

Systematic Review

Terminological Structures in Anticipatory Energy Research: A Conceptual and Bibliometric Analysis of Energy Scanning and Forecasting Approaches

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Abstract: Anticipatory approaches are increasingly vital for analyzing energy systems; however, the terminology surrounding energy monitoring, scanning, forecasting, and foresight remains fragmented and inconsistently applied. To resolve this conceptual ambiguity, this study undertakes a systematic conceptual review and bibliometric analysis of contemporary literature to synthesize and reorganize the terminological framework within anticipatory energy research. We propose an integrated, four-layer architecture that delineates these functions: Layer 1 (Energy Monitoring) establishes real-time operational baselines using empirical data streams; Layer 2 (Energy Scanning) systematically tracks external structural discontinuities and emerging weak signals outside historical datasets; Layer 3 (Energy Forecasting) employs quantitative, data-driven methodologies—including machine learning (ML) and deep learning—for short- to medium-term operational optimization; and Layer 4 (Energy Foresight) integrates these quantitative outputs with qualitative approaches, such as scenario planning and backcasting, to navigate deep uncertainty in long-term energy transitions. A primary finding of this review is the critical positioning of ML techniques. While highly effective for operational forecasting based on historical data, these data-driven models are intrinsically limited in addressing the structural policy shifts and non-linear transformations required for strategic foresight. Furthermore, the bibliometric analysis identifies a distinct conceptual divergence between data-intensive predictive studies and policy-focused long-term planning. By explicitly situating ML within the forecasting domain and structurally bridging short-term operational models with long-term strategic governance, this study mitigates the risks of conceptual conflation. The proposed framework enhances methodological coherence and provides policymakers with a theoretically grounded taxonomy to ensure that anticipatory energy strategies remain both visionary and empirically substantiated.

Keywords: Anticipatory Energy Research; Bibliometric Analysis; Energy Forecasting; Energy Foresight; Horizon Scanning; Learning Systems

1. Introduction

The global energy landscape is undergoing a significant transformation as countries implement ambitious decarbonization strategies and accelerate the adoption of renewable energy sources. This transition from traditional fossil-fuel-based generation to variable renewable energy sources, particularly wind and solar, has the potential to reduce greenhouse gas emissions and address the pressing challenges posed by climate change [1]. The transition

to renewable energy sources presents substantial operational and planning challenges due to the inherent intermittency and weather dependence of such energy generation [2]. The variability in output, which is frequently uncorrelated with demand patterns, amplifies the uncertainty in aligning supply with demand. This situation may jeopardise grid stability, compromise system reliability, and adversely affect the economics of electricity markets [3]. In light of these challenges, the utilization of forecasting tools and methodologies has become essential. Precise prediction of renewable energy generation and demand is vital for efficient scheduling, optimizing dispatch processes, and integrating flexibility resources, such as energy storage and demand response mechanisms [4]. The increasing complexity and uncertainty of modern energy systems, driven by a high proportion of renewable energy sources, changing demand patterns, and climate- and weather-related variability, necessitate the development of robust, forward-thinking analytical frameworks and forecasting tools that go beyond traditional deterministic planning methods [5]. As the global share of renewable energy sources continues to grow, the demand for reliable forecasting and uncertainty quantification becomes increasingly critical. Additionally, there is a pressing need for a robust framework that facilitates energy prediction and forecasting, as well as anticipatory planning. These elements are essential for enabling a stable, resilient, and decarbonized energy future [6].

In the realm of contemporary energy forecasting and futures-oriented research, a notable conceptual challenge arises from the proliferation of overlapping and imprecisely defined terminology. Terms such as “scanning,” “horizon scanning,” “environmental scanning,” “foresight,” “future watching,” “anticipatory,” “projection,” “prevision,” as well as metaphorical labels like “radar,” “screening,” and “soothsaying,” exhibit significant variation across disciplines, including engineering, policy, strategic management, and futures studies. These terms are frequently employed interchangeably, or with nuanced yet critical distinctions in their scope, objectives, and methodologies [7–9]. For example, Horizon Scanning (HS) is a systematic approach to identifying weak signals and emerging trends by analyzing potential threats and opportunities. Depending on the context, it may be regarded either as an independent technique or as a component within more comprehensive Foresight activities [10]. At times, HS is mistakenly equated with environmental scanning (ES). While ES encompasses broader surveillance of external socio-economic, technological, political, and ecological conditions, it does not necessarily focus on identifying weak signals or potential future disruptions [11]. The fragmentation of terminology in this field obscures conceptual clarity and hampers the comparability of studies. For example, two “scans” within the energy literature may employ radically different methods and time horizons, despite being designated with the same label. This results in ambiguity in academic communication, presents challenges in synthesizing evidence, and leads to inconsistent application of scanning and foresight methods in energy forecasting practices [12]. Such conceptual ambiguity poses significant difficulties when integrating qualitative anticipatory approaches such as foresight and horizon scanning with quantitative forecasting models; the absence of shared definitions complicates both the design and interpretation of these methodologies [13]. Therefore, establishing a more rigorous taxonomy is essential to align research across disciplines and ensure that anticipatory, future-watching, and scanning methods are used with clarity, purpose, and reproducibility [14].

