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RESEARCH ARTICLE OPEN ACCESS

Advancing Sustainability Assessment of Renewable Energy: A Study on Indicator-to-Framework Methods and Associated Rule Mining

Shoeib Faraji Abdolmaleki | Pastora M. Bello Bugallo

TECH-NASE Research Group, Department of Chemical Engineering, Universidade de Santiago de Compostela, Santiago de Compostela, Spain

Correspondence: Pastora M. Bello Bugallo (pastora.bello.bugallo@usc.es)

Received: 10 November 2023 | **Revised:** 29 November 2024 | **Accepted:** 10 December 2024

Keywords: data-driven | indicators | renewable energy | sustainable development

ABSTRACT

Divergent sustainable development perspectives, mathematical model limitations, and varying scenarios contribute to uncertainty in assessing renewable energy sustainability. To tackle these challenges, this study conducts a comprehensive literature review, employs an analogy, and utilizes knowledge discovery techniques with an indicator-to-framework approach. Qualitative classification and rule mining elucidate the interrelationships among dimensions, indicators, and scopes, enhancing assessment coherence. The study identifies 227 indicators across five dimensions and nine scopes, highlighting key rules through *Apriori* algorithm. Strong rules, meeting a support threshold of 0.22, confidence of 0.7, and *Lift* of 2.512, underscore the significance of environmental, economic, social, and technological dimensions. Environmental indicators like CO_2 emissions, NO_X emissions, and SO_2 emissions feature prominently. The harmonization of dimensions, indicators, and scopes streamlines research and mitigates ambiguities. Appendices augment rules with frequent indicators, enriching insights. This data-driven methodology provides a practical solution to the complexities of selecting appropriate indicators for such assessments.

1 | Introduction

Renewable Energy (RE) plays an important role in Sustainable Development (SD), experiencing rapid growth worldwide and expected to be a key component of future energy supply (Wang et al. 2020). Particularly in developing countries, as global energy demand surges and the detrimental impacts of fossil fuels become more evident, it is crucial to focus on sustainable energy solutions (Hosseini Dehshiri et al. 2024). Its deployment has shown positive impact over the past decade, both in economic growth and environmental improvement (Paramati, Apergis, and Ummalla 2018; Zafar et al. 2019; Mohammed et al. 2020; Shahbaz, Raghutla, Song, et al. 2020; Abbasi et al. 2020; Caglar et al. 2023; Chen, et al. 2023; Xing et al. 2023; Liu, 2023). To achieve long-term viability in RE, sustainability measurement is necessary as it ensures comprehensive evaluation across economic, environmental, and technical dimensions, enabling the identification of the most effective and sustainable solutions for projects like hydrogen production from wind energy (Almutairi et al. 2022; Kirikkaleli and Adebayo 2021).

Assessing the sustainability of RE requires an in-depth examination by experts, researchers, and stakeholders. As sustainability becomes increasingly important, evaluating the sustainability of RE systems, RE projects, RE in cities, and countries has become a focal point (e.g., Amponsah et al. 2014; Fang et al. 2018; Papież, Śmiech, and Frodyma 2018). Assessment approaches, such as utilizing indicators, assist industry professionals in defining appropriate RE targets, leading to a comprehensive understanding of sustainability integration. Considerable attention has been given to specifying appropriate SD Indicators (SDI) for RE. Some researchers have examined SDIs from the perspective of developing such indicators for RE systems. For example, Liu (2014) studied the identification and production of comprehensive indicators for RE systems, establishing General Sustainable Indicators (GSIs) by considering various concepts of sustainability, assessing existing methods, and proposing a comprehensive framework for further development. Colla, Ioannou, and Falcone (2020) investigated a set of multi-disciplinary Key Performance Indicators (KPIs) for holistic comparison across various energy projects. Hák, Janoušková, and Moldan (2016) focused on ensuring the relevance of indicators for clear, unambiguous communication to users. Heylen, Deconinck, and Van Hertem (2018) reviewed and classified reliable indicators of RE systems. Mardani et al. 2015 and Kumar et al. (2017) reviewed various methods for solving the sustainability measurements. Other studies (e.g., Ghenai, Albawab, and Bettayeb 2020; Wang et al. 2018) investigated methodologies for selecting SD indices and examined evaluation methods. Luong, Liu, and Robey (2012) assessed RE technology using essential indicators to determine their support and measurability in terms of sustainability.

However, certain SDIs are not always particularly specific due to varied and distinct definitions of the SD, leading to varied interpretations in different (Saidani et al. 2019). Also, sustainability studies at different temporal and spatial scales consider disparate policies (REN21 2021; Nchofoung and Ojong 2023). Frameworks are utilized to conceptualize or quantify human processes, behaviors, or forces, aiding in the examination and use of indicators. Behind each framework, scholars, politicians, and business—industry stakeholders focus on SD from specific viewpoint. For instance, in a “causal framework,” scholars seek cause-and-effect relationships, while in a “capital accounting framework,” dimensions are viewed as financial resources. Hence, selecting criteria (indicator) is not a straightforward task. Examples include the Triple Bottom Line (TBL) approach, which evaluates environmental, economic, and social dimensions equally (Elkington 1998), and the three nexus circles that view the economy as interconnected with environmental and social aspects (Kirchherr, Reike, and Hekkert 2017). Another perspective sees the economy as a means for resource allocation to promote environmental sustainability and enhance social well-being (Iddrisu and Bhattacharyya 2015). These perspectives create distinct cause-and-effect relationships in RE sustainability assessment and indicator selection.

The complexity and variability of RE sustainability variables introduce significant uncertainty and nonlinearly in certain measurements (Wang and Yang 2020). This complexity can lead to bias assessment results if the data is not accurately processed. These challenges obstruct integrated measurement and present difficulties in assessing sustainability, leading in disparate results.

Moreover, the existence of different scenarios hinders result integration. In some regions, economic characteristics are critical, while in others, social development scenarios may receive more emphasis. Recently, the environmental factor has gained increased attention due to its high sensitivity (Busch et al. 2020; Mehmood, Askari, and Saleem 2022; Tsagkari, Roca, and Stephanides 2022).

A review of the literature reveals various indicator-to-framework methodologies used to measure RE sustainability, employing different sets of indicators, scopes, and dimensions (Haddad, Liazid, and Ferreira 2017; Ifaei et al. 2017; Stougie et al. 2018; Boran 2018; Capellán-Pérez, Campos-Celador, and Terés-Zubiaga 2018; Collotta et al. 2019; Zafar et al. 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Mastrocinque et al. 2020; Su et al.2020). Despite extensive research, a unified outlook on these measurements is lacking. Ambiguity surrounds existing sustainability concerns associated with RE, due to varying definitions of sustainability, lack of organization's perspectives, and inconsistency in assessment methodologies. This complexity highlights the challenges in achieving integrated sustainability measurement (Figure 1).

The selection and classification of sustainability indicators have been extensively studied within the sustainability literature (e.g., Abbasi et al. 2023; European Commission 2020; Saidani et al. 2019). However, many of these studies primarily focus on the case-by-case measurement of sustainability within specific fields (e.g., Collotta et al. 2019; Solano-Olivares,

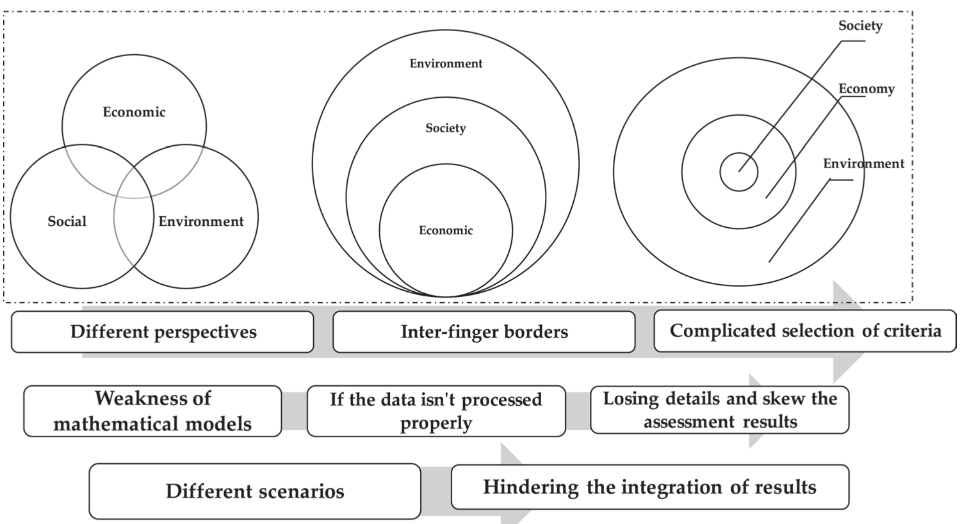


FIGURE 1 | Variety of challenges affecting sustainability assessment of RE.

Santoyo, and Santoyo-Castelazo 2024), without addressing the broader, inherent challenges. Several studies focus exclusively on existing regional and local policies (e.g., Ren, Tang, and Höök 2021; Sotnyk et al. 2022; Vides-Prado, Mora-Flórez, and Pérez-Londoño 2023). In a recent study, Abbasi et al. (2023) addressed the need for a specific and applicable set of sustainability indicators (SIs) to measure and track the performance of energy technologies within the built environment. The study employed a structured framework comprising six stages to identify, refine, and prioritize SIs, ensuring stakeholder engagement and balanced representation of environmental, economic, and social dimensions. The authors highlighted the necessity of developing quantification methods for these indicators, addressing data availability issues, and evaluating the sustainability of various low-carbon alternatives (Abbasi et al. 2023). Still, there is a need to emphasize the importance of generalizing indicators for larger-scale assessments, incorporating diverse viewpoints, and ensuring sufficient indicators for comprehensive sustainability assessments in RE across different scopes.

Additionally, the process of selecting indicators often involves referencing existing literature. Typically, once the objective function is defined, researchers conduct a literature review to identify relevant indicators that are available, meaningful, and clearly aligned with sustainability goals (Almutairi et al. 2022; Hosseini Dehshiri et al. 2024). Consequently, in studies with a similar scope, researchers may explore different dimensions of sustainability and select varying sets of indicators, leading to inconsistencies in the evaluation of sustainability. For example, three studies with the same scope (general sustainability assessment of RE) selected to address these complexities:

- Solano-Olivares, Santoyo, and Santoyo-Castelazo (2024): This study evaluated the environmental, economic, and social dimensions using 25 environmental, 17 economic, and 24 social indicators, respectively, through a comprehensive literature review.
- Cîrstea et al. (2018): This research assessed the environmental, economic, social, and institutional dimensions, employing 6 environmental, 7 economic, 5 social, and 5 institutional indicators, using Factor Analysis (FA) and Principal Component Analysis (PCA).
- Şengül et al. (2015): The study analyzed the environmental, economic, social, and technical dimensions, using 7 environmental, 8 economic, 3 social, and 6 technical indicators, with the Fuzzy TOPSIS methodology.

These studies illustrate the diversity in dimensions and the number of indicators within the same scope. Moreover, there is a lack of consensus among scholars regarding indicator selection. For instance, Şengül et al. (2015) included social acceptability, social benefit, and job creation as social indicators, whereas Cîrstea et al. (2018) selected availability of the latest technologies, affordability of financial services, capacity for innovation, company spending on R&D, and university-industry collaboration in R&D as social indicators. Additionally, due to the boundaries of sustainable development and varying perspectives, there is ambiguity in categorizing certain indicators. For example, Şengül et al. (2015) classified job creation as a social indicator, while Shaaban et al. (2018) considered it an economic indicator. More examples are provided in Supporting Information.

Given the diversity of criteria and the absence of a single point of view, the question arises about how sustainability can be better represented through measurements or how to achieve more uniformity in performing sustainability measurements for RE. Considering indicator-to-framework methods, this study aims to extract common patterns, establish rules for such assessments, and clarify the interrelationships between dimensions of SD, indicators, and scopes.

Initially, the study reviews prominent arguments and categorizes them based on SD dimensions scopes of sustainability assessment of RE (such as RE investment, RE sources, RE power generation, etc.). A database is created by extracting information from literature. To mitigate the complexity of RE sustainability assessment, an analogy from economic sciences (shopping cart analysis) is utilized. Knowledge Discovery from Data (KDD) is then applied, facilitating the identification of indicator sets using associated rule mining method.

This study tackles current sustainability challenges in RE sustainability assessments and makes their utility more organized, reasonable, and practical. It acknowledges the challenge of selecting appropriate indicators and proposes a classification scheme to simplify the process.

The primary contribution of this study is to develop a data-driven methodology to address challenges posed by diverse scenarios, overlapping boundaries of SD, and differing perspectives on indicator selection. This approach seeks to provide users with a practical and efficient solution to the complexities involved in selecting appropriate indicators.

2 | Methodology

In this study, literature review is employed as the primary research approach to make a database. The purpose is to summarize the relevant materials, identify developing patterns, analyze the findings, and propose novel applications in the context of sustainability assessment of RE. Key aspects included in the literature review are policies and frameworks, criteria, and indicators toward sustainability assessment of RE.

Once the database is ready, KDD is applied. It is used to uncover hidden insights, trends, correlations, and patterns that can help in making decisions, predictions, or recommendations (Mackinnon and Glick 1999; Benabdellah et al. 2022; Ye, Wang, and Dai 2022; Shu and Ye 2023). The aim is to understand the interrelationship between scopes of RE and SD, and to identify patterns of indicators for the sustainability assessment of RE (Figure 2).

First, qualitative classification is used to categorize data or objects based on their attributes, characteristics, or features, without using numerical values or measurements (Han, Kamber, and Pei 2012; Donada and Mbengue 2014). It is used to identify the links between dimensions of SD, indicators (criteria), and scopes of sustainability in RE. Then, data mining concepts are utilized, specifically associated rule mining, to establish rules for selecting indicators for such assessments.

3 | Development

3.1 | Establishing the Database

To systematically conduct the literature review, a four-step process (Figure 3) is followed. The study is commenced with a thorough search in digital databases. To ensure the retrieval of valid materials, specific keywords are utilized. The identified keywords for assessing the sustainability of RE are "renewable energy," "sustainable development," "sustainability assessment," "sustainability frameworks," "sustainability indicators," and "sustainability methods," enabling the association and screening of SD in the context of RE.

To obtain relevant studies, the search for related content (Figure 4) encompasses scientific platforms, national and international organization documentation, and websites focusing on RE sustainability assessment (step 1). Both scholarly and non-academic sources, such as statements and policy discussions, are investigated for comparative information. The resulting documents are then evaluated for thematic relevance, and only appropriate ones are considered for further analysis in step 2. In step 3, the selected papers are examined to determine if they address at least one of the relevant keywords. Papers not meeting these criteria are either rejected, or the search process continued. For the papers meeting the requirements, their entire contents are considered to construct the database (step 3). The data set from step 3 is then measured against a criterion in step 4. If the data can represent at least one attribute of the object, it is included in the database using quantitative or qualitative measures. Otherwise, the search for new sources was continued.

The database enables the presentation of structured information by employing classification and associated rule mining. The acquired information is subsequently interpreted to derive practical conclusions.

The results of bibliographic study reveal a total of 236 academic sources, 23 institutional publications, and 5 relevant websites. The geographical scope of the materials is predominantly global (not specified an area), with the European emerging as a significant hub for related studies. Asian countries, particularly China, and United States also contribute substantially to this sector. The statistical population of peer-reviewed articles spans from the 1990s through 2024.

