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Article

Green Finance Utilization Among G20 Nations: Assessment Using the CRITIC-TOPSIS Approach

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Abstract: This study evaluates and ranks G20 countries' green finance utilization (GFU) using the CRITIC-TOPSIS multi-criteria decision-making method, based on fifteen indicators across financial, environmental, developmental, and innovation dimensions. Germany ranks highest due to strong performance in renewable energy, environmental sustainability, human development, and innovation. Despite leading in green bond issuance, China scores lower due to high emissions and fossil fuel dependence. Brazil ranks unexpectedly high, driven by its renewable energy mix, while France, Japan, the UK, and India also perform well. Lower rankings for Saudi Arabia, Russia, and South Africa reflect weak climate action and fossil fuel reliance. Alternative methods such as VIKOR, EDAS, MOORA, and COPRAS were applied for robustness, showing consistent country rankings. Sensitivity analysis using equal indicator weights further confirmed the stability of the results. The findings emphasize that green finance (GF) effectiveness relies on integrating financial instruments within broader sustainability strategies, offering a valuable benchmark for policymakers and guiding future research in climate finance.

Keywords: Green Finance Utilization (GFU); G20 Countries; CRITIC-TOPSIS; Multi-Criteria Decision-Making (MCDM); Sustainability; Renewable Energy; Climate Policy

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1. Introduction

The global landscape faces an increasing climate crisis as temperature averages rose about 1.7°F during the 1970s until 2023 [1]. Current temperature elevation has accelerated dangerous weather activity and harmed ecosystems, apart from worsening health problems and economic pressure [2]. A coordinated international response must take immediate effect because the solution requires a reduction of emissions and enhancing resilience. Central to this endeavor is mobilizing financial resources toward sustainable development pathways. In this context, green finance (GF) is a vital tool that helps link economic operations to climate targets while enabling a worldwide low-carbon transition [3,4].

GF has evolved into a significant means of aligning financial resources with environmental objectives by directing funds into initiatives that support renewable energy, sustainable infrastructure, clean technologies, and ecological preservation [5,6]. In addition to its environmental benefits, GF carries numerous advantages, including that, it promotes economic development through the establishment of green industries, increase employment opportunities, enhances social welfare by reducing pollution and protecting public health, and fortifies governance by integrating sustainability into financial decision-making processes [7-10]. However, to fully reap those benefits, GF must be effectively employed through comprehensive regulatory frameworks, reliable financial instruments, thorough risk assessment, and increased awareness among stakeholders.

Recent research indicates that accomplishing environmental sustainability demands more than just the mobility of funds because effective green finance utilization (GFU) is essential. As evident in the earlier Studies, GFU enables improved resource allocation coupled with technological advancement and lower CO_2 emissions and generates sustainable development results in multiple regions [11-15]. While the benefits of GFU underline the worldwide significance, therefore emphasizing the role of G20 nations is essential due to their substantial contribution to global GDP, international trade, energy consumption and environmental influence [16].

The Group of Twenty (G20), comprising 19 countries, the European Union (EU), and, since 2023, the African Union (AU), collectively accounts for approximately 85% of global GDP, 75% of international trade, and two-thirds of the world's population [17]. Due to their massive greenhouse gas emission levels, G20 nations possess unparalleled influence over climate outcomes worldwide [18,19]. These economies deal with various obstacles such as the lack of standard GF definition, uncoordinated investment policies, sustainability targets and persistent ecological externalities associated with economic growth [20]. Simultaneously, they hold significant opportunities to foster global partnerships, share best practices, enhance financial stability, and promote sustainable development [21,22].

However, despite the recognized importance of GF, the existing body of literature remains fragmented. Much of the research tends to concentrate on isolated indicators, regional case studies, or qualitative assessments, without developing a comprehensive and objective framework to benchmark countries' performance on a global scale. Most studies, for instance, focus on specific dimensions such as green bond issuance, CO_2 reduction, or ESG investment flows, leaving a gap in integrated cross-country comparisons. Moreover, they fail to evaluate how financial resources are converted into tangible environmental and developmental outcomes. This limits the ability to identify leaders and laggards in sustainability transitions within the G20. The study fills this critical gap through an innovative evaluation approach combining the Criteria Importance Through Intercriteria Correlation (CRITIC) method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method that ranks G20 countries based on their GF performance through financial and environmental indicators and policy infrastructure assessment. Secondly, by providing nuanced recommendations to help lagging nations emulate leaders, leveraging best practices in governance, technology access, and funding mechanisms. The combined use of CRITIC and TOPSIS methods allows for a transparent ranking system that can be reproduced and subjected to sensitivity tests for evaluating GFU across G20 nations. The study supports GF theory and MCDM methodologies through its analysis, which creates a dynamic framework for policymakers to improve sustainability expenditure selection.

The study is structured as follows. Chapter 2 demonstrates the theoretical underpinnings of the study, while Chapter 3 reviews the relevant literature and identifies the research gap. Chapter 4 outlines the research design, data, variables, and methodological framework employed. Chapter 5 presents the empirical findings and robustness analysis. Finally, Chapter 6 concludes the study by discussing the key insights, policy implications, limitations, and avenues for future research.

2. Theoretical Framework

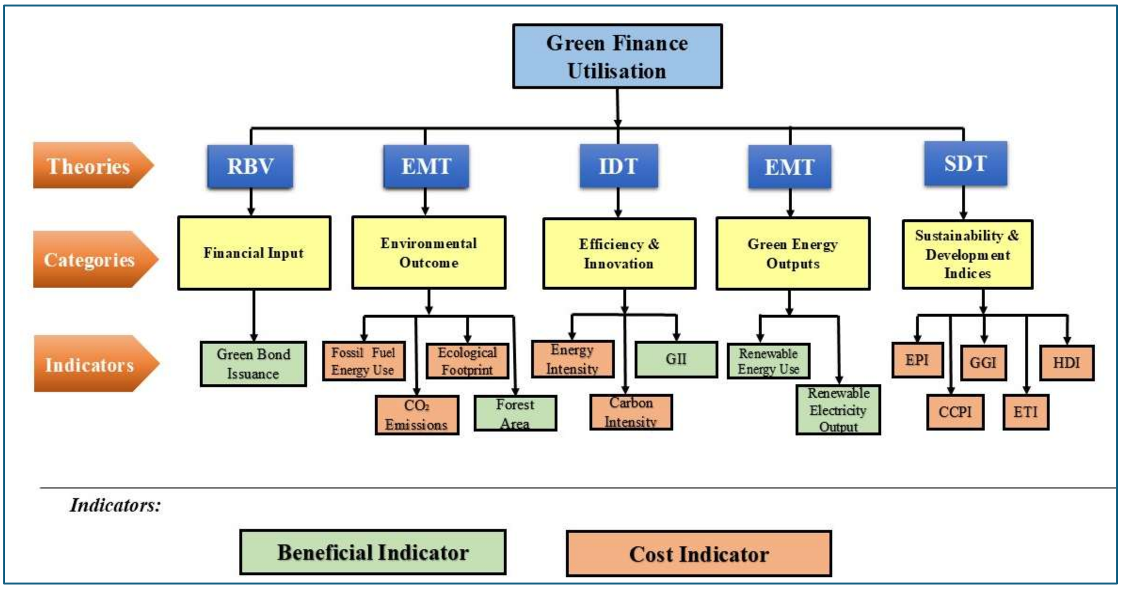

Figure 1. Conceptual framework (Sources: authors' own creation).

The theoretical framework of this study draws upon four complementary theories: Resource-Based View (RBV), Innovation Diffusion Theory (IDT), Ecological Modernization Theory (EMT), and Sustainable Development Theory (SDT), to explain the role of GF in advancing sustainability transitions across economic, environmental, and social dimensions.

From the RBV perspective, financial resources such as green bonds, climate funds, and sustainability-linked loans serve as strategic assets, enabling firms, governments, and communities to overcome capital constraints and pursue sustainability-oriented innovations [23]. Without adequate financial input, the technological and ecological ambitions of societies often remain unattainable. However, the competitive advantage created by these resources depends on their effective utilization. At this point, IDT provides additional insight. As stated by [24], IDT highlights how GF accelerates the spread of innovations, such as renewable energy technologies, electric mobility, precision agriculture, or carbon capture solutions, while recognizing that adoption rates are influenced by governance quality, institutional strength, and cultural acceptance [25].