In the realm of energy forecasting, it is essential to clarify the terminology employed, including terms such as “scanning,” “horizon scanning,” “environmental scanning,” “foresight,” “anticipatory analysis,” “future-watching,” as well as metaphorical expressions like “radar” or “screening.” This distinction is not merely an academic exercise; rather, it represents a practical necessity for effective analysis and decision-making [15–17]. As the energy transition progresses, energy planners and modelers are increasingly integrating traditional quantitative forecasting methods with anticipatory approaches and early signal detection strategies. These strategies encompass identifying emerging technological trends, shifts in policy, and changes in social behaviors [18]. By differentiating among these methodologies, organizations can choose forecasting models or planning exercises that are more appropriately aligned with the specific decision-making context. For instance, implementing a structured horizon scan may facilitate the identification of weak signals prior to making long-term commitments to infrastructure investments. Alternatively, environmental scanning can support continuous monitoring of external factors influencing demand and supply [19]. Moreover, shared, precise terminology facilitates alignment between data-driven models and qualitative foresight methodologies, such as scenario analysis, expert judgment, and weak-signal analysis [20]. This alignment fosters a comprehensive and robust planning framework that encompasses both quantifiable trends and uncertain future developments.

This study addresses a significant yet underexplored gap in the energy literature: the persistent conceptual am-

biguity surrounding anticipatory terminology and the frequent conflation of machine-learning-based forecasting with strategic foresight practices. While existing review studies primarily focus on enhancing predictive accuracy, optimizing algorithms, or benchmarking learning models within renewable energy applications—such as wind and solar forecasting—few efforts have systematically reorganized the epistemological structure and terminological foundations of anticipatory energy research.

The original contributions of this study are presented as follows. First, it integrates bibliometric mapping with a comprehensive conceptual review to illuminate existing methodological patterns, terminological overlaps, and structural imbalances within the field. To the best of our knowledge, this study constitutes one of the first efforts to link bibliometric analyses of energy forecasting with learning methodologies. Second, it introduces an innovative four-layer conceptual framework—comprising Monitoring, Scanning, Forecasting, and Foresight—that distinctly categorizes these anticipatory practices based on their temporal scope, analytical depth, orientation toward uncertainty, and policy relevance. Third, it offers a structured classification of forecasting terminology, distinguishing statistical forecasting, machine learning (ML)-based predictions, hybrid modeling, and deep learning (DL) architectures, while critically evaluating their applications in renewable energy systems, particularly wind and solar energy. Fourth, it explicitly situates ML and DL approaches within the forecasting layer, thereby addressing their frequent yet theoretically inappropriate classification as tools for foresight. Finally, it establishes a coherent and transparent reference framework that integrates data-driven energy forecasting with long-term anticipatory governance. This advancement aims to enhance theoretical precision, diminish terminological fragmentation, and provide a more robust foundation for strategic energy planning.

2. Methodology

This study employs a systematic conceptual review methodology to examine the terminological and methodological diversity in energy monitoring, scanning, foresight, and forecasting within the energy sector. The primary objective of the review is to identify, analyze, and categorize key concepts relevant to energy future monitoring and the foresight of energy systems, with a particular focus on terms such as Energy Scanning, Horizon Scanning, Environmental Scanning, Energy Foresight, and established energy forecasting methodologies. This study is a systematic conceptual review rather than a review focused on interventions or specific outcomes. As a result, there were no predefined clinical, experimental, or effect-size outcomes. Instead, the analysis focused on the conceptual and terminological characteristics, including definitions, operationalizations, methodological approaches, application contexts, and temporal orientations related to energy monitoring, scanning, foresight, and forecasting. To ensure a comprehensive and high-quality examination of the pertinent literature, bibliographic searches were conducted using the Scopus database, which is recognized for its extensive indexing of peer-reviewed journals in the fields of energy, engineering, and applied sciences. By systematically analyzing how these concepts are defined, operationalized, and contextualized across various academic disciplines, this study aims to elucidate conceptual boundaries, identify overlaps and inconsistencies, and provide a structured foundation for the coherent application of anticipatory and forecasting approaches in energy research and practice.