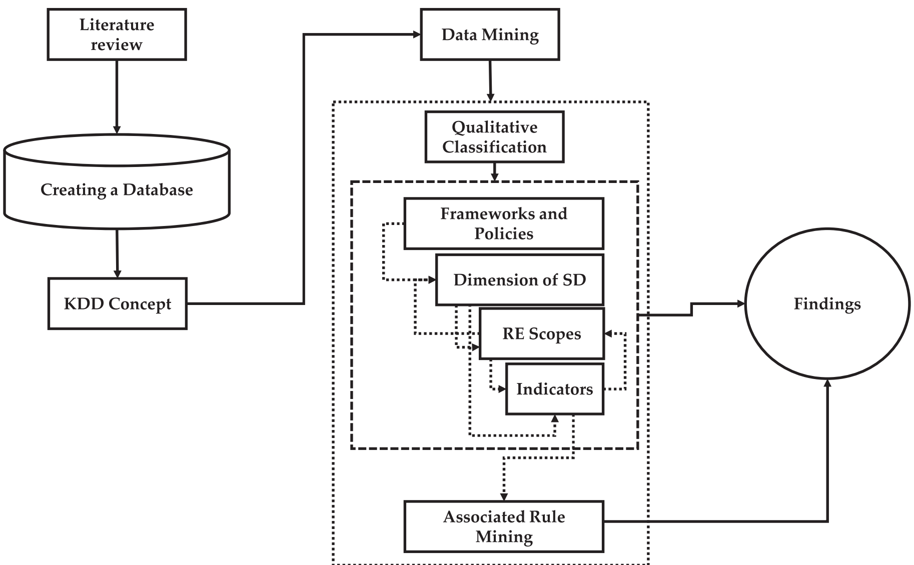


FIGURE 2 | The study methodology sketch.

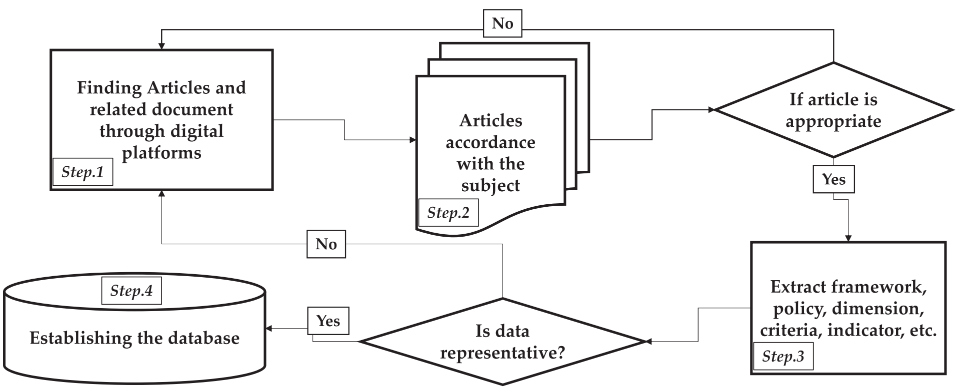


FIGURE 3 | Systematic investigation toward establishing the database.

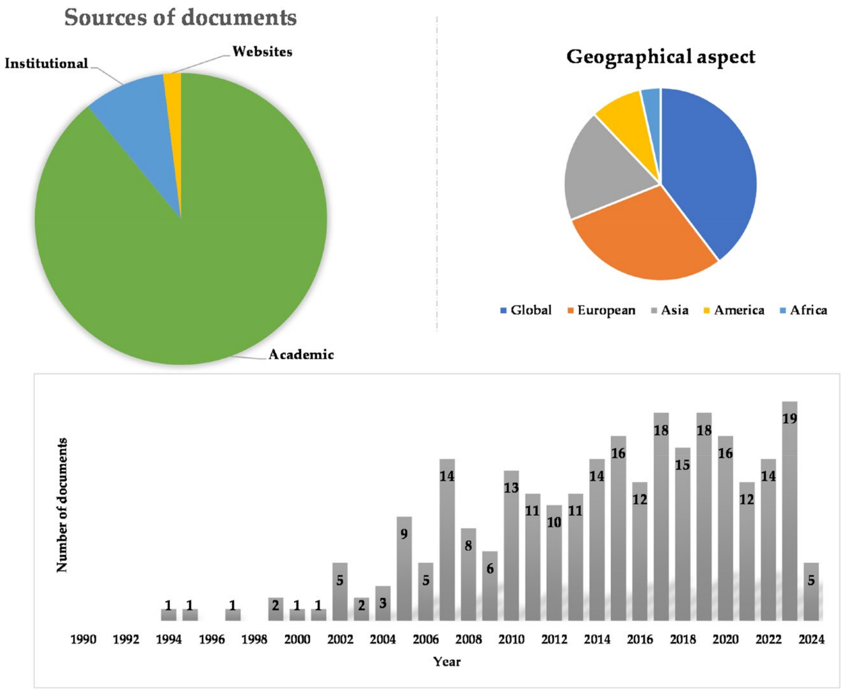


FIGURE 4 | Result of bibliographical investigation.

3.2 | Qualitative Classification

Qualitative classification is involved, the process entails training a model on labeled data, and where each data point is associated with a specific class. The method is a supervised learning technique, meaning it requires labeled training data to learn the relationship between the features and the corresponding classes. Then, we anticipate that the model will produce an output of discrete class labels for each data point, indicating the respective categories to which they belong. In this study, the desired agents are dimensions, indicators, and scopes. As a result, the data mining problem transforms into a qualitative classification problem (i.e., a qualitative content analysis), as the initial labels can be verified instead of clustering. This approach is systematic and objective, enabling the analysis of qualitative data, such as text from literature reviews, to identify patterns, themes, and relationships between different elements.

This research examines both aspects of RE sustainability, focusing on the impact of RE on sustainability and the sustainability of RE itself. The documents in the database are analyzed to determine the purpose of each evaluation conducted by the scholars, aiming to identify the scopes. Including these scopes helps to understand the key issues associated with the sustainability assessment of RE. Subsequently, the dimensions they utilized are extracted, and the indicators addressing each dimension are categorized accordingly (Figure 5).

3.3 | Rule Mining Toward indicator Selection

3.3.1 | Assumptions and Analogy

After identifying relevant literature for extracting indicator across various dimensions related to the scopes, this study adopts an interesting analogy. Each paper engaged in the field is treated as a transaction, affiliating to the realm of shopping cart analysis and customer behavior studies. Just as marketers analyze the contents of each customer's shopping cart, this study views each paper as a transaction containing various indicators within each dimension, all curated for a specific scope.

In this context, items are regarded as indicators and are grouped into item sets. The composition of items is important, whereas their sequence is not significance. From a mathematical perspective, let us denote the set of items as $I = \{I1, I2, I3, \dots, In\}$, and each transaction as Ti, which is a subset of I $(Ti \subseteq I)$. Furthermore, each transaction has a unique identifier known as *TID*. Consequently, a database can be formally described as $D = \{T1, T2, T3, \dots, Tn\}$.

This assumption facilitates the exploration of frequent patterns within the sustainability assessment of RE, paralleling the quest for robust rules in a shopping context. By using this analogy (Figure 6), the study seeks to identify prevalent patterns. It then aims to categorize the indicators and determine the dominant rules within the domain.

3.3.2 | Association Rule Mining Algorithm

In the context of association rule mining, Agrawal and El Abbadi (1994) introduced a groundbreaking solution through the Apriori algorithm (Agrawal and El Abbadi 1994). This innovation facilitated the exploration of potential associations between diverse items within customer transaction databases.

The representation of rules commonly takes the form of implication relationships, denoted as $A \rightarrow B$, where both A and B are subsets of I $(A, B \subset I)$, and their intersection is $A \cap B = \emptyset$. In this context, A is referred to as the antecedent (left-hand side or LHS), and B is the consequent (right-hand side or RHS). The

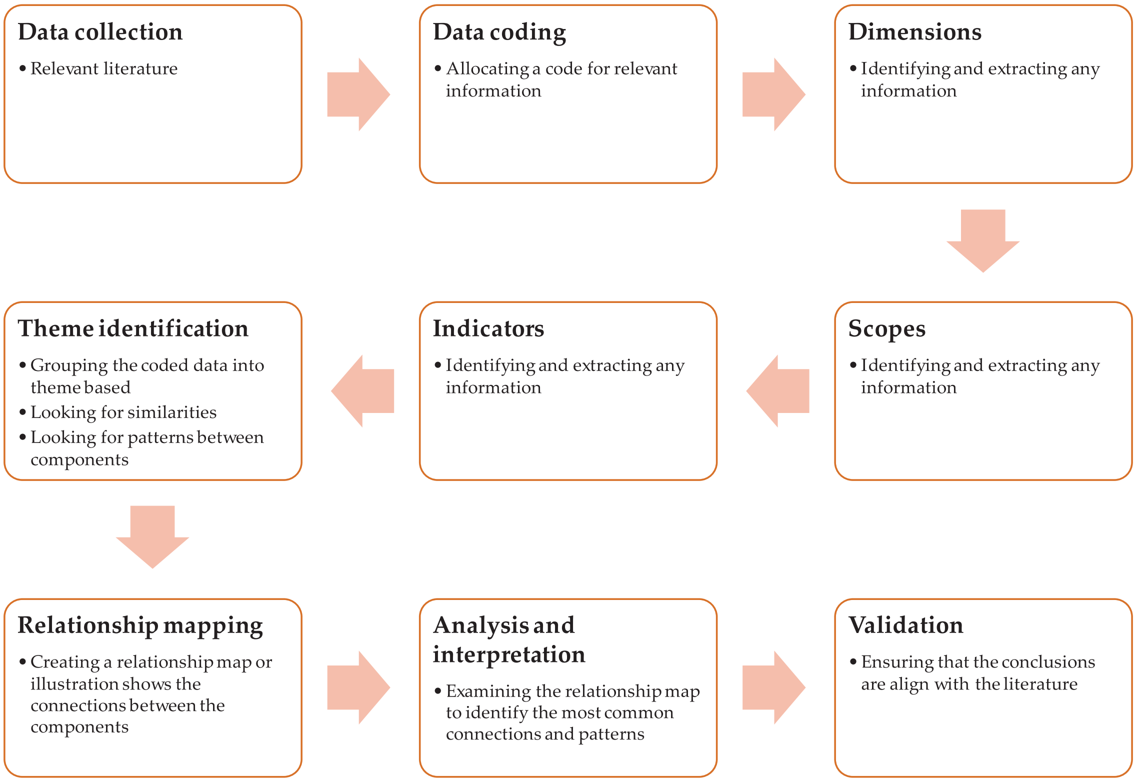


FIGURE 5 | Steps of qualitative classification.

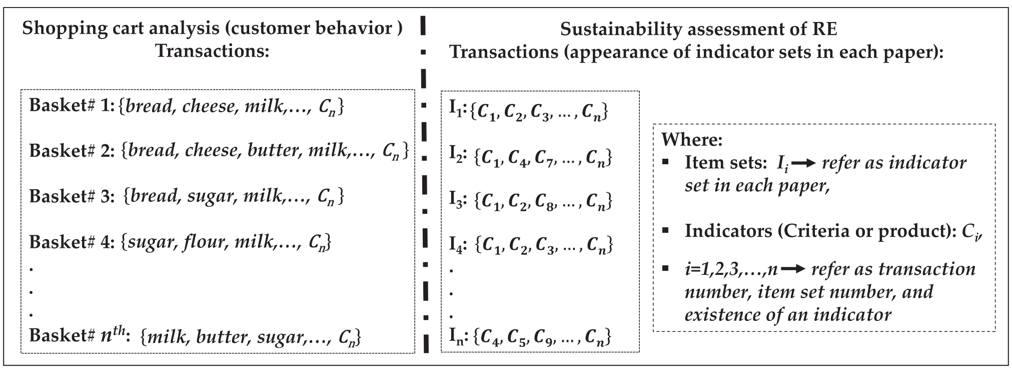


FIGURE 6 | Analogy sketch, a comparison between shopping cart analysis and an assumption of transactions in sustainability assessment of RE.

efficacy of association rules is quantified through two vital metrics: support and confidence, quantified using Equations (1) and (2), respectively.

$$Support(A \rightarrow B) = \text{frequency of } (A \cup B) / n \tag{1}$$

$$Confidence(A \rightarrow B) = P(B|A) = \text{frequency}(A \cup B) / \text{frequency}(A) \tag{2}$$

$P(B|A)$ represents the probability of B occurring given that A has occurred. The term frequency $(A \cup B)$ denotes the count or occurrence frequency of the combination of A and B, while frequency (A) represents the count or occurrence frequency of A. Additionally, n signifies the total number of transactions. For a rule to be deemed valid, it must meet the criteria of both measures by surpassing the predefined thresholds for Minimum Support Threshold (*MST*) and Minimum Confidence Threshold (*MCT*).

Support gauges the proportion of transactions (T_i) in D that include the union of A and B, reflecting across how frequently the rule appears the entire dataset. This measure is crucial as an initial filter to exclude rules with minimal occurrence, that is, low support. Confidence measures the proportion of transactions in D that containing A and also include B. This measure quantifies the degree of certainty about the rule's validity (Agrawal and El Abbadi 1994). In the context of rule mining, "*Lift*" is a statistical measure used to assess the significance of association rules between items in a dataset. When mining association rules, it often involves rules of the form: "If item A is purchased (or occurs), then item B is likely to be purchased (or occurs)." *Lift* quantifies the strength and importance of such rules.

The Lift of a rule is calculated as the ratio of the observed support to the expected support of the rule, the items are independent:

$$Lift\ (A \rightarrow B) = (Support\ (A \cap B)) / (Support(A) * Support(B)) \tag{3}$$

If $Lift = 1$, it indicates that the rule has no effect on the occurrence of item B when item A occurs. In other words, A and B are independent of each other. If $Lift > 1$, it suggests a positive association between items A and B, meaning that the occurrence of item A increases the likelihood of item B occurring. If $Lift < 1$, it indicates a negative association between items A and B, implying that the occurrence of item A decreases the likelihood of item B occurring.

A high *Lift* value (greater than 1) typically signifies a strong association between items, making the rule more interesting and potentially useful for making predictions or recommendations in various applications. However, it is essential to consider other metrics like support and confidence alongside *Lift* to ensure the generated rules are meaningful and actionable (Meruva and Bondu 2021).

3.3.3 | Implementing Apriori Algorithm

The implementation of the Apriori algorithm (Figure 7) begins with generating initial candidates by creating a set of frequent single items based on the MST and their occurrence counts (Agrawal and El Abbadi 1994). Next, the algorithm initializes a step counter to 1. For each step, it generates new candidate item sets by combining existing ones. This process involves merging item sets from the previous step to form potential candidates for the next iteration.

In the following step, the algorithm counts the occurrences of these candidate item sets in each transaction. It then filters these candidates to retain only those that meet or exceed the MST, defining them as frequent patterns. The step counter is then incremented, and the algorithm checks if there are any frequent patterns remaining. If there are, it returns to the previous step to generate new candidate sets; if not, the process moves forward.

The final step involves compiling all frequent patterns from each iteration into a complete set. Strong association rules are then extracted from this set, ensuring they meet the required confidence levels and MST. This systematic approach allows the Apriori algorithm to identify significant patterns and relationships within the dataset (for more details, see Supporting Information).