From this perspective, EMT presents the opinion that environmental protection and economic development are viable through technological, institutional, and structural modernization [26]. GF will play a major part in restructuring its energy supply; the flow of money will now head towards wind, solar, hydro, and biomass. Such changes reduce emissions to the environment while improving the quality of resources and increasing the resilience of an ecosystem. EMT therefore considers green finance not only in terms of a financing system but also as a means of integrating ecological concerns into economic systems, making them more conducive at the same time.

However, sustainability is not limited to only environmental benefits, and this is the outcrop of Sustainable Development Theory (SDT). As stated in [27], SDT advocates for the coordination of economic growth, social equity enhancement, and environmental protection. GF aligns with this perspective, as it promotes projects that contribute to achieving the Sustainable Development Goals (SDGs). All four theories are incorporated into a unified system, namely, GF as a strategic resource (RBV), an engine of innovation (IDT), a modernization engine (EMT), and a driver of balanced long-term progress (SDT). The feedback process creates a virtuous cycle in which finance can drive innovation, promote ecological development, generate social value, and attract a new wave of investments, spurring transformative shifts in sustainability. The conceptual framework of this study is demonstrated in Figure 1.

3. Literature Review

3.1. Green Finance & its Utilization

3.1.1. Conceptualizing Green Finance

GF, which originated from the concept of environmental finance [28], refers to sustainable finance operations integrated with environmental and societal factors during investment decision processes [29]. GF enables the pursuit of ecological progress that is coupled with proper resource allocation and assists in addressing the goals of climate change mitigation [30]. The instruments of GF include green bonds and sustainability-linked loans, along with ESG-based investments that generally have the function to facilitate the transition to a low-carbon economy [31-34]. Beyond the monetary gain, the role of GF is to conserve the environment and adhere to public policy mandates [35].

Research on GF development now requires attention to both the measurable volume levels of such finance and actual transformation into sustainable performance measures. The academic understanding of the GFU concept requires more development because it represents how sustainability finance systems operate in practice.

3.1.2. Green Finance Impact: Environmental and Economic Outcomes

The process of GF remains essential because it funds activities that minimize environmental impacts and promote efficient power systems and sustainable technology adoption [36,37]. GF enables sustainable pathway transitions by allowing organizations to support renewable projects and conservation plans while implementing circular economy systems [38]. These capital flows encourage organizations to adopt ESG frameworks because they result in better environmental management and lower their exposure to reputational and regulatory challenges [39,40].

The economic dimension of GF produces twofold advantages: creating environmentally friendly employment positions, funding clean technology research and development, and generating financially equitable expansion [41,42]. Multiple factors, such as regulatory structures, access to capital, and institutional transparency, determine how effective outcomes result from such investments, although the results exhibit wide variations. Although many studies evaluate GF's impact on single outcomes, e.g., CO_2 reductions or renewable energy growth, few simultaneously adopt a multidimensional approach to assess its utilization across environmental and development indicators.

3.1.3. G20 and the State of Green Finance

GF remains central to the G20 countries because they account for most global emissions and financial growth. Green bond markets, financial cooperation sectors, and environmental social governance policies have shown exceptional progress within three G20 member nations of China, the United Kingdom, and Mexico [33]. Though policy innovation occurs in India, Turkey, Brazil, and South Africa, structural barriers prevent further progress [43,44].

Recent findings indicate three principal progression points in G20 finance systems, which focus on mainstreaming green bonds into public policy frameworks alongside public-private funding enhancement and measurement mechanisms of green investment impact. However, these efforts are often hampered by fragmented governance, inadequate climate finance flows—particularly for adaptation and uneven access to green technologies [45,46].

The improvement in GF mobilization does not match the inconsistent patterns of its actual deployment. Empirical evidence indicates that countries with firm ESG policy, effective regulations, and private sector involvement result in better emission reduction and sustainability outcomes [37,43].

3.1.4. Disparities in Sustainability Performance Across G20

Within the G20 nations, variations exist between member states' sustainability performance levels despite all members having made joint sustainability commitments. The United States, Japan, and Germany lead sustainability indices because they support robust innovation systems through extensive climate policies and financial resources [47]. India, Indonesia, and South Africa face development challenges, restricted access to green funding, and infrastructure limitations.

These indicators, such as the SDG Index, the Energy Transition Index, and the Global Innovation Index, display these varying trends. The green innovation capabilities of Poland surpass Thailand, even though their income levels are comparable, and they demonstrate distinct GII performance [48]. Existing research examines GF inputs (e.g., volumes, instruments) or outcomes separately (e.g., emissions, renewable shares); hence, there is a notable gap in research that systematically connects the two to evaluate how effectively green financial resources are converted into tangible sustainability results.

3.2. Application of TOPSIS

Since its inception, the widely adopted Multi-Criteria Decision-Making (MCDM) method, TOPSIS, has gained extensive use in multiple domains. Early applications include its use in industrial automation, as seen in the work on robot selection, and financial analyses by [49], where the authors in [50], applied this method to rank companies using financial ratios. At the beginning of the 2000s, researchers applied the TOPSIS methodology to handle uncertainty using fuzzy logic techniques. For instance, [51] utilized fuzzy TOPSIS for facility location selection. Conversely, [52] and [53] employed it to optimize waste management systems. The research by [54] applied TOPSIS to transportation planning by analyzing rail and maglev and air transport systems across Europe.

The year 2010 saw a significant increase in interdisciplinary applications within different fields. [55] demonstrated through their research that TOPSIS is flexible in applying it to healthcare, supply chain management, and environmental sustainability. Concurrently, [56] investigated its role in manufacturing optimization when examining material removal rates and surface roughness under varying cutting parameter conditions. Furthermore, [57] and other subsequent researchers focused on applying TOPSIS to electro-discharge machining and other advanced manufacturing processes. [58] advanced industrial applicability of TOPSIS by implementing it in aviation and automotive engineering, along with IT and finance sectors for supplier selection and behavioral study applications. The implementation of TOPSIS has been expanded to operate with modern technological systems. Through TOPSIS, [59] evaluated the financial performance of a Czech town from public budget releases, and [60] integrated TOPSIS and GIS to produce better flood risk zone maps for uplifted disaster protection planning. The study by [61] shows how TOPSIS maintains its value for logistics operations, facility location, and sustainability decisions. Research shows that TOPSIS transformed from initial conventional use to advanced decision-making technology and has evolved into a dynamic framework for managing complex situations and real-world challenges across temporal, spatial, and sectoral boundaries.

3.3. Research Gap

Although GF has received increasing attention, significant gaps persist in understanding its utilization and effectiveness across countries. Existing studies broadly examine dimensions such as green bond issuance, CO_2 reduction, or ESG investment flows. However, they fail to evaluate how financial resources are converted into tangible environmental and developmental outcomes. This limits the ability to identify leaders and laggards in sustainability transitions within the G20. Moreover, while researchers acknowledge differences in performance across nations, little effort has been made to quantify why similar GF inflows yield divergent results. At the methodological level, MCDM tools such as TOPSIS remain underutilized in evaluating GF effectiveness. Likewise, weighting approaches that capture variability and interdependence among indicators, such as the CRITIC method, have not been applied in this context. As a result, no comprehensive framework integrates financial, environmental, developmental, and innovation indicators to rank country performance objectively. Addressing these gaps can provide actionable insights into the efficiency of GFU across the G20.

4. Research Design

This section explains the research methodology, analytical processes of determining whether the G20 countries had achieved the goal of converting green financial resources into tangible environmental outcomes and energy solutions. The study relies on the MCDM framework based on the TOPSIS methodology to come up with rankings for G20 countries with respect to their GF indicators.

4.1. Data & Sample

This study has considered five categories and 15 criteria to determine the rankings of countries based on GFU. The analysis relies on secondary data collected from reputable international databases and reports for 2022. The detailed data source is presented in Table 1.

Table 1. Detailed description of the indicators and their sources.