The search was conducted within the TITLE-ABS-KEY fields employing two complementary keyword groups. The first group focused on future-oriented and anticipatory methodologies in the energy sector, including terms such as energy horizon scanning, energy environmental scanning, energy foresight, energy trend analysis, energy monitoring, and future watching. Conversely, the second group emphasized conventional predictive terminology, which included energy forecasting, energy prediction, energy assessment, and energy mapping. This dual approach was designed to capture both qualitative scanning-based methodologies and quantitative forecasting-oriented studies effectively. The search strategy and selection criteria, along with keyword groups, are shown in **Tables 1** and **2**.

Table 1. Search strategy and selection criteria.

Component	Description
Database	Scopus
Search fields	TITLE-ABS-KEY
Core focus	Energy monitoring, scanning, foresight, and forecasting
Time span	2015–2025
Document type	Journal articles (final stage)

Table 1. *Cont.*

Component	Description
Language	English
Subject areas	Energy (ENER), Engineering (ENGI), Mathematics (MATH)

Table 2. Search keyword groups.

Groups	Keywords
Energy scanning & foresight	energy horizon scanning, energy environmental scanning, energy foresight, energy strategic scanning, future watching
Trend & monitoring	energy trend analysis, energy trend monitoring, energy monitoring
Forecasting-related	energy forecasting, energy prediction, energy assessment, energy mapping

To achieve comprehensive methodological reproducibility, the search was conducted within the Scopus database utilizing explicit Boolean logic across the relevant fields. It is essential to acknowledge that the Scopus database was last accessed on 26 February 2026. Furthermore, no additional databases, registries, websites, organizational sources, or reference lists, which could potentially compromise the integrity of the search mechanism, were consulted during this process. The selection of studies was conducted collectively by all authors. Initially, records were screened based on their titles, abstracts, and indexed keywords in accordance with the predefined eligibility and exclusion criteria. Subsequently, potentially relevant records were evaluated at the full-text level. As this review utilized a conceptual framework rather than a clinical evidence-synthesis approach, no automated screening tool was employed. The primary retrieval query string was developed by integrating the keyword groups delineated in **Table 2** with applicable field tags, language restrictions, subject area considerations, and document type filters, which specifically limit the results to peer-reviewed journal articles. The exact primary query string executed is as follows:

TITLE-ABS-KEY (("energy horizon scanning" OR "energy environmental scanning" OR "energy foresight" OR "energy strategic scanning" OR "future watching" OR "energy trend analysis" OR "energy trend monitoring" OR "energy monitoring" OR "energy forecasting" OR "energy prediction" OR "energy assessment" OR "energy mapping")) AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND DOCTYPE (ar) AND PUBSTAGE (final) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "ENER") OR LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "MATH"))

The execution of this primary query string yielded a baseline corpus consisting of 10,394 articles and 21,364 distinct keywords. The search components, as outlined in **Table 1**, were constrained to journal articles published between 2015 and 2025. These articles were required to be written in English and indexed within the subject areas of Energy, Engineering, or Mathematics. Only articles in their final stages were included to guarantee the maturity and comprehensiveness of the reported research. To sustain a focused conceptual framework emphasizing strategic and anticipatory perspectives, studies predominantly concentrated on technical simulation, optimization, machine learning models, and component-level energy systems—such as wind turbines and solar radiation—or on building-scale applications, were carefully evaluated using keyword-based filters. In the initial stream of research, these technically oriented, machine-learning-based studies were intentionally reintegrated and analyzed independently to scrutinize their terminological structure and methodological predominance. Conversely, in the second stream, studies chiefly focused on technical simulation, optimization, and machine learning-based forecasting models, along with other methodologies, were excluded to direct attention toward strategic, foresight-oriented, and conceptual energy research. This dual-layer approach facilitated a comparative evaluation between anticipatory energy research and the literature on data-driven predictive modeling. The resulting dataset was then subjected to rigorous conceptual coding and comparative analysis to investigate the definitions, operationalizations, and applications of various scanning- and forecasting-related terminology within the energy literature. For the conceptual analysis, information was systematically extracted from the selected studies concerning terminology, definitions, methodological orientation, operationalization, application context, temporal perspective, and the interrelationships among monitoring, scanning, foresight, and forecasting. The extracted data were organized into a structured coding framework and subsequently compared across the studies to identify conceptual overlaps, distinctions, and terminological inconsistencies. A conventional risk-of-bias assessment was not conducted because

the aim of this review was to analyze terminology, conceptual boundaries, methodological orientations, and patterns of application, rather than to evaluate the effectiveness of interventions or causal effects. However, study selection and conceptual coding were carried out according to predefined criteria to reduce subjective selection and interpretation. No statistical effect measures were calculated, as the review did not involve a quantitative synthesis of intervention effects or any comparable outcome measures. The intentional exclusion of studies that are primarily technical and model-driven was a deliberate choice, as the aim of this review is to elucidate the conceptual and terminological frameworks rather than to evaluate forecasting algorithms. The important examples of exclusion criteria are presented in **Table 3**.

