

Article

A Multi-Criteria Assessment of Renewable Energy Transitions: An Integrated MCDM Benchmarking Approach

Nhat-Luong Nhieu *  and Hoang-Kha Nguyen * 

Institute of Intelligent & Interactive Technologies, College of Technology and Design, University of Economics Ho Chi Minh City—UEH University, Ho Chi Minh City 724210, Vietnam

* Correspondence: luongnn@ueh.edu.vn (N.-L.N.); khanh@ueh.edu.vn (H.-K.N.)

Abstract

The global energy system is undergoing a structural transformation as countries pursue decarbonization while safeguarding energy security and economic resilience. However, renewable energy transition performance remains difficult to assess because existing evidence is often fragmented across single indicators, capacity-based measures, or isolated policy dimensions, while transition outcomes are shaped by multiple environmental, economic, institutional, technological, and cost-related factors. This study addresses this gap by benchmarking renewable energy transition performance across G7 economies through an integrated multi-criteria decision-making framework. The proposed methodology combines distance-based CRITIC (D-CRITIC) for objective criteria weighting and COBRA for compromise-based ranking to translate heterogeneous transition indicators into transparent cross-country comparisons. Using a secondary dataset covering fourteen indicators and seven G7 economies, the framework first derives objective criterion weights from cross-country dispersion and distance-based inter-criteria dependence, and then ranks countries by measuring their compromise distances from positive ideal, negative ideal, and average solutions. Using fourteen indicators spanning renewable energy penetration, environmental pressure, economic conditions, governance capacity, technology cost feasibility, and innovation capability, the D-CRITIC results identify CO₂ emissions per capita as the most informative criterion, followed by the share of electricity generated by bioenergy, the share of primary energy consumption from renewable sources, and solar LCOE. The COBRA-based assessment ranks Canada first, followed by the United Kingdom, Italy, Germany, Japan, the United States, and France. Robustness and sensitivity analyses show broad consistency in ranking patterns across alternative MCDM methods, while weight perturbation tests confirm that the ranking remains unchanged under $\pm 5\%$ and $\pm 10\%$ relative changes in criterion weights. These findings indicate that stronger renewable energy transition performance is associated with balanced progress across emissions reduction, renewable energy penetration, technology cost feasibility, institutional capacity, and innovation-related conditions, rather than superiority in a single indicator. The proposed framework offers a transparent and replicable tool for renewable energy transition benchmarking and evidence-based policy learning, while the results should be interpreted as cross-sectional comparative performance under the selected dataset and criteria rather than as a causal evaluation of specific policy instruments.



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1. Introduction

The global energy system is undergoing a profound transformation as countries seek to accelerate decarbonization while maintaining energy security, economic resilience, and technological competitiveness. Renewable energy transition is increasingly viewed not only as the expansion of renewable installed capacity, but also as a multidimensional transformation involving environmental performance, renewable deployment, economic feasibility, technological capability, institutional readiness, and long-term sustainability. Recent evidence on carbon neutrality highlights that energy transition depends on the interaction between clean energy development, policy coordination, technology diffusion, and system-level transformation [1]. Decarbonization pathways across electricity generation, transportation, and heating further show that renewable energy transition cannot be evaluated through a single sector or indicator but requires a broader view of how clean energy contributes to economy-wide emission reduction [2]. In parallel, studies on carbon neutrality emphasize the joint role of energy efficiency, renewable energy, carbon trading, and advanced energy policies in shaping transition performance [3], while global evidence suggests that renewable energy development can also reduce climate-risk exposure [4]. These insights indicate that renewable energy transition performance should be assessed as a comprehensive outcome rather than as a narrow measure of renewable energy expansion.

A multidimensional assessment is particularly important because renewable energy transition is shaped by both enabling conditions and binding constraints. Financial development has been shown to influence the potential for energy net-zero transformation, suggesting that the ability to mobilize capital and absorb clean technologies can differentiate transition outcomes across countries [5]. Technological capability also plays an important role, as artificial intelligence and digital innovation can support high-quality energy development through efficiency improvement and innovation channels [6]. At the same time, renewable deployment generates new sustainability challenges, including the management of end-of-life renewable infrastructure and the circular transformation of clean-energy components [7]. Broader evidence also indicates that renewable energy sources can catalyze energy transition only when technological innovation, system compatibility, and supportive transition conditions are aligned [8]. Moreover, the supply sustainability of critical metals for clean energy technologies has become a major feasibility constraint, especially under rapid deployment scenarios that increase demand for lithium, cobalt, and other strategic materials [9]. These studies collectively suggest that renewable energy transition assessment should capture both achieved performance and the structural conditions that determine whether such performance can be sustained.

The G7 countries provide a highly relevant empirical context for benchmarking renewable energy transition performance. As advanced economies with substantial technological capacity, mature financial systems, and strong climate commitments, G7 members are expected to lead the global transition. However, their transition trajectories remain heterogeneous. The selection of the G7 is particularly appropriate because these countries combine high energy demand, advanced technological capability, mature governance systems, and long-standing decarbonization commitments, while still differing considerably in electricity mix, renewable resource endowment, fossil-fuel dependence, industrial structure, and policy implementation pathways. Evidence from G7 economies shows that renewable energy investment, environmental regulation, and financial development jointly shape renewable energy transition, indicating that transition performance depends on the interaction of multiple enabling factors [10]. At the same time, fiscal policy structures, energy consumption patterns, and environmental stringency may produce different transition outcomes even among advanced economies [11]. Comparative sustainability-efficiency evidence for G7 and BRICS economies also confirms that meaningful performance differences persist across

major economic groups, reinforcing the need for systematic benchmarking [12]. Therefore, evaluating the G7 through a multidimensional framework can provide useful evidence on relative performance, structural bottlenecks, and policy-learning opportunities among countries with comparable development levels but different transition outcomes.

Despite the growing literature on renewable energy transition, several limitations remain. First, many studies rely on single indicators, sector-specific measures, or capacity-centered metrics that do not fully reflect the multidimensional nature of transition performance. Second, econometric studies are valuable for identifying relationships among transition drivers, but they are not always designed to provide transparent country rankings under multiple conflicting criteria. Third, existing benchmarking studies often do not sufficiently integrate environmental outcomes, renewable deployment, economic feasibility, technological capability, and sustainability constraints into a single decision-oriented framework. Fourth, many conventional assessment frameworks do not explicitly account for nonlinear and non-monotonic interdependence among transition indicators, even though the relationships among emissions intensity, renewable energy shares, technology costs, governance quality, economic readiness, and innovation capability are unlikely to be purely linear. Fifth, relatively few studies combine distance-sensitive objective weighting with a compromise-based ranking mechanism to provide a stable and interpretable benchmarking structure. These limitations are especially relevant for G7 benchmarking, where the key analytical question is not only whether transition drivers matter, but also how countries compare when multiple performance dimensions and trade-offs are considered simultaneously.

Multi-criteria decision-making provides a suitable methodological foundation for this problem because it allows alternatives to be evaluated under multiple and potentially conflicting criteria. Recent reviews show that MCDM has become increasingly important for sustainability evaluation, particularly when decision problems involve heterogeneous indicators, conflicting objectives, and the need for transparent prioritization [13,14]. In the energy domain, MCDM-based approaches have been applied to renewable energy investment evaluation and renewable technology comparison, demonstrating their usefulness for structuring complex energy decisions and supporting comparative assessment [15,16]. However, the reliability of MCDM benchmarking depends strongly on how criteria are weighted and how final rankings are generated. Objective weighting is therefore important because it reduces reliance on subjective judgment and allows criterion importance to be derived from the information contained in the data.

Within this context, CRITIC-based methods are particularly relevant because they determine criteria weights by considering both contrast intensity and conflict among criteria. Recent applications show that CRITIC can be effectively incorporated into MCDM models to capture data-driven criterion importance [13]. D-CRITIC extends this logic by incorporating distance-based information, making it especially useful when alternatives exhibit heterogeneous performance dispersion, as is often the case in cross-country benchmarking [17]. Unlike the traditional CRITIC approach, which commonly relies on standard deviation and conventional correlation information, D-CRITIC introduces a distance-based dependence structure that can reflect both linear and nonlinear associations among criteria. This feature is important for renewable energy transition assessment because the relationships among environmental, institutional, technological, cost-related, and innovation indicators may be complex and not adequately captured by linear correlation alone. Objective weighting has also been shown to be useful in sustainability assessment across large-scale comparative contexts, supporting its relevance for national-level benchmarking without imposing subjective preferences [18]. Related integrated approaches using D-CRITIC in optimization and ranking frameworks further demonstrate the value of combining distance-sensitive

weighting with multi-criteria evaluation when competing objectives must be balanced systematically [19]. These methodological developments support the use of D-CRITIC in the present study to derive objective and discriminating weights for renewable energy transition indicators.

Beyond weighting, credible transition-performance benchmarking requires a ranking method capable of producing interpretable compromise solutions under benefit–cost trade-offs. The COBRA method is appropriate for this purpose because it ranks alternatives through comprehensive distance-based evaluation and is suitable for benchmarking settings involving heterogeneous criteria. Recent applications of COBRA in financial performance evaluation and resource assessment show that the method can support stable and interpretable rankings in complex decision environments [20,21]. In renewable energy transition assessment, this feature is important because countries may perform well on some dimensions, such as renewable deployment or technological capability, while facing weaknesses in others, such as emissions intensity, technology cost, or feasibility constraints. A compromise-oriented ranking procedure is therefore needed to synthesize these trade-offs into a transparent comparative evaluation.

In addition, robustness and sensitivity analysis are essential when MCDM results are used to support comparative performance interpretation. Sensitivity analysis helps examine whether final rankings remain stable when methodological assumptions, criteria weights, or evaluation parameters change. Recent state-of-the-art research confirms that sensitivity analysis has become a central component of MCDM because it strengthens confidence in the reliability of ranking outcomes [22]. Foundational studies further emphasize that stability analysis is necessary to evaluate how changes in weights or decision parameters may influence MCDM results [23,24]. Applied evidence from hybrid MCDM sustainability assessment also demonstrates that sensitivity analysis can verify the robustness of model outputs in complex sustainability-related decision problems [25]. These studies directly support the inclusion of robustness checks in the present framework, particularly because cross-country transition rankings may inform policy learning and comparative performance interpretation.

To further clarify the positioning of the present study, Table A1 compares the current research with related studies in terms of research context, methodological orientation, treatment of criterion interdependence, ranking mechanism, and robustness assessment.