Categories	Label	Indicators	Justification	Type	Source
Financial Input	Cte_1	Green Bond Issuance	Shows how much money a country is raising specifically for green	Benefit	Refinitiv

			projects. This is the starting point for green finance.		
Environmental Outcomes	Cte_2	CO_2 Emissions per Capita	High emissions mean more pollution. If green finance is working, this should go down.	Cost	OWD
	Cte_3	Fossil Fuel Energy Use (%)	Green finance should reduce dependence on fossil fuels. High levels show poor progress.	Cost	OWD
	Cte_4	Forest Area (% of total land)	Forests help absorb CO_2. A rise in forest cover is a positive indicator of environmental health.	Benefit	WDI
	Cte_5	Ecological Footprint (Gha/capita)	This shows the total environmental demand per person. A lower footprint means greener living.	Cost	GFN
Efficiency & Innovation	Cte_6	Carbon Intensity (CO_2/GDP)	Measures emissions per dollar of economic activity. Lower values mean cleaner growth.	Cost	WDI
	Cte_7	Energy Intensity (MJ/$GDP)	Measures the energy used to produce economic output. Lower values mean better energy use.	Cost	WDI
	Cte_8	Global Innovation Index	Innovation is essential for clean technology. Countries with high innovation can use green finance more smartly.	Benefit	WIPO
Green Energy Outputs	Cte_9	Renewable Energy Use (%)	Shows how much of a country's energy comes from clean sources. Higher is better.	Benefit	WDI
	Cte_{10}	Renewable Electricity Output (%)	Measures how green the electricity sector is. This is a significant target for green finance.	Benefit	OWD
Sustainability & Development Indices	Cte_{11}		Tracks environmental health and ecosystem vitality. High scores show success.	Benefit	Yale EPI
	Cte_{12}	Climate Change Performance Index (CCPI)	Measures climate policy strength and emissions trends. Higher is better.	Benefit	German watch
	Cte_{13}	Green Growth Index (GGI)	Shows how countries balance growth with sustainability. Core to green finance goals.	Benefit	GGGI
	Cte_{14}	Energy Transition Index (ETI)	Measures a country's readiness for a clean energy shift. Directly relevant to green finance impact.	Benefit	WEF
	Cte_{15}	Human Development Index (HDI)	Reflects health, education, and income. Green finance should support long-term	Benefit	OWD

	development, not just the environment.	

Notes: OWD: Our World in Data; WEF: World Economic Forum; GGGI: Global Green Growth Institute (Sources: authors' own creation).

4.2. Methodological Approach

4.2.1. CRITIC Method

Among the various MCDM weighting methods, the CRITIC approach is a well-known weighting method for incorporating the objective weight into the criteria. This approach was first suggested by [62]. This technique overcomes the problems associated with subjective weighting biases by establishing a criterion weight based on the data structure. We apply the CRITIC approach to assess the contrast between criteria, which calculates the variability of the normalized value (SD) column by column and the inter-column correlation coefficient [63].

Step 1: Construct the decision, Matrix.

$$Y = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1m} \\ v_{21} & v_{22} & \cdots & v_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mm} \end{bmatrix}, \quad (1)$$

The first step involves creating the decision matrix, where each row represents a country and each column corresponds to one of the selected GF indicators. This forms the foundation of the analysis, as it systematically organizes the performance of all G20 countries across multiple dimensions of GFU. This is presented in Table 2.

Step 2: Compute the Normalized decision matrix.

$$v_{ij}^{Q} = \frac{v_{ij} - min(v_{ij})}{\max(v_{ij}) - min(v_{ij})}, \quad (2)$$

Here, the values of the decision matrix are normalized to ensure comparability across indicators with different units and scales. we determined the best and worst values of each criterion. The optimal value is $\min(v_{ij})$ for non-beneficial criteria and $\max(v_{ij})$ for beneficial criteria. On the other hand, $\max(v_{ij})$ is the worst value for non-benefit criteria and $\min(v_{ij})$ is the worst for beneficial criteria. The normalised value of the decision matrix is shown by v_{ij}^{Q} in equation (2) and presented in Table A1.

Step 3: Determine the Standard deviation (S_j) of each criterion.

$$S_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(v_{ij} - \bar{v}_j\right)^2}, \quad (3)$$

At this stage, the variability of each indicator across countries is calculated. A higher standard deviation suggests that the criterion has stronger discriminatory power, as it better differentiates between country performances.

Step 4: Compose an m x m correlation matrix R, containing the correlation coefficient between the v_j and v_k.

$$R = [r_{jk}]_{m\times m}, \quad (4)$$

$$r_{jk} = \frac{\sum_{i=1}^{m}(v_{ij} - \overline{v_j})(v_{ik} - \bar{v}_k)}{\sqrt{\sum_{i=1}^{m}(v_{ij} - \overline{v_j})^2 (v_{ik} - \bar{v}_k)^2}}, \quad (5)$$

In equation (5), we compute the pairwise correlation coefficient among all criteria to determine their degree of conflict. r_{jk} denotes the correlation between criteria. Strong correlations indicate redundancy, whereas weaker correlations reveal that criteria provide unique and complementary information about GFU. The outcome is presented in Table A2.

Step 5: Ascertain the strength of each criterion. (L_j)

$$L_j = s_j \sum_{k=1}^{m} (1 - r_{jk}), \quad (6)$$

At this point, we compute the measure of conflict generated by criterion j compared to the other criteria. Next, assess the amount of information conveyed by each criterion is determined by combining its variability with its level of conflict with other criteria. Indicators that are both highly variable and less correlated with others contribute more unique information, making them more influential in the final evaluation. This is shown in equation no. (6).

Step 6: Computation of Criteria weights (w_j)

$$w_j = \frac{L_j}{\sum_{k=1}^{m} L_k}, \quad (7)$$

Finally, the relative weight of each indicator is obtained by normalizing its information content. These weights reflect the objective importance of each criterion in distinguishing between the G20 countries. Indicators with greater information value are given higher weights, ensuring that the evaluation process is both data-driven and unbiased. These weights are presented in Table 3 and Figure 2.

4.2.2. TOPSIS Method

Once the criteria weights were established, the next step involved ranking the alternatives. For this purpose, the study applied the TOPSIS technique. TOPSIS operates on the principle of identifying both an ideal solution and an anti-ideal solution, and then measuring the closeness of each alternative to the ideal option. In this way, it provides a clear and structured way to evaluate and rank alternatives based on their overall performance. This makes TOPSIS a valuable tool within the broader field of MCDM, as it helps decision-makers systematically compare different options and select the most suitable one.

Step 1: Calculating the normalized decision matrix (NDM).

$$r_{ij} = \frac{v_{ij}}{\sqrt{\sum_{1}^{n} v_{ij}^2}}, \quad (8)$$

At this stage, the decision matrix values are normalized using vector normalization. This process ensures that all indicators, irrespective of their original units or measurement scales, are converted into comparable values. In this way, the data becomes standardized, allowing each criterion to contribute fairly and proportionately to the subsequent analysis. The outcomes of this normalization are presented in Table A3 and further illustrated through a heatmap in Figure 3.

Step 2: Computation of weighted normalized decision matrix (T_{ij}).

$$T_{ij} = r_{ij} \times W_j, \quad (9)$$

The normalized values are then multiplied by the weights obtained from the CRITIC method. This produces the weighted normalized decision matrix, where each criterion's contribution reflects both its variability and uniqueness among all indicators. This step integrates the relative importance of each factor into the evaluation. The formulation is presented in Equation No. (9). The outcome is shown in Table A4.

Step 3: Determining the ideal positive and negative of each criterion.

$$B^{+} = \{(\max T_{ij} | j \in J, (\min T_{ij} | j \in J^{-})\}, \quad (10)$$

$$B^{-} = \{(\min T_{ij} | j \in J, (\max T_{ij} | j \in J^{-})\}, \quad (11)$$

Using Equations no. (10) and (11) in step 3, we calculate the ideal positive (B^{+}) and negative (B^{-}) of each criterion. where B^{+} denotes the best possible performance and B^{-} the worst possible performance for each criterion. This step identifies benchmark values, representing the most and least desirable outcomes across all countries.

Step 4: Assessing the proximity of ideal and non-ideal solutions.

$$S_i^{+} = \sqrt{\textstyle\sum_i^n \left(T_{ij} - T_j^{+}\right)^2}, \quad (12)$$

$$S_i^{-} = \sqrt{\textstyle\sum_i^n \left(T_{ij} - T_j^{-}\right)^2}, \quad (13)$$

In the fourth step, Euclidean distances are computed for each element of the weighted decision unit from its respective ideal and non-ideal value. Here, S_i^{+} indicate the distance of the decision unit from the positive ideal solution and S_i^{-} implies the distance of the decision unit from the negative ideal solution. These distances quantify each country's relative proximity to optimal GFU.

Step 5: Determine performance score and ranking of alternatives.

$$z_i = \frac{S_i^{-}}{S_i^{-} + S_i^{+}}, \quad (14)$$

Finally, using equation No. (14), the performance score (z_i) for each country is computed, representing how close a country is to the ideal GF profile. Alternatives are then ranked according to this score, with higher values indicating better overall performance. This step converts the multi-criteria evaluation into a clear ranking of G20 countries based on their effectiveness in utilising GF. The outcome is shown in Table 4 and visualized through Bar graph presented in Figure 4.

