewable energy markets.

From a strategic perspective, these findings imply that renewable energy firms must view technological development not merely as an operational upgrade but as a dynamic capability. Continuous investment in research and monitoring global technological advancements enables firms to reduce costs over time and strengthen competitive positioning. Early adoption of emerging technologies may generate first-mover advantages and reinforce customer trust through improved reliability and service responsiveness. Therefore, customer-centric innovation in green energy should be interpreted as an integrated capability combining technological flexibility, cost management, and demand-oriented adaptation rather than as a purely technical efficiency issue.

The superior performance of solar energy projects further supports this interpretation. While rapid technological advancement explains part of this outcome, a deeper explanation can be derived from innovation adoption theory. Solar technologies, particularly modular photovoltaic systems, exhibit characteristics such as scalability, declining installation costs, and observable performance outcomes. According to innovation diffusion and technology adoption models, innovations that are perceived as cost-effective, compatible with existing infrastructure, and easy to implement tend to achieve faster market penetration. Empirical studies by Brown *et al.* (2021) and Best *et al.* (2021) demonstrate that small-scale solar systems increase electricity generation efficiency and accessibility. These structural and economic attributes enhance perceived usefulness and adoption likelihood, thereby strengthening customer acceptance and reinforcing customer-centric innovation performance.

Overall, the results suggest that the effectiveness of customer-centric innovation in renewable energy depends not only on technological progress but also on the strategic alignment between innovation characteristics and customer adoption dynamics. Solar energy projects perform better not solely because of rapid development, but because their technological structure aligns more closely with customer expectations, modular investment capacity, and service-oriented value creation.

6. Conclusions

This study examines the effectiveness of customer-centric innovation in green energy projects using an integrated decision-making framework. We evaluate the indicators through the M-SWARA method with quantum spherical fuzzy numbers and assess renewable energy alternatives for demand-side management using TOPSIS. The findings reveal that customization is the most critical determinant of renewable energy efficiency in the context of customer-centric innovation. The results also indicate that solar energy is the most successful renewable energy type in terms of customer-centric innovation performance. Overall, technological development emerges as the key factor enabling green energy companies to manage demand more effectively.

This study contributes to the literature in several respects. First, it integrates the customer-centric innovation perspective with renewable energy performance assessment by employing Balanced Scorecard-based criteria within a multi-criteria decision-making framework. Second, it advances methodological research by combining M-SWARA and TOPSIS with quantum spherical fuzzy numbers to better handle uncertainty and capture interrelationships among criteria. Third, the study provides a structured prioritization approach that enhances analytical rigour in sustainability-oriented decision models.

From a managerial perspective, the results provide practical guidance for green energy investors and policymakers. The identification of customization as the most influential factor suggests that firms should prioritize technological flexibility, modular systems, and innovation-driven infrastructure. The superior ranking of solar energy indicates that investments in rapidly developing solar technologies may yield stronger customer-centric innovation performance. Moreover, the prioritization framework enables managers to allocate limited resources more efficiently by focusing on high-impact determinants rather than distributing investments equally across all factors.

Despite these contributions, the study has certain limitations. It focuses only on selected factors affecting customer-centric innovation performance. Future research may develop econometric models incorporating macroeconomic and energy demand variables to analyse national-level energy planning. Such extensions would allow researchers to identify the most influential determinants of customer-centric innovation across countries and to improve long-term energy demand forecasting.

Statements and Declarations

Data Availability
The data that support the findings of this study are listed in Table 1 in this manuscript.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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References

Abbasi, K.R., Shahbaz, M., Zhang, J., Irfan, M., Alvarado, R. (2022). Analyze the environmental sustainability factors of China: the role of fossil fuel energy and renewable energy. *Renewable Energy*, 187, 390–402.

Abedrabboh, O., Koç, M., Biçer, Y. (2022). Modelling and analysis of a renewable energy-driven climate-controlled sustainable greenhouse for hot and arid climates. *Energy Conversion and Management*, 273, 116412.

Agarwal, S., Kant, R., Shankar, R. (2022). Exploring sustainability balanced scorecard for performance evaluation of humanitarian organizations. *Cleaner Logistics and Supply Chain*, 3, 100026.

Aksoy, T., Yüksel, S., Dınçer, H., Hacioglu, U., Maialeh, R. (2022). Complex fuzzy assessment of green flight activity investments for sustainable aviation industry. *IEEE Access*, 10, 127297–127312.

Amin, M., Shah, H.H., Fareed, A.G., Khan, W.U., Chung, E., Zia, A., Farooqi, Z.U.R., Lee, C. (2022). Hydrogen production through renewable and non-renewable energy processes and their impact on climate change. *International Journal of Hydrogen Energy*, 47, 33112–33134.

Ang, Y.Q., Polly, A., Kulkarni, A., Chambi, G.B., Hernandez, M., Haji, M.N. (2022). Multi-objective optimization of hybrid renewable energy systems with urban building energy modeling for a prototypical coastal community. *Renewable Energy*, 201, 72–84.