4 | Results and Discussion

4.1 | Scopes of Sustainability Assessment of RE

Regarding qualitative classification, nine scopes are recognized. Table 1 presents the compiled information for each scope.

TABLE 1 | RE sustainability assessment scopes (practical objectives).

No.	Scope	Code	Contribution (%)
1	General sustainability assessment of RE	A	28.8
2	RE technology and system assessment	B	23.3
3	KPIs/indicators for RE systems	C	2.7
4	Assessing RE power generation	D	8.2
5	RE sources	E	9.6
6	RE projects	F	9.6
7	RE investment	G	2.7
8	RE technology and energy planning	H	5.5
9	Impact of RE on sustainable growth	I	9.6

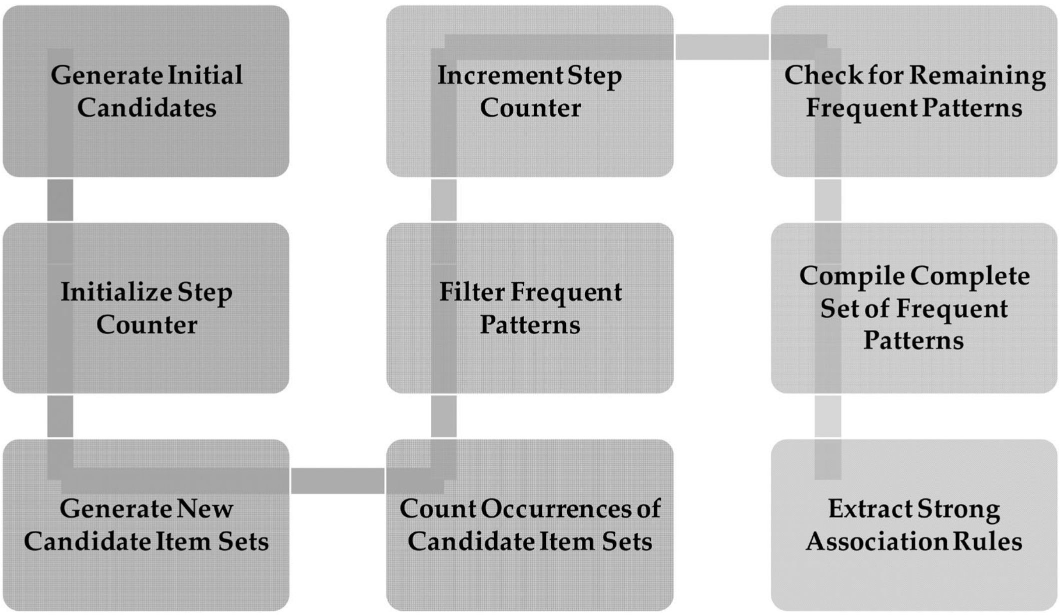


FIGURE 7 | Algorithm implementation steps.

The general sustainability assessment of RE (scope A) encompasses those studies in which scholars have not explicitly specified objectives for assessing the sustainability of RE; rather, the sustainability of RE is addressed as an overarching concept and the central focus of the papers (e.g., Dhital et al. 2014; Ifaei et al. 2017; Wang et al. 2020; Tan et al. 2023, etc.). This particular scope stands out as the most frequently cited indicating that a vast majority of scholars have approached the assessment from a broad perspective.

Among the spectrum of activities entailing technical scrutiny and the evaluation of distinct forms of renewable systems, RE technology and system assessment (scope B) are found the second position. The subsequent categories are attributed to RE sources (scope E), impact of RE on sustainable growth (scope I), and RE projects (F) constituting 9.6% Scope D (RE power generation) and scope H (RE technology & energy planning) are scoring 8.25% and 5.5%, respectively. Scopes related to RE investment (scope G) and indicators for RE systems (scope C) both achieved a score of 2.7%, placing them in the lowest tier of the study's classification.

4.2 | Dimensions

Sustainability is often viewed as the adept balance between addressing current needs while safeguarding the prospects of successive generations to meet their own exigencies. This construct encompasses a triad of imperatives: environmental, social, and economic considerations. Beyond these foundational dimensions, the scholarly discourse also acknowledges the roles of institutional (governmental) and technical dimensions. Consequently, this investigation employs a comprehensive framework that includes the “environmental, economic, social, technical, and institutional” dimensions.

Through thematic categorization, a series of dimension groups emerges. As outlined in Table 2, five predominant dimension groups are identified, representing the most frequently used dimensions in sustainability assessments of RE. Each of these groups highlights a combination of the foundational triad of dimensions—environmental, social, and economic—along with technical, institutional, or a combination of these. A distinctive category, labeled as “driven dimensions” (group “V”), highlights instances where sustainability assessment is limited to one or, at most, two dimensions (e.g., Suvitha et al. 2024). Notable examples include the focus on energy and technical drivers in the technical assessment of RE (Kourkoumpas et al. 2018), and the evaluation of RE sustainability in alongside economic and technical drivers (Diemuodeke, Hamilton, and Addo 2016).

4.3 | Interrelationship Between Dimensions and Scopes

Regarding Table 2, it becomes evident that dimension group “II” is garnered the highest degree of attention. Consequently, evaluating sustainability in RE has become closely intertwined with these dimensions. Group “I” emerges as the second most extensively employed dimension group. The third frequent dimension, denoted as group “V,” accounts for 18%. Group “IV” is targeted towards researchers who consider the fundamental triad of SD in addition to technical drivers and institutional facets. Examples of this category include studies by Štreimikiene, Šliogeriene, and Turskis (2016), Zhao and Chen (2018), and Onat and Bayar (2010), which focus on socio-political, techno-political, and econo-political factors relevant to the field of RE. Ultimately, a subset of studies, accounting for 3% showed interest in category “III.” Fewer scholars focused directly on the institutional dimension in their research.

TABLE 2 | Frequency of dimensions toward RE sustainability assessment.

Dimension groups	Symbol	Percentage (%)
Environment, economic, social	“I”	30
Environment, economic, social, technical	“II”	38
Environment, economic, social, institutional	“III”	3
Environment, economic, social, technical, institutional	“IV”	11
Driven dimensions	“V”	18
Total		100

One way to identify pattern(s) is to examine which dimension group is used in the scope and whether there is a specific trend. A deeper understanding of potential patterns is achieved through Figure 6, which explores the correlations between dimensions and the scopes. The associations revealed through this process are delineated as follows:

General Sustainability Assessment of RE:

- The chart forms a triangular shape spanning dimensions I, II, V, and III.
- The highest scores are in dimension I and II, respectively at level 8 and 7.
- Dimension V is at level 4, dimension III at level 1, while dimension IV have no values.

KPIs/Indicators for RE System:

- The chart shows a very small area with values only in dimension I.
- Dimension I has a low score at level 2.
- All other dimensions (II, III, IV, V) have no values.

RE Technology & Systems Assessment:

- The chart forms a triangular shape spanning dimensions I, II, and V.
- Dimension I and II score highest at level 7.

- Dimension V is at level 2, indicating less frequently used.
- Dimensions III and IV have no values.

Assessing RE Power Generation:

- The chart forms a small triangular shape mainly in dimension I, II, IV.
- Dimensions I, II, and IV have a score of 2.
- Dimensions III and V have no values.

RE Sources:

- The chart forms a shape along dimensions II, I, and V.
- Dimension II has a score of 5, indicating the dominated used dimension in this scope followed by dimensions I and V (at level 1).
- Dimensions III and IV have no values.

RE Projects:

- The chart forms a small shape spanning dimensions I, II, IV and V.
- Dimension V has scores of 3, followed by IV and II at level 2 and I at level 1.
- Dimension III has no value.

RE Technology & Energy Planning:

- The chart forms a line by dimension II, indicating the only used dimension for this scope.

RE Investment:

- The chart forms a small triangular shape spanning dimensions II and III at level 1. It indicates less studies used this scope and there is a need for further studies.

Impact of RE on Sustainable Growth:

- The chart forms a small triangular shape spanning dimensions I, II, and V.
- Dimension V scores highest at level 3.
- Dimension I is at level 2, and dimension II is at level 1.
- Dimensions III and IV have no values.

Each radar chart shows different scopes of sustainability assessment in RE, indicating how each scope interacts with dimensions I, II, III, IV, and V. The highest levels of assessment are mainly observed in dimensions I, II and V, while dimensions III and IV often have no values, suggesting these dimensions are less emphasized in these particular scopes (Figure 8).

The contemplation of interdisciplinary sustainability paradigms can induce scholars to adopt multifaceted perspectives when addressing issues concerning SD and RE. It is noteworthy that, in contrast to the conventional three pillars of SD, an observable augmentation in the incorporation of technical and institutional drivers has been witnessed, expanding the contemplation of SD in RE sector. Consequently, dimension groupings, indicators, frameworks, policies, and other parameters pertinent to sustainability assessment may transcend extant boundaries and progressively encompass novel considerations.

4.4 | Sustainability Indicators for RE

The assessment of sustainability holds particular significance in the context of optimal selection of RE systems, fostering the development of sustainable energy solutions, and informing policy decisions concerning the integration of sustainability indicators (Ghenai, Albawab, and Bettayeb 2020). The selection of indicators for the evaluation of RE sustainability necessitates careful consideration, with key attributes encompassing readability, comprehensiveness, inclusivity of diverse viewpoints, monotonous consistency, and non-redundancy, ensuring that each criterion remains unique (Bouyssou 1990). The pursuit of adequate and applicable sustainability indicators represents an evolutionary and educative journey (Meadows 1998).

The assemblage of indicators employed for gauging the sustainability of RE are explored by this study. Accordingly, the repository includes 58 indicators pertaining to environmental facets, 68 indicators addressing economic dimensions, 41 indicators encompassing social considerations, 11 indicators pertaining to institutional aspects, and 49 indicators elucidating technological realms. Appendix A is structured to visually depict the interrelationship among indicators, dimensions, scopes, and their respective frequencies.

4.4.1 | Environmental Indicators

The most frequent environmental indicators used in various evaluations are CO_2 emissions (21%), land use (16%), impacts on ecosystems (10%), NO_X emissions, and SO_2 emissions (10%). Figure 9 illustrates the abundance of each indicator in the environmental dimension, the relationship of indicators with each scope, and the indicator sets. For example, in Figure 9 (middle), the relationship between CO_2 emissions and scopes of RE is recognizable. Also, CO_2 emissions have employed in all scopes. Likewise, the significance of utilizing this indicator in each scope is examinable.

The percentage of CO_2 emissions in all scopes indicates the importance of this indicator while scholars deliberately employed it. The fact that CO_2 emissions applied as an indicator—in scopes A (31%), B (23%), D (4%), E (19%), F (4%), and G (8%)—demonstrates the importance of this indicator.

Analogously, this approach can be extended to encompass a diverse array of assessments. By doing so, it becomes feasible to discern both the nature and significance of environmental indicators across various domains. For example, within scope E, a total of 11 indicators have been identified, wherein CO_2 emissions (five times is seen in the database for this scope—21%), ecosystem impacts (21%), land use (17%), NO_X emissions (8.5%), SO_2 emissions (8.5%), overall emissions (4%), noise (4%), particle

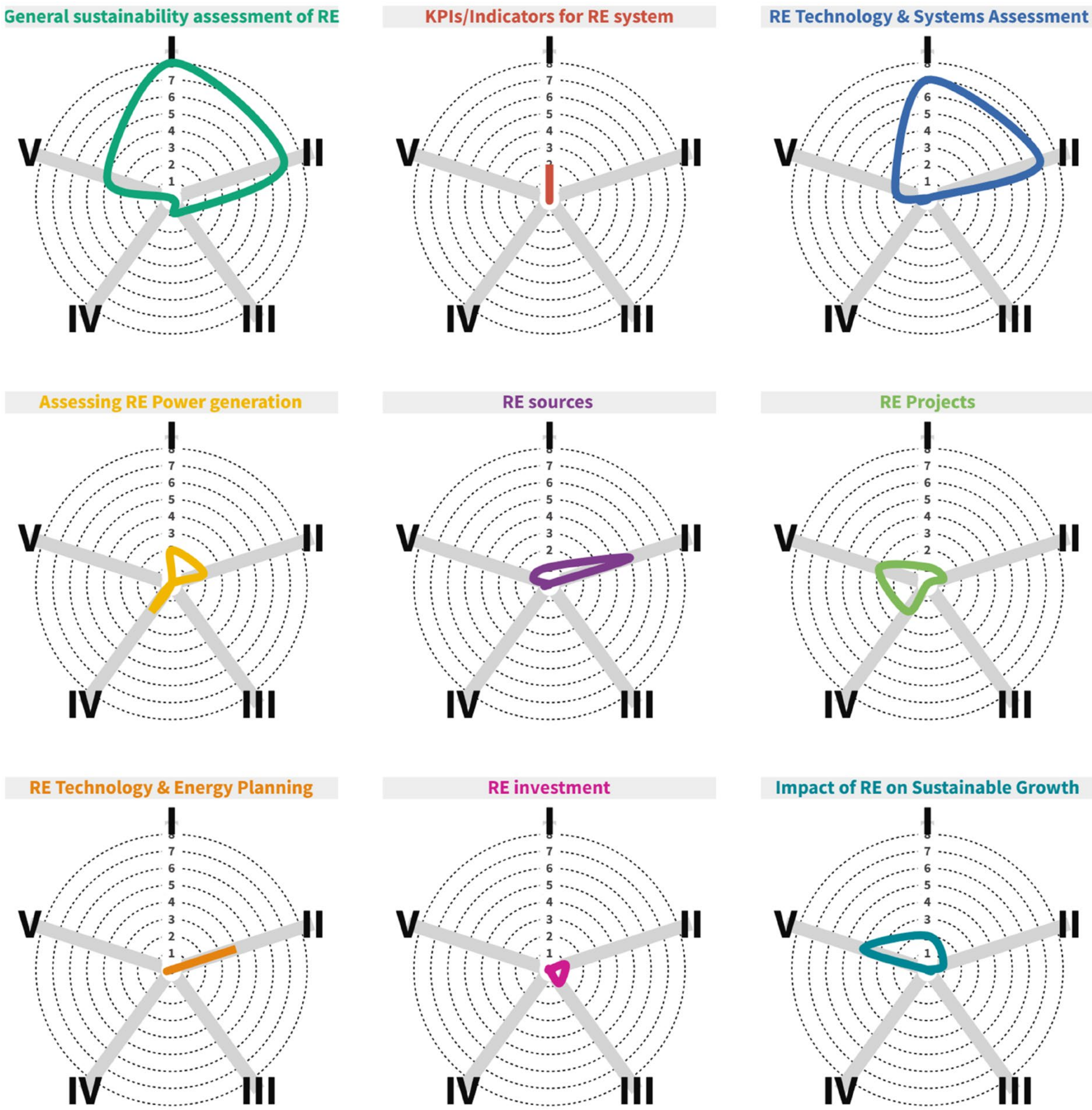


FIGURE 8 | Scopes of RE sustainability assessment versus dimension groups.

emissions (4%), GHG emissions reduction (4%), freshwater consumption (4%), and energy efficiency (4%) emerge as the most frequently employed indicators within this domain.