4.2.3. Sensitivity Analysis

We conducted a sensitivity analysis by assigning equal weights to all criteria to assess whether the ranking of alternatives was influenced by the original weighting scheme or if it provided an unbiased estimation. The results of the analysis are presented in Table 5. To evaluate the consistency of the rankings, we applied Spearman's Rank Correlation Analysis to test for significant differences among them, and the results were visualized using a scatter plot (Figure 5).

4.2.4. Robustness Checks

To assess the robustness of our findings, we employed several widely used MCDM methods. These methods, VIKOR, EDAS, MOORA, and COPRAS, were applied using objective weights determined through the CRITIC method (See Table 6). To examine whether there were significant differences among the rankings produced by these approaches, we conducted Spearman's Rank Correlation Analysis (See Table 7) and visualized the results using scatter plots (See Figure 6) and box plots (See Figure 7).

5. Empirical Results

This section presents the results of weight determination using the CRITIC method, ranking of alternatives through TOPSIS, sensitivity analysis using equal weight assignment, and robustness assessment using VIKOR, EDAS, MOORA, and COPRAS.

5.1. Criteria Weight Assessment (CRITIC)

In the 1st step of the CRITIC method, the decision Matrix was constructed.

Table 2. Decision matrix.

Alt.	Cte_{1}	Cte_{2}	Cte_{3}	Cte_{4}	Cte_{5}	Cte_{6}	Cte_{7}	Cte_{8}	Cte_{9}	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
Argentina	0.2	4.5	86.0	10.4	3.2	0.2	1.2	28.6	12.2	28.7	47.0	47.1	54.7	58.1	0.8
Australia	4.3	14.7	86.1	17.4	5.8	0.2	1.2	47.1	13.9	33.2	63.1	30.1	60.0	64.7	0.9
Brazil	0.5	2.3	50.2	59.1	2.6	0.1	1.2	32.5	48.8	87.4	53.0	54.9	62.0	66.8	0.8
Canada	12.8	14.2	64.0	39.5	7.4	0.1	2.3	50.8	30.6	68.3	61.1	26.0	59.9	65.8	0.9
China	99.4	8.0	81.7	23.8	3.6	0.3	1.7	55.3	15.9	30.2	35.4	52.2	59.8	60.7	0.8
France	28.0	4.4	53.3	31.8	4.3	0.1	0.9	55.0	14.6	24.3	67.0	61.0	70.9	71.5	0.9
Germany	83.8	8.0	76.1	32.7	4.5	0.2	0.9	57.2	21.4	44.3	74.5	63.5	75.0	67.8	1.0
India	1.2	2.0	88.6	24.4	1.0	0.3	1.0	36.6	10.3	20.5	27.6	69.2	46.4	54.1	0.6
Indonesia	5.0	2.6	90.1	48.0	1.7	0.3	0.8	27.9	9.9	19.6	33.6	57.2	57.4	57.2	0.7
Italy	19.0	5.7	83.5	32.7	4.0	0.2	0.8	46.1	16.5	35.8	60.3	55.4	70.9	63.9	0.9
Japan	23.0	8.3	85.8	68.4	4.0	0.2	1.0	53.6	11.6	22.0	61.4	48.5	65.0	64.0	0.9
Mexico	0.5	3.6	89.1	33.7	2.3	0.2	1.1	31.0	9.7	24.0	44.2	56.1	61.0	58.6	0.8
Russia	0.9	12.4	87.3	49.8	5.8	0.2	2.3	34.3	6.2	17.6	46.7	34.7	55.0	57.9	0.8
Saudi Arabia	3.0	22.5	99.8	0.5	5.7	0.2	1.7	33.4	0.2	0.2	42.5	24.3	38.3	54.9	0.9
South Africa	0.6	6.5	94.3	14.0	3.2	0.3	1.9	29.8	3.8	9.8	42.7	51.1	50.7	50.9	0.7
South Korea	16.3	11.6	83.0	64.2	0.2	0.2	1.7	57.8	4.6	8.3	50.6	26.7	54.7	61.8	0.9
Turkey	0.0	5.0	81.5	29.3	3.4	0.2	0.8	38.1	18.5	41.9	37.2	50.5	39.2	56.3	0.9
United Kingdom	7.9	4.6	74.5	13.3	3.6	0.2	0.8	59.7	19.6	41.4	72.6	73.1	71.6	69.7	0.9
United States	28.5	14.9	81.0	33.9	7.5	0.2	1.4	61.8	11.3	22.4	57.2	37.4	61.9	66.8	0.9

Sources: authors' own creation.

Table 2 presents the decision matrix values for each criterion across the G20 countries. China (99.4) records the highest green bond issuance (Cte1), followed by Germany (83.8), while Turkey (0.0) ranks the lowest. In terms of CO_2 emissions per capita (Cte2), Saudi Arabia (22.5) stands first, followed by the United States (14.9), whereas India (2.0) reports the lowest emissions. Saudi Arabia (99.8) also leads in fossil fuel consumption (Cte3), with South Africa (94.3) second, while Brazil (50.2) consumes the least. Japan (68.4) has the highest forest area share (Cte4), whereas Saudi Arabia (0.5) has the smallest. South Korea (0.2) reports the lowest ecological footprint (Cte5) while the United States (7.5) and Canada (7.4) record the highest. Carbon intensity values (C6) are relatively similar across countries, ranging between 0.1 and 0.3. Russia and Canada jointly rank highest in energy intensity (Cte7) (2.3), while the United Kingdom, Turkey, Italy, and Indonesia have the lowest (0.8). In terms of innovation, the United States (61.8) leads the Global Innovation Index (Cte8), followed by the United Kingdom (59.7), with Indonesia (27.9) at the bottom. Brazil (48.8%) performs best in renewable energy consumption (Cte9) followed by Canada (30.6%), while Saudi Arabia ranks last

(0.2%). Similarly, Brazil leads in electricity generation from renewable sources (87.4%), followed by Canada (68.3%), with Saudi Arabia again at the bottom. Germany achieves the highest Environmental Performance Index score (Cte11) (74.5), followed by the United Kingdom (72.6) and France (67.0), while India ranks lowest (27.6). The United Kingdom (73.1) leads in the Climate Change Performance Index (Cte12) with India second (69.8) and Canada performing the worst (26.0). Germany (75.0) ranks highest in the Green Growth Index (Cte13), followed by the United Kingdom (71.6) and France (70.9), while Saudi Arabia ranks lowest (38.3). France (71.5) leads the Energy Transition Index (Cte14), followed by the United Kingdom (69.7), Brazil (66.8), and the United States (66.8), with South Africa ranking last (50.9). Finally, Germany (1.0) achieves the highest Human Development Index (Cte15) score while India holds the lowest score (0.6).

In the next step, the values were normalized, as shown in Table A.1. Subsequently, the correlation among all the criteria was calculated, and the corresponding correlation matrix is presented in Table A.2. Based on the information derived from this matrix, the final weights for all the criteria were computed and are presented in Table 3.

Table 3. Final Weights of Criteria.

Crit.	Cte_1	Cte_2	Cte_3	Cte_4	Cte_5	Cte_6	Cte_7	Cte_8	Cte_9	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
δ_c	0.222	0.287	0.273	0.23	0.28	0.30	0.35	0.277	0.301	0.279	0.282	0.318	0.257	0.267	0.269
C_c	2.045	2.626	3.194	2.24	3.31	3.46	3.58	2.237	3.346	2.120	2.538	3.458	2.126	3.081	3.948
W_c	0.047	0.061	0.074	0.05	0.07	0.08	0.08	0.052	0.077	0.049	0.059	0.080	0.049	0.071	0.091

Sources: authors' own creation.

As shown in Table 3, w_c represents the weights assigned to each criterion. The Human Development Index (C15) holds the highest weight at 0.09, followed by Energy Intensity (C7) at 0.082, and Carbon Intensity (C6) at 0.08. In contrast, Green Bond Issuance carries the lowest weight at 0.047. These criterion weights are also illustrated in Figure 2.