Aragón, G., Pandian, V., Krauß, V., Werner-Kytölä, O., Thybo, G., Pautasso, E. (2022). Feasibility and economic analysis of energy storage systems as enabler of higher renewable energy sources penetration in an existing grid. *Energy*, 251, 123889.

Ashraf, S., Abdullah, S., Mahmood, T., Ghani, F., Mahmood, T. (2019). Spherical fuzzy sets and their applications in multi-attribute decision making problems. *Journal of Intelligent & Fuzzy Systems*, 36(3), 2829–2844.

Bedi, P., Goyal, S.B., Rajawat, A.S., Shaw, R.N., Ghosh, A. (2022). Application of AI/IoT for smart renewable energy management in smart cities. In: *AI and IoT for Smart City Applications*. Springer, Singapore, pp. 115–138.

Benmouna, A., Becherif, M., Boulon, L., Dépature, C., Ramadan, H.S. (2021). Efficient experimental energy management operating for FC/battery/SC vehicles via hybrid artificial neural networks-passivity based control. *Renewable Energy*, 178, 1291–1302.

Best, R., Chareunsy, A., Li, H. (2021). Equity and effectiveness of Australian small-scale solar schemes. *Ecological Economics*, 180, 106890.

Brown, J., Abate, A., Rogers, A. (2021). Disaggregation of household solar energy generation using censored smart meter data. *Energy and Buildings*, 231, 110617.

Cheekatamarla, P.K., Sharma, V., Shrestha, S. (2022). Energy-efficient building technologies. In: *Advanced Nanomaterials and Their Applications in Renewable Energy*. Elsevier, pp. 3–33.

Cirocco, L., Pudney, P., Riahi, S., Liddle, R., Semsarilar, H., Hudson, J., Bruno, F. (2022). Thermal energy storage for industrial thermal loads and electricity demand side management. *Energy Conversion and Management*, 270, 116190.

Dinçer, H., Yüksel, S. (2018). Financial sector-based analysis of the G20 economies using the integrated decision-making approach with DEMATEL and TOPSIS. In: *Emerging Trends in Banking and Finance*. Springer, Cham, pp. 210–223.

Elavarasan, R.M., Leoponraj, S., Vishnupriyan, J., Dheeraj, A., Sundar, G.G. (2021). Multi-criteria decision analysis for user satisfaction-induced demand-side load management for an institutional building. *Renewable Energy*, 170, 1396–1426.

Elbanna, S., Kamel, H., Fatima, T., Eid, R. (2022). An investigation of the causality links in the balanced scorecard: the case of the Gulf Cooperation Council hospitality industry. *Tourism Management Perspectives*, 41, 100934.

Gunarathna, C.L., Yang, R.J., Jayasuriya, S., Wang, K. (2022). Reviewing global peer-to-peer distributed renewable energy trading projects. *Energy Research & Social Science*, 89, 102655.

Haq, E.U., Lyu, C., Xie, P., Yan, S., Ahmad, F., Jia, Y. (2022). Implementation of home energy management system based on reinforcement learning. *Energy Reports*, 8, 560–566.

Härkönen, K., Hannola, L., Pyrhönen, O. (2022). Advancing the smart city objectives of electric demand management and new services to residents by home automation—learnings from a case. *Energy Efficiency*, 15(5), 1–13.

Hu, X., Guo, Y., Zheng, Y., Liu, L.C., Yu, S. (2022). Which types of policies better promote the development of renewable energy? Evidence from China's provincial data. *Renewable Energy*, 198, 1373–1382.

Kafka, K.I., Dinçer, H., Yüksel, S. (2024). Impact-relation map of innovative service development regarding the sustainable growth for emerging markets. *Journal of the Knowledge Economy*, 15, 180–203.

Kaplan, R.S., Norton, D.P. (2007). Balanced scorecard. In: *Das Summa Summarum des Management*. Gabler. 137–148.

Kaplan, R.S., Norton, D.P. (2015). *Balanced Scorecard Success: The Kaplan-Norton Collection*. Harvard Business Review Press.

Kutlu Gündoğdu, F., Kahraman, C. (2020). Spherical fuzzy sets and decision making applications. In: *Intelligent and Fuzzy Techniques in Big Data Analytics and Decision Making: Proceedings of the INFUS 2019 Conference*, Istanbul, Turkey, July 23–25, 2019. Springer International Publishing, pp. 979–987.

Lankeshwara, G., Sharma, R., Yan, R., Saha, T.K. (2022). Control algorithms to mitigate the effect of uncertainties in residential demand management. *Applied Energy*, 306, 117971.

Liu, P., Wang, D. (2022). An extended taxonomy method based on normal T-spherical fuzzy numbers for multiple-attribute decision-making. *International Journal of Fuzzy Systems*, 24(1), 73–90.

Lorente, D.B., Mohammed, K.S., Cifuentes-Faura, J., Shahzad, U. (2023). Dynamic connectedness among climate change index, green financial assets and renewable energy markets: novel evidence from sustainable development perspective. *Renewable Energy*, 204, 94–105.

