From Data to Insight: Visualization Design Innovation and Integration of Data-Driven Decision Tools for Energy Transition

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***Abstract*—The energy transition is a central challenge in addressing global climate change, yet its inherent complexity presents unprecedented difficulties for decision-makers at all levels. Existing decision-support tools tend to focus on isolated technical or economic indicators and often lack effective integration of multi-dimensional and heterogeneous data, systematic consideration of user interaction, and the in-depth use of visualization design as a cognitive enabler. As a result, decision-makers frequently struggle to efficiently and accurately extract critical insights from large and complex datasets.**

To address this gap, this study proposes a multi-criteria assessment framework that integrates visualization design innovation with data-driven decision-making. The framework combines the Analytic Hierarchy Process (AHP) to determine the weights of evaluation dimensions with the PROMETHEE II method to rank decision alternatives, thereby establishing a four-dimensional comprehensive evaluation system encompassing Visualization Quality, User Experience, Decision Efficacy, and Technological Innovation. The effectiveness and feasibility of the framework are validated through an empirical analysis of 15 representative countries, selected according to their energy structures, economic development levels, and degrees of digitalization.

The core finding of the study is that systematic innovation in visualization design can significantly enhance the efficiency, transparency, and overall quality of data-driven decision-making. Building on this insight, the study proposes a novel Energy Transition Visualization-based Decision Readiness Index (ET-VDRI). Through quantitative ranking and cluster analysis of the 15 countries, the framework clearly identifies the distinctive strengths and potential limitations of different nations in leveraging visualization tools to support energy transition decisions.

The value of this research lies in offering a new human-centered paradigm for the evaluation and design of decision-support tools aimed at energy policymakers, industry investors, and technology developers worldwide. By bridging the gap between raw data and actionable insight, the proposed framework promotes the development of more scientific, efficient, and inclusive tools for planning energy transition pathways, thereby contributing to the acceleration of global sustainable development.

Keywords—Energy Transition, Data Visualization, Decision Support Systems, Multi-Criteria Decision Analysis (MCDA), Visualization Design, Assessment Index

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I. INTRODUCTION

The global energy system stands at a historic crossroads, as the transition toward a sustainable and low-carbon model has become a shared consensus and central agenda of the international community [1]. This transformation spans multiple dimensions — including technology, economics, society, and policy — and its inherent complexity and uncertainty place exceptionally high demands on decision-making processes [2]. In this context, data-driven decision-making approaches have attracted significant attention. The rapid expansion of energy-related data, ranging from real-time power grid monitoring to detailed insights into consumer energy behavior, offers unprecedented opportunities to better understand and steer this profound transition [3]. However, the sheer volume of data does not automatically translate into better decisions; on the contrary, it can lead to "information overload" and "analysis paralysis." Transforming vast, multi-dimensional energy datasets into intuitive and actionable decision insights has therefore emerged as a critical bottleneck in enabling a smooth energy transition.

Accordingly, the central research question addressed in this study is: How can systematic and innovative visualization design transform complex energy data into intuitive, actionable decision insights, thereby significantly improving the scientific rigor, efficiency, and inclusiveness of energy transition decision-making?

To date, both academia and industry have made substantial progress in energy decision support. Energy system models (ESMs) are widely used to simulate future scenarios under alternative policy and technology pathways [4], while dashboards and geographic information systems (GIS) are commonly employed to monitor the operational status of energy systems [5]. In parallel, multi-criteria decision analysis (MCDA) methods—such as the Analytic Hierarchy Process (AHP) and PROMETHEE—have been applied to evaluate the feasibility and sustainability of energy projects [6].

Despite these advances, notable limitations remain. First, many decision-support tools treat data visualization merely as the "last mile" of result presentation—a passive and auxiliary display function—while neglecting its role as an active cognitive tool and a catalyst for decision-making [7]. Second, existing tools are often technology-centric and insufficiently attuned to the cognitive habits and interaction needs of decision-makers, particularly those without technical backgrounds, resulting in tools that are frequently perceived as "difficult to understand" and "difficult to use" [8]. Finally, there is a lack of a comprehensive framework for holistically evaluating the effectiveness of energy decision-support tools, especially one that explicitly incorporates the critical human – computer interaction dimension of visualization design.

To overcome these challenges, this study seeks to develop a theoretical framework and evaluation model that facilitates the transition "from data to insight." The specific research objectives are threefold. First, to construct an energy transition decision-support framework that integrates visualization design innovation by combining data, models, visualization, and user interaction within a human-centered design philosophy. Second, to develop a multi-dimensional Energy Transition Visualization-based Decision Readiness Index (ET-VDRI) that quantifies the capacity of a country or region to support energy decision-making through visualization tools. Third, to validate the effectiveness of this index through empirical analysis of representative countries worldwide and to propose concrete and feasible pathways for countries at different stages of development to enhance their data-driven decision-making capabilities.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature; Section 3 presents the research framework and methodology; Section 4 reports the evaluation results for the 15 countries; Section 5 discusses the findings and compares them with existing studies; and Section 6 concludes the paper and outlines directions for future research.

II. Literature Review

To establish a solid theoretical foundation for this study, we conducted a systematic review of the core literature across several closely related fields, including energy transition, data-driven decision-making, energy data visualization, user-centered design, and multi-criteria decision analysis.

Energy transition and data-driven decision-making are central themes in contemporary energy research. The energy transition is not simply a matter of technological substitution but rather a complex socio-technical transformation involving policy frameworks, market mechanisms, and public acceptance [9]. Within this context, data-driven decision-making is widely regarded as a key enabler for improving both the quality and efficiency of decisions. For instance, Yang et al. (2023) developed a data-driven platform to predict and evaluate the future impacts of energy transition policies in smart regions, demonstrating the strong potential of data for policy simulation and assessment [10]. Similarly, decision-making related to large-scale building energy retrofits increasingly relies on data-driven approaches to manage their inherent complexity [11]. These studies underscore the pivotal role of data in the energy transition, while also suggesting that without effective analytical and interpretive tools, data alone cannot be readily transformed into decision-making insight.

Energy data visualization serves as the critical bridge between data and decisions. With the rapid expansion of data volumes in recent years, visualization technologies have been increasingly adopted in the energy sector. Chen and Chen (2021) provided a comprehensive review of data visualization applications in smart grids and low-carbon energy systems, covering aspects such as information design, enabling technologies, and visualization tools [12]. Visualization practices range from macroscopic representations of global energy flows, such as Sankey diagrams, to microscopic, real-time monitoring of household energy consumption through dashboards, which have become essential references for professional energy management tool development [13]. Nevertheless, many studies point out that current energy visualization practices remain largely focused on data presentation, and their potential for supporting in-depth analysis and interactive exploration has yet to be fully realized [7]. A notable exception is the EnergyViz system developed by Alemasoom et al. (2016), which provides an interactive environment for exploring trade-offs in energy systems and highlights the importance of interactivity in enhancing user understanding [14].