4.4.2 | Economic Indicators

The economic dimension has the most indicator heterogeneity among all the economic dimension has the most indicator heterogeneity among all (Figure 10). However, the most important indicators are: Operation and maintenance cost (10%), investment cost (7%), energy cost/implementation cost (6%) and fuel cost/savings (13%). Here, the important purpose is how researchers select these indicators. Except for some indicators, a bulk is attached to a scope with a small thickness. It means that most of them are used for that scope at most once. In other words, researchers have had less unity of procedure in selecting economic indicators to assess the sustainability of RE, which indicates the breadth and complexity of selecting the most appropriate set of indicators for evaluation. Scopes such as A, B, D, E, H, G, and F have used the most varied economic indicators, respectively. However, it is not possible to make a definite statement about scope F due to its abnormal dependence on only three indicators (supply capability, economic feasibility, and supply durability).

4.4.3 | Social Indicators

Social indicators are recognized fewer in number through literature. Social acceptability (23%), job creation/labor impact (22%), social benefits (13%), and impacts on health (7%) are the most mentioned indicators. Social acceptability, job creation, and social benefits are concerned in most scopes (Figure 11). An average of five to nine social indicators has applied for each scope. The lowest number is related to scope B (with 5 indicators), and the highest belongs to scope A.

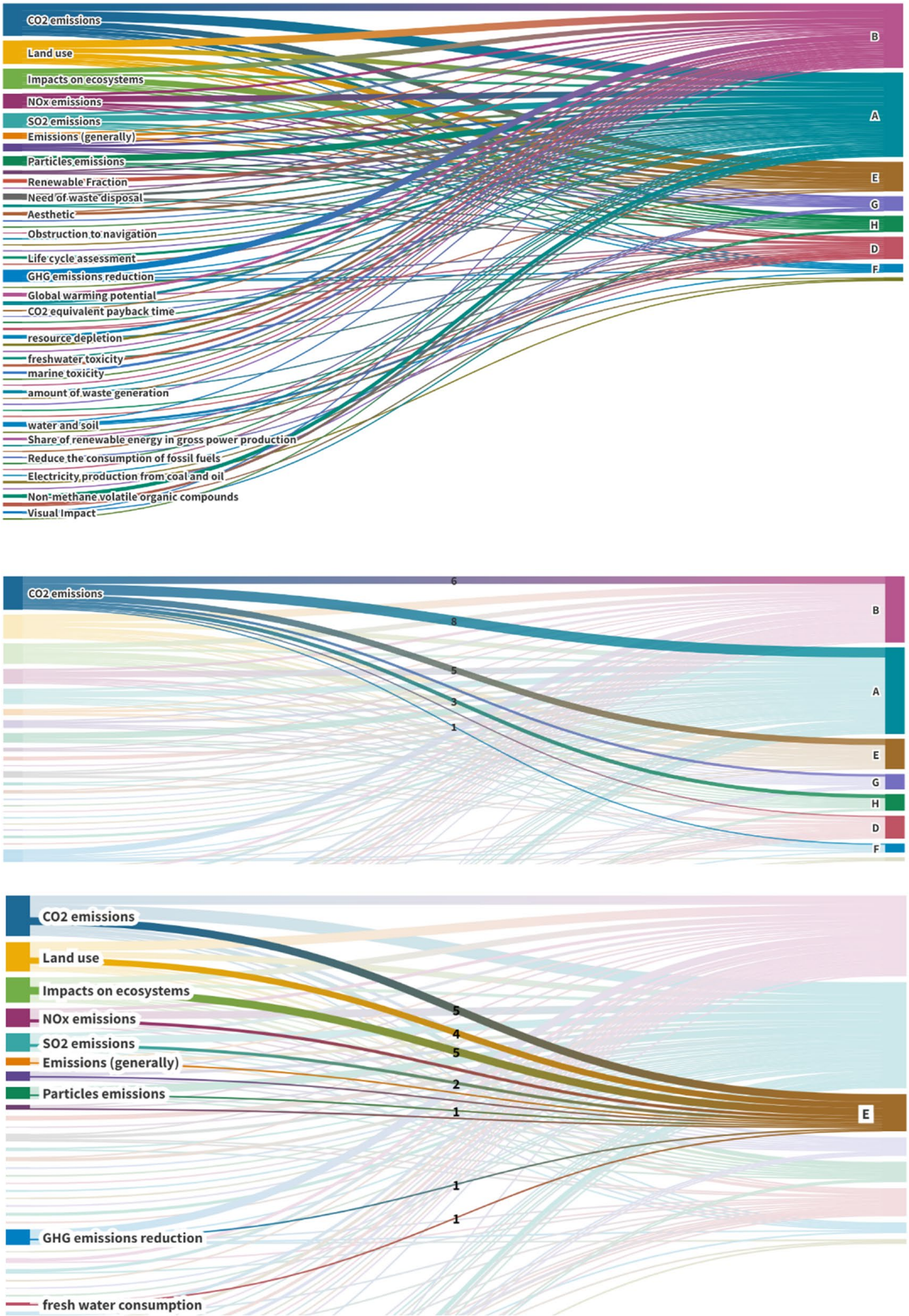


FIGURE 9 | Sankey diagram of environmental indicators for scopes (up), CO_2 emission versus scopes (middle), and environmental indicators related to RE source (scope E) (down).

4.4.4 | Technical Indicators

Although SD typically rests upon three main pillars, the technical dimension, derived from these pillars, is notably impacted by RE sustainability assessment. Notably, Reliability (12%), maturity (12%), efficiency (10%), and safety (8%) garner the greatest attention among researchers. Scopes A, H, B, D, G, and F have emerged as the leaders, each incorporating a significant number of technical indicators in assessments (Figure 12).

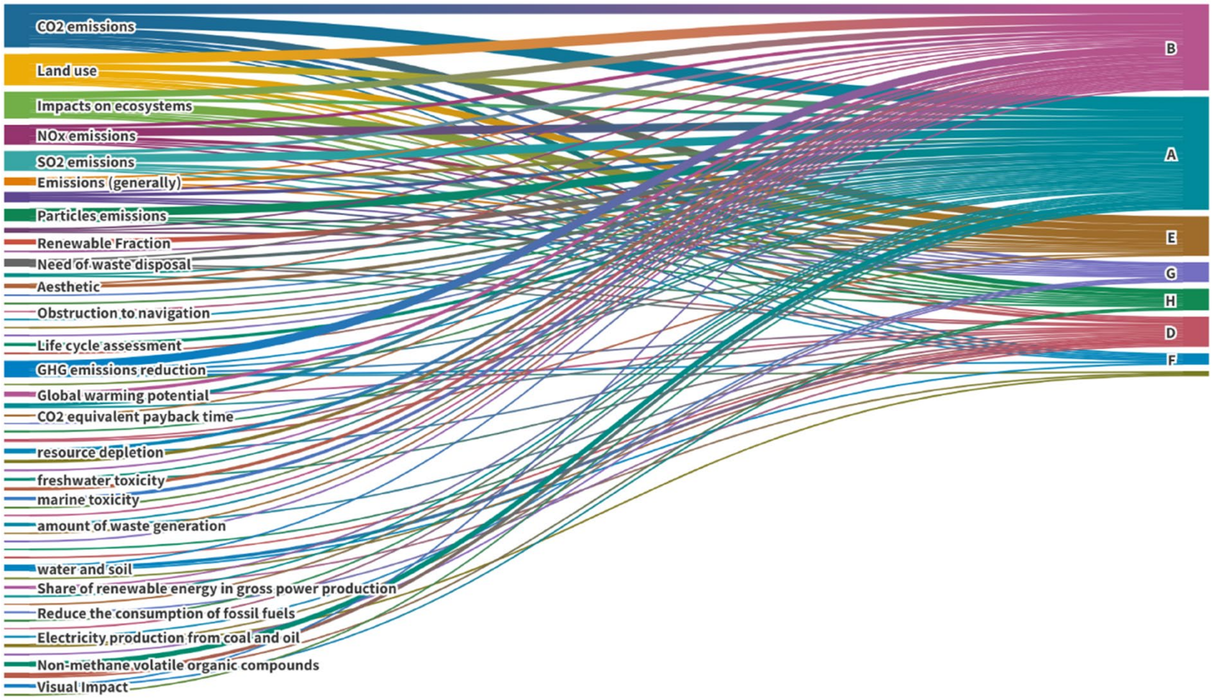


FIGURE 10 | Economic indicators and RE's scopes.

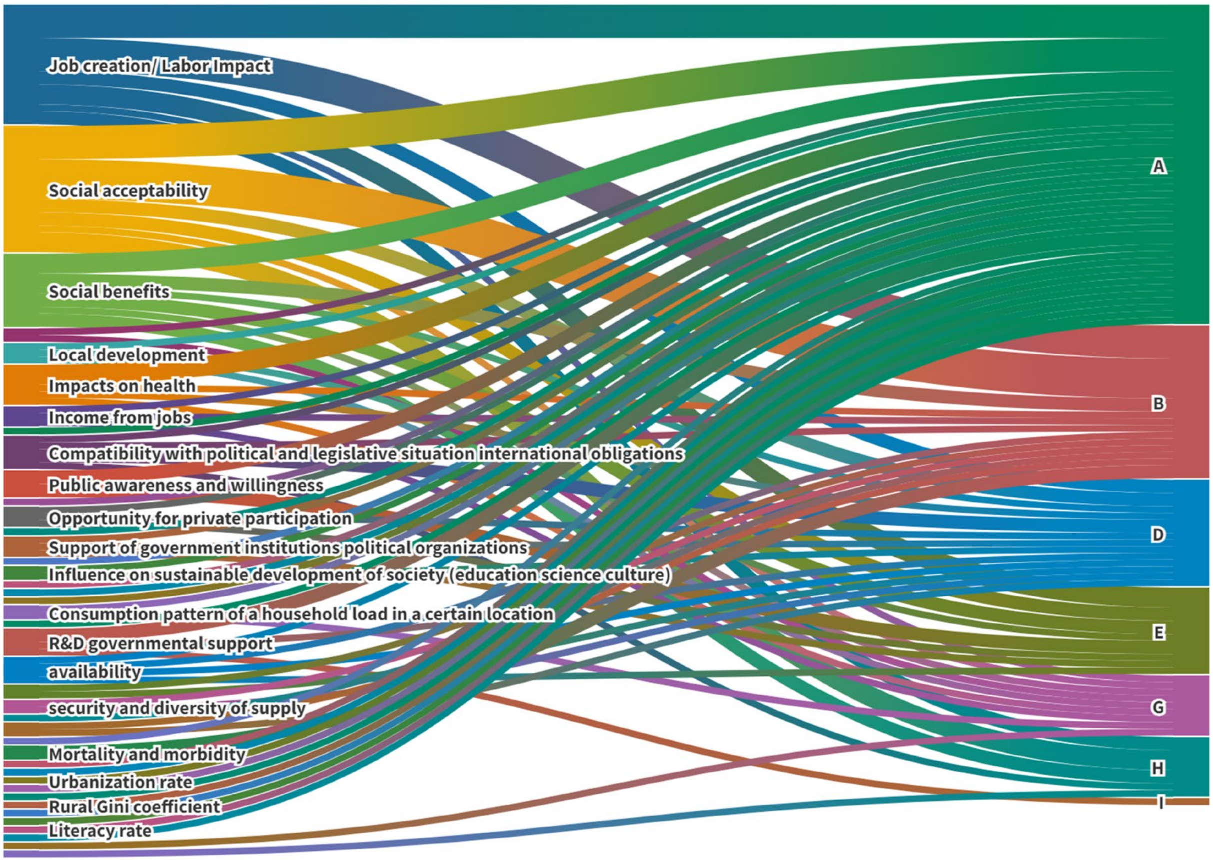


FIGURE 11 | Social indicators and RE's scopes.

4.4.5 | Institutional (Governmental) Indicators

Researchers investigating political factors and government guidelines for SD have used institutional indicators to evaluate RE sustainability. Prominent among these indicators are legal activity regulations (27%), government support (17%), and political stability with the absence of violence/terrorism (17%). Although fewer in number compared to other indicator types,

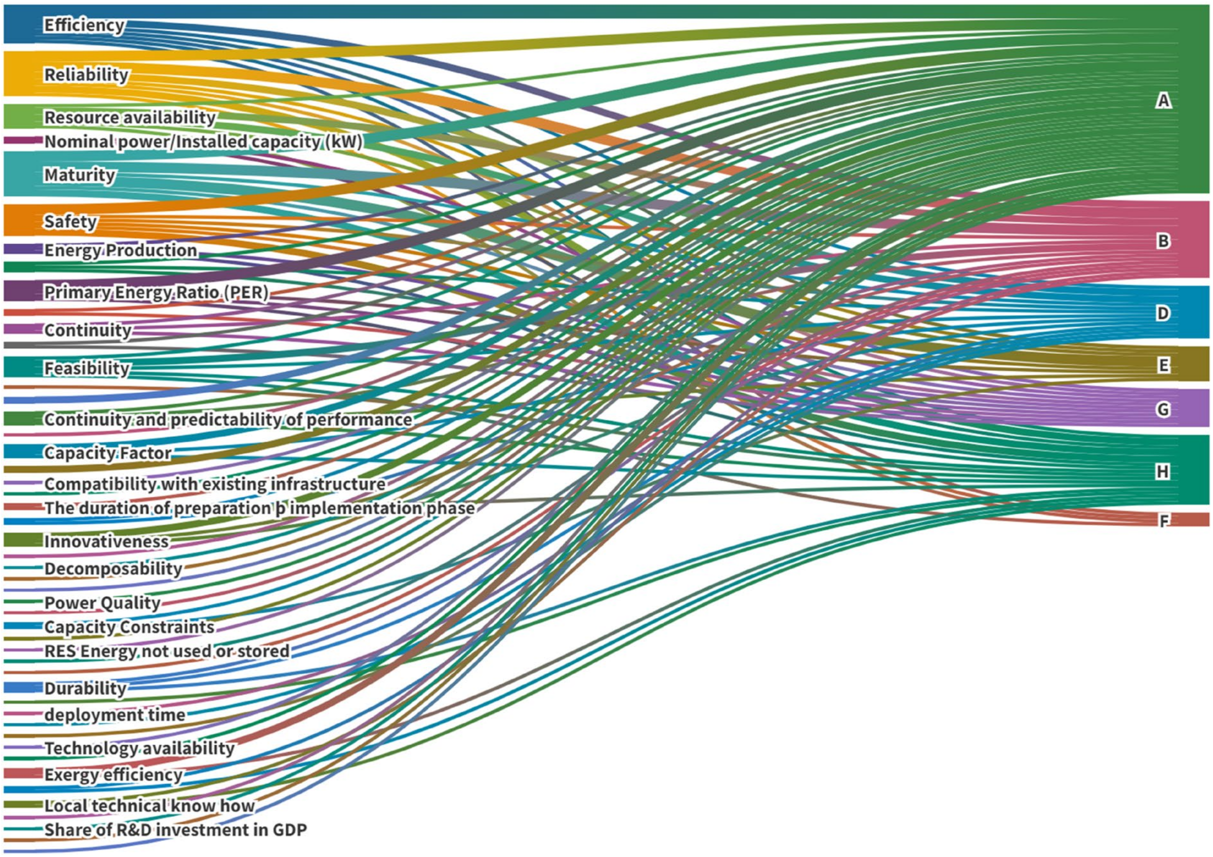


FIGURE 12 | Technical indicators and RE's scopes.

they are concentrated in scopes D, G, and A within the literature (Figure 13).

4.5 | Evidence of Trends and Mined Rules in Indicators and the RE Sustainability Assessment

To discern recurrent rules pertaining to sustainable indicators in RE literature, this investigation takes into account the inherent limitation of the dataset's size, thereby adopting a comprehensive, non-specific scope for the inquiry. After a significant number of transactions are recorded in different areas, we will need to conduct a detailed investigation in each area to identify the relevant rules.