Lotfabadi, A.K., Hajinezhad, A., Kasaeian, A., Moosavian, S.F. (2022). Energetic, economic, environmental and climatic analysis of a solar combisystem for different consumption usages with PSI method ranking. *Renewable Energy*, 197, 178–196.

Mardani, A., Nilashi, M., Zakuan, N., Loganathan, N., Soheilirad, S., Saman, M.Z.M., Ibrahim, O. (2017). A systematic review and meta-Analysis of SWARA and WASPAS methods: Theory and applications with recent fuzzy developments. *Applied Soft Computing*, 57, 265–292.

Mellouk, L., Ghazi, M., Aaroud, A., Boulmalf, M., Benhaddou, D., Zine-Dine, K. (2019). Design and energy management optimization for hybrid renewable energy system-case study: Laayoune region. *Renewable Energy*, 139, 621–634.

Mio, C., Costantini, A., Panfilo, S. (2022). Performance measurement tools for sustainable business: a systematic literature review on the sustainability balanced scorecard use. *Corporate Social Responsibility and Environmental Management*, 29(2), 367–384.

Mojumder, M.R.H., Hasanuzzaman, M., Cuce, E. (2022). Prospects and challenges of renewable energy-based microgrid system in Bangladesh: a comprehensive review. *Clean Technologies and Environmental Policy*, 24(7), 1987–2009.

Mostafa, N., Ramadan, H.S.M., Elfarouk, O. (2022). Renewable energy management in smart grids by using big data analytics and machine learning. *Machine Learning with Applications*, 9, 100363.

Mungai, E.M., Ndiritu, S.W., Da Silva, I. (2022). Unlocking climate finance potential and policy barriers—a case of renewable energy and energy efficiency in Sub-Saharan Africa. *Resources, Environment and Sustainability*, 7, 100043.

Munir, M., Mahmood, T., Hussain, A. (2021). Algorithm for T-spherical fuzzy MADM based on associated immediate probability interactive geometric aggregation operators. *Artificial Intelligence Review*, 54(8), 6033–6061.

Nair, V.M., Ameer, A., Toms, A.A., Prasanth, N.S., Sreekumar, V., Sreekumar, M. (2022). Role of artificial intelligence in demand management system for houses. In: *Innovations in Computer Science and Engineering*. Springer, Singapore, pp. 407–415.

Oliinyk, M., Džmura, J., Kolcun, M., Humenik, J., Kanalik, M., Pavlik, M., Pál, D., Medved', D. (2022). Impact of electric vehicles and demand management systems on electrical distribution networks. *Electrical Engineering*, 104(2), 667–680.

Piano, S.L., Smith, S.T. (2022). Energy demand and its temporal flexibility: approaches, criticalities and ways forward. *Renewable and Sustainable Energy Reviews*, 160, 112249.

Rajan, P., Jeevananthan, S. (2022). Towards energy sustainability-domestic power station, tariff acquiescent EMS and procedure to rejuvenate petrol scooter into electric scooter for accelerated participation of rural consumers in energy demand management. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 114, 4442–4452.

Rusu, E. (2022). Assessment of the wind power dynamics in the North Sea under climate change conditions. *Renewable Energy*, 195, 466–475.

Siddiqui, S.A., Ahmad, M.O., Ahmed, J. (2022). Smart home for efficient energy management. In: *Smart Technologies for Energy and Environmental Sustainability*. Springer, Cham, pp. 97–103.

Suman, A. (2021). Role of renewable energy technologies in climate change adaptation and mitigation: a brief review from Nepal. *Renewable and Sustainable Energy Reviews*, 151, 111524.

Tang, R., Fan, C., Zeng, F., Feng, W. (2022). Data-driven model predictive control for power demand management and fast demand response of commercial buildings using support vector regression. *Building Simulation*, 15(3), 317–331.

Thirunavukkarasu, G.S., Seyedmahmoudian, M., Jamei, E., Horan, B., Mekhilef, S., Stojcevski, A. (2022). Role of optimization techniques in microgrid energy management systems—a review. *Energy Strategy Reviews*, 43, 100899.

Timilsina, G.R. (2021). Are renewable energy technologies cost competitive for electricity generation? *Renewable Energy*, 180, 658–672.

Torkan, R., Ilinca, A., Ghorbanzadeh, M. (2022). A genetic algorithm optimization approach for smart energy management of microgrids. *Renewable Energy*, 197, 852–863.

Wei, J., Zhang, Y., Wang, J., Wu, L., Zhao, P., Jiang, Z. (2022). Decentralized demand management based on alternating direction method of multipliers algorithm for industrial park with CHP units and thermal storage. *Journal of Modern Power Systems and Clean Energy*, 10(1), 120–130.

Xu, X., Yüksel, S., Dinçer, H. (2023). An integrated decision-making approach with golden cut and bipolar Q-ROFSs to renewable energy storage investments. *International Journal of Fuzzy Systems*, 25, 168–181.

Zahedi, R., Hasan Ghodusinejad, M., Aslani, A., Hachem-Vermette, C. (2022). Modelling community-scale renewable energy and electric vehicle management for cold-climate regions using machine learning. *Energy Strategy Reviews*, 43, 100930.

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