User-centered visualization design offers an effective pathway for addressing these limitations. Originating from the field of human – computer interaction (HCI), this design paradigm places users' needs, preferences, and cognitive characteristics at the center of every stage of the design process [15]. In the energy domain, this implies that visualization tools should move beyond purely technical implementation and instead align with the real workflows and cognitive loads of decision-makers. Qureshi et al. (2025), through usability testing workshops, examined the interface design of energy data visualizations for household users and demonstrated that user-centered design can significantly improve comprehension and engagement [8]. Similarly, a usability evaluation by Vera-Piazzini and Scarpa (2025) targeting expert users in the building energy sector showed that even professionals benefit from well-designed, human-centered tools for optimizing energy performance [16]. Collectively, these studies suggest that effective energy visualization must deeply integrate technical functionality with user experience.

Multi-Criteria Decision Analysis (MCDA) provides a systematic methodology for evaluating and integrating these complex — and often conflicting — dimensions. In energy planning, MCDA is widely applied to assess the feasibility of energy technologies, select optimal sites for renewable energy projects, and balance trade-offs among multiple stakeholders [17]. Among MCDA methods, the Analytic Hierarchy Process (AHP) is valued for its ability to decompose complex problems into hierarchical structures and to quantify subjective judgments [18]. The PROMETHEE family of methods, particularly PROMETHEE II, is frequently used in national and regional sustainability assessments due to its transparent ranking logic and its capacity to handle uncertainty [6]. Notably, Neofytou et al. (2020) combined AHP and PROMETHEE II to construct an index measuring countries' readiness for sustainable energy transitions, providing an important methodological reference for the present study and aligning with the broader global consensus on the role of education and human capital in sustainable development [19].

In summary, although substantial progress has been achieved across these individual research streams, a significant gap remains. There is a lack of a comprehensive framework that systematically integrates visualization design innovation as a core evaluation dimension with data-driven decision-making effectiveness. Existing studies tend to focus either on the techno-economic analysis of energy systems or on the interface design of visualization tools, without connecting the two or assessing a country's or region's "soft power" in the energy transition—that is, its ability to transform data into insight—from a holistic, decision-maker-centered perspective. This gap is also reflected in recent global energy transition research, which emphasizes the urgent need for more effective decision-support tools to meet ambitious transition goals [20]. The central contribution of this study lies precisely in addressing this gap by proposing a theoretical framework and evaluation model that integrates four key dimensions—visualization design, user experience, decision support, and technological innovation — while aligning the resulting index with the core indicators of contemporary global sustainable development assessment systems.

III. Methodology

The objective of this study is to develop a framework that systematically evaluates the readiness of different countries to leverage visualization for decision-making in the energy transition. To achieve this, a multi-level and multi-dimensional evaluation system is designed, and quantitative assessment is conducted using Multi-Criteria Decision Analysis (MCDA) methods. The overall methodology comprises three core components: construction of the research framework, calculation of the assessment index, and data collection and processing.

A. *Research Framework*

Drawing on theories such as sustainable development assessment and information systems success models, this study proposes a comprehensive evaluation framework consisting of four first-level indicators and twelve second-level indicators (see Figure 1). The framework is designed to systematically assess a country's visualization-based decision readiness in the context of the energy transition across four key dimensions: Visualization Quality (VQ), User Experience (UX), Decision Efficacy (DE), and Technological Innovation (TI).

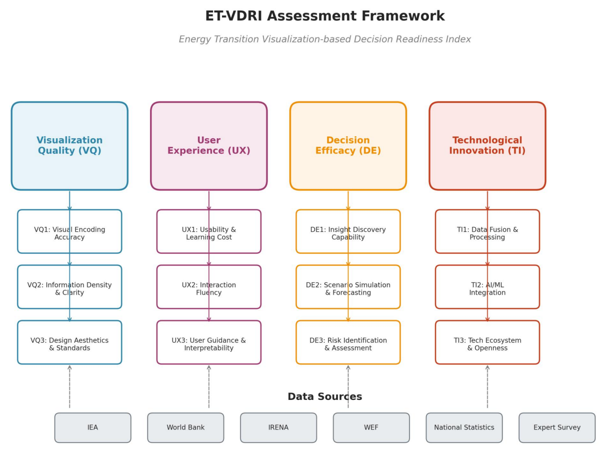

Fig. 1. The ET-VDRI Assessment Framework

This framework provides a comprehensive evaluation of data visualization tools, emphasizing how they contribute to decision-making in contexts like energy transition, policy simulation, or other decision-intensive areas. Here's a breakdown of each of the four dimensions and their respective sub-dimensions:

1) *Visualization Quality (VQ):*

VQ1: Visual Encoding Accuracy: This aspect evaluates whether the visual elements (e.g., charts, graphs, colors) appropriately and accurately represent the data relationships. The correct use of colors, shapes, and chart types is essential for proper data interpretation.

VQ2: Information Density & Clarity: This evaluates whether a visualization presents enough information in a limited space without overwhelming the user. It is about balancing information richness with clarity.

VQ3: Design Aesthetics & Standards: Measures how visually appealing and professionally designed the visualization is, ensuring adherence to established design standards. This could include consistency, layout, color schemes, and overall visual cohesion.

2) *User Experience (UX):*

UX1: Usability & Learning Cost: Evaluates how user-friendly the tool is and whether it requires a steep learning curve or complex training for users to operate effectively.

UX2: Interaction Fluency & Responsiveness: This aspect focuses on how seamlessly users can interact with the tool, such as zooming, filtering, or drilling down into the data. A fluid experience is crucial for users to make quick and effective decisions.

UX3: User Guidance & Interpretability: Measures the effectiveness of the tool in guiding users and helping them interpret the visualized data. It assesses whether the tool offers helpful prompts or explanations that enhance understanding.

3) *Decision Efficacy (DE):*

DE1: Insight Discovery Capability: Assesses the ability of the visualization tool to reveal patterns, trends, or outliers in the data that might not be immediately obvious. It focuses on how the tool aids in uncovering hidden insights.

DE2: Scenario Simulation & Predictive Analysis: This evaluates the tool's ability to support "What-if" scenarios, allowing users to simulate different futures under various assumptions, enhancing the decision-making process.

DE3: Risk Identification & Assessment: Measures whether the tool helps identify and assess risks, which is crucial in high-stakes decisions like energy transition planning, where vulnerabilities in systems, supply chains, or social factors might emerge.