To address the above gaps, this study develops and empirically applies an integrated D-CRITIC–COBRA framework to benchmark observable renewable energy transition performance and enabling conditions across G7 countries. The proposed framework first uses D-CRITIC to derive objective criteria weights based on cross-country dispersion and inter-criteria relationships. It then applies COBRA to generate a compromise-oriented ranking of G7 countries under benefit-type and cost-type transition indicators. Finally, sensitivity analysis is conducted to verify the stability of the ranking outcomes under alternative analytical conditions. This design allows the study to move beyond single-indicator assessment and produce a transparent, data-driven benchmark of renewable energy transition performance.

Against this background, the motivation and novelty of the present study are threefold. First, the study is motivated by the need for a transparent and reproducible benchmarking framework that evaluates renewable energy transition performance as a multidimensional outcome rather than as a single deployment, emissions, or policy indicator. Second, it addresses the need for a decision-oriented assessment structure capable of incorporating criterion dispersion, inter-criteria dependence, benefit–cost trade-offs, and ranking robustness within a unified framework. Third, it responds to the lack of a G7-focused renewable energy

transition benchmarking model that combines distance-sensitive objective weighting with compromise-based ranking.

This study makes four main contributions. First, it contributes to the renewable energy transition literature by providing a holistic assessment of G7 transition performance that jointly considers environmental outcomes, renewable deployment, economic feasibility, technological capability, and sustainability-related constraints. Second, it advances the MCDM literature by operationalizing an integrated distance-sensitive weighting and distance-based ranking architecture through the combination of D-CRITIC and COBRA. Third, it clarifies the value of distance-based criterion dependence in renewable energy transition assessment, where the relationships among emissions, renewable energy penetration, governance quality, technology costs, and innovation capability may be nonlinear or non-monotonic. Fourth, it strengthens the reliability of transition-performance benchmarking by incorporating sensitivity analysis to examine whether the derived rankings are robust rather than artifacts of a single methodological configuration. By doing so, the study provides both methodological value for energy-policy evaluation and practical insights for identifying performance differentials and bottlenecks among advanced economies.

The study is structured into six interrelated sections to ensure a coherent theoretical empirical progression. Section 1 introduces the research topic, articulates the underlying motivation, and delineates the study's objectives and guiding research questions. Section 2 details the methodological design, including the analytical framework, D-CRITIC weighting procedure, COBRA ranking procedure, and methodological validation logic. Section 3 provides an empirical illustration by implementing the proposed approach on the selected G7 renewable energy transition dataset, reporting descriptive evidence and the main empirical results. Building on these findings, Section 4 offers an in-depth discussion that interprets the results in relation to relevant theory and prior literature and critically reflects on plausible explanations and limitations. Section 5 then derives the study's theoretical contributions and managerial implications, highlighting how the evidence informs both scholarly debates and practical decision-making. Section 6 concludes by synthesizing the key insights, summarizing the principal contributions, acknowledging constraints, and outlining promising avenues for future research.

2. Methodology

The CRITIC method is a rigorous and fully objective tool used to determine the weights of evaluation criteria without the influence of expert judgment. This method quantifies the importance of each criterion by simultaneously considering the level of contrast among alternatives and the degree of correlation among criteria. Through this dual consideration, CRITIC highlights criteria that both exhibit high variability and provide non-redundant information. Its mathematical framework allows analysts to detect the most influential attributes with precision, making it particularly valuable in decision contexts involving complex systems. Nonetheless, a well-known limitation of the traditional CRITIC method is its inability to fully capture total correlation, because positive and negative correlations may offset each other. To address this drawback, the present study adopts the distance-based CRITIC method by incorporating a distance-based dependence structure into the criterion weighting process.

The main difference between traditional CRITIC and distance-based CRITIC lies in how inter-criteria dependence is represented. Traditional CRITIC generally combines standard deviation with conventional correlation information, which is mainly designed to reflect linear association among criteria. However, renewable energy transition indicators may interact in nonlinear or non-monotonic ways. For example, the relationship among renewable energy shares, emissions intensity, governance quality, technology costs, and

innovation capability may not follow a simple linear pattern. D-CRITIC is therefore more suitable for this study because it uses distance covariance and distance correlation to capture broader dependence structures among criteria. In this sense, the role of distance in D-CRITIC is not merely a general MCDM concept, but a specific dependence-measurement mechanism used to improve the objectivity and discriminatory capacity of criterion weighting. Wang et al. developed the distance-based CRITIC model for a comparative analysis of the resilience of telecommunications infrastructure in BRICS countries [26]. The distance-based CRITIC is detailed in the next section.

In parallel, the COBRA method with its distinct functional orientation, provides a strong analytical basis for evaluating the performance efficiency of alternatives by quantifying their deviation from positive ideal, negative ideal, and average solution. This method determines the degree to which each alternative diverges from the best and worst possible outcomes and simultaneously evaluates how closely each option aligns with an “optimal” solution. By integrating multiple deviation measures, COBRA provides a comprehensive assessment of the relative performance of alternatives [27,28]. The use of COBRA is appropriate for the present benchmarking problem because renewable energy transition performance involves both benefit-type and cost-type indicators, and countries may perform strongly in some dimensions while showing weaknesses in others. A compromise-based distance-ranking method is therefore needed to synthesize these trade-offs into a single interpretable ranking.

The integration of D-CRITIC and COBRA is also methodologically coherent. D-CRITIC first provides objective criterion weights derived from the information structure of the decision matrix, thereby reducing reliance on subjective expert judgment. COBRA then uses these weights to rank alternatives through a comprehensive distance-based comparison with positive ideal, negative ideal, and average solutions. This two-stage structure is suitable for decision makers because it separates the weighting problem from the ranking problem while preserving a transparent connection between criterion information and final country performance. To further examine whether the final rankings are dependent on the selected ranking procedure, the results are compared with TOPSIS, SAW, and CODAS in the sensitivity and robustness analysis section. The integrated MCDM framework combining objective weighting and performance evaluation is illustrated in Figure 1. This unified approach is executed through the following structured steps:

Step 1: Define a decision-making problem comprising a alternatives and b criteria. Construct the decision matrix N , where each indicator n_{ij} denotes the performance of the i^{th} alternative with respect to the j^{th} criterion.

$$N = [n_{ij}]_{a \times b} \quad (1)$$

Step 2: Classify the criteria into beneficial and non-beneficial groups. Normalize the decision matrix using Equations (2) for benefit criteria and (3) for cost criteria to obtain the normalized matrix U , as shown in Equation (4).

$$u_{ij} = \frac{n_{ij} - \min_i n_{ij}}{\max_i n_{ij} - \min_i n_{ij}}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (2)$$

$$u_{ij} = \frac{n_{ij} - \max_i n_{ij}}{\min_i n_{ij} - \max_i n_{ij}}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (3)$$

$$U = [u_{ij}]_{a \times b} \quad (4)$$

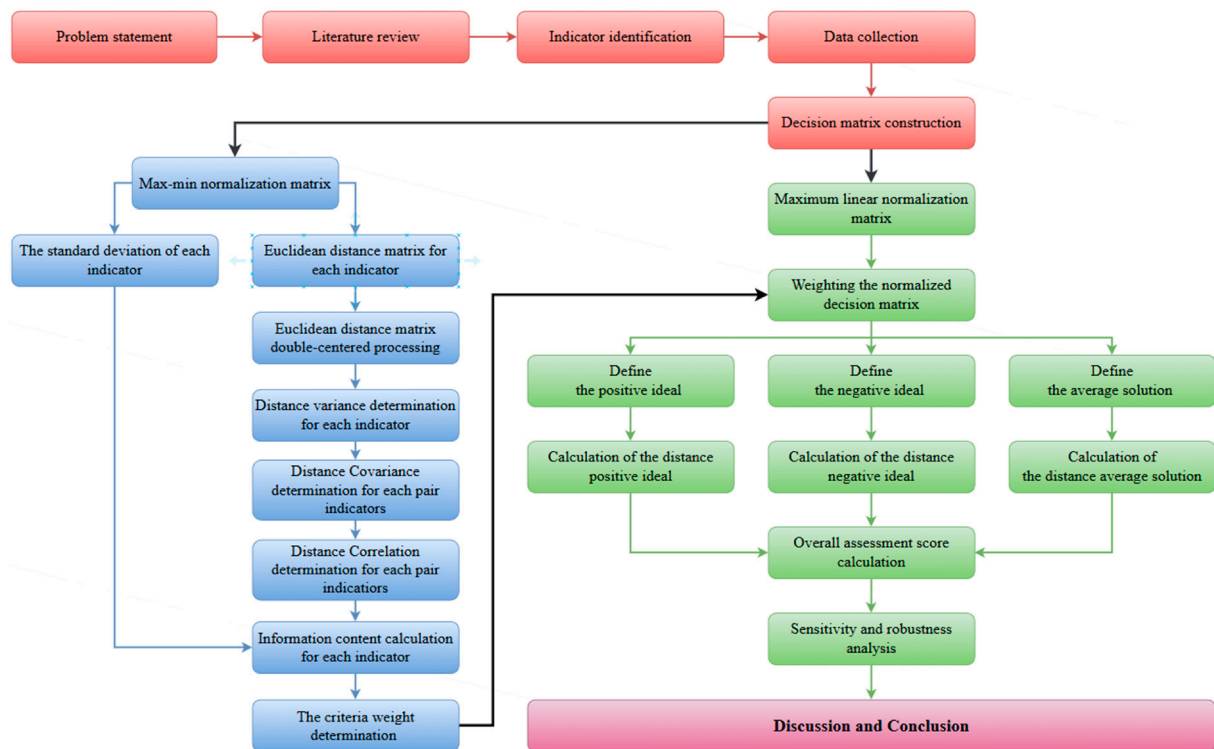


Figure 1. The flowchart of the proposed MCDM methodology.