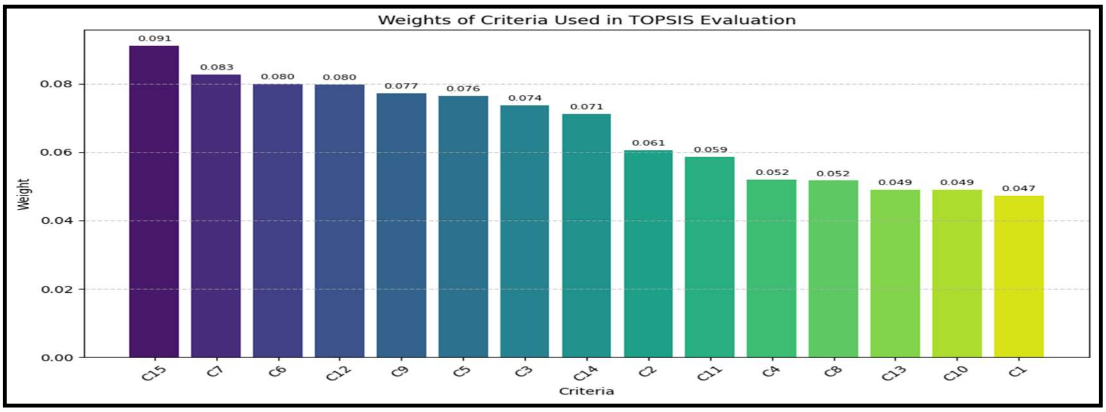

Figure 2. Bar chart illustrating the final weights of the criteria (Sources: authors' own creation).

In the next step, these weights are used to rank countries using TOPSIS.

5.2. Baseline Ranking of Countries Using TOPSIS

After determining the criteria weights using the CRITIC method, these weights were applied in the TOPSIS method to rank the countries based on their GFU. In this ranking, the country with the best performance is assigned rank 1, while the country with the weakest performance is ranked 19.

The TOPSIS process involves a series of steps. First, vector normalization was performed on the decision matrix presented in Table 2 to create the normalized matrix, shown in Table A.3. Additionally, a heatmap is presented in Figure 3 to illustrate how the criteria values vary across different alternatives visually.

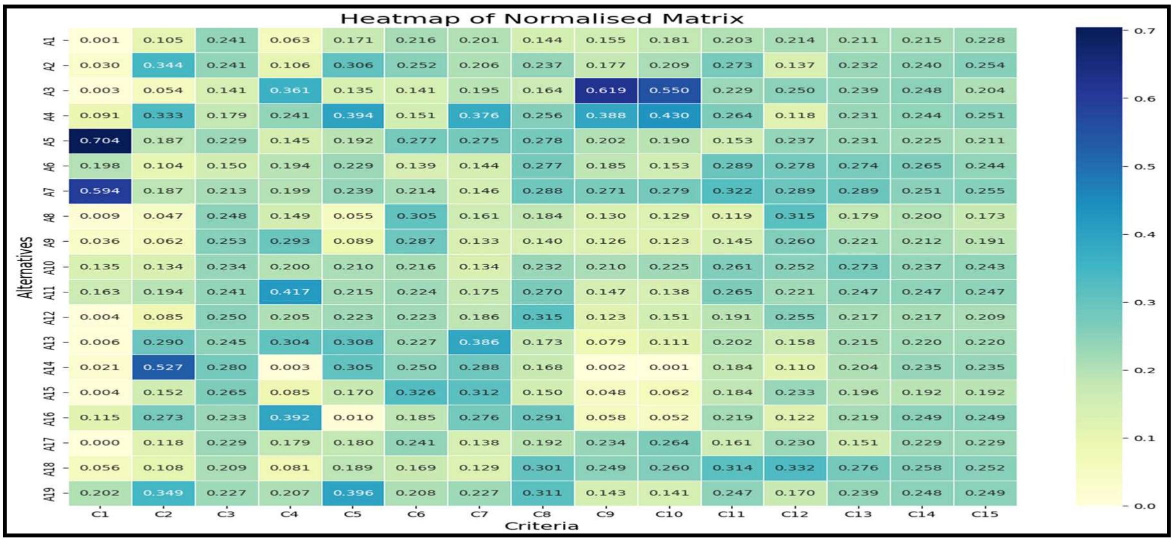

Figure 3. Heatmap of normalized matrix (Sources: authors' own creation).

Table 4. Closeness coefficient matrix and country rankings.

Alternatives	S+	S-	Z	Rank
Argentina	0.071227	0.043175	0.3774	13
Australia	0.07412	0.030543	0.291818	17
Brazil	0.057352	0.068153	0.543026	3
Canada	0.069789	0.041644	0.373714	14
China	0.043866	0.066885	0.603922	2
France	0.055277	0.052219	0.485777	4
Germany	0.037151	0.066648	0.642088	1
India	0.068667	0.054063	0.440504	10
Indonesia	0.065367	0.054632	0.455269	8
Italy	0.05758	0.048963	0.459561	7
Japan	0.057326	0.051752	0.474452	5
Mexico	0.067511	0.049001	0.420564	11
Russia	0.077383	0.031545	0.289595	18
Saudi Arabia	0.089568	0.014057	0.135652	19
South Africa	0.076376	0.036524	0.323506	16
South Korea	0.064381	0.053581	0.454224	9
Turkey	0.066268	0.047556	0.417805	12
United Kingdom	0.062445	0.053232	0.460178	6
United States	0.068169	0.035836	0.344562	15

Sources: authors' own creation.

In the next step, the TOPSIS Weighted Normalized Matrix was calculated by multiplying the criteria weights derived from CRITIC by the normalized values of the decision matrix. This weighted normalized Matrix is presented in Table A.4. In the following step, the ideal best and worst values for each criterion were identified. Subsequently, the distance of each criterion from the ideal best and ideal worst was calculated. In the next step, the closeness coefficient matrix was calculated. Finally, based on the closeness coefficients, the alternatives were ranked. The calculated coefficients and corresponding ranks are presented in Table 4. A bar graph illustrating the ranking of countries based on their TOPSIS scores is also presented in Figure 4 for visual representation.

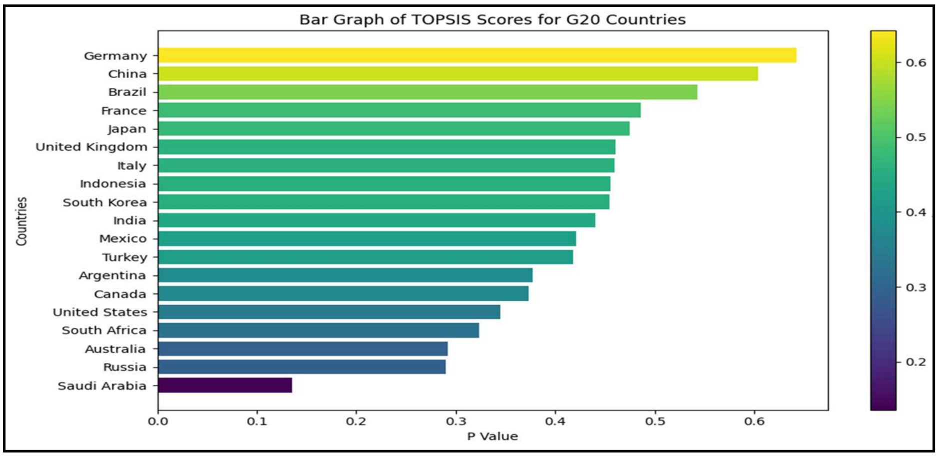

Figure 4. Ranking of countries based on TOPSIS score (Sources: authors' own creation).

The TOPSIS scores (presented in Table 4) for GFU rank Germany first, followed by China, Brazil, France, and Japan. The next group of countries includes the United Kingdom, Italy, Indonesia, South Korea, and India. Middle performers include Mexico, Turkey, Argentina, Canada, and the United States, while the lowest ranks are held by South Africa, Australia, Russia, and Saudi Arabia. This distribution highlights that financial scale alone does not determine success; instead, outcomes depend on how finance is combined with renewable adoption, innovation, governance, and social development.

Germany leads the ranking due to its strong Environmental Performance Index, Green Growth Index, Energy Transition Index, and Human Development Index. Its integrated model shows that adequate GF relies on coupling financial mobilization with innovation, institutional governance, and social progress [64], [65]. By contrast, China holds the second position primarily due to its dominant green bond issuance [66]. However, its high fossil fuel consumption and CO_2 emissions weaken sustainability outcomes, showing that financial leadership is insufficient when ecological burdens remain unaddressed.