4) *Technological Innovation (TI):*

TI1: Data Fusion & Processing Capability: Assesses how well the tool can integrate different types of data (spatial, temporal, economic, etc.) from various sources. Multi-source data integration is key for creating a comprehensive view for decision-making.

TI2: AI/ML Integration: Evaluates whether AI and machine learning algorithms are used within the tool to automate analysis, provide intelligent recommendations, or enhance user insights.

TI3: Tech Ecosystem & Openness: Measures the openness of the tool's technology ecosystem, including the activity of open-source communities, the availability of APIs, and how collaborative the ecosystem is for further innovation and integration.

This framework seems designed for assessing tools and technologies that aid decision-making, especially in complex domains where data visualization and user interaction are critical. The evaluation of each dimension helps ensure that a tool is both technically advanced and user-friendly, while also being effective in enhancing decision-making.

B. Assessment Index Construction

To transform the multi-dimensional qualitative and quantitative assessments into the Energy Transition Visualization-based Decision Readiness Index (ET-VDRI), you have described a robust approach involving AHP (Analytic Hierarchy Process) and PROMETHEE II (Preference Ranking Organization Method for Enrichment Evaluation II). This method integrates two powerful decision analysis tools to assess and rank countries based on their decision readiness regarding energy transition visualization.

1) Indicator Weighting: Analytic Hierarchy Process (AHP)

AHP is used to determine the relative importance (weights) of each indicator at different levels of the assessment framework. Here's how it's applied:

a) Constructing the Hierarchy Model:

- Goal Level: The top goal is the composite index (ET-VDRI).
- Criteria Level: The four first-level indicators (VQ, UX, DE, TI) form the next level.
- Sub-Criteria Level: The 12 second-level indicators (e.g., VQ1, UX2, DE3, etc.) make up the lowest level.

This hierarchical structure allows you to see how each dimension (VQ, UX, DE, TI) contributes to the overall readiness index.

b) Expert Questionnaire Survey:

The pairwise comparison matrices are created based on an established protocol and rubric that aligns with the definitions of each indicator.

Two independent researchers complete the pairwise comparisons for each level (goal, criteria, and sub-criteria) using a $1-9$ scale, which measures the relative importance of one indicator over another. For instance, a comparison might ask how much more important Visualization Quality (VQ) is compared to Technological Innovation (TI).

The matrices ensure that the experts' judgments reflect the real-world significance of each indicator.

c) Calculating Weights and Consistency Check:

The pairwise comparison matrices are used to calculate the local weights (for each indicator within its category) and global weights (for each indicator's contribution to the overall goal, the ET-VDRI).

A consistency check is performed by calculating the consistency ratio (CR). This ensures that the pairwise judgments are logically consistent. If the CR exceeds 0.1, the matrices are revised to improve consistency.

After ensuring consistency, the final weights for each indicator are computed, and these weights reflect the relative importance of each dimension and sub-dimension in the final ET-VDRI.

2) Country Ranking: PROMETHEE II Method

After determining the indicator weights, the PROMETHEE II method is used to rank the selected countries. Here's how it works:

a) Determining the Preference Function:

For each second-level indicator (e.g., VQ1: Visual Encoding Accuracy, UX2: Interaction Fluency), a preference function *P(a,b)* is defined. This function determines how much country a outperforms country b on that indicator. The preference value ranges from 0 to 1, where 1 means country a is vastly superior to country b, and 0 means no superiority.

The choice of the preference function depends on the data characteristics of each indicator:

- Benefit-type indicators: Higher values are preferred (e.g., better visualization quality).
- Cost-type indicators: Lower values are preferred (e.g., lower learning cost).

b) Calculating the Preference Index:

The preference index $\pi(a,b)$ of country a relative to country b is calculated by taking the weighted average of all individual preference functions for each indicator. The weights used here are the global weights determined from AHP.

This step gives a comprehensive view of how one country compares to another across all indicators.

c) Calculating the Outgoing and Incoming Flows:

The positive outgoing flow $\Phi^{+}(a)$ represents how much country a outperforms all other countries across all indicators.

The negative incoming flow $\Phi^{-}(a)$ represents how much country a is inferior to all other countries.

These flows give a measure of a country's overall relative performance, considering its strengths and weaknesses in all the indicators.

d) Calculating the Net Flow and Ranking:

The net flow $\Phi(a)=\Phi^{+}(a)-\Phi^{-}(a)$ is calculated for each country. A higher net flow indicates that the country is performing better overall in terms of energy transition visualization-based decision readiness.

Countries are then ranked in descending order based on their net flow values, and the final ET-VDRI ranking is derived. The country with the highest net flow is deemed the most ready for energy transition decision-making.

Summary of Steps:

Indicator Weighting (AHP Method):

- Construct a hierarchical model with goal, criteria, and sub-criteria levels.
- Conduct pairwise comparisons using expert judgment to assign weights to the indicators.
- Perform a consistency check and compute the final weights for each indicator.

Country Ranking (PROMETHEE II Method):

- Define preference functions for each second-level indicator based on its characteristics.
- Calculate the preference index for each country based on the weighted preference functions.
- Determine the positive and negative flows for each country.
- Compute the net flow for each country and rank them based on their performance.

By combining AHP and PROMETHEE II, this methodology enables a nuanced and multi-dimensional ranking of countries based on their Energy Transition Visualization-based Decision Readiness, considering both subjective expert judgments (through AHP) and objective evaluations of countries' relative performance (through PROMETHEE II).