Table 3. Examples of exclusion criteria.

Exclusion Category	Example
Pure simulation and modeling	simulation, optimization, performance
AI/ML-focused	neural networks, LSTM, deep learning
Component-level energy	wind turbines, solar radiation, battery
Non-strategic domains	buildings, housing, manufacturing

According to **Table 3**, to ensure conceptual coherence and maintain analytical focus, studies primarily concerned with short-term technical forecasting, machine learning algorithms, artificial intelligence, neural networks, or numerical simulations—such as wind speed prediction and solar irradiance estimation—were excluded from the final conceptual analysis. While some of these terms may appear in preliminary bibliometric keyword networks, their presence signifies the broader energy literature’s intersection with data-driven modeling approaches rather than a direct engagement with strategic energy scanning or foresight. Therefore, to differentiate strategic and anticipatory concepts from purely technical or micro-level engineering studies, the exclusion criteria presented in **Table 3** were applied. When operationalized directly within the database using negation operators (AND NOT), the refined query string integrates the excluded domain keywords as outlined:

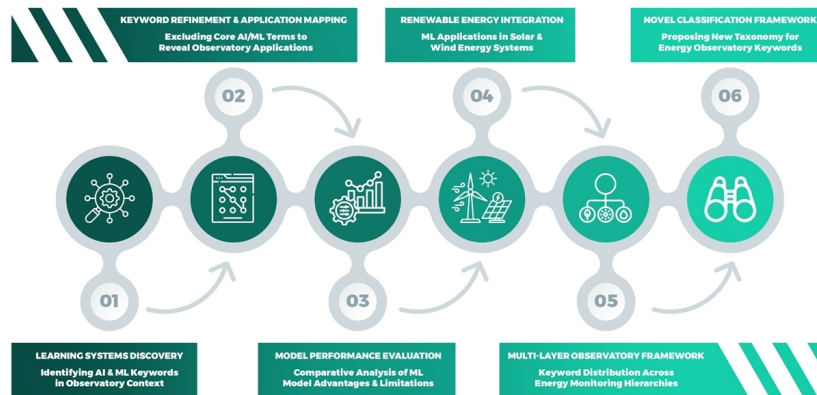
TITLE-ABS-KEY ((“energy horizon scanning” OR “energy environmental scanning” OR “energy foresight” OR “energy strategic scanning” OR “future watching” OR “energy trend analysis” OR “energy trend monitoring” OR “energy monitoring” OR “energy forecasting” OR “energy prediction” OR “energy assessment” OR “energy mapping”)) AND NOT TITLE-ABS-KEY (“neural networks” OR “LSTM” OR “deep learning” OR “wind turbines” OR “solar radiation” OR “battery” OR “buildings” OR “housing” OR “manufacturing”) AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND DOCTYPE (ar) AND PUBSTAGE (final) AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO (SUBJAREA, “ENER”) OR LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “MATH”))

This multi-stage process of retrieval and filtering effectively ensured both the empirical comprehensiveness of the bibliometric mapping and the necessary thematic focus for qualitative conceptual coding.