Brazil ranks third despite modest green bond issuance. Its strength lies in renewable energy, with leading shares in both consumption and electricity generation, demonstrating how clean energy transitions can offset limited financial inputs [67]. France and the United Kingdom perform well by integrating GF into broader policies that support energy transition and innovation, highlighting how coordinated policies can sustain financial, environmental, and social achievements [68]. Japan and South Korea also perform strongly in innovation, where regulatory capacity ensures financial investments translate into long-term sustainability benefits [69].

India benefits from strong climate performance and renewable energy adoption in the middle ranks, but is constrained by low human development and weak environmental performance. The United States, in contrast, demonstrates the limits of innovation-led growth: despite strong scores in innovation and energy transition, high emissions and ecological footprint reduce its effectiveness.

Mexico and Turkey struggle due to weaker innovation and governance systems, which hold back their capacity to expand renewable energy investments [70].

At the lower end, Saudi Arabia, Russia, and South Africa reflect how fossil fuel dependency undermines financial effectiveness. Saudi Arabia's minimal renewable contribution and high carbon intensity place it last, while Russia's high energy intensity and South Africa's reliance on fossil fuels similarly constrain their performance. These results confirm that energy transition is crucial: leaders move away from fossil fuels, invest in clean energy, and reform energy markets, while laggards remain trapped in carbon-intensive systems.

Overall, the findings confirm that GF effectiveness emerges not from the volume of capital flows but from their alignment with renewable energy adoption, innovation, governance, and human development. Countries that integrate finance into broader sustainability strategies demonstrate the strongest results, while those reliant on fossil-based growth models lag.

5.3. Sensitivity Analysis Using Equal Weights

Furthermore, a sensitivity analysis was conducted by assigning equal weights to all the criteria. These results are presented below in Table 5.

Table 5. TOPSIS ranking with equal weights.

Alternatives	Baseline TOPSIS	Equal-Weight TOPSIS
Argentina	13	14
Australia	17	16
Brazil	3	2
Canada	14	8
China	2	3
France	4	4
Germany	1	1
India	10	11
Indonesia	8	9
Italy	7	6
Japan	5	7
Mexico	11	13
Russia	18	18
Saudi Arabia	19	19
South Africa	16	17
South Korea	9	12
Turkey	12	10
United Kingdom	6	5
United States	15	15

Sources: authors' own creation.

The above table compares country rankings between the baseline TOPSIS results, which used criteria weights derived through the CRITIC method, and the TOPSIS results obtained by assigning equal weights to all criteria. The comparison shows that the rankings remain largely consistent across both approaches, indicating that the results are robust and not sensitive to the weighting method. This consistency strengthens the credibility of the analysis. It confirms that the rankings reflect the actual performance of the countries in GFU, rather than being influenced by the weighting scheme.

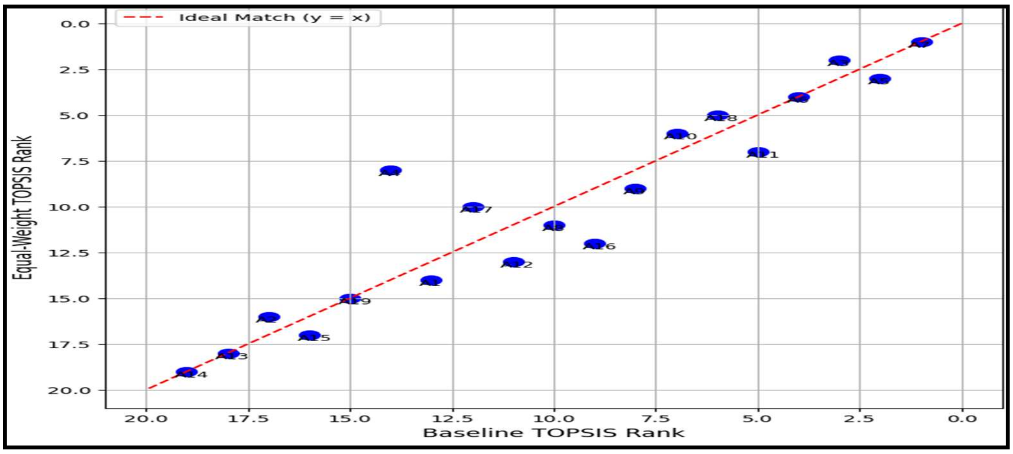

Figure 5. Scatter plot visualization of rank consistency under different weights (Sources: authors' own creation).

The above figure confirms that the rankings obtained under different weighting methods are highly consistent. The rankings exhibit a strong correlation of 0.9421, indicating that using either CRITIC-derived weights or equal weights does not significantly alter the results. The scatter plot visually supports this finding, as the points are closely clustered around a common trend, reinforcing the robustness of the ranking outcomes.

5.4. Robustness Check Using Alternative MCDM Methods

The robustness of the rankings was assessed by employing supplementary MCDM methods, namely VIKOR, EDAS, MOORA, and COPRAS. These methods are well-suited for validating the TOPSIS rankings, as they utilize objective weights derived from the CRITIC method.

Table 6. Comparative rankings of countries using alternative MCDM methods.

Alternatives	TOPSIS	VIKOR	EDAS	MOORA	COPRAS
Argentina	13	12	15	15	15
Australia	17	9	16	16	16
Brazil	3	7	3	2	2
Canada	14	16	13	13	10
China	2	3	2	5	3
France	4	2	4	3	4
Germany	1	1	1	1	1
India	10	14	10	12	11
Indonesia	8	13	9	9	8
Italy	7	5	7	7	7
Japan	5	4	6	6	6
Mexico	11	10	12	11	12
Russia	18	17	18	17	17
Saudi Arabia	19	19	19	19	19
South Africa	16	18	17	18	18
South Korea	9	8	8	8	9
Turkey	12	11	11	10	13
United Kingdom	6	6	5	4	5
United States	15	15	14	14	14

Sources: authors' own creation.

The alternative MCDM methods also produced rankings similar to those obtained from the TOPSIS method. Spearman's rank correlation analysis was conducted to verify the consistency of these rankings. The results of this analysis are presented in Table 7.

Table 7. Spearman's rank correlation analysis.

Comparison	Coefficient
TOPSIS & VIKOR	0.8737***
TOPSIS & EDAS	0.9877***
TOPSIS & MOORA	0.9667***
TOPSIS & COPRAS	0.9702***

Notes: '***' denotes 1% significance level. Sources: authors' own creation.

All the methods showed strong and positive correlation in the ranking of the countries, suggesting the robustness of our results. These rankings were presented in the scatter plot (Figure 6) and box plot (Figure 7) to visually confirm the results.

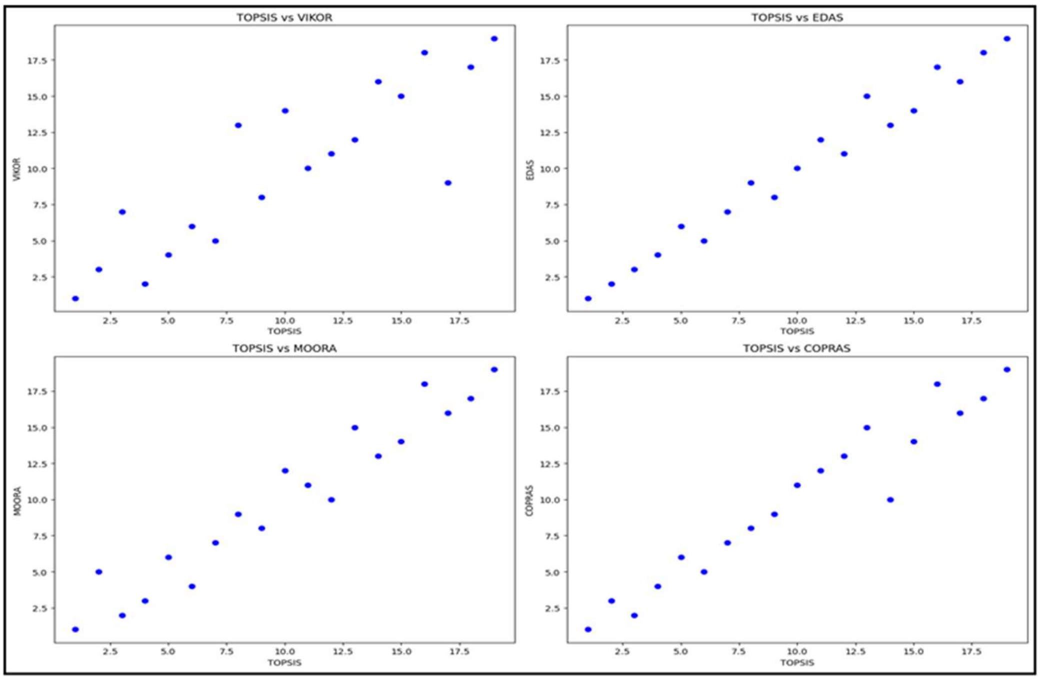

Figure 6. Scatter plot visualization of rank consistency (Sources: authors' own creation).