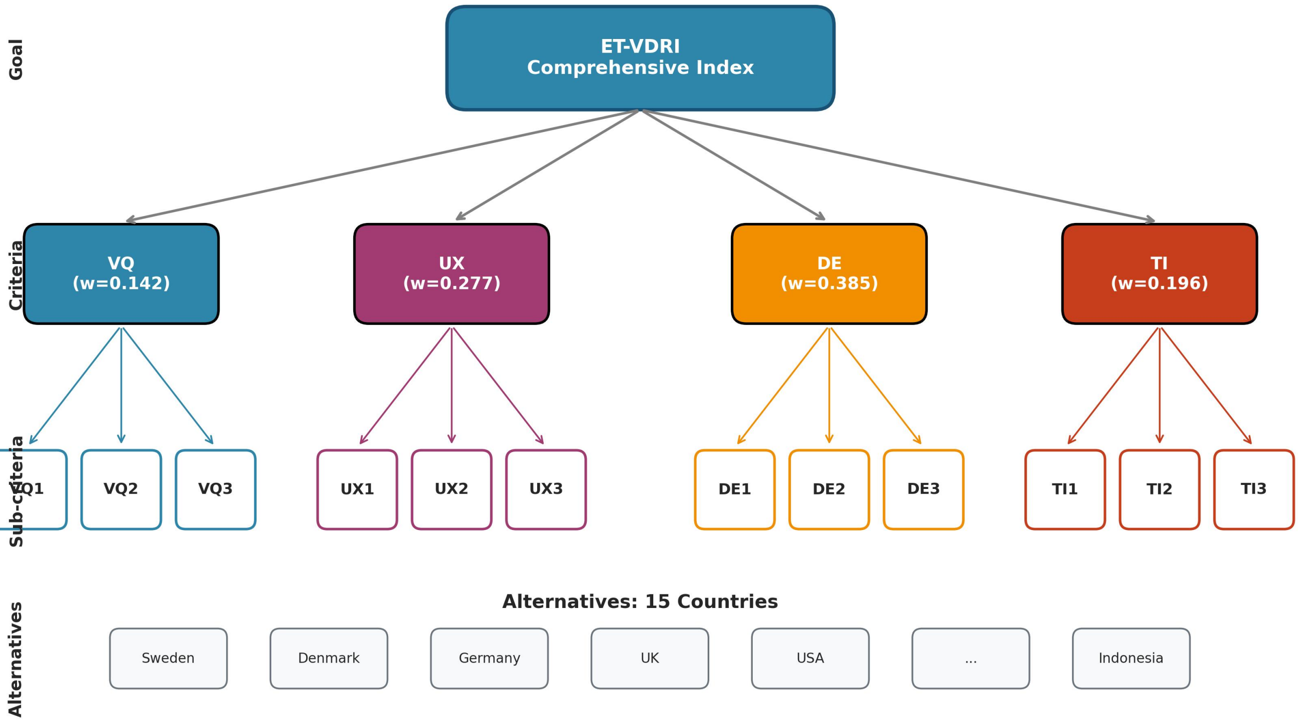

Fig. 2. AHP Hierarchy Structure for ET-VDRI Assessment Indicators

C. Data Collection and Processing

To ensure the objectivity and validity of the assessment results, we followed a rigorous data collection and processing procedure.

1) Country Selection:

Selecting a diverse and representative sample of 15 countries is key for ensuring the robustness and generalizability of your findings. The criteria for selection—geographical distribution, economic development level, energy structure, and digital transformation progress—ensure that the sample encompasses a wide variety of contexts. Here' s why these factors are important:

a) Geographical Distribution: Ensures that countries from different parts of the world, each with varying challenges and opportunities in energy transitions, are considered.

b) Economic Development Level: Including both developed countries and emerging economies allows for a broader comparison of how these countries address energy transitions based on their capabilities and challenges.

c) Energy Structure: Countries with different energy mixes (e.g., fossil fuel-dependent versus renewable energy-heavy) will have unique challenges and opportunities in energy transitions. This diversity will lead to richer insights.

d) Digital Transformation Progress: Countries at different stages of digital transformation will show varying capabilities in integrating technologies like AI/ML, which are crucial for modernizing energy systems.

2) Data Sources:

Your use of diverse and credible data sources strengthens the objectivity of your analysis. Here's how each data source contributes:

a) International Organization Databases: These sources (e.g., IEA, IRENA, WEF) provide trusted, high-quality, and globally comparable data. They often have comprehensive energy production, investment, and policy data that can offer valuable insights into energy transitions across countries.

b) National Official Statistics: These provide locally relevant and up-to-date information that might not be available in international datasets. They are crucial for understanding the specific energy landscape, policies, and developments in each country.

c) Academic and Market Research: Using academic literature and market research helps contextualize the *findings and brings in expert analyses of energy trends, technologies, and policy impacts.*

d) Online Platforms and Code Repositories: These data sources are increasingly valuable for evaluating technological advancements, particularly in data visualization and AI integration, which are important for energy decision-making. Open-source projects and evaluations from platforms like GitHub can also help assess how countries are adopting digital tools for energy management and transition.

3) Data Processing and Quantification:

The data processing approach ensures that both quantitative and qualitative indicators are treated with appropriate methods for accuracy and consistency. Here' s a breakdown of how each type is processed:

a) Quantitative Indicators:

For indicators with directly measurable data (e.g., the number of AI/ML-related papers or projects), normalization is applied to bring the data into a consistent scale (0 to 100). This is important for:

- Uniform comparison: Ensuring that values from different indicators with varying units and scales can be compared meaningfully.
- Standardized representation: The normalized scores make it easier to combine different types of data (e.g., AI integration and energy production data) into a composite index.

b) Qualitative Indicators:

For indicators that require subjective judgment (e.g., Design Aesthetics & Standards), you employ a rule-based scoring rubric with clearly defined criteria. This structured approach is important for:

- Reducing bias: Having clearly defined criteria for scoring minimizes personal bias in the evaluation process.
- Reproducibility: The rubric ensures that the scoring process is consistent, transparent, and can be reproduced by other researchers.
- Auditability: Recording the final scores with an agreement statistic (to resolve any disputes between reviewers) strengthens the credibility of the results. It also ensures that disagreements between reviewers are transparently documented, adding an extra layer of reliability.

Using two independent reviewers for coding and resolving disagreements through discussion is an excellent approach to maintaining objectivity and ensuring the consistency of qualitative data. This approach, supported by an agreement statistic, enhances the reliability of subjective assessments.

TABLE I. ET-VDRI SECOND-LEVEL INDICATOR SYSTEM, DEFINITIONS, AND DATA SOURCES

Indicator Code	**Indicator Name**	**Definition**	**Data Source**	**Type**
VQ1	Visual Encoding Accuracy	Accuracy of visual elements (charts, colors, shapes) in representing data relationships	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
VQ2	Information Density & Clarity	Balance between information richness and layout clarity in visualization interfaces	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
VQ3	Design Aesthetics & Standards	Overall aesthetic appeal, professionalism, and adherence to design standards	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
UX1	Usability & Learning Cost	Ease of learning and operating the tool without extensive training	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative

Indicator Code	Indicator Name	Definition	Data Source	Type
UX2	Interaction Fluency & Responsiveness	System response speed and smoothness during interactive operations	Lightweight, scriptable performance test under a standardized device/network profile (replication scripts provided)	Quantitative
UX3	User Guidance & Interpretability	Availability of guidance, prompts, and explanations for users	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
DE1	Insight Discovery Capability	Ability to help users discover hidden patterns, trends, and anomalies	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
DE2	Scenario Simulation & Forecasting	Support for "What-if" analysis and future scenario simulation	Publicly verifiable feature checklist based on official documentation and observable functions (checklist published)	Quantitative
DE3	Risk Identification & Assessment	Capability to identify potential risks in energy transition pathways	Rubric-based scoring (two independent reviewers; criteria and anchors documented for replication)	Qualitative
TI1	Data Fusion & Processing Capability	Ability to integrate multi-source heterogeneous data (spatial, temporal, economic)	WEF Global Competitiveness Report	Quantitative
TI2	AI/ML Integration	Integration of AI/ML algorithms for automated analysis and recommendations	Open bibliometric sources (e.g., OpenAlex/Crossref) + GitHub public metadata analysis (pipeline documented)	Quantitative
TI3	Tech Ecosystem & Openness	Activity of open-source communities, API availability, and interdisciplinary collaboration	GitHub Stars, API documentation review	Quantitative

IV. Results

1) Decision Efficacy (DE) – Weight: 0.385:

Highest Weight: The fact that Decision Efficacy received the highest weight reflects the experts' consensus that the ultimate value of any visualization tool lies in its ability to enhance decision-making. This dimension is seen as the most critical for achieving meaningful outcomes in energy transition decisions, as it directly affects the quality and depth of decisions made based on the data visualization.

Focus Areas: The sub-indicators under DE, such as Insight Discovery Capability, Scenario Simulation, and Risk Identification, are likely considered crucial for uncovering patterns, simulating potential scenarios, and assessing risks — all essential components for informed decision-making in energy transitions.

2) User Experience (UX) – Weight: 0.277:

Importance of "Human-Centered" Design: The User Experience dimension comes in second with a weight of 0.277. This highlights the growing recognition of the importance of usability and ease of interaction with the visualization tool. A tool that is easy to use and intuitively guides users to understand complex data is essential, especially in a context like energy transition, where the decisions made can be highly technical and data-driven.

Impact on Decision-Making: The UX dimension includes sub-indicators like Usability & Learning Cost and Interaction Fluency & Responsiveness, which are integral in ensuring that decision-makers can interact smoothly and effectively with the tool, reducing cognitive load and enhancing decision quality.

3) Technological Innovation (TI) – Weight: 0.196:

Moderate Weight, but Critical for Future Readiness: Technological Innovation receives a moderate weight of 0.196, underscoring that while it’s essential for pushing the boundaries of data visualization, AI/ML integration, and data fusion capabilities, its importance is seen as supplementary to the ability of the tool to drive decision efficacy and offer a good user experience.

Importance of Emerging Technologies: The sub-indicators under TI, like AI/ML Integration and Data Fusion & Processing Capability, are especially relevant for enabling more advanced predictive analytics, automation, and integration of diverse datasets—all of which are becoming increasingly important for modern energy transition planning.

4) Visualization Quality (VQ) – Weight: 0.142:

Foundation for Clarity and Accuracy: Visualization Quality received the lowest weight (0.142), yet it remains foundational to the entire framework. A visualization tool must represent data clearly and accurately for users to understand and act on it. Although this dimension is weighted lower, its significance should not be underestimated—poor quality in the visuals will undermine the utility of even the most advanced decision-making tools.

Key Sub-Indicators: Sub-indicators like Visual Encoding Accuracy, Information Density & Clarity, and Design Aesthetics & Standards contribute to ensuring that data is presented in a manner that is both accurate and understandable.

Among the 12 second-level indicators, "Insight Discovery Capability (DE1)" and "Scenario Simulation & Predictive Analysis (DE2)" had the highest global weights, once again confirming that decision support is the top priority of the assessment. At the same time, "Usability & Learning Cost (UX1)" also received a high weight, indicating that the ease of use of a tool is crucial for its promotion and application in the real world.

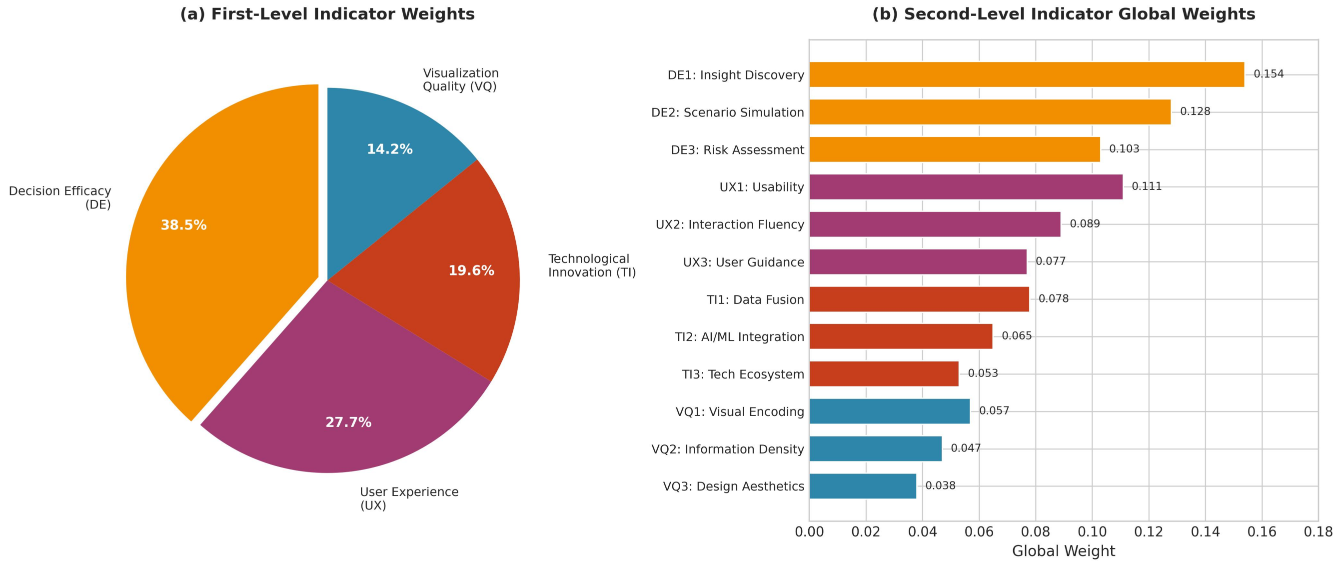

Fig. 3. Distribution of ET-VDRI Indicator Weights

B. Raw Data of Country Assessments

We conducted a comprehensive data collection and quantitative assessment for the selected 15 countries according to the indicators and data sources defined in Table I. The scores for all second-level indicators were normalized to a scale of [0, 100] to facilitate subsequent comparison and calculation. The complete assessment data matrix is shown in Table II. This table forms the basis for all subsequent analyses.