Given the size of the database for this study compared to the scale of the rule mining challenge, it is imperative to delineate the thresholds of *MST* and *MCT* for the extraction of rules.

Following several iterative cycles of the algorithm, the determined thresholds stand as follows: $MST = [0.22–0.27]$ and $MCT = [0.1–1]$. The lower *MST* within this study signifies the presence of sought-after items (indices) in no fewer than 20% of the sourced articles. In essence, at least one specific indicator is referenced in every quintet of articles. Conversely, the upper threshold, set at $MST = 0.27$, signifies a restraint that stems from the confines of the database. It denotes that the count of articles or instances wherein a particular indicator is referenced does not surpass this predefined limit. This provides a clearer understanding of how often each distinct indicator is referenced in the study. Moreover, this established range serves to demarcate the classification of specific indicators with respect to distinct dimensions of sustainability; for instance, determining whether "job creation" qualify as a social indicator. In essence, this range encapsulates the likelihood of selecting a particular indicator from studies (transactions) and determining whether researchers classify it as a social indicator or not. This nomenclature is based on the assumption that the intrinsic nature of the indicators is not obvious in contrast to the dimensions of sustainability.

In the realm of evaluating *MCT*, a meticulous scrutiny was undertaken to assess the potency of the extracted rules across a spectrum spanning from 0.1 to 1. Notably, all outcomes pertinent to prospective rules exhibiting *Lift* values surpassing 1 are systematically collated and presented comprehensively in Table 3.

Regarding Table 3, this investigation deems the rules acquired through *MST*: 0.22, *MCT*: 0.7, and *Lift*: 2.512 as particularly robust among the assorted rules.

Nevertheless, rules with high level of confidence introduce the mined rules with the utmost accuracy. It is essential to acknowledge that a sufficient number of indicators must be introduced by a set of indicators to account for the dimensions of SD. By enhancing the algorithm's confidence (while maintaining a consistent level of support), exclusive prominence is given to environmental indicators (i.e., CO_2 emissions, NO_X emissions, and SO_2 emissions). This highlights their pivotal contribution to the

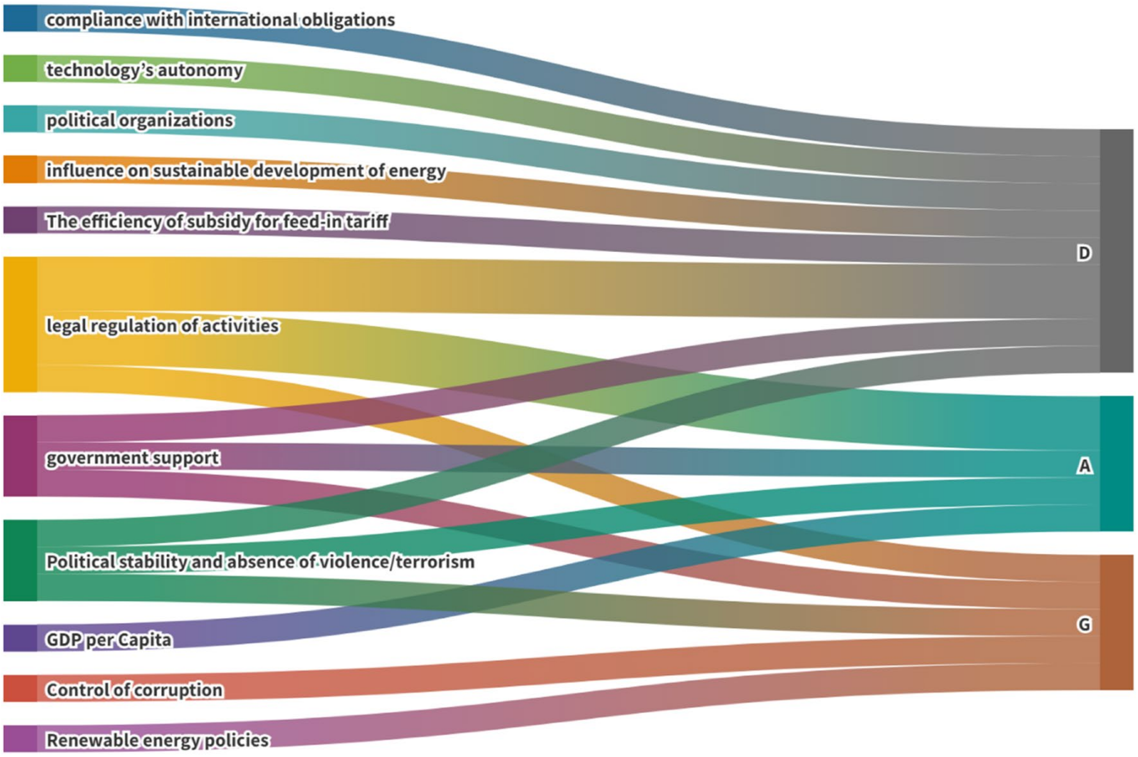


FIGURE 13 | Institutional indicators and RE's scopes.

assessment of sustainability in the context of RE (i.e., rules 9, 10, 13, and 14). Furthermore, exemplifying this trend, several studies highlight the significance of indicators and the allocation of weights to them, often positioning environmental and economic indicators in primary positions (e.g., Ghenai, Albawab, and Bettayeb 2020).

Although the acquired rules lack definitive evidence, their presence and prevalence can be reasonably assured. Concerning rule#7, the classification results detailed in Appendix A suggest that the environmental, economic (operation and maintenance cost, etc.), social (job creation/labor impact, social acceptability, etc.), and technological (reliability, maturity, etc.) are key dimensions in the sustainability of RE. Therefore, it can be concluded that the inclusion of indicators present in rule#7 is imperative to consider for such assessments.

4.6 | Discussions and Concepts

4.6.1 | Addressing the Challenges and Gap Fill

Effective sustainability indicators should adhere to principles of transparency, relevance, reliability, and accessibility. These principles encompass both data and methodological aspects, ensuring that the indicators provide accurate and meaningful insights into the sustainability of the evaluated system (Bell and Morse 2003; United Nations and Department of Economic and Social Affairs 2007; United Nations Statistics Division 2015; Hák, Moldan, and Dahl 2007; Hák, Janoušková, and Moldan 2016; Wu and Wu 2012; Al Garni et al. 2016; Campos-Guzmán et al. 2019). To ensure the pertinence of indicators and facilitate effective communication with decision-makers and the public, it is essential to establish a clear connection between the indicators and the underlying factual information they represent (Hák, Janoušková, and Moldan 2016). However, challenges persist in aligning indicators with decision-making objectives, given the diversity of goals and targets (Pintér, Hardi, and Bartelmus 2005; Krellenberg, Kopfmüller, and Arton 2011).

Wang and Yang (2020) utilized the DPSIR framework to integrate the four dimensions of sustainability, acknowledging the inherent challenges of dealing with the randomness and fuzziness of multi-dimensional metadata and the absence of standard benchmarks, which remain unresolved and are addressed in this study. Ghenai, Albawab, and Bettayeb (2020) studied sustainability indicators for various RE systems, specifically solar PV, wind, phosphoric acid fuel cells, and solid oxide fuel cells. It incorporated five sustainability criteria (resource, environmental, economic, social, and technology) and fourteen sub-categories related to these criteria. However, there is a need focusing on refining the criteria and sub-categories to ensure they encompass all relevant aspects of sustainability, possibly incorporating additional perspectives or emerging technologies. Further development could also include real-world data, enhancing the robustness of the sustainability assessments and improving decision-making for RE policy. Abbasi et al. (2023) developed a framework to identify, refine, and prioritize SIs for evaluating energy technologies ensuring stakeholder engagement and balanced representation of environmental, economic, and social dimensions. Despite their efforts, challenges remain in generalizing these indicators for larger-scale assessments, incorporating diverse perspectives, and ensuring a comprehensive set of indicators

TABLE 3 | Extracted rules for sustainability indicators in RE assessment.

Row	*MST*	*MCT*	*Lift*	Mined rules of indicator set
1	0.22	0.1	1.997	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability, Maturity
2	0.23	0.1	2.073	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability
3	0.26	0.1	2.178	CO_2 emissions, Land use, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability
4	0.22	0.2	1.997	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability, Maturity
5	0.22	0.5	2.082	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability, Maturity
6	0.22	0.6	2.239	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability, Maturity
7	0.22	0.7	2.512	CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability, Maturity
8	0.22	0.8	2.602	CO_2 emissions, Land use, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability
9	0.22	0.9	3.013	CO_2 emissions, NO_X emissions, SO_2 emissions
10	0.22	1	3.013	CO_2 emissions, NO_X emissions, SO_2 emissions
11	0.27	0.5	2.328	CO_2 emissions, Land use, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/Labor Impact, Social acceptability, Reliability
12	0.27	0.6	2.846	CO_2 emissions, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost
13	0.27	0.9	3.013	CO_2 emissions, NO_X emissions, SO_2 emissions
14	0.27	1	3.013	CO_2 emissions, NO_X emissions, SO_2 emissions

for RE sustainability across various scopes. In several recent studies, similar challenges persist, as their focus is not on resolving these issues but rather on selecting a number of available and relevant indicators by referencing the literature (e.g., Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo 2023; Ee et al. 2024; Olabi et al. 2024; Solano-Olivares, Santoyo, and Santoyo-Castelazo 2024; Suvitha et al. 2024). Balancing the complexity of sustainability with the comprehensibility of indicators is critical. The process of selecting indicators should begin with identifying a comprehensive array of potential indicators and applying well-defined methodologies to select the most appropriate ones (Alfsen and Greaker 2007; Rickels et al. 2016).

This study introduces a data-driven methodology to assist researchers and other stakeholders in selecting appropriate indicators for the sustainability assessment of RE. By examining various classes, mining association rules, and elucidating the interrelationships between scopes, dimensions, and indicators as documented in the literature, this approach enhances the understanding and selection process of sustainability indicators by overcoming challenges such as:

- Unambiguous attributes: by creating clearly defined criteria, ensuring that each indicator is precisely articulated to avoid any confusion.
- Comprehensive coverage: by establishing criteria that cover all relevant aspects of sustainability, ensuring a holistic evaluation.
- Perspective representation: by integrating different viewpoints, ensuring that the indicators reflect a diverse range of perspectives and concerns.
- Monotonic relationship: by creating a consistent relationship between the criteria and sustainability, ensuring that each indicator reliably correlates with sustainable outcomes.
- Non-redundancy: by ensuring that the criteria do not overlap unnecessarily, maintaining the distinctiveness of each indicator to avoid redundancy.
- Distinctiveness: by ensuring each criterion is unique, following Bouyssou's (1990) principles to guarantee that all indicators are distinct and contribute individually to the assessment.

This study identifies frequent patterns of indicators across different scopes to curate suitable indicator sets for each distinct scope. An indicator is considered frequent if its likelihood within the class exceeds 20% (Appendix B). The study highlights frequent patterns for various dimensions:

- Environmental indicators: frequent in scopes A, B, and E.
- Economic indicators: frequent in scopes A and B.

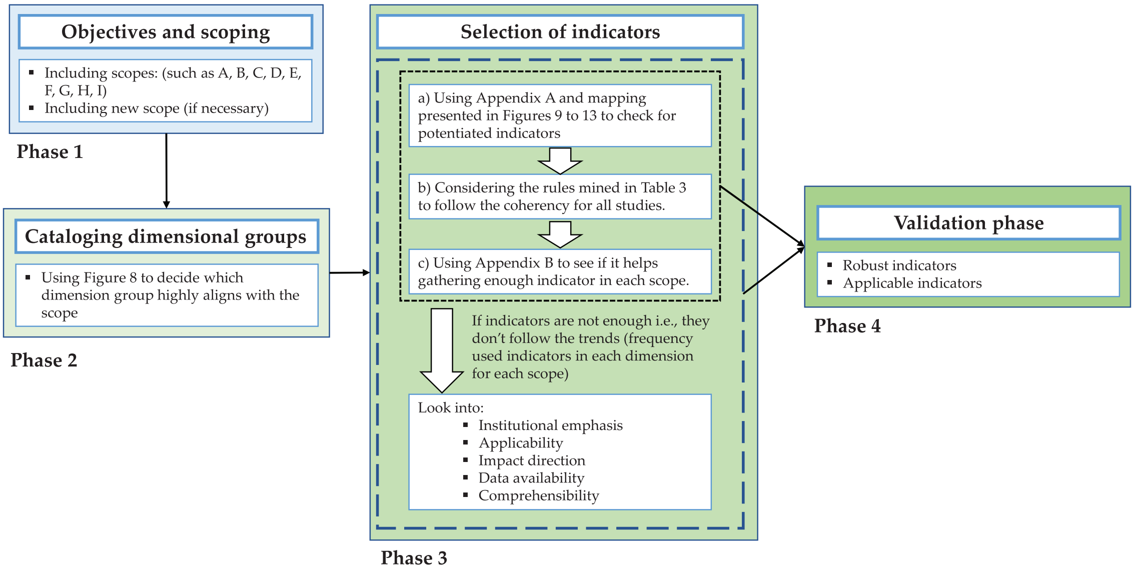


FIGURE 14 | Data-driven and participatory method of indicator selection.

- Social indicators: frequent in scopes A, B, and E.
- Technical indicators: frequent in scopes A, B, D, E, and E.
- Institutional indicators: frequent in scopes A and D.

Frequent patterns help enhance the understanding of the interrelationships among dimensions, indicators, and scopes. However, the current quantity of indicators or sets remains inadequate. The study suggests the following for potential indicator selection:

- Institutional emphasis: indicators emphasized by institutions, organizations, governments, and those present in the literature.
- Applicability: indicators applicable at a country-wide level and adaptable from a localized to a global perspective.
- Impact direction: clear impact direction of the criteria on RE and SD (beneficial or detrimental).
- Data availability: sufficient existing data availability.
- Comprehensibility: clear connection between RE and SD.

4.6.2 | Implementation of the Results

Decision-making often involves selecting and applying assessment tools. In sustainability, numerous criteria and indicators are available for assessment, yet there is no established and clear approach to determine which criteria-indicator sets are appropriate. This study presents an extensive inventory of indicators and a methodology that facilitates the efficient and effective selection of these indicators, thereby improving decision-making for policymakers and scholars in uniform sustainability assessment.

The selection methodology follows four main phases (Figure 14):

a. Objectives and scoping phase: clearly defining the goals and scope of the sustainability assessment.
b. Cataloging dimensional groups: organizing dimensions into relevant RE scopes.
c. Selection of indicators: utilizing a structured method to choose the most appropriate indicators based on predefined criteria, dependencies on dimensions, interrelationship with scopes, mined rules and frequent patterns.
d. Validation phase: ensuring the selected indicators are robust and applicable through validation processes.

This approach combines elements of data-driven analysis with the participatory involvement of mined rules. It addresses challenges such as the lack of clear selection methodologies, ensuring that the chosen indicators are comprehensive, representative of different perspectives, and distinct. By enhancing the clarity and coverage of the indicators, the methodology supports consistent and reliable sustainability assessments.

Furthermore, this methodology is flexible for rapid integration and uptake, building on the current limited range and scope of approaches to indicator selection. It provides a systematic framework that helps decision-makers select appropriate indicators, thus facilitating more informed and effective sustainability decisions.