Step 3: Calculate the standard deviation (τ) of each criterion using Equation (5), which serves as the basis for measuring contrast intensity across alternatives.

$$\tau_j = \sqrt{\frac{\sum_{i=1}^a |u_{ij} - \bar{u}_j|^2}{a}} \text{ where } \bar{u}_j = \frac{\sum_{i=1}^a u_{ij}}{a} \quad (5)$$

Step 4: Construct the Euclidean distance matrix for each criterion by computing pairwise distances between the normalized values of alternatives using Equations (6) and (7).

$$T_j = \begin{bmatrix} 0 & t_{12}^j & \dots & t_{1a}^j \\ t_{21}^j & 0 & \dots & t_{2a}^j \\ \vdots & \vdots & \ddots & \vdots \\ t_{a1}^j & t_{a2}^j & \dots & 0 \end{bmatrix}; \quad j = 1, \dots, b \quad (6)$$

where

$$t_{il}^j = |u_{ij} - u_{lj}|; \quad i = 1, \dots, a; \quad j = 1, \dots, b; \quad l = 1, \dots, a; \quad i \neq l \quad (7)$$

Step 5: Determine the row means, column means, and overall matrix means for each Euclidean distance matrix following Equations (8)–(10).

$$\bar{D}_i^j = \frac{1}{a} \sum_{l=1, l \neq i}^a t_{il}^j; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (8)$$

$$\bar{E}_l^j = \frac{1}{a} \sum_{i=1, i \neq l}^a t_{il}^j; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (9)$$

$$\bar{O}^j = \frac{1}{a^2} \sum_{i=1}^a \sum_{l=1}^a t_{il}^j; \quad j = 1, \dots, b \quad (10)$$

Step 6: Apply the double-centering transformation to each Euclidean distance matrix. The resulting double-centered matrices are calculated using Equations (11) and (12).

$$C_j = \begin{bmatrix} c_{11}^j & c_{12}^j & \cdots & c_{1a}^j \\ c_{21}^j & c_{22}^j & \cdots & c_{2a}^j \\ \vdots & \vdots & \ddots & \vdots \\ c_{a1}^j & c_{a2}^j & \cdots & c_{aa}^j \end{bmatrix}; \quad j = 1, \dots, b \quad (11)$$

where

$$c_{il}^j = t_{il}^j - \bar{D}_i^j - \bar{E}_l^j + \bar{O}^j; \quad i = 1, \dots, a; \quad j = 1, \dots, b; \quad l = 1, \dots, a \quad (12)$$

Step 7: Compute the distance covariance between the j^{th} and k^{th} criteria (dC_{jk}) following three sub-procedures:

- Multiply double-centered matrices elementwise using the Schur product.
- Determine the average value of the elementwise multiplication matrix.
- Determine the square root of the average value.

Step 8: Compute the distance correlation (dR_{jk}) between the j^{th} and k^{th} criteria using Equation (13).

$$dR_{jk} = \frac{dV_{jk}}{\sqrt{dV_{jj} \times dV_{kk}}} \quad (13)$$

Step 9: Determine the amount of information carried by each criterion according to Equation (14), which combines both variability and dependence.

$$\phi_j = \tau_j \sum_{k=1}^b (1 - dR_{jk}); \quad j = 1, \dots, b \quad (14)$$

Step 10: Calculate the objective weights for each criterion using Equation (15), producing the improved CRITIC weighting.

$$\omega_j = \frac{\phi_j}{\sum_{j=1}^b \phi_j}; \quad j = 1, \dots, b \quad (15)$$

Step 11: Normalize the original decision matrix again, this time using the modified normalization formulas in Equations (16) and (17), which differ from the initial CRITIC normalization. The resulting normalized matrix M is provided in Equation (18).

$$m_{ij} = \frac{n_{ij}}{n_{jmax}}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad \text{for benefit criteria} \quad (16)$$

$$m_{ij} = \frac{n_{jmin}}{n_{ij}}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad \text{for cost criteria} \quad (17)$$

$$M = [m_{ij}]_{a \times b} \quad (18)$$

Step 12: Multiply each element of the normalized matrix by the corresponding objective weight obtained in Step 10, yielding the weighted normalized matrix as shown in Equation (19).

$$R = [r_{ij}]_{a \times b} \quad (19)$$

$$r_{ij} = m_{ij} \cdot \omega_j \quad i = 1, \dots, a; \quad j = 1, \dots, b$$

Step 13: Define the positive ideal solution B_j , the negative ideal solution NB_j , and the average solution A_j for each criterion, following Equations (20)–(24).

$$B_j = \max_i r_{ij}; \quad j = 1, \dots, b \quad \text{for benefit criteria} \quad (20)$$

$$B_j = \min_i r_{ij}; \quad j = 1, \dots, b \quad \text{for cost criteria} \quad (21)$$

$$NB_j = \min_i r_{ij}; \quad j = 1, \dots, b \quad \text{for benefit criteria} \quad (22)$$

$$NB_j = \max_i r_{ij}; \quad j = 1, \dots, b \quad \text{for cost criteria} \quad (23)$$

$$A_j = \frac{\sum_{i=1}^a r_{ij}}{a}; \quad j = 1, \dots, b \quad (24)$$

Step 14: In this step, calculate all types of distances required for the COBRA assessment, including: distance to the positive ideal $d(B_j)$, distance to the negative ideal $d(NB_j)$, positive distance from the average solution $d(A_j^+)$ and negative distance from the average solution $d(A_j^-)$. This process is performed according to Equation (25).

$$d(X_j) = dE(X_j) + \eta \times dE(X_j) \times dT(X_j); \quad j = 1, \dots, b \quad (25)$$

where X_j is any solution (B_j , NB_j or A_j), η represents the correction coefficient defined by using the following Equation (26):

$$\eta = \max_i dE(X_j)_i - \min_i dE(X_j)_i \quad (26)$$

where $dE(X_j)_i$ and $dT(X_j)_i$ represent the Euclidian and Taxicab distances, respectively, which are calculated for the positive ideal solution calculated is computed using Equations (27) and (28).

$$dE(B_j)_i = \sqrt{\sum_{j=1}^b (B_j - r_{ij})^2}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (27)$$

$$dT(B_j)_i = \sum_{j=1}^b |B_j - r_{ij}|; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (28)$$

For the negative ideal solutions, the Euclidian and Taxicab distances are computed using Equations (29) and (30).

$$dE(NB_j)_i = \sqrt{\sum_{j=1}^b (NB_j - r_{ij})^2}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (29)$$

$$dT(NB_j)_i = \sum_{j=1}^b |NB_j - r_{ij}|; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (30)$$

For the positive distance from the average solution the Euclidian and Taxicab distances are calculated as shown in Equations (31)–(33).

$$dE(A_j)_i^+ = \sqrt{\sum_{j=1}^b \theta^+ (A_j - r_{ij})^2}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (31)$$

$$dT(A_j)_i^+ = \sum_{j=1}^b \theta^+ |A_j - r_{ij}|; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (32)$$

$$\theta^+ = \begin{cases} 1 & \text{if } A_j < r_{ij} \\ 0 & \text{if } A_j \geq r_{ij} \end{cases} \quad (33)$$

Finally, for the negative distance from the average solution the Euclidian and Taxicab distances are calculated as shown in Equations (34)–(36).

$$dE(A_j)_i^- = \sqrt{\sum_{j=1}^b \theta^- (A_j - r_{ij})^2}; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (34)$$

$$dT(A_j)_i^- = \sum_{j=1}^b \theta^- |A_j - r_{ij}|; \quad i = 1, \dots, a; \quad j = 1, \dots, b \quad (35)$$

$$\theta^- = \begin{cases} 1 & \text{if } A_j > r_{ij} \\ 0 & \text{if } A_j \leq r_{ij} \end{cases} \quad (36)$$

Step 15: Compute the final performance score for each alternative using Equation (37). Rank all alternatives in ascending order based on their comprehensive distance values dC_i , where a smaller distance indicates a better-performing alternative.

$$dC_i = \frac{d(B_j)_i - d(NB_j)_i - d(A_j)_i^+ + d(A_j)_i^-}{4}; \quad i = 1, \dots, a \quad (37)$$

Computational complexity of the proposed framework:

Let a denote the number of alternatives and b denote the number of evaluation criteria. The computational complexity of the proposed framework can be discussed in terms of the D-CRITIC weighting stage and the COBRA ranking stage. In the D-CRITIC stage, normalization and standard deviation calculation require $O(ab)$ operations. The construction of the pairwise Euclidean distance matrix for each criterion requires $O(a^2b)$ operations. The calculation of distance covariance and distance correlation between pairs of criteria requires pairwise criterion comparisons, leading to an approximate complexity of $O(a^2b^2)$. Therefore, the D-CRITIC stage is mainly driven by the distance-correlation calculation.

In the COBRA stage, normalization, weighted matrix construction, and the determination of positive ideal, negative ideal, and average solutions require $O(ab)$ operations. The calculation of Euclidean and Taxicab distances from the reference solutions also scales approximately as $O(ab)$ for each distance component. Thus, the COBRA stage has linear complexity with respect to the size of the decision matrix. Overall, the computational burden of the integrated D-CRITIC–COBRA framework is dominated by the D-CRITIC dependence-analysis stage, with an approximate overall complexity of $O(a^2b^2)$. In the present empirical application, where $a = 7$ G7 countries and $b = 14$ criteria, the computational cost is low and the procedure is fully reproducible.

3. Empirical Illustration

3.1. Case Description and Data Collection

This study empirically assesses renewable energy transition performance through a comparative multi-criteria benchmarking framework across major advanced economies. Rather than estimating the causal effects of specific renewable energy policies or policy instruments, the proposed framework evaluates observable transition outcomes and enabling conditions that reflect how countries progress across multiple dimensions of renewable energy transition. The decision problem therefore focuses on comparing country-level performance under several, and often conflicting, economic, environmental, institutional, technological, and cost-related criteria. To this end, seven G7 economies, namely the United States (US), the United Kingdom (UK), Canada (CA), France (FR), Germany (DE), Italy (IT), and Japan (JA), are selected as decision alternatives. These countries are characterized by high energy demand, long-standing climate mitigation commitments, mature institutional systems, and diverse renewable energy transition pathways, thereby providing a relevant empirical setting for cross-country benchmarking. Accordingly, the empirical setting should be understood as a population-based comparison of the G7 economies rather than a statistical sample designed for inferential estimation.

This study does not rely on expert-based subjective assessments or multiple decision-maker matrices. Instead, it uses a single objective decision matrix constructed from secondary data. The matrix consists of seven alternatives and fourteen evaluation criteria. This design is consistent with the objective nature of the D-CRITIC weighting procedure, in which criterion importance is derived from the dispersion and interdependence structure of

the data rather than from expert preference scores. As a result, the role of decision makers in this study is not to assign subjective weights, but to define the benchmarking problem, classify benefit and cost criteria, and interpret the resulting performance patterns.