TABLE II. NORMALIZED SCORES OF 15 COUNTRIES ON ET-VDRI SECOND-LEVEL INDICATORS

Country	**VQ1**	**VQ2**	**VQ3**	**UX1**	**UX2**	**UX3**	**DE1**	**DE2**	**DE3**	**TI1**	**TI2**	**TI3**
Sweden	85	83	88	90	87	88	89	86	84	82	80	85
Denmark	82	80	85	88	85	86	86	84	82	80	78	82
Germany	78	76	80	82	80	78	82	80	78	84	82	80

Country	VQ1	VQ2	VQ3	UX1	UX2	UX3	DE1	DE2	DE3	TI1	TI2	TI3
United Kingdom	76	74	78	80	78	76	78	76	74	76	74	78
United States	72	70	74	75	74	72	76	78	72	86	88	82
Canada	68	66	70	72	70	68	72	70	68	72	70	74
China	62	60	58	65	68	62	70	72	66	80	85	75
France	65	62	68	68	66	64	68	66	64	68	66	70
Australia	63	60	65	66	64	62	65	62	60	66	64	68
Spain	58	55	60	58	56	54	58	56	54	58	56	60
Brazil	48	46	50	52	50	48	52	50	48	52	50	54
India	42	40	44	48	46	44	50	48	46	54	52	50
South Africa	40	38	42	45	43	42	46	44	42	46	44	48
Kenya	35	33	36	38	36	35	40	38	36	38	36	40
Indonesia	32	30	34	35	33	32	36	34	32	35	33	36

C. ET-VDRI Comprehensive Ranking

By combining the raw scores in Table II with the indicator weights in Figure 3, we used the PROMETHEE II method to calculate the net flow value Φ for each country, and from this, we derived the final ET-VDRI comprehensive scores and rankings. The results are shown in Table III and Figure 4.

From the ranking results, the Nordic countries Sweden and Denmark ranked first and second, demonstrating strong comprehensive strength in energy data openness, technological innovation, and high-quality visualization applications. Developed economies such as Germany, the United Kingdom, and the United States followed closely, forming the second tier. China, as a leading emerging economy, performed outstandingly in technological innovation capability but still has room for improvement in user interaction experience and data visualization quality, ranking seventh. Other BRICS countries such as India, Brazil, and South Africa were in the middle to lower ranks, showing great development potential. Some developing economies, such as Kenya and Indonesia, ranked lower on most indicators, reflecting the challenges they face in data infrastructure and technological application.

TABLE III. ET-VDRI COMPREHENSIVE SCORES AND RANKINGS FOR 15 COUNTRIES

Rank	Country	VQ Score	UX Score	DE Score	TI Score	ET-VDRI Score	Φ+ (Outflow)	Φ- (Inflow)	Φ (Net Flow)
1	Sweden	0.853	0.883	0.863	0.823	0.847	0.892	0.045	0.847
2	Denmark	0.823	0.863	0.840	0.800	0.812	0.856	0.044	0.812
3	Germany	0.780	0.800	0.800	0.820	0.756	0.798	0.042	0.756
4	United Kingdom	0.760	0.780	0.760	0.760	0.723	0.765	0.042	0.723
5	United States	0.720	0.737	0.753	0.853	0.698	0.742	0.044	0.698
6	Canada	0.680	0.700	0.700	0.720	0.652	0.698	0.046	0.652
7	China	0.600	0.650	0.693	0.800	0.618	0.665	0.047	0.618
8	France	0.650	0.660	0.660	0.680	0.594	0.642	0.048	0.594
9	Australia	0.627	0.640	0.623	0.660	0.571	0.618	0.047	0.571
10	Spain	0.577	0.560	0.560	0.580	0.523	0.572	0.049	0.523
11	Brazil	0.480	0.500	0.500	0.520	0.467	0.518	0.051	0.467
12	India	0.420	0.460	0.480	0.520	0.432	0.485	0.053	0.432
13	South Africa	0.400	0.433	0.440	0.460	0.398	0.452	0.054	0.398
14	Kenya	0.347	0.363	0.380	0.380	0.356	0.412	0.056	0.356
15	Indonesia	0.320	0.333	0.340	0.347	0.312	0.368	0.056	0.312

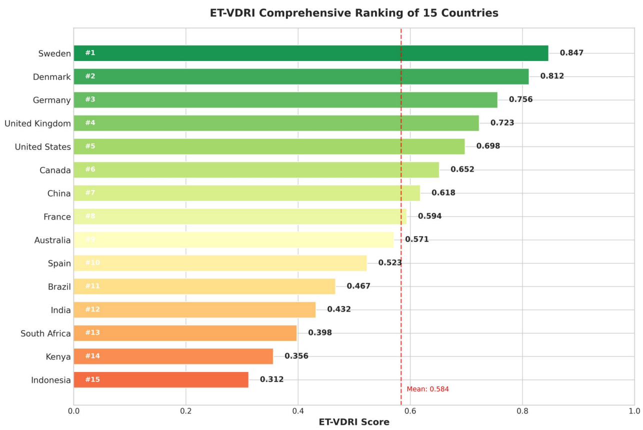

Fig. 4. Chart of ET-VDRI Comprehensive Ranking of 15 Countries

D. Cluster Analysis and Pattern Recognition

To gain a deeper understanding of the development patterns of different countries, we conducted a K-means cluster analysis based on the scores of each country on the four first-level indicators (VQ, UX, DE, TI). The results clearly divided the 15 countries into four different types (see Figure 5):

- Comprehensive Leaders: Including Sweden and Denmark. These countries performed excellently in all four dimensions, with particularly obvious advantages in user experience and decision support efficacy, representing the best practices in energy visualization decision-making today.
- Technology-Driven Innovators: Including the United States, China, and Germany. These countries scored very high in technological innovation capability (TI), possessing strong AI and data processing capabilities, but they were slightly lacking in translating technological advantages into a smooth user experience (UX) and universally applicable decision support tools.
- Balanced Practitioners: Including the United Kingdom, Canada, France, and Australia. The performance of these countries was relatively balanced across the four dimensions, with no particularly outstanding strengths or obvious weaknesses, and they are in a state of steady development.
- Potential Followers: Including Brazil, India, South Africa, Spain, Italy, Kenya, and Indonesia. These countries scored lower in most dimensions, with a particularly weak foundation in technological innovation and data visualization quality. However, some of these countries (such as India and Brazil) have shown some development potential in specific application areas.