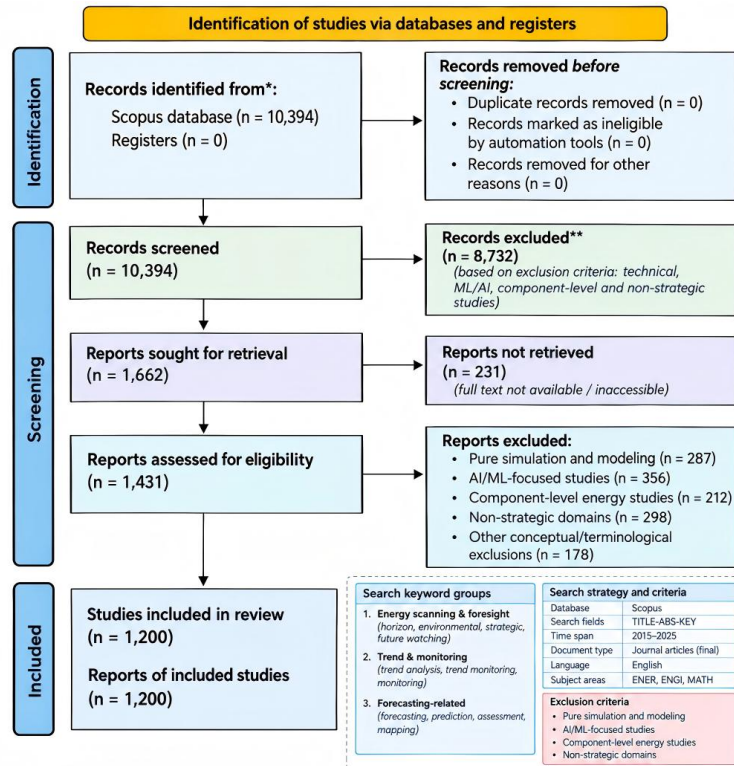
Figure 1 illustrates the structured methodological workflow that guides this research. The process initiates with the identification of AI and ML-related keywords within both the observatory and energy forecasting contexts, designated as Step 1. This is followed by Step 2, which involves refining keywords by excluding core AI/ML terms and general learning systems, thereby revealing application-oriented dimensions that focus on energy scanning and foresight contexts. Subsequently, Step 3 entails a bibliometric analysis of energy forecasting terminology, both with and without learning systems. This phase focuses on evaluating model performance and comparative advantages to understand methodological dominance, with particular attention to various ML methods and their applications in renewable energy. The framework then maps ML applications specifically to renewable energy systems, emphasizing solar and wind, which are the most frequently addressed sources requiring future forecasting, as outlined in Step 4. In Step 5, the framework organizes keyword distributions across the monitoring and energy management hierarchies, where energy monitoring is categorized into layers. The analysis culminates in the development of a novel multi-layer classification framework for energy observatory terminology, determining which terminology is best suited for each layer. Finally, Step 6 ensures a sequential design that promotes conceptual clarity, methodological rigor, and a systematic transition from bibliometric exploration to taxonomy development. This step also aims to explore the implications of energy forecasting concepts, identifying key issues, main insights from the study, and practical implications. Therefore, the eligibility of studies for each analytical phase was determined in accordance with the established methodological framework. The comprehensive baseline corpus retrieved from Scopus

was maintained for the initial bibliometric mapping to elucidate the broader terminological landscape. Thereafter, the predefined exclusion criteria were implemented to create a refined corpus for conceptual analysis. Studies primarily focused on technical simulations, machine-learning algorithms, component-level energy systems, or non-strategic domains were systematically excluded from the conceptual synthesis.

Figure 1b presents a comprehensive summary of the literature identification, screening, eligibility assessment, and the workflow for conceptual study selection employed in this review. This PRISMA workflow encompasses the initial retrieval from Scopus, a bibliometric baseline analysis, the application of established exclusion criteria, and the subsequent conceptual coding of the literature that was retained. Additionally, it delineates the three complementary groups of keywords and the primary search and eligibility restrictions utilized to establish a consistent and reproducible evidence base. The systematic review details are available in the Supplementary Materials.



(a)



(b)

Figure 1. (a) Methodological workflow illustrating the six-step analytical framework adopted in this study; (b) Systematic PRISMA workflow for literature identification, screening, eligibility assessment, and conceptual study selection.

3. Results and Discussion

This section commences with a thorough bibliometric analysis to provide an in-depth understanding of the relevant keywords. The subsequent objective is to establish the interrelationships among these keywords and to analyze their precise definitions and applications.

3.1. Bibliometric Overview of Energy Scanning and Forecasting Literature

Using the proposed methodological framework, a bibliometric analysis was conducted with the Bibliometrix package in RStudio (version 4.5.1). This analysis served as a complementary and exploratory phase to support the systematic conceptual review. The bibliometric procedures concentrated on examining keyword frequency distributions and constructing keyword co-occurrence networks to investigate the prevalence, interrelationships, and thematic clustering of key terms within the selected corpus of literature. These quantitative mappings were used as an exploratory basis for the subsequent qualitative conceptual synthesis rather than as an independent evidence-synthesis endpoint. Rather than functioning as an independent analytical objective, the bibliometric analysis provided an empirical overview of terminological usage patterns, which subsequently informed and validated the qualitative conceptual coding of concepts related to energy scanning, foresight, and forecasting. The collected records and indexed keywords were standardized and assessed for terminological consistency. The occurrences and co-occurrence relationships of keywords were analyzed utilizing the Bibliometrix package. Subsequently, conceptually related terms were interpreted and categorized during the qualitative coding phase. As established in the initial retrieval search, the bibliometric mapping was conducted on a comprehensive pre-exclusion corpus comprising 10,394 articles and 21,364 indexed keywords. This approach allowed us to map the entire terminological landscape and empirically demonstrate the macro-level dominance of literature in both data-driven forecasting and pure energy mapping, as well as various learning-based and modeling techniques. Following this, we refined our analytical focus for the subsequent qualitative conceptual review by narrowing the query string (refer to **Table 3**). **Figure 2** illustrates the distribution of published articles per year within this complete dataset.