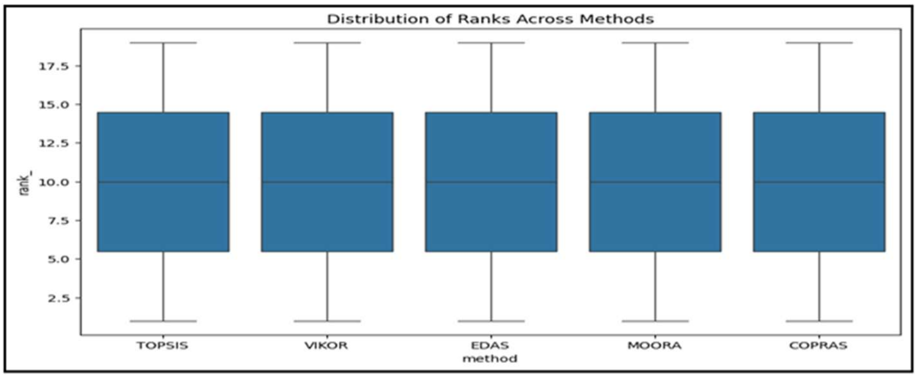

Figure 7. Box-plot visualization of rank consistency (Sources: authors' own creation).

Both figures provide a detailed picture of the robustness of our findings.

6. Conclusion, Policy Implications, and Limitations

This study evaluated and ranked G20 countries based on their GFU using the CRITIC–TOPSIS approach. Fifteen financial, environmental, developmental, and innovation indicators were employed to provide a holistic performance assessment. The results show that countries with balanced progress across renewable energy adoption, innovation, institutional strength, and human development are more successful in transforming GF into sustainable outcomes. Germany emerged as the top performer, while China ranked lower despite its leadership in green bond issuance due to fossil fuel dependence. Brazil demonstrated that strong renewable integration can compensate for weaker financial metrics, while Saudi Arabia, Russia, and South Africa ranked lowest due to high emissions and weak energy transition. The sensitivity analysis, conducted by assigning equal weights and applying alternative MCDM methods, confirms the robustness and generalizability of the results. The study confirms that GF effectiveness depends on financial inputs, governance, innovation, and policy integration.

6.1. Policy Implications

The findings provide actionable insights for policymakers in both advanced and emerging economies. First, GF should be prioritized in integrating renewable energy expansion, energy transition, and climate policy frameworks. Second, strengthening innovation ecosystems and governance structures is essential to maximizing the conversion of financial resources into tangible sustainability outcomes. Third, emerging economies like India and Brazil demonstrate that focusing on renewable deployment and cost-effective clean energy can deliver strong outcomes even with limited financial volumes. Finally, low-performing countries, particularly fossil-fuel-dependent economies, must diversify their energy mix and strengthen institutional capacities to avoid stranded assets and lagging progress in sustainability transitions.

6.2. Limitations and Future Scope

Despite its contributions, the study acknowledges several limitations. First, the analysis is limited to G20 countries, which, while significant in global emissions and finance, excludes smaller or developing economies that may lead in innovative GF practices. Second, though objective, the CRITIC weighting method does not account for qualitative policy contexts or regional disparities that may affect performance. Third, the chosen indicators do not fully capture dimensions such as social equity, adaptation finance, or private sector participation, which are increasingly relevant in GF research. Future studies can expand the scope by including more diverse countries, additional indicators, and dynamic methods considering interdependencies among criteria. Integrating case studies and scenario-based approaches may also strengthen understanding of how financial tools can accelerate climate and sustainability outcomes globally.

Contributions: P.A. conceptualized the study, performed the analysis, and prepared the final draft. D.N. supervised the study and provided critical revisions. J.A. contributed to the interpretation of results and assisted in data analysis. I.S. supported the methodology development. S.C. prepared the initial draft.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Normalised decision matrix.

Alter.	Cte_1	Cte_2	Cte_3	Cte_4	Cte_5	Cte_6	Cte_7	Cte_8	Cte_9	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
Argentina	0.00	0.88	0.28	0.15	0.58	0.59	0.72	0.02	0.25	0.33	0.41	0.47	0.45	0.35	0.67
Australia	0.04	0.38	0.28	0.25	0.23	0.40	0.70	0.57	0.28	0.38	0.76	0.12	0.59	0.67	0.99
Brazil	0.00	0.98	1.00	0.86	0.68	0.99	0.74	0.14	1.00	1.00	0.54	0.63	0.65	0.77	0.38
Canada	0.13	0.40	0.72	0.57	0.01	0.94	0.04	0.68	0.62	0.78	0.71	0.04	0.59	0.73	0.95
China	1.00	0.71	0.36	0.34	0.53	0.26	0.43	0.81	0.32	0.34	0.17	0.57	0.59	0.48	0.47
France	0.28	0.88	0.94	0.46	0.43	1.00	0.94	0.80	0.30	0.28	0.84	0.75	0.89	1.00	0.87
Germany	0.84	0.71	0.48	0.47	0.41	0.60	0.93	0.86	0.44	0.51	1.00	0.80	1.00	0.82	1.00
India	0.01	1.00	0.23	0.35	0.88	0.11	0.88	0.26	0.21	0.23	0.00	0.92	0.22	0.16	0.00
Indonesia	0.05	0.97	0.20	0.70	0.80	0.21	0.98	0.00	0.20	0.22	0.13	0.67	0.52	0.31	0.23
Italy	0.19	0.82	0.33	0.47	0.48	0.59	0.98	0.54	0.34	0.41	0.70	0.64	0.89	0.63	0.86
Japan	0.23	0.69	0.28	1.00	0.47	0.54	0.82	0.76	0.23	0.25	0.72	0.50	0.73	0.64	0.90
Mexico	0.00	0.92	0.22	0.49	0.71	0.55	0.78	0.09	0.20	0.27	0.35	0.65	0.62	0.38	0.45
Russia	0.01	0.49	0.25	0.73	0.23	0.53	0.00	0.19	0.12	0.20	0.41	0.21	0.45	0.34	0.58
Saudi Arabia	0.03	0.00	0.00	0.00	0.24	0.41	0.38	0.16	0.00	0.00	0.32	0.00	0.00	0.20	0.75
South Africa	0.01	0.78	0.11	0.20	0.58	0.00	0.29	0.06	0.07	0.11	0.32	0.55	0.34	0.00	0.24
South Korea	0.16	0.53	0.34	0.94	1.00	0.75	0.43	0.88	0.09	0.09	0.49	0.05	0.45	0.53	0.93
Turkey	0.00	0.85	0.37	0.42	0.56	0.45	0.96	0.30	0.38	0.48	0.20	0.54	0.03	0.26	0.69
United Kingdom	0.08	0.87	0.51	0.19	0.54	0.84	1.00	0.94	0.40	0.47	0.96	1.00	0.91	0.91	0.97
United States	0.29	0.37	0.38	0.49	0.00	0.63	0.62	1.00	0.23	0.25	0.63	0.27	0.64	0.77	0.92

Sources: authors' own creation.

Table A2. Correlation matrix.