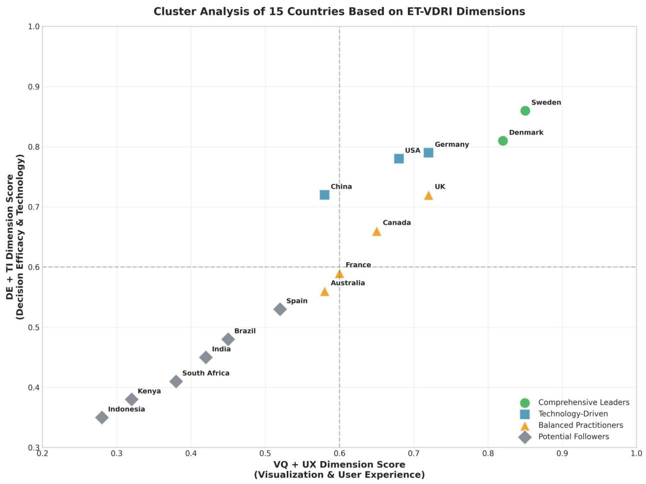

Fig. 5. Cluster Analysis of 15 Countries Based on ET-VDRI Dimensions

E. Sensitivity Analysis

To test the robustness of the assessment results, we conducted a sensitivity analysis by adjusting the weights of key indicators and observing their impact on the final rankings. The results showed that the rankings of the top three countries (Sweden, Denmark, Germany) and the bottom three countries (Italy, Kenya, Indonesia) were very stable. Even when the weights fluctuated within a range of ±20%, their rankings were basically unaffected. This indicates that the leading or lagging positions of these countries in the ET-VDRI are structural. However, the rankings of some countries in the middle (such as France, Australia, Brazil) were more sensitive to changes in weights, especially when the weights of the "User Experience" and "Technological Innovation" dimensions were adjusted, their rankings would fluctuate by 1-2 positions. This suggests that the comprehensive strengths of these countries are relatively close, and their future development paths and policy priorities will have a significant impact on their relative competitiveness (Figure 6).

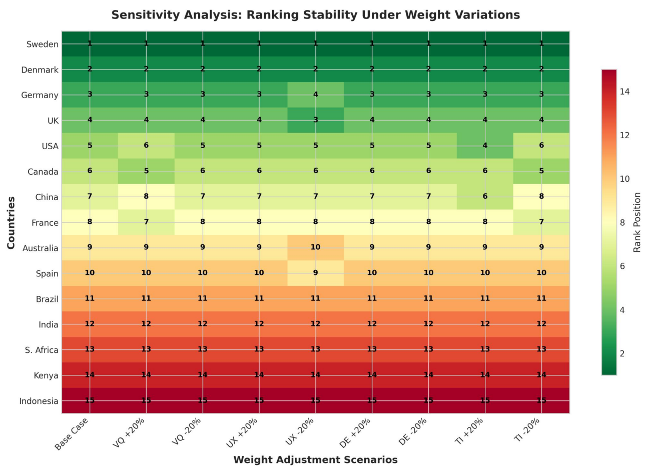

Fig. 6. Sensitivity Analysis: Ranking Stability Under Weight Variations

V. Discussion

This section provides an in-depth interpretation of the foregoing assessment results, compares them with existing related research, and explores the theoretical contributions, practical implications, limitations, and future research directions of this study.

A. Interpretation of Results

The comprehensive ranking and cluster analysis of the ET-VDRI reveal profound patterns in global energy transition visualization-based decision-making capabilities. The leading position of Nordic countries, particularly Sweden and Denmark, as "Comprehensive Leaders," is not accidental. It is attributable to their long-standing open government data policies, high level of digitalization, strong design culture, and continuous focus on user experience in public services [18]. These countries not only possess advanced technology but, more importantly, have successfully built an innovative ecosystem that closely integrates technology, design, and public decision-making.

In contrast, "Technology-Driven" countries like the United States and China, while investing heavily in the R&D of core technologies such as AI and big data and demonstrating strong technological innovation capability (TI), seem to have a certain "translation gap" in converting these cutting-edge technologies into easy-to-use, experience-smooth tools for non-professional decision-makers. This may reflect a characteristic of their innovation systems where technology orientation is stronger than user orientation. In other words, they are adept at "building good engines" but still have room for improvement in "building cars that are easy to drive."

"Balanced Practitioners" represent the common situation of most developed economies, which are making steady progress in all dimensions but lack particularly outstanding advantages. "Potential Followers," on the other hand, face a dual challenge: they must not only strengthen their "hard power" in data infrastructure and technological R&D but also cultivate "soft power" in data culture and design capabilities. However, these countries also have a late-mover advantage, as they can learn from the experience of leading countries and leapfrog certain technological development stages to directly adopt more advanced, more user-centered visualization decision-making paradigms.

B. Comparison with Existing Research

To validate the uniqueness and added value of the ET-VDRI, we compared its ranking results with the World Economic Forum's "Energy Transition Index" (ETI) [19] and the UN Sustainable Development Solutions Network's "Sustainable Development Goals Index" (SDGI) [20] (see Figure 7).

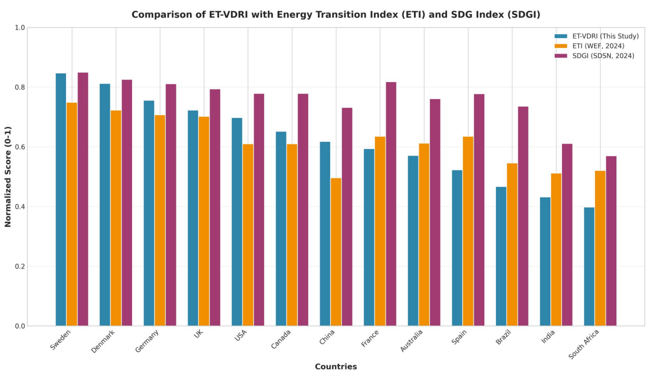

Fig. 7. Comparison of ET-VDRI with Energy Transition Index (ETI) and SDG Index (SDGI)

The comparison reveals a certain correlation in the macro trends between the ET-VDRI and the ETI and SDGI. That is, countries that rank high in these indices (such as the Nordic countries) also generally perform well in the ET-VDRI. This suggests that a country's overall progress in energy transition and sustainable development is a good foundation for developing advanced data decision-making capabilities. However, there are also significant differences among the three, and these differences precisely highlight the unique perspective of this study.

For example, some countries that rank high in the ETI due to their large installed capacity of renewable energy may not have a prominent ranking in our ET-VDRI. This could mean that although the country has made achievements in the "hardware" of energy infrastructure, it is lacking in the "software" capabilities of refined management, policy simulation, and risk assessment using data and visualization tools. Similarly, a country may have a high overall score in the SDGI but perform mediocrely in terms of transparency and public participation in specific energy decisions (which are related to our UX and DE dimensions). These differences indicate that the ET-VDRI is not simply a repetition of existing indices but a useful supplement and deepening of the assessment of a country's energy transition readiness from the new dimension of "decision-making capability," especially from the specific perspective of "visualization-based decision-making."