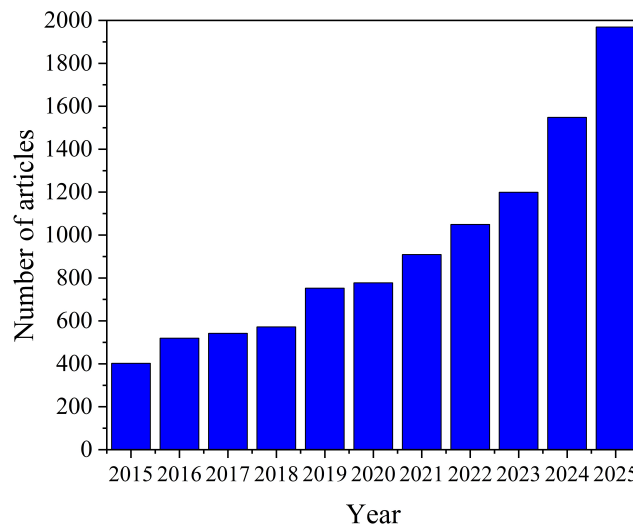


Figure 2. Annual scientific production.

Figure 2 presents the annual publication trajectory within the baseline dataset across the 10-year study period from 2015 to 2025. As illustrated, scientific production has increased significantly, rising from approximately 400 articles in 2015 to nearly 2,000 by 2025. This represents a substantial compound annual growth rate of 21.36%. Such a pronounced upward trend indicates a growing scholarly emphasis on quantitative energy monitoring and algorithmic learning-based modeling.

Figure 3a illustrates the thematic structure of the literature with a specific focus on prediction-oriented methods and learning systems. The prominence of keywords such as forecasting, energy utilization, machine learning, and energy prediction signifies a pronounced methodological focus on data-driven modeling and algorithmic

approaches. The frequent occurrence of machine learning and deep learning underscores the crucial role of advanced computational techniques in contemporary energy forecasting research. Additionally, terms such as energy mapping and energy monitoring indicate an operational emphasis on spatial-temporal analysis and system-level observability. Overall, this analysis highlights a technically rigorous research domain in which predictive accuracy and model development serve as the primary motivating factors. In contrast, **Figure 3b** illustrates the distribution of keywords following the exclusion of prediction methodologies and terms related to learning systems, thereby unveiling a more application-oriented and policy-driven perspective. Although forecasting and energy utilization remain significant, there is a marked increase in emphasis on energy management, energy assessment, renewable energy, and energy monitoring. This evolution suggests that, in the absence of explicit modeling techniques, the literature tends to focus more on system evaluation, decision-making, and sustainability-oriented themes. The comparison between panels (a) and (b) highlights a distinct conceptual divergence: studies centered on prediction are primarily method-focused and computationally driven, whereas non-predictive studies prioritize strategic assessment, management, and the practical applications of energy systems. Collectively, the figures illustrate how methodological choices influence the intellectual framework and research priorities within the field of energy studies.