The evaluation framework is constructed using fourteen criteria (C1–C14), encompassing both benefit-type and cost-type indicators to capture the multidimensional nature of renewable energy transition performance, as summarized in Table 1. The criteria were selected based on three principles: theoretical relevance to renewable energy transition performance, cross-country comparability across all G7 economies, and availability of consistent data for the selected reference period. To improve cross-country comparability and reduce the potential scale bias associated with absolute energy-output indicators, the revised indicator system emphasizes relative, intensity-based, per capita, institutional, cost, and innovation-related measures. Benefit-oriented criteria include the share of primary energy consumption from renewable sources, the share of electricity generated by bioenergy, per capita renewable energy consumption, annual percentage change in renewable energy generation, political stability and absence of violence/terrorism, corruption perception index, government effectiveness, GDP per capita, share of electricity production from hydropower, and patents on environmental technologies. In contrast, cost-oriented criteria capture environmental and economic burdens associated with the transition process, including CO₂ emissions per capita, carbon intensity of electricity generation, and the levelized costs of solar and wind power.

More specifically, the selected criteria are organized into six conceptual dimensions of renewable energy transition performance. The first dimension is renewable energy penetration, represented by C1, C2, C4, C5, and C13, which capture the relative contribution, consumption, growth, and resource-based deployment of renewable energy. The second dimension is environmental pressure, represented by C3 and C10, which reflect the emissions burden at the economy-wide and electricity-generation levels. The third dimension is institutional and governance capacity, represented by C6, C7, and C8, because stable, effective, and transparent institutions are important enabling conditions for implementing and sustaining transition strategies. The fourth dimension is economic readiness, represented by C9, which captures the general economic capacity to support investment, technology adoption, and infrastructure development. The fifth dimension is technology cost feasibility, represented by C11 and C12, which reflects the economic feasibility of solar and wind power deployment. The sixth dimension is innovation capability, represented by C14, which captures the contribution of environmental technology development to long-term transition capacity.

This indicator structure enables the assessment to reflect not only renewable energy deployment and consumption patterns, but also environmental pressure, governance capacity, economic conditions, technology cost feasibility, and environmental innovation capability. Although other sub-criteria such as energy storage deployment, grid flexibility, transmission infrastructure, renewable energy investment intensity, electric vehicle adoption, energy security, and social acceptance are also important for understanding renewable energy transition, they were not included in the main decision matrix because consistent, complete, and directly comparable data across all G7 economies and the selected reference period were not uniformly available. These aspects are therefore acknowledged as important extensions for future research rather than omitted as conceptually irrelevant factors.

The empirical analysis relies on a secondary data collection strategy, drawing on publicly available and internationally recognized statistical sources commonly used in renewable energy and sustainability research, including Our World in Data [29], the World Bank [30], the International Renewable Energy Agency [31], the OECD (Organization for Economic Co-operation and Development) [32] and various national and sectoral reports,

ensuring a high degree of credibility and comparability [33,34]. The data-collection procedure followed four steps. First, the indicators were identified and classified as benefit or cost criteria according to their expected contribution to renewable energy transition performance. Second, raw data were collected from the above-mentioned sources using a consistent reference year or the closest available comparable year. Third, all indicators were checked for unit consistency, directional consistency, and cross-country comparability. Fourth, the final decision matrix was screened for missing observations and logical coherence before being used in the MCDM analysis. The resulting decision matrix summarizes the performance of each country across the selected criteria and reflects a consistent reference period to avoid temporal distortions, as shown in Table 2. Prior to analysis, the dataset was examined for completeness, unit consistency, and logical coherence, and no missing observations were identified. The replacement of absolute energy-output indicators with share-based measures strengthens the validity of the cross-country comparison by limiting the influence of country size on the final MCDM ranking. Overall, the use of authoritative data sources, combined with a balanced set of well-established indicators, enhances the reliability and comparability of the empirical dataset while minimizing subjective bias in the benchmarking process.

Table 1. Description of evaluation indicators.

Type	Indicator	Units	Source
Benefit	C1—Share of primary energy consumption from renewable sources	%	[29]
Benefit	C2—Share of electricity generated by bioenergy	%	[29]
Cost	C3—CO ₂ emissions per capita	tCO ₂ /capita	[29]
Benefit	C4—Per capita renewable energy consumption	kWh/person	[29]
Benefit	C5—Annual percentage change in renewable energy generation	%	[29]
Benefit	C6—Political Stability and Absence of Violence/Terrorism	%	[30]
Benefit	C7—Corruption Perception Index	Score	[29]
Benefit	C8—Government Effectiveness	Score	[30]
Benefit	C9—GDP per capita	US\$	[30]
Cost	C10—Carbon intensity of electricity generation	gCO ₂	[29]
Cost	C11—Levelized cost of energy for solar (solar LCOE)	US\$ per kw/h	[29]
Cost	C12—Levelized cost of energy for wind (wind LCOE)	US\$ per kw/h	[29]
Benefit	C13—Share of electricity production from hydropower	%	[29]
Benefit	C14—Patents on environment technologies	%	[32]

Table 2. Decision matrix description.

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
US	12.05	1.02	14.3	9192	8.3	47.39	65	77.8	85,809	384	0.07	0.04	5.39	5.9
UK	21.29	14.1	4.44	5903	6.1	62.09	71	74.4	52,636	211	0.08	0.05	1.96	7.3
CA	27.16	1.61	13.98	26,117	5	76.3	75	85.5	54,282	175	0.1	0.03	55.28	7
FR	16.47	1.8	4.1	6139	8.37	55.92	67	74.7	46,150	44	0.07	0.06	12.42	7.9
DE	23.97	10.1	7.05	8950	1.1	66.35	75	81.4	55,800	344	0.06	0.05	4.91	8.2
IT	20.93	5.9	5.27	5932	11.36	64.93	54	66.7	40,226	288	0.06	0.06	19.19	6.7
JA	12.7	5.33	7.95	4887	4.52	81.52	71	91.9	32,475	482	0.12	0.14	7.63	8.4

3.2. Criteria Weighting Results

Building on the empirically grounded indicator system established in Section 3.1, this study applies the D-CRITIC method to derive objective criterion weights for assessing renewable energy transition performance. This approach is particularly appropriate because it avoids subjective prioritization while allowing the data to reveal which dimensions carry the greatest informational significance for distinguishing performance across countries.

The normalized decision matrix in Table 3 constitutes the common analytical basis for computing both dispersion and inter-criteria dependence. Normalization is a critical step given the heterogeneous nature of the indicators, ranging from renewable energy shares and per capita values to institutional scores, economic indicators, emissions measures, and technology cost variables. This design choice ensures that the weighting process is not driven by differences in measurement scale but by the intrinsic structure of the dataset.

Table 3. The normalized decision matrix of distance-based CRITIC method.

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
US	0.000	0.000	0.000	0.203	0.702	0.000	0.524	0.440	1.000	0.224	0.833	0.909	0.064	0.000
UK	0.612	1.000	0.967	0.048	0.487	0.431	0.810	0.306	0.378	0.619	0.667	0.818	0.000	0.560
CA	1.000	0.045	0.031	1.000	0.380	0.847	1.000	0.746	0.409	0.701	0.333	1.000	1.000	0.440
FR	0.293	0.060	1.000	0.059	0.709	0.250	0.619	0.317	0.256	1.000	0.833	0.727	0.196	0.800
DE	0.789	0.694	0.711	0.191	0.000	0.556	1.000	0.583	0.437	0.315	1.000	0.818	0.055	0.920
IT	0.588	0.373	0.885	0.049	1.000	0.514	0.000	0.000	0.145	0.443	1.000	0.727	0.323	0.320
JA	0.043	0.330	0.623	0.000	0.333	1.000	0.810	1.000	0.000	0.000	0.000	0.000	0.106	1.000

The standard deviation values reported in Figure 2 are calculated from the normalized decision matrix using Equation (5). In the D-CRITIC framework, standard deviation is required to measure the contrast intensity of each criterion across alternatives. A criterion with a higher standard deviation provides stronger discriminatory information because it shows greater variation among the evaluated countries. Therefore, standard deviation is not used merely as a descriptive statistic, but as a key component for determining how strongly each criterion can differentiate renewable energy transition performance across the G7 economies.

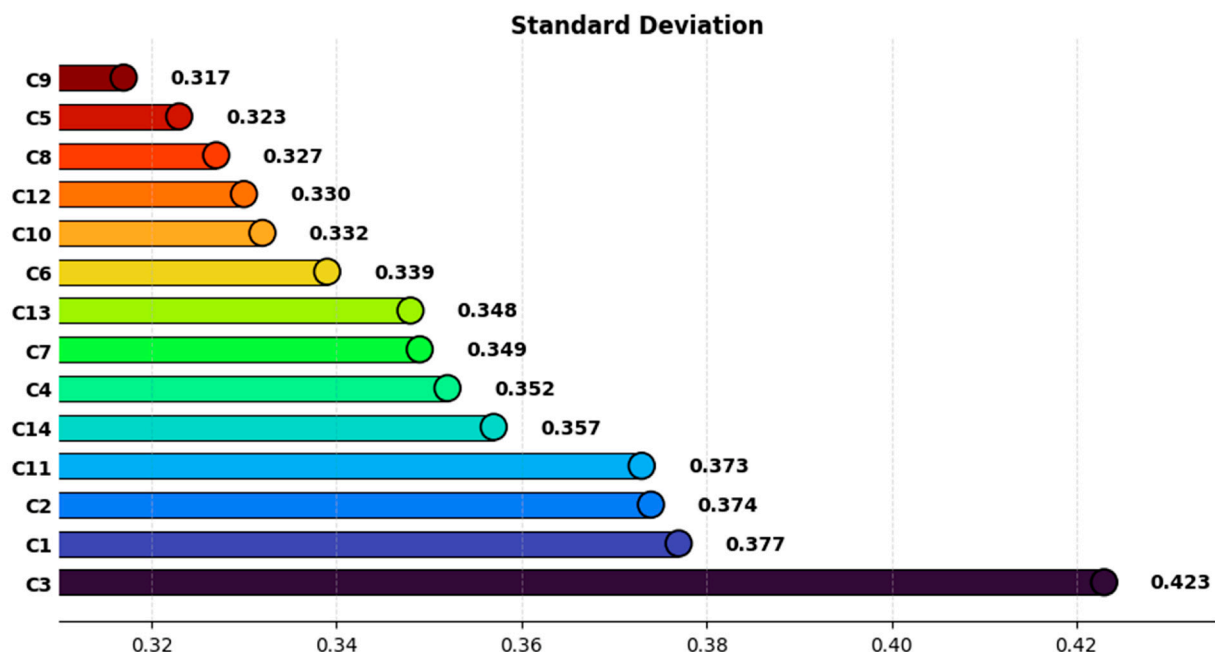


Figure 2. The standard deviation of each criterion.