Crit.	Cte_1	Cte_2	Cte_3	Cte_4	Cte_5	Cte_6	Cte_7	Cte_8	Cte_9	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
$Ctea_1$	1.00	-0.05	0.16	0.02	-0.13	-0.01	0.04	0.59	0.10	0.07	0.22	0.18	0.44	0.35	0.23
$Ctea_2$	-0.05	1.00	0.29	0.18	0.67	-0.03	0.61	-0.24	0.32	0.29	-0.16	0.84	0.27	0.00	-0.50
$Ctea_3$	0.16	0.29	1.00	0.33	-0.11	0.80	0.14	0.35	0.81	0.76	0.49	0.22	0.51	0.75	0.24
$Ctea_4$	0.02	0.18	0.33	1.00	0.23	0.34	-0.03	0.17	0.28	0.23	0.09	-0.09	0.26	0.26	0.04
$Cteas_5$	-0.13	0.67	-0.11	0.23	1.00	-0.23	0.40	-0.30	-0.08	-0.15	-0.44	0.46	-0.13	-0.33	-0.54
$Ctea_6$	-0.01	-0.03	0.80	0.34	-0.23	1.00	0.05	0.43	0.58	0.56	0.67	-0.08	0.51	0.80	0.60
$Ctea_7$	0.04	0.61	0.14	-0.03	0.40	0.05	1.00	0.09	0.17	0.12	0.17	0.72	0.34	0.28	0.01
$Cteas_8$	0.59	-0.24	0.35	0.17	-0.30	0.43	0.09	1.00	0.11	0.09	0.65	-0.01	0.57	0.74	0.71
$Ctea_9$	0.10	0.32	0.81	0.28	-0.08	0.58	0.17	0.11	1.00	0.98	0.33	0.23	0.37	0.54	0.07
$Ctea_{10}$	0.07	0.29	0.76	0.23	-0.15	0.56	0.12	0.09	0.98	1.00	0.34	0.18	0.36	0.51	0.12
$Ctea_{11}$	0.22	-0.16	0.49	0.09	-0.44	0.67	0.17	0.65	0.33	0.34	1.00	0.04	0.78	0.85	0.82
$Ctea_{12}$	0.18	0.84	0.22	-0.09	0.46	-0.08	0.72	-0.01	0.23	0.18	0.04	1.00	0.40	0.14	-0.35
$Ctea_{13}$	0.44	0.27	0.51	0.26	-0.13	0.51	0.34	0.57	0.37	0.36	0.78	0.40	1.00	0.81	0.45
$Ctea_{14}$	0.35	0.00	0.75	0.26	-0.33	0.80	0.28	0.74	0.54	0.51	0.85	0.14	0.81	1.00	0.69
$Ctea_{15}$	0.23	-0.50	0.24	0.04	-0.54	0.60	0.01	0.71	0.07	0.12	0.82	-0.35	0.45	0.69	1.00

Sources: authors' own creation.

Table A3. Normalized decision matrix using TOPSIS.

Alt.	Cte_1	Cte_2	Cte_3	Cte_4	Cte_5	Cte_6	Cte_7	Cte_8	Cte_9	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
Argentina	0.001	0.105	0.241	0.063	0.171	0.216	0.201	0.144	0.155	0.181	0.203	0.214	0.211	0.215	0.228
Australia	0.030	0.344	0.241	0.106	0.306	0.252	0.206	0.237	0.177	0.209	0.273	0.137	0.232	0.240	0.254
Brazil	0.003	0.054	0.141	0.361	0.135	0.141	0.195	0.164	0.619	0.550	0.229	0.250	0.239	0.248	0.204
Canada	0.091	0.333	0.179	0.241	0.394	0.151	0.376	0.256	0.388	0.430	0.264	0.118	0.231	0.244	0.251
China	0.704	0.187	0.229	0.145	0.192	0.277	0.275	0.278	0.202	0.190	0.153	0.237	0.231	0.225	0.211
France	0.198	0.104	0.150	0.194	0.229	0.139	0.144	0.277	0.185	0.153	0.289	0.278	0.274	0.265	0.244
Germany	0.594	0.187	0.213	0.199	0.239	0.214	0.146	0.288	0.271	0.279	0.322	0.289	0.289	0.251	0.255
India	0.009	0.047	0.248	0.149	0.055	0.305	0.161	0.184	0.130	0.129	0.119	0.315	0.179	0.200	0.173
Indonesia	0.036	0.062	0.253	0.293	0.089	0.287	0.133	0.140	0.126	0.123	0.145	0.260	0.221	0.212	0.191
Italy	0.135	0.134	0.234	0.200	0.210	0.216	0.134	0.232	0.210	0.225	0.261	0.252	0.273	0.237	0.243
Japan	0.163	0.194	0.241	0.417	0.215	0.224	0.175	0.270	0.147	0.138	0.265	0.221	0.251	0.237	0.247
Mexico	0.004	0.085	0.250	0.205	0.121	0.223	0.186	0.156	0.123	0.151	0.191	0.255	0.235	0.217	0.209
Russia	0.006	0.290	0.245	0.304	0.308	0.227	0.386	0.173	0.079	0.111	0.202	0.158	0.212	0.215	0.220
Saudi Arabia	0.021	0.527	0.280	0.003	0.305	0.250	0.288	0.168	0.002	0.001	0.184	0.110	0.148	0.204	0.235
South Africa	0.004	0.152	0.265	0.085	0.170	0.326	0.312	0.150	0.048	0.062	0.184	0.233	0.196	0.188	0.192
South Korea	0.115	0.273	0.233	0.392	0.010	0.185	0.276	0.291	0.058	0.052	0.219	0.122	0.211	0.229	0.249
Turkey	0.000	0.118	0.229	0.179	0.180	0.241	0.138	0.192	0.234	0.264	0.161	0.230	0.151	0.209	0.229
United Kingdom	0.056	0.108	0.209	0.081	0.189	0.169	0.129	0.301	0.249	0.260	0.314	0.332	0.276	0.258	0.252
United States	0.202	0.349	0.227	0.207	0.396	0.208	0.227	0.311	0.143	0.141	0.247	0.170	0.239	0.248	0.249

Sources: authors' own creation.

Table A4. Weighted normalized decision matrix.

Alter.	Cte_1	Cte_2	Cte_3	Cte_4	Cte_5	Cte_6	Cte_7	Cte_8	Cte_9	Cte_{10}	Cte_{11}	Cte_{12}	Cte_{13}	Cte_{14}	Cte_{15}
Argentina	0.000	0.007	0.012	0.005	0.016	0.013	0.016	0.012	0.007	0.009	0.012	0.017	0.011	0.011	0.018
Australia	0.002	0.024	0.012	0.008	0.028	0.015	0.016	0.020	0.008	0.011	0.017	0.011	0.012	0.012	0.020
Brazil	0.000	0.004	0.007	0.027	0.012	0.008	0.016	0.014	0.029	0.029	0.014	0.019	0.012	0.012	0.016
Canada	0.007	0.024	0.009	0.018	0.036	0.009	0.030	0.021	0.018	0.022	0.016	0.009	0.012	0.012	0.020
China	0.054	0.013	0.011	0.011	0.017	0.016	0.022	0.023	0.010	0.010	0.009	0.018	0.012	0.011	0.017
France	0.015	0.007	0.007	0.014	0.021	0.008	0.011	0.023	0.009	0.008	0.018	0.021	0.014	0.013	0.019
Germany	0.045	0.013	0.010	0.015	0.022	0.013	0.012	0.024	0.013	0.014	0.020	0.022	0.015	0.012	0.020
India	0.001	0.003	0.012	0.011	0.005	0.018	0.013	0.015	0.006	0.007	0.007	0.024	0.009	0.010	0.014
Indonesia	0.003	0.004	0.012	0.022	0.008	0.017	0.011	0.012	0.006	0.006	0.009	0.020	0.011	0.010	0.015
Italy	0.010	0.010	0.011	0.015	0.019	0.013	0.011	0.019	0.010	0.012	0.016	0.019	0.014	0.012	0.019
Japan	0.012	0.014	0.012	0.031	0.020	0.013	0.014	0.022	0.007	0.007	0.016	0.017	0.013	0.012	0.020
Mexico	0.000	0.006	0.012	0.015	0.011	0.013	0.015	0.013	0.006	0.008	0.012	0.020	0.012	0.011	0.017
Russia	0.000	0.021	0.012	0.022	0.028	0.013	0.031	0.014	0.004	0.006	0.012	0.012	0.011	0.010	0.018
Saudi Arabia	0.002	0.038	0.014	0.000	0.028	0.015	0.023	0.014	0.000	0.000	0.011	0.009	0.008	0.010	0.019
South Africa	0.000	0.011	0.013	0.006	0.016	0.019	0.025	0.012	0.002	0.003	0.011	0.018	0.010	0.009	0.015
South Korea	0.009	0.019	0.011	0.029	0.001	0.011	0.022	0.024	0.003	0.003	0.013	0.009	0.011	0.011	0.020
Turkey	0.000	0.008	0.011	0.013	0.016	0.014	0.011	0.016	0.011	0.014	0.010	0.018	0.008	0.010	0.018
United Kingdom	0.004	0.008	0.010	0.006	0.017	0.010	0.010	0.025	0.012	0.014	0.019	0.026	0.014	0.013	0.020
United States	0.015	0.025	0.011	0.015	0.036	0.012	0.018	0.026	0.007	0.007	0.015	0.013	0.012	0.012	0.020

Sources: authors' own creation.

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