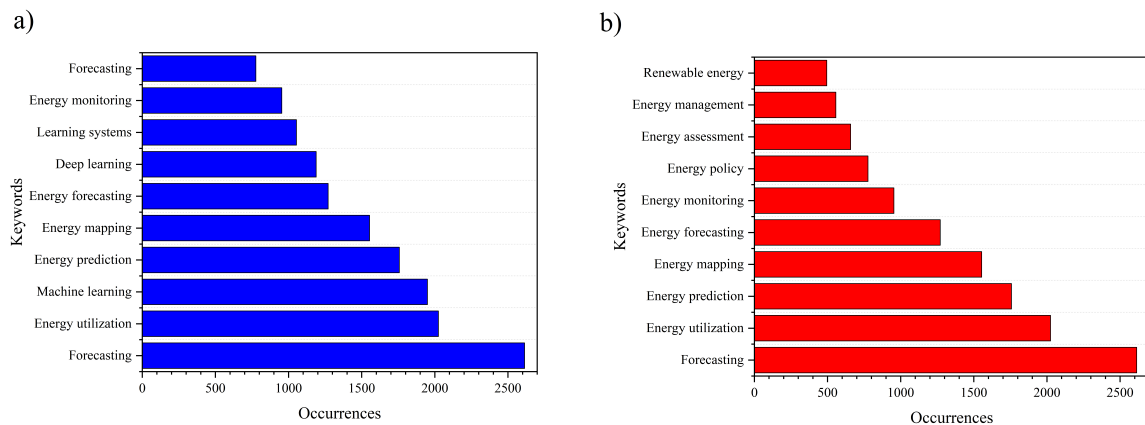


Figure 3. Most frequent words (a) Incorporating prediction methods and learning systems; (b) Energy-related studies excluding prediction and learning-based methods.

To quantitatively support the observed conceptual divergence between panels (a) and (b), **Table 4** classifies the core keywords into three principal thematic clusters.

Table 4. Counts and relative frequencies of key thematic clusters based on keyword occurrences.

Thematic Cluster	Key Terms Included in the Cluster	Occurrences (Count)	Share of Total (%)
Data-Driven & ML Forecasting	Machine learning, Deep learning, Learning systems	4,200	34.3%
General Predictive Modeling	Forecasting, Energy prediction, Energy forecasting	5,600	45.7%
Strategic Assessment & Policy (Foresight proxies)	Energy policy, Energy assessment, Energy management, Renewable energy	2,450	20.0%
Total Analyzed Core Keywords	-	12,250	100%

According to the analysis presented in **Table 4**, examining the occurrence counts and relative frequencies reveals a notable methodological bias in the existing literature. The data indicate that general predictive modeling terminology serves as the baseline, accounting for 45.7% of the analyzed occurrences. Additionally, specific data-driven and machine learning methodologies, including terms such as “machine learning,” “deep learning,” and “learning systems,” account for 34.3% of the thematic focus. In contrast, the cluster that includes strategic assessment, management, and policy, which are the closest thematic proxies for strategic foresight and technology scanning in this bibliometric study, comprises a distinctly smaller portion at precisely 20.0%. This quantitative breakdown clearly substantiates the assertion that contemporary energy studies are predominantly oriented towards algorithmic predictive accuracy and data-driven methodologies, which collectively account for approximately 80%

of the discourse, while underrepresenting strategic scanning, qualitative foresight, and long-term policy assessment. It is important to emphasize that the occurrence counts presented in **Table 4** pertain specifically to the high-frequency core keywords identified through the thematic network analysis (as illustrated in **Figure 3**). These counts do not encompass the complete set of 21,364 raw keywords extracted from the overarching dataset.

To rigorously assess the robustness of the proposed conceptual framework, an expanded post hoc sensitivity analysis was conducted using a randomly selected, representative subset of the excluded literature. Specifically, the validation sample was scaled up to encompass 200 scholarly articles focused on machine learning that were initially excluded due to their exclusive emphasis on short-term predictive algorithmic optimization. These articles were systematically evaluated against our proposed taxonomy. The expanded analysis definitively demonstrated that all sampled articles inherently aligned with the traditional 'Forecasting' layer. They exhibited a significant reliance on historical data continuity and lacked mechanisms for qualitative horizon scanning or out-of-distribution shock analysis. Consequently, the integration of this substantially larger sample of purely machine-learning-driven articles did not alter the conceptual boundaries of our taxonomy. Rather, it robustly reinforced the distinct epistemological differentiation between data-driven forecasting and strategic foresight, thereby confirming the statistical stability and reliability of the proposed conclusions.

Figure 4 illustrates the keyword co-occurrence, known as a word cloud, to visualize the most frequent keywords.