As shown in Figure 2, the standard deviation analysis highlights pronounced cross-country heterogeneity in indicators directly linked to environmental pressure and transition feasibility. In particular, CO₂ emissions per capita exhibit the highest dispersion ($\tau = 0.423$), followed by the share of primary energy consumption from renewable sources ($\tau = 0.377$), the share of electricity generated by bioenergy ($\tau = 0.374$) and solar LCOE ($\tau = 0.373$). From a methodological perspective, these indicators possess strong discriminatory power; from

a transition-performance perspective, they correspond to core dimensions of renewable energy transition, namely emissions pressure, renewable penetration, bioenergy contribution, and technology cost competitiveness. The high dispersion of CO₂ emissions per capita is especially meaningful in the G7 context. Although all G7 countries are advanced economies with strong climate commitments, their energy structures differ considerably. Some economies remain more dependent on fossil fuels in electricity generation, transport, and industrial energy use, whereas others benefit from lower-carbon electricity mixes, higher renewable shares, hydropower resources, or nuclear energy contributions. As a result, CO₂ emissions per capita captures important structural differences in fossil-fuel dependence, energy consumption patterns, industrial composition, and the pace of decarbonization. This explains why C3 provides the strongest contrast among the evaluated countries and later receives the highest D-CRITIC weight. By contrast, lower dispersion in indicators such as GDP per capita suggests limited marginal discriminatory power once other transition-related dimensions are considered.

To address potential redundancy among indicators, a frequent concern in multi-dimensional sustainability assessments, the D-CRITIC framework further incorporates interdependence analysis. Using the share of primary energy consumption from renewable sources as an illustrative example, Tables 4 and 5 present the Euclidean distance matrix and its double-centered form, respectively, which form the basis for distance covariance calculations. This distance-based approach is particularly suitable for renewable energy transition analysis, where relationships among economic, environmental, institutional, technological, and cost-related variables may be nonlinear and inadequately captured by traditional correlation measures.

Table 4. The Euclidean Distance matrix for C1.

Country	US	UK	CA	FR	DE	IT	JA	Row Mean
US	0.000	0.612	1.000	0.293	0.789	0.588	0.043	0.475
UK	0.612	0.000	0.388	0.319	0.177	0.024	0.568	0.298
CA	1.000	0.388	0.000	0.707	0.211	0.412	0.957	0.525
FR	0.293	0.319	0.707	0.000	0.496	0.295	0.250	0.337
DE	0.789	0.177	0.211	0.496	0.000	0.201	0.746	0.374
IT	0.588	0.024	0.412	0.295	0.201	0.000	0.545	0.295
JA	0.043	0.568	0.957	0.250	0.746	0.545	0.000	0.444
Column mean	0.475	0.298	0.525	0.337	0.374	0.295	0.444	0.393

Table 5. The double-centered Euclidean Distance matrix for C1.

Country	US	UK	CA	FR	DE	IT	JA
US	−0.557	0.231	0.393	−0.127	0.332	0.211	−0.483
UK	0.231	−0.204	−0.042	0.076	−0.103	−0.177	0.219
CA	0.393	−0.042	−0.658	0.238	−0.296	−0.015	0.380
FR	−0.127	0.076	0.238	−0.282	0.178	0.056	−0.139
DE	0.332	−0.103	−0.296	0.178	−0.356	−0.075	0.320
IT	0.211	−0.177	−0.015	0.056	−0.075	−0.197	0.198
JA	−0.483	0.219	0.380	−0.139	0.320	0.198	−0.495

The resulting distance covariance and distance correlation patterns reveal low-to-moderate interdependencies among several criteria, as shown in Figures 3 and 4. Importantly, the absence of near-unity distance correlations indicates that no indicator is fully redundant, despite the expected interlinkages inherent in energy transition processes. Methodologically, this finding justifies retaining the full indicator set; substantively, it

reflects the reality that renewable energy transition performance is shaped by interacting, but not interchangeable, economic, environmental, institutional, technological, and cost-related factors.

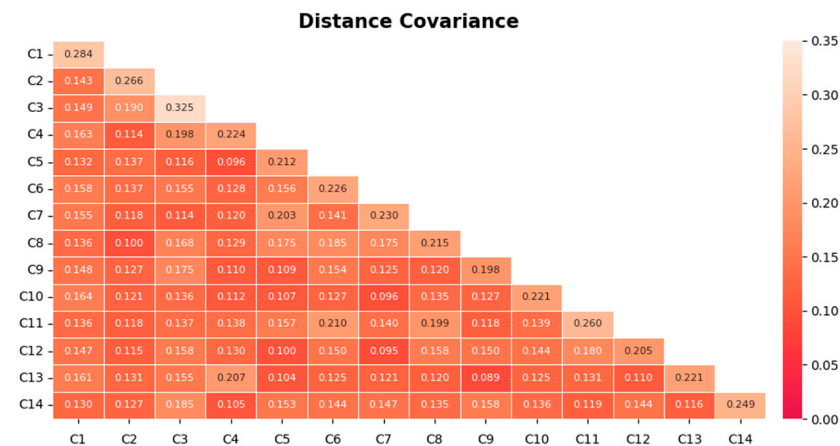


Figure 3. The distance covariance coefficient between indicators.

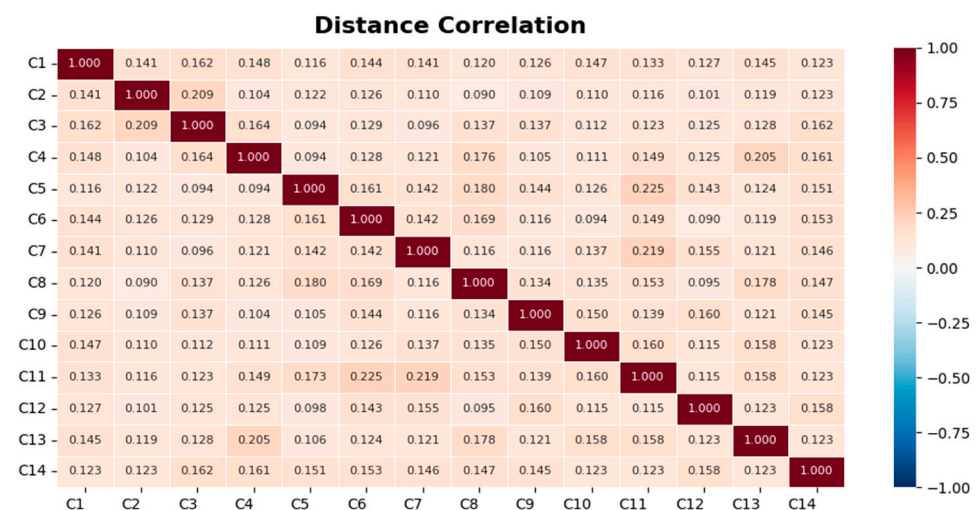


Figure 4. The distance correlation coefficient between indicators.

Figure 5 synthesizes dispersion and dependence information into the information content of each criterion. Indicators that combine high contrast with relatively low redundancy emerge as the most informative contributors to the evaluation framework. Notably, environmental pressure, renewable energy shares, and technology cost indicators rank prominently, reinforcing the interpretation that renewable energy transition performance should be assessed through multiple observable outcomes and enabling conditions rather than through absolute energy-output quantities alone.

The final objective weights derived from the D-CRITIC method are shown in Figure 6. The weight distribution is relatively balanced, indicating that the evaluation is not dominated by a single dimension and thereby enhancing the robustness of subsequent country rankings. Nonetheless, C3 receives the highest weight ($\omega = 0.086$), followed by C2 ($\omega = 0.077$), C1 ($\omega = 0.076$) and C11 ($\omega = 0.074$). This pattern is methodologically consistent with their high informational content and substantively indicates that emissions performance, bioenergy contribution, renewable energy penetration, and solar cost feasibility play central roles in differentiating renewable energy transition performance across the G7 economies. These criteria can therefore be regarded as the most influential factors in the weighting stage of the proposed framework. Conversely, the relatively lower weight

assigned to C9 suggests that economic affluence alone does not sufficiently explain differences in transition performance once environmental, institutional, technological, and cost-related factors are jointly considered.

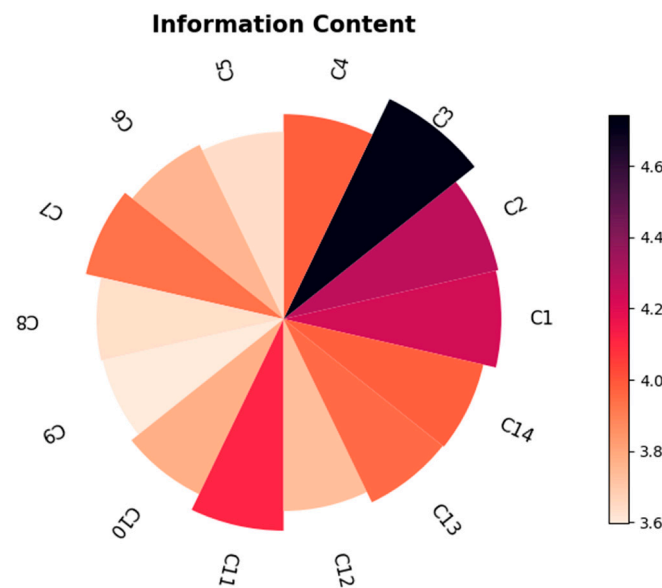


Figure 5. The information content of indicators.

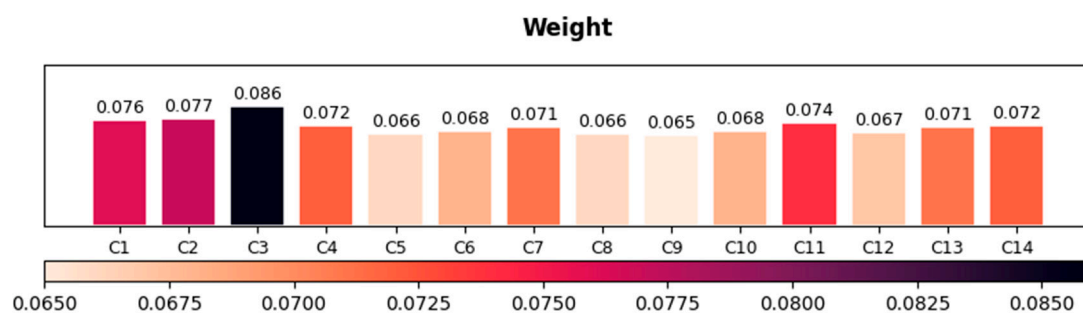


Figure 6. The objective weight of indicators.