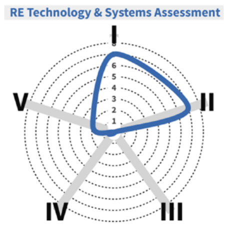
As a case study, we conducted a RE technology & system assessment (scope B) to evaluate the method's implementation and compare our findings with those of previous studies in the field (e.g., Abbasi et al. 2023; Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo 2023; Shaaban et al. 2018) (Figure 15).

In the first phase, we identify the scope of the study. In phase two, we determine the appropriate dimension group that fits the scope using Figure 8. As demonstrated, dimension groups I and II are highly related. Considering the details of the assessment, we select dimension group II, which encompasses all relevant dimensions and drivers.

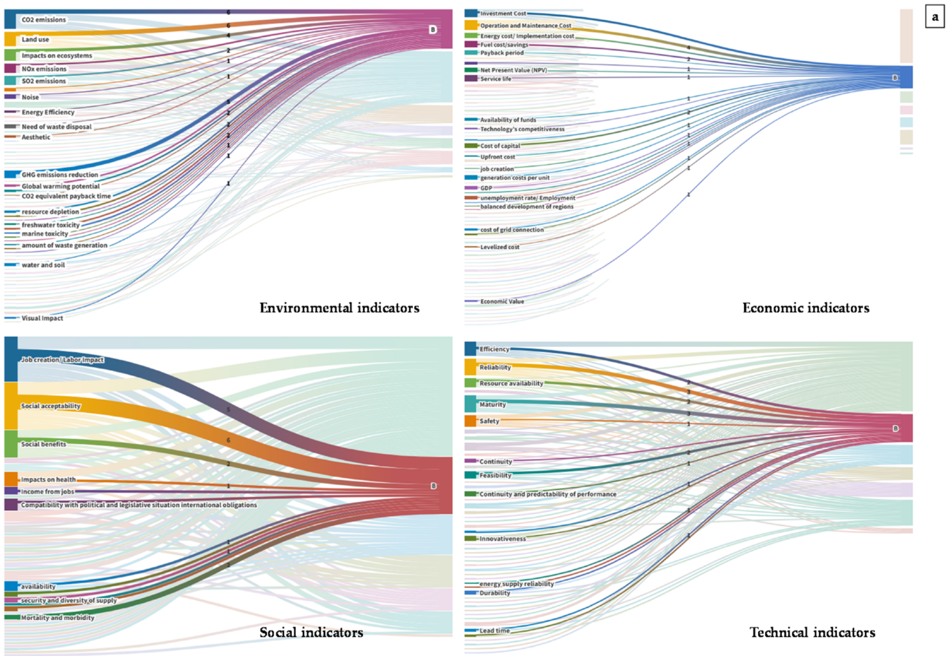
In phase three, utilizing Appendix A and a Sankey diagram, we analyze the frequency of indicators in each dimension for scope

Phase 1 | Scope: RE technology & system assessment (scope B)

Phase 2



Phase 3



b | CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, Operation and Maintenance Cost, Job creation/ Labor Impact, Social acceptability, Reliability, Maturity

c

Dimension	Indicator(s) for each scope
Environmental	A: CO_2 emission, land use, impact on the ecosystem, NOx, SO_X emission, Emission (generally), GHG emission reduction, particle emission, Non-methane volatile organic compounds. B: CO_2 emission, land use, impact on the ecosystem, GHG emission reduction, particle emission. E: CO_2 emission, land use, impact on ecosystem.
Economic	A: investment cost, operation and maintenance cost, energy cost, fuel cost, payback period, net present value, service life, cost of capital, GDP, employment rate, renewable energy share. B: energy cost.
Social	A: social acceptability, job creation, social benefit, impact on health, R&D governmental support, HDI, income from jobs. B: job creation, social acceptability. E: social acceptability, job creation, social acceptability, social benefits.
Technical	A: efficiency, reliability, installed capacity, maturity, safety, energy production, primary energy ratio, lifespan, feasibility, local technical know-how, capacity factor, compatibility with future capacity expansion, innovativeness, exergy efficiency, number of R&D stuff, shared of R&D investment in GDP. B: efficiency, reliability, resource availability, maturity, load demand, primary energy ratio, feasibility. D: reliability, resource availability. E: efficiency, reliability, maturity, safety, feasibility, Continuity and predictability of performance. H: reliability.
Institutional	A: legal regulation of activity, government support, political stability and absence of violence/terrorism, control of corruption. D: the legal regulation of activity, influence on sustainable development of energy, political stability and absence of violence/terrorism.

Phase 4 | Selecting Robust and Applicable indicators aligned with the goal and scope (following the rules, the most frequent patterns, accepted by expert)

FIGURE 15 | Implementation of the proposed method for RE technology and system assessment.

B to form a general idea about the selection. We then refer to the appropriate rule (rule #7) and highlight the related indicators in each dimension (marked in red in Table 4). Subsequently, we consult Appendix B to explore additional indicators in scope B by following the most frequent patterns (green indicators in Table 4). If sufficient available and applicable indicators are found, experts assess their representativeness in phase four. If not, the process continues to ensure enough indicators are

TABLE 4 | Comparative analysis of RE technology and system assessment indicators across different studies.

Study	Dimension group	Indicators	References
1	Environment, economic, social	Environment: Global warming potential, Land requirement, Primary energy consumption, Water consumption, Share of renewable energy, Energy efficiency, Acidification potential Economic: Upfront cost, Operation & management cost, Net present value, Availability of funds and subsidies, Economic lifetime Social: Job creation, Thermal comfort, Social acceptance, Health impacts, Acoustic performance, Safety, Reliability and security, Usability and functionality, Aesthetic aspects	Abbasi et al. (2023)
2	Environment, economic, technical	Environment: CO_2 emission reduction, Land use, Water consumption Economic: Levelized cost of energy, Investment cost, Operational costs Technical: Efficiency, Ability to respond to demand, Autonomy of the primary resource	Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo (2023)
3	Environment, economic, social, technical	Environment: CO_2 emission, NOx emission, SO_2 emission Economic: Investment cost, Job creation, Cost of electricity, Operation and maintenance cost Social: Safety risks, Social acceptability Technical: Efficiency of energy generation, Reliability of energy supply, Resource potential, Water consumption	Shaaban et al. (2018)
4	Environment, economic, social, technical	Environment: CO_2 emissions, Land use, Impacts on ecosystems, NO_X emissions, SO_2 emissions, GHG emission reduction, particle emission Economic: Operation and Maintenance Cost, Energy cost Social: Job creation/Labor Impact, Social acceptability Technical: Reliability, Maturity, Efficiency, Resource availability, Load demand, Primary energy ratio, Feasibility	This study

provided, following the criteria mentioned at the end of phase three (Figure 14).

The process for selecting indicators must adhere to the rules, patterns, and their prevalence as outlined in Appendices A and B, followed by the specified characteristics, which remain under expert supervision due to the size of the database.

This study incorporates a comprehensive set of environmental indicators. Abbasi et al. (2023) also cover a wide range of environmental indicators but focus more on broader aspects such as global warming potential, land requirement, and primary energy consumption, without specific pollutant indicators like NOx or SO_2. In contrast, Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo (2023) and Shaaban et al. (2018) include fewer environmental indicators, primarily focusing on CO_2 emissions and additional parameters like land use and water consumption.

This study integrates significant social indicators such as job creation/labor impact and social acceptability, ensuring a holistic view of the social implications of RE systems. Abbasi et al. (2023) provides a broad spectrum of social indicators, including health impacts, thermal comfort, and usability, rendering it socially comprehensive, though some of these indicators (e.g., thermal comfort) are not frequently used. Conversely, Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo (2023) lack social indicators, concentrating solely on economic and technical dimensions. Shaaban et al. (2018) includes basic social indicators like safety risks and social acceptability but lacks the depth provided by this study.

This study offers a robust set of technical indicators, such as reliability, maturity, efficiency, resource availability, load demand, primary energy ratio, and feasibility, providing a clear view of the technical feasibility and performance of RE systems. While Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo (2023) and Shaaban et al. (2018) also include technical indicators, they feature fewer parameters compared to this study. Abbasi et al. (2023) does not incorporate technical indicators, restricting its assessment to environmental, economic, and social dimensions.

Therefore, this study is more comprehensive due to its inclusion of all four major dimensions (environment, economic, social, and technical) with detailed and specific indicators within each category. While Abbasi et al. (2023) provides extensive environmental and social indicators, it lacks technical indicators. Barrera-Zapata, Zuñiga-Cortes, and Caicedo-Bravo (2023) and Shaaban et al. (2018) include technical indicators but are less detailed in environmental and social aspects. Overall, this study presents a more unified and thorough approach to sustainability assessment in RE by encompassing a wider range of indicators across all crucial dimensions. This makes it more comprehensive for stakeholders and decision-makers aiming for a holistic understanding of RE sustainability.

4.6.3 | Future Works

This study introduced a primary data-driven model aimed at enhancing the uniform sustainability assessment of RE. The database provided by this study requires annual updates to continuously reflect new patterns and address the need for ongoing improvement. These updates are essential for identifying trade-offs, meeting international commitments, and conducting holistic evaluations in the field of RE sustainability. Maintaining an up-to-date database increases the accuracy of the derived rules and enhances the consistency of the assessments. There is a need to establish a comprehensive database of indicators that encompasses all viewpoints and concerns.

This method offers a broader perspective for users involved in such assessments, facilitating an understanding of the interrelationships between scopes, dimensions, and the selection of indicators. However, it is important to consider both "rule-based" and "cause-based" models and compare them with the data-driven model. Therefore, this study suggests the development of a semantic model for RE sustainability assessment.

5 | Conclusion

This study presents a data-driven method for the uniform sustainability assessment of RE. Through an extensive literature review, a comprehensive database was constructed, and KDD techniques were employed to identify the most frequent patterns in scopes, dimensions, and indicators. Considering the interrelationships and machine learning, a four-phase method was designed to facilitate the assessments. Rule mining using the Apriori algorithm streamlined the identification of relevant rules, and the inclusion of appendices facilitated the process of selecting appropriate indicators.

It examines an inventory of indicators across five dimensions, including 41 social, 68 economic, 58 environmental, 49 technical, and 11 institutional, within nine scopes and five distinct dimension groups.

Mapping the relationship among dimensions, indicators, and scopes enhances comprehension of sustainability factors and accelerates related studies. While qualitative analysis can be detailed and time-consuming, it offers valuable insights into the interrelationships within RE sustainability assessments. Appendix A details the nomenclature of indicators, their frequencies, and associated references, aiding in tracking trends and associations among indicators, dimensions, and scopes.

The associated rule mining process highlights the importance of environmental, economic, social, and technical drivers. Rules are focusing on three parameters: *MST*: 0.22–0.27, *MCT*: 0.1–1, and rule applicability strength (*Lift*). Despite some database limitations, robust rules identified include environmental indicators (CO_2 emissions, land use, ecosystem impacts, NO_X and SO_2 emissions), economic indicators (operation and maintenance cost), social indicator (social acceptability, job creation/labor impact), and technical indicators (reliability, maturity).

Environmental indicators, particularly CO_2, NO_X, and SO_2 emissions, are crucial in these evaluations, with their significance growing as the *MCT* value increases. However, the mined rules may lack sufficient indicators for comprehensive assessment. Therefore, Appendix B lists the most frequent indicators for each dimension and scope. Comparing Appendices A and B with mined rules provides deeper insights.

Maintaining a comprehensive database enhances the clarity of rules and patterns, advocating for a uniform database to improve sustainable assessment and advance energy digitalization.

Acknowledgments

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A

Tracked Drivers, Indicators and Their Frequency, Practical Sustainable Development Objectives (Scopes) in Renewable Energy, and References

Dimension	Indicators	Scope contribution	Total frequency	References
Environmental	CO_2 emissions	12A, 5B, 1D, 6E, 2G, 3H	28	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki and Bello Bugallo 2021; Wang and Yang 2020; Ghenai, Albawab, and Bettayeb 2020; Wang and Zhan 2019; Yu, Zheng, and Li 2019; Kourkoumpas et al. 2018; Diemuodeke, Hamilton, and Addo 2016; Zhao and Chen 2018; Onat and Bayar 2010; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Shaaban et al. 2018; Boran 2018; Ligus 2017; Haddad, Liazid, and Ferreira 2017; Ifaei et al. 2017; Strantzali and Aravossis 2016; Lee and Zhong 2015; Şengül et al. 2015; Zhao and Guo 2015; Ahmad and Tahar 2014; Dhital et al. 2014; Mourmouris and Potolias 2013; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009; Doukas and Psarras 2009)
	Land use	6A, 7B, 1D, 5E, 1G, 2H	22	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Collotta et al. 2019; Onat and Bayar 2010; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Stougie et al. 2018; Strantzali and Aravossis 2016; Al Garni et al. 2016; Şengül et al. 2015; Ahmad and Tahar 2014; Dhital et al. 2014; Troldborg, Heslop, and Hough 2014; Dombi, Kuti, and Balogh 2014; Demirtas 2013; Ertay, Kahraman, and Kaya 2013; Luong, Liu, and Robey 2012; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009; Doukas and Psarras 2009)
	Impacts on ecosystems	5A, 4B, 2D, 4E, 1G, 2H, 1I	19	(Faraji Abdolmaleki and Bello Bugallo 2021; Collotta et al. 2019; Diemuodeke, Hamilton, and Addo 2016; Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020; Stougie et al. 2018; Ligus 2017; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Al Garni et al. 2016; Zhao and Guo 2015; Ahmad and Tahar 2014; Dombi, Kuti, and Balogh 2014; Troldborg, Heslop, and Hough 2014; Demirtas 2013; Mourmouris and Potolias 2013; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009; Zafar et al. 2019)
	NO_x emissions	7A, 2B, 3E, 1G, 1H	14	(Faraji Abdolmaleki and Bello Bugallo 2021; Wang and Yang 2020; Wang and Zhan 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Shaaban et al. 2018; Boran 2018; Ifaei et al. 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009)
	SO_2 emissions	7A, 2B, 3E, 1G, 1H	14	(Faraji Abdolmaleki and Bello Bugallo 2021; Wang and Yang 2020; Wang and Zhan 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Shaaban et al. 2018; Boran 2018; Ifaei et al. 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009)
	Emissions (generally)	4A, 1B, 1E, 1G, 1H	8	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Ifaei et al. 2017; Strantzali and Aravossis 2016; Atilgan and Azapagic 2016; Luong, Liu, and Robey 2012; Kahraman, Kaya, and Cebi 2009)
	Noise	3A, 1B, 1E, 1G, 1H	7	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Stougie et al. 2018; Strantzali and Aravossis 2016; Dhital et al. 2014; Heo, Kim, and Boo 2010)
	Particles emissions	8A, 1E, 1G, 1H	11	(Faraji Abdolmaleki and Bello Bugallo 2021; Wang and Yang 2020; Collotta et al. 2019; Wang and Zhan 2019; Yu, Zheng, and Li 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010)