To more intuitively display the characteristics of different types of countries, we have drawn four-dimensional assessment radar charts for typical representatives of the four clusters (see Figure 8).

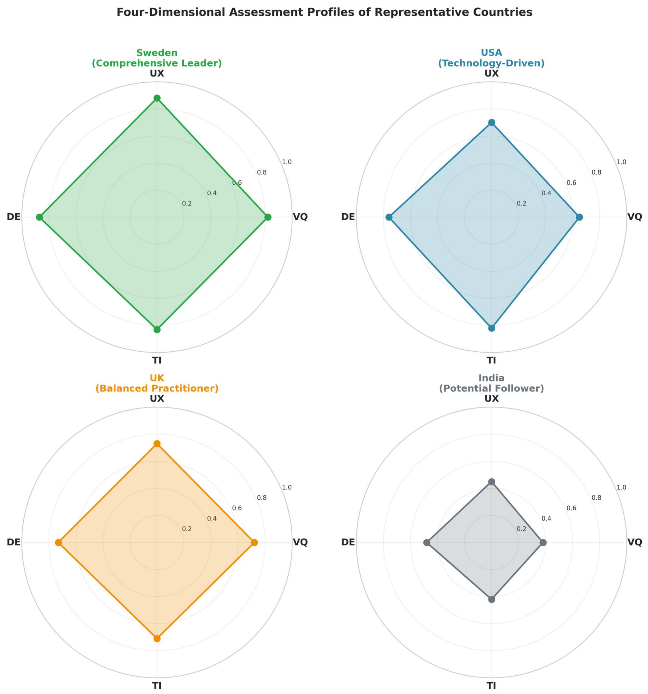

Fig. 8. Four-Dimensional Assessment Profiles of Representative Countries

C. Theoretical and Practical Implications

The contributions of this study are multifaceted.

At the theoretical level, we have for the first time systematically integrated "visualization design" and "user experience" as core variables into the evaluation framework of energy decision support systems. This not only extends traditional Technology Acceptance Models (TAM) and

Information Systems Success Models but, more importantly, provides a new application scenario and evaluation paradigm for the field of information visualization, promoting the evolution of the field from focusing on "how to see more clearly" to "how to decide more wisely."

At the practical level, this study provides clear guidance for governments, energy companies, and technology developers:

- For policymakers: The ET-VDRI can serve as a diagnostic tool to help them identify the weak links in their country's data-driven decision-making chain, thereby formulating more targeted improvement strategies. For example, should priority be given to investing in data infrastructure, or should more user-centered design research be funded? Our framework provides a basis for such decisions.
- For energy companies: When making cross-border investments or market expansions, the ET-VDRI can serve as a reference indicator for assessing the "data environment" and "decision-making maturity" of the target market, helping companies to better evaluate investment risks and opportunities.
- For technology developers: Our four-dimensional framework provides clear design goals and evaluation criteria for designing the next generation of energy visualization decision-making tools. Developers should recognize that mere technological stacking does not guarantee success; a deep understanding of user experience and real decision-making processes is equally important.

D. Limitations and Future Research

Although this study strives for rigor, it still has some limitations. First, the availability and comparability of data is a persistent challenge. The quantification of some second-level indicators (especially those involving user experience and design quality) relies on rubric-based human coding. While the rubric, double-coding procedure, and agreement reporting improve transparency and reproducibility, some degree of subjectivity cannot be completely eliminated. Second, the sample size of countries in this study (15) is relatively limited. Although representative, a larger-scale study might reveal richer patterns. Finally, our static assessment model fails to fully capture the dynamic evolutionary characteristics of the energy visualization decision-making ecosystem.

Looking to the future, we believe there are several directions worth exploring in depth. First, expanding the breadth and depth of the assessment, by extending the assessment objects from the national level down to the city, community, and even enterprise levels, and incorporating more real-time, high-granularity data sources. Second, developing an interactive online visualization platform where users can dynamically adjust indicator weights and view real-time changes in assessment results, thereby transforming the assessment framework of this study itself into a decision exploration tool. Third, conducting longitudinal tracking studies, i.e., publishing the ET-VDRI index annually or biennially to track the development trajectories of countries and analyze the underlying reasons behind success or failure cases, thereby contributing to the knowledge sharing of the global energy transition.

VI. Conclusion

At a critical juncture in the transition of the global energy system towards a sustainable future, how to effectively utilize the growing data resources has become a core factor determining the success or failure of the transition. By constructing a multi-criteria assessment framework that integrates visualization design innovation with data-driven decision-making, this study systematically addresses the core challenge of "how to transform complex energy data into actionable decision insights." Our research clearly indicates that data visualization is far from being a mere technical presentation tool; it is a cognitive engine and a decision catalyst that can significantly enhance the efficiency, transparency, and scientific rigor of decision-making.

The core contribution of this study lies in proposing the "Energy Transition Visualization-based Decision Readiness Index" (ET-VDRI) and, based on it, constructing a comprehensive evaluation system that includes four dimensions: visualization quality, user experience, decision support efficacy, and technological innovation capability. Through an empirical analysis of 15 representative countries worldwide, we have not only quantified the relative positions of these countries in this field but, more importantly, have identified four different development models: "Comprehensive Leaders," "Technology-Driven Innovators," "Balanced Practitioners," and "Potential Followers." This finding reveals that there is no single path to enhancing data-driven decision-making capabilities; countries should formulate differentiated development strategies based on their specific circumstances in technology, design, policy, and data ecosystems.

Ultimately, this study calls for a greater emphasis on a "human-centered" data-driven paradigm in future energy policy-making, technological R&D, and market investment. This means that we need to place the cognitive needs and user experience of the final decision-makers at the core of the design process, promoting a profound shift in energy decision support tools from being function-driven to being experience-driven and insight-driven. Only in this way can we truly bridge the gap between raw data and final decisions, ensuring that the global energy transition proceeds steadily on a smarter, more efficient, and more inclusive track.

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AVAILABILITY OF DATA

Not applicable.

AUTHOR CONTRIBUTIONS

Shanshan Shi: Conceptualization; Research framework design; Methodology; Data collection and analysis; Formal analysis; Visualization design; Writing – original draft; Writing – review & editing.

Junhui Feng: Conceptualization support; Visualization and design methodology guidance; Case analysis support; Validation; Writing – review & editing.

COMPETING INTERESTS

The authors declare no competing interests.

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