3.3. Alternatives Assessment and Ranking

Using the objective criterion weights derived from the D-CRITIC method in Section 3.2, this study proceeds to assess and rank renewable energy transition performance through the COBRA method. This integration ensures that the ranking results are grounded in data-driven weighting and a compromise-based evaluation logic, which is particularly suitable for multidimensional benchmarking problems involving both benefit and cost criteria.

Table 6 presents the normalized decision matrix of the COBRA method, which constitutes the initial input for evaluating country performance under a unified measurement scale. The normalization step preserves the relative performance patterns identified in Section 3.1 while enabling consistent aggregation across heterogeneous indicators. Building on this foundation, Table 7 reports the weighted normalized decision matrix obtained by incorporating the D-CRITIC-derived objective weights. This step embeds the informational importance of each criterion into the performance evaluation, thereby ensuring that indicators with greater discriminatory power and lower redundancy exert proportionally stronger influence on the ranking outcomes.

Table 6. The normalized decision matrix of COBRA method.

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
US	0.444	0.072	0.287	0.352	0.731	0.581	0.867	0.847	1.000	0.115	0.857	0.750	0.098	0.702
UK	0.784	1.000	0.923	0.226	0.537	0.762	0.947	0.810	0.613	0.209	0.750	0.600	0.035	0.869
CA	1.000	0.114	0.293	1.000	0.440	0.936	1.000	0.930	0.633	0.251	0.600	1.000	1.000	0.833
FR	0.606	0.128	1.000	0.235	0.737	0.686	0.893	0.813	0.538	1.000	0.857	0.500	0.225	0.940
DE	0.883	0.716	0.582	0.343	0.097	0.814	1.000	0.886	0.650	0.128	1.000	0.600	0.089	0.976
IT	0.771	0.418	0.778	0.227	1.000	0.796	0.720	0.726	0.469	0.153	1.000	0.500	0.347	0.798
JA	0.468	0.378	0.516	0.187	0.398	1.000	0.947	1.000	0.378	0.091	0.500	0.214	0.138	1.000

Table 7. Weighting the normalized decision matrix.

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
US	0.034	0.006	0.025	0.025	0.048	0.039	0.062	0.056	0.065	0.008	0.064	0.051	0.007	0.051
UK	0.060	0.077	0.079	0.016	0.035	0.052	0.067	0.053	0.040	0.014	0.056	0.040	0.003	0.062
CA	0.076	0.009	0.025	0.072	0.029	0.064	0.071	0.061	0.041	0.017	0.045	0.067	0.071	0.060
FR	0.046	0.010	0.086	0.017	0.048	0.047	0.064	0.053	0.035	0.068	0.064	0.034	0.016	0.068
DE	0.067	0.055	0.050	0.025	0.006	0.055	0.071	0.058	0.042	0.009	0.074	0.040	0.006	0.070
IT	0.059	0.032	0.067	0.016	0.066	0.054	0.051	0.048	0.030	0.010	0.074	0.034	0.025	0.057
JA	0.036	0.029	0.044	0.013	0.026	0.068	0.067	0.066	0.025	0.006	0.037	0.014	0.010	0.072

The distance-based evaluation results are illustrated in Figure 7, which depicts each country's distances from the positive benchmark and negative benchmark solutions. Countries characterized by more favorable distances relative to the positive, negative, and average reference solutions are interpreted as exhibiting stronger overall renewable energy transition performance. The figure reveals clear cross-country differences, reflecting the combined effects of emissions performance, renewable energy shares, technology costs, institutional conditions, and innovation-related factors emphasized by the D-CRITIC weighting scheme. These patterns indicate that country performance cannot be attributed to a single dominant dimension but emerges from the interaction of multiple transition-related criteria.

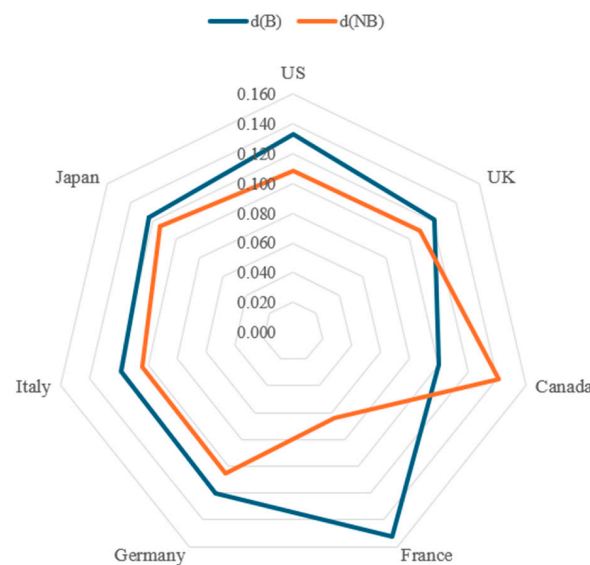
**Figure 7.** The distance positive-negative ideal.

Figure 8 further illustrates the average solution analysis, which captures the relative positioning of each country with respect to the overall performance centroid. This representation provides complementary insight into the consistency of national performance across

criteria, rather than focusing solely on extreme best–worst comparisons. Countries located closer to the favorable average solution demonstrate more balanced transition performance, whereas those deviating less favorably from the centroid tend to exhibit weaknesses in selected high-weight criteria, such as emissions performance, renewable energy shares, or technology cost feasibility.

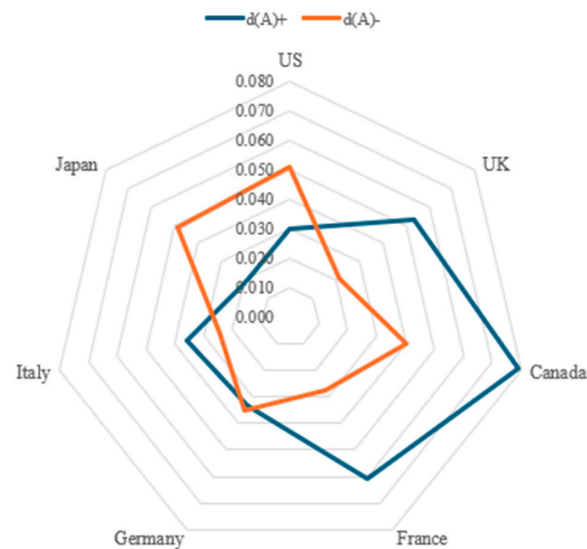


Figure 8. The average solution.

The overall preference performance values and corresponding rankings are summarized in Figure 9. The results indicate a clear performance hierarchy among the evaluated countries. Canada ranks first, reflecting its strong performance in several transition-related dimensions, particularly renewable energy penetration, per capita renewable energy consumption, hydropower contribution, institutional quality, and wind cost feasibility. The United Kingdom ranks second, supported by relatively favorable emissions performance and institutional indicators. Italy follows in third position, mainly due to its strong renewable energy growth and competitive technology cost indicators. Germany and Japan occupy the fourth and fifth positions, respectively, indicating intermediate transition performance with strengths in selected institutional, technological, or innovation-related dimensions but also weaknesses in other criteria. The United States ranks sixth, suggesting that its performance is constrained under the revised share-based indicator system, particularly because absolute energy-output advantages no longer dominate the assessment. France is positioned last in the COBRA ranking, indicating that despite strengths in some environmental and cost-related indicators, its overall compromise performance is less favorable when all weighted criteria are jointly considered.

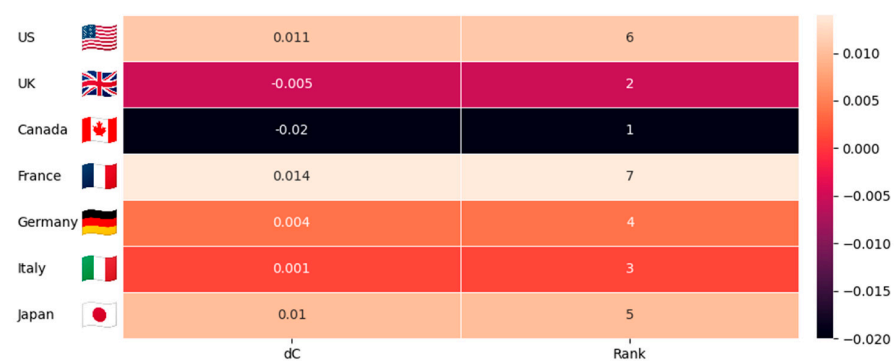


Figure 9. The overall preference performance.

3.4. Sensitivity and Robustness Analysis

Given the multi-criteria and method-dependent nature of composite performance evaluation, a sensitivity and robustness analysis is conducted to examine the stability of the ranking results derived in Section 3.3. This step is particularly important in renewable energy transition assessment, where different aggregation logics may emphasize distinct aspects of transition performance. To this end, the ranking outcomes, obtained from the D-CRITIC–COBRA framework, are systematically compared with those generated by three widely used MCDM methods, namely TOPSIS, SAW, and CODAS. TOPSIS is an ideal-solution-based distance method, SAW is a classical additive aggregation benchmark, and CODAS is a distance-based dominance method. Therefore, comparing COBRA with these methods allows the study to examine whether the ranking pattern is specific to the COBRA formulation or remains broadly consistent across alternative MCDM perspectives.

Figure 10 illustrates the sensitivity analysis results for the G7 countries under the four methods. Despite methodological differences in normalization, aggregation, and preference construction, the results show broadly comparable ranking patterns across the alternative methods. Countries that perform relatively well under the COBRA framework tend to maintain favorable positions under other methods, although some rank fluctuations are observed. These differences are expected in multi-criteria evaluations because each method applies a different compromise logic and may assign different emphasis to distances from ideal solutions, additive performance, or relative dominance structures. Accordingly, the purpose of this comparison is not to obtain identical rankings across all methods, but to determine whether the main performance hierarchy remains reasonably stable when alternative ranking mechanisms are applied.