Dimension	Indicators	Scope contribution	Total frequency	References
	Energy efficiency	1A, 1B, 1E	3	(Onat and Bayar 2010; Cuesta, Castillo-Calzadilla, and Borges 2020; Dombi, Kuti, and Balogh 2014)
	Renewable fraction	3A	3	(Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Cîrstea et al. 2018)
	Local environmental impact	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Need of waste disposal	3A, 1B, 1D, 2H	7	(Faraji Abdolmaleki and Bello Bugallo 2021; Wang and Zhan 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Al Garni et al. 2016; Luong, Liu, and Robey 2012; Demirtas 2013; Kahraman, Kaya, and Cebi 2009)
	Effect on climate change and pollution cuts	1A, 1D	2	(Štreimikiene, Šliogeriene, and Turskis 2016; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Aesthetic	2A, 2B	4	(Cuesta, Castillo-Calzadilla, and Borges 2020; Stougie et al. 2018; Grilli et al. 2017; Hanne, Ingunn, and Tor 2012)
	Pollution compared to the year 1992	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Energy sources conservations (non-renewables)	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Obstruction to navigation	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Impact on marine life	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Reduced sea usage	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Embodied energy	1A, 1B	2	(Kourkoumpas et al. 2018; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Life cycle assessment	2A	2	(Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Compliance with 2020 PV share	2A	2	(Mastrocinque et al. 2020; Wang and Zhan 2019)
	GHG emissions reduction	4A, 5B, 1D, 2E, 1I	13	(Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Troldborg, Heslop, and Hough 2014; Wang and Zhan 2019; Stougie et al. 2018; Al Garni et al. 2016; Dombi, Kuti, and Balogh 2014; Ertay, Kahraman, and Kaya 2013; Hanne, Ingunn, and Tor 2012; Shen et al. 2010; Zafar et al. 2019; Böhringer et al. 2017)
	Disposal green policies	2A	2	(Mastrocinque et al. 2020; Wang and Zhan 2019)
	Global warming potential	1A, 2B, 1D	4	(Collotta et al. 2019; Kourkoumpas et al. 2018; Štreimikiene, Šliogeriene, and Turskis 2016; Santoyo-Castelazo and Azapagic 2014)
	Reduction of the direct CO_2 emissions	2B, 1D	3	(Kourkoumpas et al. 2018; Štreimikiene, Šliogeriene, and Turskis 2016; Santoyo-Castelazo and Azapagic 2014)
	CO_2 equivalent payback time	1B	1	(Kourkoumpas et al. 2018)
	CO_2 intensity of electricity	1A	1	(Pratama et al. 2017)
	CO_2 intensity of economy	1A	1	(Pratama et al. 2017)
	Fresh water consumption	2A, 1E	3	(Collotta et al. 2019; Yu, Zheng, and Li 2019; Onat and Bayar 2010)
	Resource depletion	2B, 1D	3	(Campos-Guzmán et al. 2019; Atilgan and Azapagic 2016; Santoyo-Castelazo and Azapagic 2014)
	Acidification	1A, 2B	3	(Collotta et al. 2019; Campos-Guzmán et al. 2019; Santoyo-Castelazo and Azapagic 2014)
	Eutrophication	1B	1	(Santoyo-Castelazo and Azapagic 2014)
	Freshwater toxicity	1B, 1D	2	(Zhao and Chen 2018; Santoyo-Castelazo and Azapagic 2014)

Dimension	Indicators	Scope contribution	Total frequency	References
	Human toxicity	1A, 2B	3	(Collotta et al. 2019; Campos-Guzmán et al. 2019; Santoyo-Castelazo and Azapagic 2014)
	Marine toxicity	1A, 2B	3	(Collotta et al. 2019; Campos-Guzmán et al. 2019; Santoyo-Castelazo and Azapagic 2014)
	Ozone depletion	1A, 1B	2	(Collotta et al. 2019; Santoyo-Castelazo and Azapagic 2014)
	Summer smog and terrestrial toxicity	1B	1	(Santoyo-Castelazo and Azapagic 2014)
	Amount of waste generation	1B, 2D	3	(Zhao and Chen 2018; Štreimikiene, Šliogeriene, and Turskis 2016; Ligus 2017)
	Resource efficiency of the economy	1B	1	(Ligus 2017)
	Risk of failure/accident	1B	1	(Ligus 2017)
	Contribution of renewable energy resources	1D	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	Compliance with local natural conditions	1D	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	Water and soil	1B, 2D, 1F	4	(Štreimikiene, Šliogeriene, and Turskis 2016; Atilgan and Azapagic 2016; Zhao and Guo 2015; Hanne, Ingunn, and Tor 2012)
	Disturbance of ecological balance	1D	1	(Atilgan and Azapagic 2016)
	Share of renewable energy in gross power production	1A, 1I	2	(Cîrstea et al. 2018; Böhringer et al. 2017)
	Stringency of environmental regulation	1A	1	(Cîrstea et al. 2018)
	Enforcement of environmental regulation	1A	1	(Cîrstea et al. 2018)
	Reduce the consumption of fossil fuels	1D	1	(Zhao and Guo 2015)
	Agricultural and forest products provisioning	1A	1	(Grilli et al. 2017)
	Habitat quality	1A	1	(Grilli et al. 2017)
	Electricity production from coal and oil	1G (W/technological and economical)[a]	1	(Lee and Zhong 2015)
	Electricity production from renewable sources, including hydroelectric	1G, 1I (W/technological and economical)	2	(Lee and Zhong 2015; Böhringer et al. 2017)
	Renewable energy resource	1G	1	(Lee and Zhong 2015)
	Non-methane volatile organic compounds	4A	4	(Wang and Yang 2020; Wang and Zhan 2019; Şengül et al. 2015; Dhital et al. 2014)
	CO emission	2A, 1H	3	(Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010)
	Visual impact	1B, 1H	2	(Ertay, Kahraman, and Kaya 2013; Heo, Kim, and Boo 2010)
	Social acceptability	1E (W/social)	1	(Shen et al. 2010)

Dimension	Indicators	Scope contribution	Total frequency	References
Economic	Investment cost	4A, 3B, 3E, 1G, 1H, 1I	13	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Mourmouris and Potolias 2013; Ertay, Kahraman, and Kaya 2013; Luong, Liu, and Robey 2012; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010; Kahraman, Kaya, and Cebi 2009; Zafar et al. 2019)
	Operation and maintenance cost	8A, 3B, 1D, 2E, 1F, 2G	17	(Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Collotta et al. 2019; Wang and Zhan 2019; Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Shaaban et al. 2018; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Lee and Zhong 2015; Şengül et al. 2015; Dhital et al. 2014; Mourmouris and Potolias 2013; Ertay, Kahraman, and Kaya 2013; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010)
	Energy cost/ implementation cost	4A, 5B, 1D, 1E, 1G, 2H	14	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Collotta et al. 2019; Kourkoumpas et al. 2018; Štreimikiene, Šliogeriene, and Turskis 2016; Onat and Bayar 2010; Campos-Guzmán et al. 2019; Shaaban et al. 2018; Stougie et al. 2018; Strantzali and Aravossis 2016; Al Garni et al. 2016; Dombi, Kuti, and Balogh 2014; Shen et al. 2010; Kahraman, Kaya, and Cebi 2009)
	Fuel cost/savings	7A, 2B, 2D, 1H	12	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Wang and Zhan 2019; Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Stougie et al. 2018; Strantzali and Aravossis 2016; Al Garni et al. 2016; Şengül et al. 2015; Dhital et al. 2014; Ertay, Kahraman, and Kaya 2013; Heo, Kim, and Boo 2010)
	Payback period	4A, 1B, 1D, 2E, 1F	9	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Kourkoumpas et al. 2018; Haddad, Liazid, and Ferreira 2017; Şengül et al. 2015; Dhital et al. 2014; Mourmouris and Potolias 2013; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010)
	Internal rate of return (IRR)	1A, 1G	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Life cycle cost (LCC)	1A, 1B, 1D, 1G	4	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Atilgan and Azapagic 2016; Santoyo-Castelazo and Azapagic 2014)
	Net present value (NPV)	5A, 1B, 1G, 1H	8	(Faraji Abdolmaleki and Bello Bugallo 2021; Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Ertay, Kahraman, and Kaya 2013; Heo, Kim, and Boo 2010)
	Service life	5A, 1B, 2E, 1G, 1F (W/technical)	10	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Şengül et al. 2015; Ahmad and Tahar 2014; Dhital et al. 2014; Mourmouris and Potolias 2013; Ertay, Kahraman, and Kaya 2013; Heo, Kim, and Boo 2010)
	Equivalent annual cost (EAC)	3A, 1G, 1H	5	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010)
	Return of investment (ROI)	1A, 1D	2	(Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Cost of saved primary energy	2A	2	(Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Learning rate	1A (W/social)	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Current market share	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Dependence on fossil fuel	2A	2	(Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Tax incentives	2A, 1D	3	(Wang and Zhan 2019; Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Interference with other utilities	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)

Dimension	Indicators	Scope contribution	Total frequency	References
	Availability of funds	1A, 1B, 1E, 1D, 1H	5	(Cuesta, Castillo-Calzadilla, and Borges 2020; Şengül et al. 2015; Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
	Economic efficiency	1A	1	(Onat and Bayar 2010)
	Technology's competitiveness	1A, 1B (W/technical)	2	(Onat and Bayar 2010; Ligus 2017)
	External costs	1A	1	(Onat and Bayar 2010)
	Proportion of cost being utilized in foreign currency	1A	1	(Onat and Bayar 2010)
	National economy contributions	1A, 2B	3	(Troldborg, Heslop, and Hough 2014; Onat and Bayar 2010; Demirtas 2013)
	Cost of capital	5A, 2B, 1D, 1E	9	(Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Ghenai, Albawab, and Bettayeb 2020; Wang and Zhan 2019; Diemuodeke, Hamilton, and Addo 2016; Campos-Guzmán et al. 2019; Boran 2018; Al Garni et al. 2016; Santoyo-Castelazo and Azapagic 2014)
	Sourcing costs/technology cost	3A, 1E	4	(Mastrocinque et al. 2020; Ghenai, Albawab, and Bettayeb 2020; Wang and Zhan 2019; Ahmad and Tahar 2014)
	Upfront cost	2A, 1B	3	(Mastrocinque et al. 2020; Wang and Zhan 2019; Shaaban et al. 2018)
	Tariffs and incentives	2A, 1D, 1E	4	(Mastrocinque et al. 2020; Wang and Zhan 2019; Zhao and Chen 2018; Ahmad and Tahar 2014)
	Final energy yield	3A	3	(Mastrocinque et al. 2020; Wang and Yang 2020; Wang and Zhan 2019)
	Job creation	1B (W/social)	1	(Shaaban et al. 2018)
	Incentives and subventions	1E	1	(Boran 2018)
	Generation costs per unit	3A, 1B, 2D, 1E	7	(Faraji Abdolmaleki and Bello Bugallo 2021; Yu, Zheng, and Li 2019; Štreimikiene, Šliogeriene, and Turskis 2016; Boran 2018; Stougie et al. 2018; Pratama et al. 2017; Zhao and Guo 2015)
	Economic potential	1E	1	(Boran 2018)
	GDP	5A, 1B, 1G, 1I	8	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki and Bello Bugallo 2021; Wang et al. 2020; Wang and Zhan 2019; Ligus 2017; Lee and Zhong 2015; Böhringer et al. 2017)
	Trade balance	1B	1	(Ligus 2017)
	Unemployment rate/employment	11A, 1B, 1G, 1H, 1I (W/social)	10	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki and Bello Bugallo 2021; Collotta et al. 2019; Ligus 2017; Ifaei et al. 2017; Grilli et al. 2017; Lee and Zhong 2015; Kahraman, Kaya, and Cebi 2009; Böhringer et al. 2017)
	Energy security of enterprise and public sector	1B	1	(Ligus 2017)
	Balanced development of regions	1B	1	(Ligus 2017)
	Land requirement	1B	1	(Ligus 2017)
	Economic efficiency	1D	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	Competitiveness	1D, 1H	2	(Štreimikiene, Šliogeriene, and Turskis 2016; Kahraman, Kaya, and Cebi 2009)
	Value of technological complex	1D	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	R&D cost	1D (W/social)	1	(Al Garni et al. 2016)

Dimension	Indicators	Scope contribution	Total frequency	References
	Operational life	1D, 1E	2	(Al Garni et al. 2016; Ahmad and Tahar 2014)
	Cost of grid connection	1A, 1B, 1D	3	(Al Garni et al. 2016; Yu, Zheng, and Li 2019; Hanne, Ingunn, and Tor 2012)
	Market maturity	1B, 1D, 1H	3	(Al Garni et al. 2016; Kahraman, Kaya, and Cebi 2009; Stougie et al. 2018)
	Site advantage	1D	1	(Al Garni et al. 2016)
	National economic development	1D, 1H	2	(Al Garni et al. 2016; Kahraman, Kaya, and Cebi 2009)
	Levelized cost	1A, 3B	4	(Stougie et al. 2018; Strantzali and Aravossis 2016; Troldborg, Heslop, and Hough 2014; Demirtas 2013)
	Inflation rate	2A, 1G	3	(Lee and Zhong 2015; Cîrstea et al. 2018; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023)
	Economic growth rate	3A	3	(Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Yu, Zheng, and Li 2019; Cîrstea et al. 2018)
	Electrical capacity—hydro, wind, solar	1A (W/technical)	1	(Cîrstea et al. 2018)
	Electrical capacity—combustion fuels	1A (W/technical)	1	(Cîrstea et al. 2018)
	GHG from energy sectors	1A (W/ environmental)	1	(Cîrstea et al. 2018)
	Primary production of renewable energy	1A, 1D, 1I (W/ technical)	3	(Cîrstea et al. 2018; Zhao and Chen 2018; Böhringer et al. 2017)
	Total gross electricity generation	2A	2	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Cîrstea et al. 2018)
	Self-sufficiency	1A	1	(Pratama et al. 2017)
	Renewable energy share	5A, 1B (W/technical and environmental)	6	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Wang and Yang 2020; Yu, Zheng, and Li 2019; Kourkoumpas et al. 2018; Pratama et al. 2017)
	Diversification	1A	1	(Pratama et al. 2017)
	Reserve to production ratio	1A	1	(Pratama et al. 2017)
	Share of electricity cost to GDP	1A	1	(Pratama et al. 2017)
	Currency movement	1G	1	(Lee and Zhong 2015)
	Economic value	1B, 1E, 1H	3	(Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
	Electric cost	3A, 1H	4	(Wang and Zhan 2019; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010)
	Resource potential	1E	1	(Ahmad and Tahar 2014)
	Supply capability	1E	1	(Shen et al. 2010)
	Economic feasibility	1E	1	(Shen et al. 2010)
	Supply durability	1E	1	(Shen et al. 2010)
	Industrial structure	1A	1	(Wang and Zhan 2019)
Social	Job creation/ labor impact	7A, 5B, 2D, 3E, 1F, 1G, 1H, 1I	21	(Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Wang and Zhan 2019; Luong, Liu, and Robey 2012; Al Garni et al. 2016; Campos-Guzmán et al. 2019; Doukas and Psarras 2009; Yu, Zheng, and Li 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Strantzali and Aravossis 2016; Şengül et al. 2015; Ahmad and Tahar 2014; Dhital et al. 2014; Heo, Kim, and Boo 2010; Stougie et al. 2018; Dombi, Kuti, and Balogh 2014; Ertay, Kahraman, and Kaya 2013; Zafar et al. 2019; Atilgan and Azapagic 2016; Kahraman, Kaya, and Cebi 2009)