At the individual country level, the comparison indicates that the overall performance hierarchy is reasonably stable, although not identical across methods. Canada remains among the strongest performers across the alternative MCDM approaches, while France generally occupies a lower position. The United Kingdom and Italy also remain relatively competitive, whereas the United States, Germany, and Japan show more method-dependent positioning. These patterns suggest that the main benchmarking results are not solely driven by the COBRA formulation, but they also indicate that ranking stability should be interpreted cautiously rather than as complete invariance across methods.

To quantitatively assess ranking consistency, Table 8 reports the Spearman rank correlation coefficients between the COBRA-based ranking and those obtained from the benchmark MCDM methods. The correlation between COBRA and TOPSIS is the highest, with $r_s = 0.75$ and a p -value of 0.053, indicating a strong positive association that is close to the 5% significance threshold and can be interpreted as marginally significant at the 10% level. The correlations between COBRA and SAW ($r_s = 0.60$, p -value = 0.154) and between COBRA and CODAS ($r_s = 0.61$, p -value = 0.146) indicate moderate positive associations, although these relationships are not statistically significant at conventional levels. Therefore, the rank correlation results provide supportive evidence of ranking consistency, but they should not be interpreted as definitive statistical confirmation of high-ranking stability. This interpretation is especially important because the number of alternatives is limited to the seven G7 economies; therefore, the p -values should be read as supplementary evidence rather than as the sole basis for robustness evaluation.

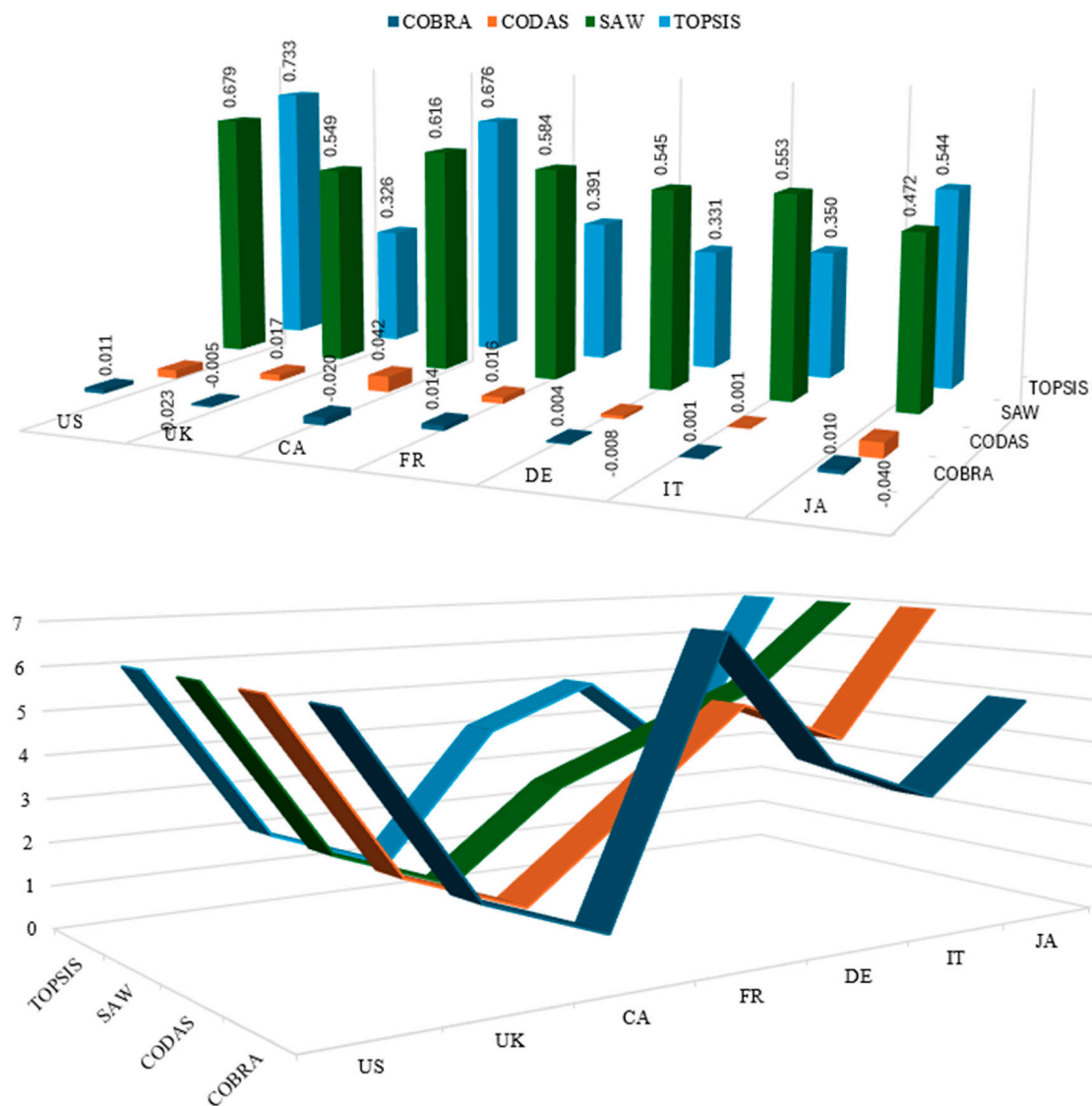


Figure 10. The sensitivity analysis results of G7 countries under the four MCDM methods.

Table 8. Rank Correlation Coefficients among MCDM methods.

Comparison	Spearman's r_s	p -Value	Interpretation
COBRA-TOPSIS	0.75	0.053	Strong correlation
COBRA-SAW	0.6	0.154	Moderate correlation
COBRA-CODAS	0.61	0.146	Moderate correlation

From a methodological standpoint, the robustness comparison suggests that the D-CRITIC–COBRA framework produces rankings that are broadly consistent with alternative MCDM aggregation procedures, especially with TOPSIS. However, the observed rank differences and non-significant p -values for some comparisons also confirm the importance of conducting sensitivity analysis in multidimensional benchmarking. From a substantive perspective, the results indicate that the identified renewable energy transition performance hierarchy is generally robust to alternative evaluation lenses, while still reflecting some method-dependent variation inherent in MCDM-based assessment.

To further examine the robustness of the COBRA ranking with respect to changes in criterion importance, a weight perturbation analysis was conducted using $\pm 5\%$ and $\pm 10\%$ relative deviations from the baseline D-CRITIC weights. In each scenario, the

perturbed weights were re-normalized to ensure that the total weight remained equal to one, and the COBRA scores and rankings were recalculated. This procedure is useful because the D-CRITIC weights are relatively balanced, and small differences in weights may still influence the final distance-based ranking when they are aggregated across multiple criteria. The results show that although the comprehensive distance values change slightly across the perturbation scenarios, the ranking order remains unchanged. Specifically, Canada consistently ranks first, followed by the United Kingdom, Italy, Germany, Japan, the United States, and France. This finding indicates that the proposed ranking is stable under moderate changes in the weighting structure and is not driven by small variations in individual criterion weights.

The sensitivity analysis also helps identify the most influential factors in the evaluation framework. As shown in Table 9, the criteria with the greatest influence are C3, C2, C1, and C11, corresponding to CO₂ emissions per capita, the share of electricity generated by bioenergy, the share of primary energy consumption from renewable sources, and solar LCOE, respectively. These criteria have higher informational content because they combine relatively strong cross-country dispersion with lower redundancy. Therefore, changes in these criteria are more likely to affect the comprehensive distance values than changes in lower-weighted indicators. Nevertheless, the perturbation results show that the final ranking remains unchanged under the tested $\pm 5\%$ and $\pm 10\%$ scenarios, suggesting that the overall ranking structure is not overly dependent on marginal changes in any single high-weight criterion.

Table 9. Weight perturbation.

Countries	<i>dC</i>				Ranking			
	−5%	+5%	−10%	+10%	−5%	+5%	−10%	+10%
US	0.011	0.012	0.010	0.012	6	6	6	6
UK	−0.005	−0.005	−0.004	−0.005	2	2	2	2
CA	−0.019	−0.021	−0.018	−0.022	1	1	1	1
FR	0.013	0.014	0.012	0.015	7	7	7	7
DE	0.004	0.005	0.004	0.005	4	4	4	4
IT	0.001	0.001	0.001	0.001	3	3	3	3
JA	0.009	0.010	0.009	0.011	5	5	5	5

It should also be noted that the robustness results are conditional on the selected dataset, reference period, indicator system, and normalization procedure. As with other deterministic MCDM applications, the ranking may vary if a different set of indicators, a different country group, or a longitudinal dataset is used. Therefore, the results should be interpreted as a transparent cross-sectional benchmark of G7 renewable energy transition performance under the specified analytical design, rather than as a universal or time-invariant ranking. This dataset-dependent nature of MCDM evaluation is acknowledged as a limitation and provides a direction for future research using alternative datasets, extended time horizons, or scenario-based assessments.

4. Discussion

This study provides a multidimensional MCDM-based assessment of renewable energy transition performance across G7 economies by integrating environmental, economic, institutional, technological, innovation-related, and cost dimensions. Rather than measuring the causal effectiveness of specific policy instruments, the proposed D-CRITIC–COBRA framework benchmarks observable transition outcomes and enabling conditions in a cross-sectional setting. This distinction is important because the results should be interpreted as

relative comparative performance under the selected criteria, rather than as a definitive judgment on the overall success or failure of national energy-transition policies.

The D-CRITIC weighting results show that renewable energy transition performance is mainly differentiated by environmental pressure, renewable energy penetration, bioenergy contribution, and technology cost feasibility. CO₂ emissions per capita receives the highest weight, followed by the share of electricity generated by bioenergy, the share of primary energy consumption from renewable sources, and solar LCOE. The prominence of CO₂ emissions per capita is meaningful in the G7 context because these countries differ substantially in fossil-fuel dependence, electricity-generation mix, industrial energy use, and the pace of decarbonization. Meanwhile, the use of share-based and intensity-based indicators helps reduce scale bias and improves the comparability of transition-performance benchmarking across countries with different economic and energy-system sizes.

The COBRA-based ranking reveals clear heterogeneity among the evaluated countries. Canada ranks first, followed by the United Kingdom and Italy, while Germany and Japan occupy intermediate positions. The United States ranks sixth, and France is positioned last. These results suggest that stronger benchmark performance is associated with balanced progress across multiple dimensions rather than superiority in one isolated indicator. Countries with favorable rankings tend to combine stronger renewable energy penetration, lower environmental burden, supportive institutional conditions, and more competitive technology cost structures, whereas lower-ranked countries tend to exhibit bottlenecks in selected high-weight criteria. Therefore, the ranking should be understood as a compromise-based performance comparison under the proposed indicator system, not as an absolute evaluation of national transition success.