Dimension	Indicators	Scope contribution	Total frequency	References
	Social acceptability	8A, 6B, 1D, 4E, 1F, 1G, 2H	23	(Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Štreimikiene, Šliogeriene, and Turskis 2016; Wang and Zhan 2019; Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Mourmouris and Potolias 2013; Cuesta, Castillo-Calzadilla, and Borges 2020; Shaaban et al. 2018; Boran 2018; Strantzali and Aravossis 2016; Şengül et al. 2015; Ahmad and Tahar 2014; Troldborg, Heslop, and Hough 2014; Dhital et al. 2014; Heo, Kim, and Boo 2010; Stougie et al. 2018; Demirtas 2013; Ertay, Kahraman, and Kaya 2013; Zhao and Guo 2015; Grilli et al. 2017; Santoyo-Castelazo and Azapagic 2014; Kahraman, Kaya, and Cebi 2009)
	Social benefits	5A, 2B, 1D, 3E, 1F, 1G	13	(Faraji Abdolmaleki and Bello Bugallo 2021; Collotta et al. 2019; Štreimikiene, Šliogeriene, and Turskis 2016; Campos-Guzmán et al. 2019; Mourmouris and Potolias 2013; Onat and Bayar 2010; Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010; Ertay, Kahraman, and Kaya 2013)
	Visual impact	1A, 1G (W/ environment)	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Local development	1A, 1G, 1E	3	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Zafar et al. 2019)
	Impacts on health	4A, 1B, 1D, 1G	7	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Strantzali and Aravossis 2016; Grilli et al. 2017; Al Garni et al. 2016)
	Income from jobs	3A, 1G	4	(Wang and Yang 2020; Yu, Zheng, and Li 2019; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Benefited residents	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Compatibility with political and legislative situation international obligations	2A, 1B, 2D, 1E, 1H	7	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Atilgan and Azapagic 2016; Al Garni et al. 2016; Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
	Public awareness and willingness	3A, 2E (W/ institutional)	5	(Faraji Abdolmaleki and Bello Bugallo 2021; Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Haddad, Liazid, and Ferreira 2017)
	Conflict with other applications	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Opportunity for private participation	1A, 1D, 1E	3	(Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020; Stougie et al. 2018)
	Degree of local ownership	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Support of government institutions political organizations	1A, 1D, 1E (W/ institutional)	3	(Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017)
	Economic security	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Influence on sustainable development of society (education science culture)	1A, 1D	2	(Štreimikiene, Šliogeriene, and Turskis 2016; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Social losses due to power outage	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)

Dimension	Indicators	Scope contribution	Total frequency	References
	Human development index (HDI)	3A	3	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Social cost of carbon	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Consumption pattern of a household load in a certain location	1A, 1G	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Lee and Zhong 2015)
	Stakeholders influence	2A	2	(Mastrocinque et al. 2020; Wang and Zhan 2019)
	R&D governmental support	4A, 1D, 1I	6	(Faraji Abdolmaleki and Bello Bugallo 2021; Mastrocinque et al. 2020; Wang and Zhan 2019; Zhao and Chen 2018; Cîrstea et al. 2018; Böhringer et al. 2017)
	Availability	2A, 1B, 1D, 1E	5	(Faraji Abdolmaleki and Bello Bugallo 2021; Zhao and Chen 2018; Onat and Bayar 2010; Cîrstea et al. 2018)
	Safety risks	1B, 1D	2	(Shaaban et al. 2018; Atilgan and Azapagic 2016)
	Security and diversity of supply	1B, 1D	2	(Shaaban et al. 2018; Al Garni et al. 2016)
	Eliminating social inequality	1B	1	(Ligus 2017)
	Energy security of households	1B, 1D	2	(Atilgan and Azapagic 2016)
	Local income	1A	1	(Dhital et al. 2014)
	Mortality and morbidity	2B	2	(Campos-Guzmán et al. 2019; Stougie et al. 2018)
	Affordability of financial service	1A	1	(Cîrstea et al. 2018)
	Capacity for innovation	1A (W/technical)	1	(Cîrstea et al. 2018)
	Urbanization rate	2A	2	(Wang and Yang 2020; Ifaei et al. 2017)
	Vocational to high school graduates ratio	1A	1	(Ifaei et al. 2017)
	Infant mortality rate	1A	1	(Ifaei et al. 2017)
	Rural gini coefficient	1A	1	(Ifaei et al. 2017)
	Urban gini coefficient	1A	1	(Ifaei et al. 2017)
	Economic association rate	1A	1	(Ifaei et al. 2017)
	Literacy rate	1A	1	(Ifaei et al. 2017)
	Life expectancy in the first year after birth	2A	2	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Ifaei et al. 2017)
	Electric power transmission and distribution losses	1G	1	(Lee and Zhong 2015)
	Political acceptance	1E, 1H	2	(Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
Institutional	Compliance with international obligations	1D (W/social)	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	Legal regulation of activities	3A, 2D, 1G	6	(Faraji Abdolmaleki and Bello Bugallo 2021; Wang et al. 2020; Štreimikiene, Šliogeriene, and Turskis 2016; Lee and Zhong 2015; Cîrstea et al. 2018; Zhao and Chen 2018)
	Technology's autonomy	1D (W/technical)	1	(Štreimikiene, Šliogeriene, and Turskis 2016)

Dimension	Indicators	Scope contribution	Total frequency	References
	Government support	2A, 1D, 1G (W/social)	4	(Faraji Abdolmaleki and Bello Bugallo 2021; Štreimikiene, Šliogeriene, and Turskis 2016; Lee and Zhong 2015; Cîrstea et al. 2018)
	Political organizations	1D	1	(Štreimikiene, Šliogeriene, and Turskis 2016)
	Influence on sustainable development of energy	1A, 1D	2	(Faraji Abdolmaleki and Bello Bugallo 2021; Štreimikiene, Šliogeriene, and Turskis 2016)
	GDP per capita	2A (W/economic)	2	(Wang et al. 2020; Cîrstea et al. 2018)
	Political stability and absence of violence/terrorism	2A, 1D, 1G	4	(Faraji Abdolmaleki and Bello Bugallo 2021; Lee and Zhong 2015; Cîrstea et al. 2018; Zhao and Chen 2018)
	The efficiency of subsidy for feed-in tariff	1D	1	(Zhao and Chen 2018)
	Control of corruption	2A, 1G	3	(Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023; Faraji Abdolmaleki and Bello Bugallo 2021; Lee and Zhong 2015)
	Renewable energy policies	1G	1	(Lee and Zhong 2015)
Technical	Efficiency	5A, 2B, 1D, 2E, 1G, 1H	12	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Al Garni et al. 2016; Onat and Bayar 2010; Shaaban et al. 2018; Ifaei et al. 2017; Şengül et al. 2015; Ahmad and Tahar 2014; Dhital et al. 2014; Heo, Kim, and Boo 2010; Ertay, Kahraman, and Kaya 2013; Shen et al. 2010)
	Reliability	4A, 4B, 2D, 3E, 1G, 2H	16	(Faraji Abdolmaleki and Bello Bugallo 2021; Štreimikiene, Šliogeriene, and Turskis 2016; Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Mourmouris and Potolias 2013; Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Troldborg, Heslop, and Hough 2014; Dhital et al. 2014; Heo, Kim, and Boo 2010; Shen et al. 2010; Demirtas 2013; Ertay, Kahraman, and Kaya 2013; Kahraman, Kaya, and Cebi 2009)
	Resource availability	1A, 2B, 2D, 1G, 1F	7	(Al Garni et al. 2016; Campos-Guzmán et al. 2019; Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Heo, Kim, and Boo 2010; Ertay, Kahraman, and Kaya 2013)
	Nominal power/installed capacity (kW)	3A, 1G	4	(Esfandiary Abdolmaleki, Faraji Abdolmaleki, and Bello Bugallo 2023; Wang et al. 2020; Ghenai, Albawab, and Bettayeb 2020; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Maturity	4A, 4B, 1D, 3E, 1F, 1G, 1H	15	(Faraji Abdolmaleki and Bello Bugallo 2021; Al Garni et al. 2016; Campos-Guzmán et al. 2019; Mourmouris and Potolias 2013; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Ahmad and Tahar 2014; Troldborg, Heslop, and Hough 2014; Dhital et al. 2014; Heo, Kim, and Boo 2010; Stougie et al. 2018; Demirtas 2013)
	Safety	4A, 1B, 1D, 2E, 1F, 1G (W/social)	10	(Faraji Abdolmaleki and Bello Bugallo 2021; Al Garni et al. 2016; Mourmouris and Potolias 2013; Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010; Ertay, Kahraman, and Kaya 2013)
	Energy production	2A, 1B, 1G, 1H	5	(Troldborg, Heslop, and Hough 2014; Mourmouris and Potolias 2013; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016; Faraji Abdolmaleki, Esfandiary Abdolmaleki, and Bello Bugallo 2023)
	Load demand	1A, 2B, 1D, 1G	5	(Zhao and Chen 2018; Cuesta, Castillo-Calzadilla, and Borges 2020; Kourkoumpas et al. 2018; Strantzali and Aravossis 2016; Hanne, Ingunn, and Tor 2012)

Dimension	Indicators	Scope contribution	Total frequency	References
	Primary energy ratio (PER)	4A, 2B, 1E, 1G, 1H (W/economic)	9	(Faraji Abdolmaleki and Bello Bugallo 2021; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Kourkoumpas et al. 2018; Strantzali and Aravossis 2016; Şengül et al. 2015; Dhital et al. 2014; Hanne, Ingunn, and Tor 2012; Heo, Kim, and Boo 2010)
	Lifespan	2A, 1G	2	(Ghenai, Albawab, and Bettayeb 2020; Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Continuity	1A, 1B, 1G, 1H	4	(Luong, Liu, and Robey 2012; Cuesta, Castillo-Calzadilla, and Borges 2020; Kahraman, Kaya, and Cebi 2009; Strantzali and Aravossis 2016)
	Stability	1A, 1G	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Strantzali and Aravossis 2016)
	Feasibility	2A, 2B, 1D, 2E, 1H (W/social)	8	(Faraji Abdolmaleki and Bello Bugallo 2021; Luong, Liu, and Robey 2012; Kahraman, Kaya, and Cebi 2009; Al Garni et al. 2016; Doukas and Psarras 2009; Cuesta, Castillo-Calzadilla, and Borges 2020; Campos-Guzmán et al. 2019; Shen et al. 2010)
	Risk	1E, 1H	2	(Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
	Consistence of installation and maintenance requirements with local technical know-how	2A	2	(Diemuodeke, Hamilton, and Addo 2016; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Continuity and predictability of performance	2A, 1B, 2E	5	(Faraji Abdolmaleki and Bello Bugallo 2021; Luong, Liu, and Robey 2012; Cuesta, Castillo-Calzadilla, and Borges 2020; Boran 2018; Shen et al. 2010)
	Target of primary energy saving	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Capacity factor	3A, 1D, 1F (W/economic)	5	(Faraji Abdolmaleki and Bello Bugallo 2021; Ghenai, Albawab, and Bettayeb 2020; Štreimikiene, Šliogeriene, and Turskis 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Heo, Kim, and Boo 2010)
	Compatibility with future capacity expansion	2A	2	(Ghenai, Albawab, and Bettayeb 2020; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Compatibility with existing infrastructure	1A (W/economic)	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Weather and climate condition dependence	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	The duration of preparation and implementation phase	1A, 1E, 1H	3	(Kahraman, Kaya, and Cebi 2009; Doukas and Psarras 2009; Cuesta, Castillo-Calzadilla, and Borges 2020)
	Technology's autonomy (dependence on resource provision)	1A, 1B (W/institutional)	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Shaaban et al. 2018)
	Innovativeness	2A, 1B, 1D, 1E (W/social)	5	(Faraji Abdolmaleki and Bello Bugallo 2021; Štreimikiene, Šliogeriene, and Turskis 2016; Cuesta, Castillo-Calzadilla, and Borges 2020; Shen et al. 2010; Stougie et al. 2018)
	Energy not supplied unmet load	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Decomposability	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Non-redundancy	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Hardware component availability	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)

Dimension	Indicators	Scope contribution	Total frequency	References
	Power quality	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Load management	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	Capacity constraints	1A, 1E	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Haddad, Liazid, and Ferreira 2017)
	Unpredictability	1A	1	(Cuesta, Castillo-Calzadilla, and Borges 2020)
	RES energy not used or stored	1A, 1B	2	(Cuesta, Castillo-Calzadilla, and Borges 2020; Kourkoumpas et al. 2018)
	Energy supply reliability	1B	1	(Shaaban et al. 2018)
	Water consumption	1B	1	(Shaaban et al. 2018)
	Durability/ the duration of implementation phase	1B, 1D, 1E, 1H	4	(Štreimikiene, Šliogeriene, and Turskis 2016; Luong, Liu, and Robey 2012; Kahraman, Kaya, and Cebi 2009; Doukas and Psarras 2009)
	The duration of preparation phase	1H	1	(Doukas and Psarras 2009)
	Deployment time	1D	1	(Al Garni et al. 2016)
	Expert human resource	1D	1	(Al Garni et al. 2016)
	Ease of decentralization	1D	1	(Al Garni et al. 2016)
	Technology availability	1A	1	(Diemuodeke, Hamilton, and Addo 2016)
	Ease of installation	1A	1	(Diemuodeke, Hamilton, and Addo 2016)
	Exergy efficiency	2A, 1F	3	(Şengül et al. 2015; Dhital et al. 2014; Heo, Kim, and Boo 2010)
	Lead time	1B, 1E	2	(Luong, Liu, and Robey 2012; Ahmad and Tahar 2014)
	Local technical know how	1B, 1E, 1H	3	(Luong, Liu, and Robey 2012; Doukas and Psarras 2009; Kahraman, Kaya, and Cebi 2009)
	Number of R&D stuff	2A	2	(Wang et al. 2020; Yu, Zheng, and Li 2019)
	Shared of R&D investment in GDP	2A	2	(Wang et al. 2020; Yu, Zheng, and Li 2019)
	Unit investment in power generation of RE	1A	1	(Yu, Zheng, and Li 2019)
	Power transmission line loss rate	1A	1	(Yu, Zheng, and Li 2019)

[a] (W/dimension name) = with (a dimension). For example, (W/social) means this indicator is seen also in Social dimension.

Appendix B

Appropriate Indicator/Set for Each Scope

Dimension	Indicator(s) for each scope
Environmental	A: CO_2 emission, land use, impact on the ecosystem, NO_x, SO_X emission, Emission (generally), GHG emission reduction, particle emission, Non-methane volatile organic compounds. B: CO_2 emission, land use, impact on the ecosystem, GHG emission reduction, particle emission. E: CO_2 emission, land use, impact on ecosystem.
Economic	A: investment cost, operation and maintenance cost, energy cost, fuel cost, payback period, net present value, service life, cost of capital, GDP, employment rate, renewable energy share. B: energy cost.
Social	A: social acceptability, job creation, social benefit, impact on health, R&D governmental support, HDI, income from jobs. B: job creation, social acceptability. E: social acceptability, job creation, social acceptability, social benefits.
Technical	A: efficiency, reliability, installed capacity, maturity, safety, energy production, primary energy ratio, lifespan, feasibility, local technical know-how, capacity factor, compatibility with future capacity expansion, innovativeness, exergy efficiency, number of R&D stuff, shared of R&D investment in GDP. B: efficiency, reliability, resource availability, maturity, load demand, primary energy ratio, feasibility. D: reliability, resource availability. E: efficiency, reliability, maturity, safety, feasibility, Continuity and predictability of performance. H: reliability.
Institutional	A: legal regulation of activity, government support, political stability and absence of violence/terrorism, control of corruption. D: the legal regulation of activity, influence on sustainable development of energy, political stability and absence of violence/terrorism.