From a methodological perspective, the integration of D-CRITIC and COBRA provides a transparent structure for renewable energy transition benchmarking. D-CRITIC captures both criterion dispersion and interdependence, while COBRA translates the resulting objective weights into a compromise-based ranking under benefit and cost criteria. The sensitivity analysis further supports the credibility of the results, as the ranking pattern remains broadly consistent across alternative MCDM methods and unchanged under $\pm 5\%$ and $\pm 10\%$ weight perturbation scenarios. However, the presence of method-dependent variation also confirms that MCDM rankings should be interpreted cautiously. Overall, the proposed framework offers a replicable decision-support tool for identifying relative strengths and bottlenecks among advanced economies, while acknowledging that the results are conditional on the selected dataset, reference period, normalization procedure, and indicator system.

5. Theoretical and Managerial Implications

The findings of this study provide several theoretical implications for renewable energy transition assessment. First, the results reinforce the view that renewable energy transition performance should be understood as a multidimensional system-level outcome rather than a single measure of renewable deployment, emissions reduction, or economic capacity. By integrating environmental pressure, renewable energy penetration, institutional quality, economic readiness, technology cost feasibility, and innovation capability, the study shows that cross-country transition performance is shaped by the interaction of multiple dimensions. This implication is particularly important because renewable energy transition cannot be sufficiently explained by installed capacity or aggregate renewable output alone. Instead, it reflects a broader structural process in which environmental outcomes, institutional readiness, economic conditions, technology costs, and innovation capacity jointly determine transition performance. This supports the need for assessment frameworks that

move beyond isolated indicators and capture the broader structural conditions underlying renewable energy transition.

Second, the study contributes to the MCDM literature by demonstrating how objective weighting and compromise-based ranking can be integrated for renewable energy transition benchmarking. The D-CRITIC method enables criterion importance to be derived from the information structure of the dataset by considering both dispersion and inter-criteria dependence, while the COBRA method translates these weights into a compromise ranking under benefit and cost criteria. This integration is theoretically meaningful because it links two complementary analytical functions: identifying informative and non-redundant criteria through distance-sensitive weighting, and synthesizing country performance through a compromise-based ranking mechanism. As a result, the proposed framework helps address the challenge of evaluating alternatives that perform unevenly across environmental, economic, institutional, technological, and cost-related dimensions. This methodological integration provides a transparent and reproducible structure for comparative sustainability assessment, especially when alternatives exhibit strengths and weaknesses across different dimensions.

From a managerial and policy-oriented perspective, the proposed framework can support decision makers in identifying relative strengths and bottlenecks in renewable energy transition performance. The results suggest that stronger benchmark performance depends on balanced progress across renewable penetration, emissions reduction, institutional capacity, technology cost feasibility, and innovation-related conditions. Therefore, policymakers and energy planners should not focus solely on expanding renewable energy capacity, but should also address emissions intensity, cost competitiveness, governance effectiveness, and technological innovation. For example, countries with weaker performance in high-weight criteria such as CO₂ emissions per capita, renewable energy shares, or solar LCOE may need to prioritize deeper decarbonization of the energy mix, accelerated renewable integration, and cost-reduction strategies for clean technologies. Similarly, countries with relatively strong renewable deployment but weaker institutional or innovation-related indicators may benefit from improving governance effectiveness, regulatory coordination, and support for environmental technology development.

At the same time, the rankings should be interpreted as decision-support evidence based on the selected dataset and criteria, rather than as a causal evaluation of specific national policy instruments. This makes the framework useful for policy learning, strategic benchmarking, and identifying priority areas for future transition planning. In practical terms, the proposed approach can help policymakers, energy planners, and sustainability managers compare national transition performance, diagnose structural bottlenecks, and prioritize policy attention across multiple dimensions. However, it should be used as a diagnostic benchmarking tool rather than as a definitive measure of policy effectiveness, because the ranking outcomes remain conditional on the selected indicators, reference period, data availability, and methodological assumptions.

6. Conclusions

This study developed and applied an integrated multi-criteria decision-making framework to assess renewable energy transition performance across the G7 economies. Motivated by the limitations of single-indicator and capacity-focused assessments, the study captured the multidimensional nature of renewable energy transitions by jointly considering environmental pressure, renewable energy penetration, economic conditions, institutional quality, technology cost feasibility, and innovation capability. Rather than estimating the causal effectiveness of specific policy instruments, the proposed framework provides a structured and transparent basis for benchmarking observable transition outcomes and

enabling conditions across advanced economies. Accordingly, the findings should be interpreted as a cross-sectional benchmarking result based on the selected indicators and reference dataset, rather than as a causal or time-invariant evaluation of national renewable energy policies.

Drawing on a revised empirical dataset for the G7 countries, the results show that renewable energy transition performance is most strongly differentiated by indicators reflecting environmental pressure, renewable energy shares, and technology cost conditions. In particular, CO₂ emissions per capita receive the highest D-CRITIC weight, followed by the share of electricity generated by bioenergy, the share of primary energy consumption from renewable sources, and solar LCOE. These findings indicate that cross-country differences in transition performance are shaped not by economic scale alone, but by the combined influence of emissions performance, relative renewable energy uptake, bioenergy contribution, and cost feasibility. The relatively lower weight assigned to GDP per capita further suggests that economic affluence does not automatically translate into stronger renewable energy transition performance when multiple dimensions are jointly considered.

The application of the D-CRITIC method reveals that the informational importance of the selected indicators is unevenly distributed and shaped by both cross-country heterogeneity and inter-criteria dependence. By allowing criterion weights to emerge from data variability and redundancy structures, the study avoids subjective prioritization and ensures that the evaluation reflects the intrinsic characteristics of the dataset. Building on these weights, the COBRA method provides a compromise-based assessment that accounts for trade-offs between benefit and cost criteria. The resulting ranking identifies Canada as the best-performing country, followed by the United Kingdom, Italy, Germany, Japan, the United States, and France. This hierarchy highlights that strong transition performance depends on balanced progress across several dimensions rather than superiority in a single indicator. However, this ranking should be understood as relative compromise performance under the proposed indicator system, not as an absolute judgment on the overall success or failure of each country's renewable energy transition.

The sensitivity and robustness analyses further strengthen the credibility of the empirical findings, while also confirming the importance of cautious interpretation in MCDM-based benchmarking. The comparison with alternative MCDM methods indicates broad consistent ranking patterns, particularly between COBRA and TOPSIS, although moderate correlations with SAW and CODAS suggest some method-dependent variation. In addition, the weight perturbation analysis shows that the COBRA ranking remains unchanged under $\pm 5\%$ and $\pm 10\%$ relative changes in criterion weights after re-normalization. These results indicate that the ranking is stable under the examined sensitivity scenarios and is not driven by small or moderate changes in the weighting structure. Nevertheless, the results may vary when different datasets, reference years, country groups, normalization procedures, or indicator systems are used. Therefore, future studies should test the proposed framework under alternative datasets and longitudinal settings to examine whether the ranking structure remains stable over time and across different empirical contexts.

Taken together, the findings contribute to the renewable energy transition literature by demonstrating that meaningful cross-country comparison requires both multidimensional indicator systems and transparent aggregation mechanisms. The study shows that renewable energy transition performance should be understood as a system-level outcome shaped by the interaction of environmental, economic, institutional, technological, innovation-related, and cost dimensions. By offering a transparent, objective, and empirically grounded benchmarking framework, the research provides scholars, policymakers, and energy planners with a useful tool for comparing transition performance, identifying

structural bottlenecks, and supporting evidence-based policy learning without claiming to isolate the causal effect of individual policy instruments.

Despite these contributions, several limitations should be acknowledged. First, the reliance on aggregated national-level data may mask subnational variation and sector-specific dynamics within each country. Second, the static nature of the analysis does not capture the temporal evolution of renewable energy transition pathways. Third, although the revised indicator system improves cross-country comparability by using share-based renewable energy measures, future studies may incorporate additional social, infrastructural, and policy-specific variables to enrich the assessment. More specifically, future research may consider additional sub-criteria such as energy storage deployment, grid flexibility, transmission infrastructure, renewable energy investment intensity, electric vehicle adoption, energy security, social acceptance, and sector-specific decarbonization indicators when consistent and comparable data become available. Future research could extend the proposed framework to longitudinal analysis, compare broader groups of countries, incorporate uncertainty in input data, and examine how specific policy instruments interact with multidimensional transition outcomes over time. Further extensions may also apply fuzzy, stochastic, or scenario-based MCDM models to capture uncertainty in criterion values, weighting assumptions, and future energy-transition pathways.

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Appendix A

Table A1. Comparative positioning of the present study is relative to related literature.

Study/Stream	Research Context	Methodological Focus	Treatment of Criterion Interdependence	Ranking/Benchmarking Orientation
Carbon neutrality and energy-transition studies [1–4]	Global or sectoral energy transition and decarbonization	Conceptual, empirical, or review-based assessment	Not the central methodological focus	Limited country-level MCDM ranking
G7 renewable energy and policy studies [10,11]	G7 energy transition, regulation, fiscal policy, and financial development	Econometric or policy-oriented analysis	Relationships among drivers are usually modeled statistically rather than through MCDM criterion dependence	Not primarily designed for compromise-based country ranking
Sustainability and MCDM review studies [13,14]	Sustainability, logistics, and low-carbon systems	Review of MCDM techniques and applications	Discussed generally across methods	Not focused on G7 renewable energy transition ranking
Renewable energy MCDM applications [15,16]	Renewable energy investment and technology selection	MCDM-based evaluation of renewable alternatives	Generally, method-specific	Technology or investment-oriented ranking

Table A1. Cont.

Study/Stream	Research Context	Methodological Focus	Treatment of Criterion Interdependence	Ranking/Benchmarking Orientation
D-CRITIC-related integrated approaches [17–19]	Charging stations, industrial systems, sustainability, and routing problems	Objective weighting using distance-sensitive information	Explicitly considered through distance-based weighting	Context-specific ranking or optimization
COBRA applications [20,21]	Financial performance and resource/geotourism assessment	Comprehensive distance-based ranking	Primarily addressed through the ranking framework rather than weighting	Compromise-based ranking
Present study	Renewable energy transition performance of G7 economies	Integrated D-CRITIC–COBRA framework	Distance-based criterion interdependence is incorporated through D-CRITIC	Compromise-based cross-country benchmarking using COBRA

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