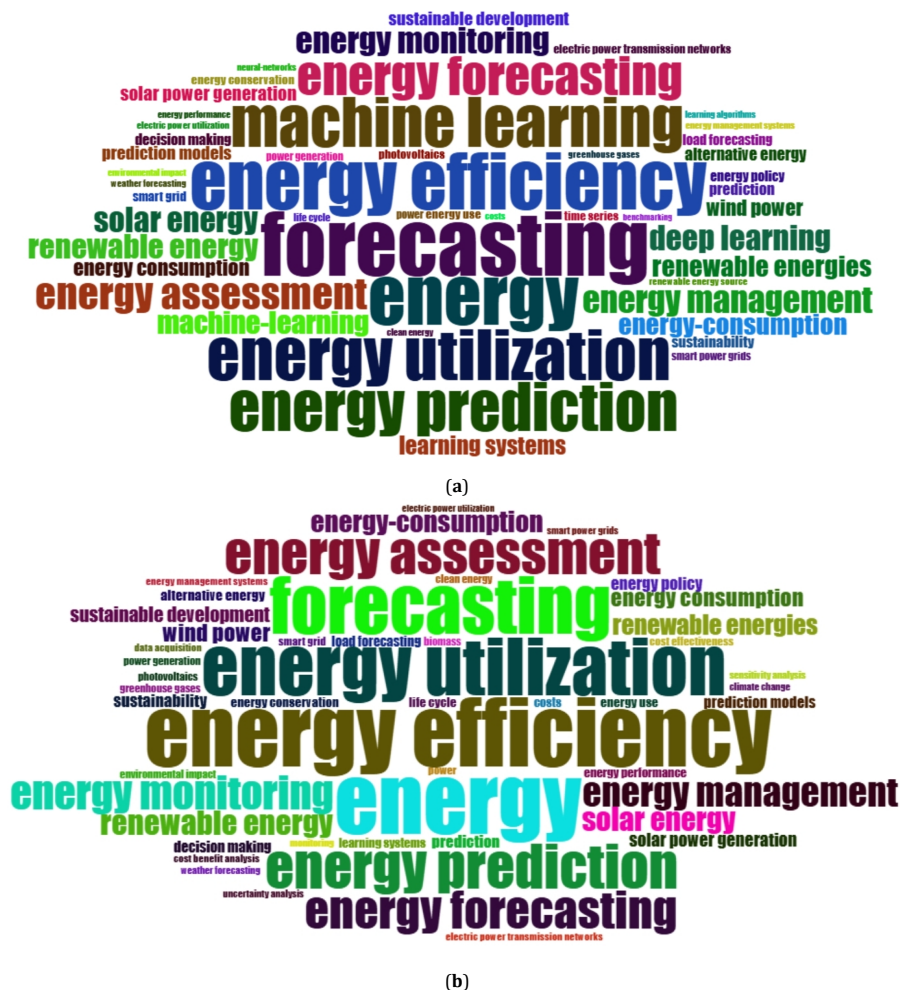


Figure 4. Word co-occurrence visualization (word cloud) (a) Incorporating prediction methods and learning systems; (b) Energy-related studies excluding prediction and learning-based methods.

Figure 4a illustrates keyword co-occurrence visualization and the conceptual framework of the literature in

which learning systems are explicitly addressed. The prevalence of terms such as machine learning, deep learning, energy forecasting, and energy prediction demonstrates a significant methodological inclination towards data-driven and algorithmic strategies. These terms are intricately associated with application-oriented concepts, including energy efficiency, energy utilization, energy management, and renewable energy, emphasizing the pivotal role of learning systems in connecting predictive modeling with operational energy objectives. The coexistence of time series analysis, prediction models, smart grid technology, and load forecasting further underscores a concentrated focus on high-resolution, dynamic energy systems, where uncertainty, variability, and real-time decision support constitute central research challenges. Collectively, this word cloud delineates a technologically advanced research domain in which learning-based methodologies facilitate improved forecasting, optimization, and system intelligence. Associated terms such as renewable energy, solar energy, wind power, and photovoltaics signify that forecasting research is predominantly applicable to renewable energy systems, where variability and uncertainty present inherent challenges. Simultaneously, the co-occurrence of terms including energy monitoring, energy management, energy policy, and sustainable development reveals an expanding conceptual framework that extends beyond mere short-term predictions to encompass system-level assessments, informed decision-making, and sustainability-oriented planning. This trend indicates a developing convergence between sophisticated forecasting techniques and comprehensive energy management and policy strategies. In contrast, **Figure 4b** delineates the thematic landscape after excluding learning systems and prediction-oriented methodologies. While forecasting remains a visible element, the focus transitions toward system-level and evaluative concepts, including energy efficiency, energy utilization, energy assessment, energy management, and energy consumption. The prominence of renewable energy, sustainable development, life cycle considerations, costs, and energy policy indicates a stronger alignment with planning, policy analysis, and sustainability assessment rather than with methodological innovation. The diminished presence of computational terminology suggests that forecasting within this context is predominantly conceptual or scenario-based, relying on aggregated indicators and analytical frameworks rather than on advanced algorithms. Collectively, this comparison elucidates a clear conceptual bifurcation: learning-based studies prioritize predictive capabilities and system intelligence, whereas non-learning studies concentrate on assessment, governance, and strategic energy planning. This distinction highlights the complementary roles of data-driven forecasting and conceptual energy scanning in advancing comprehensive energy foresight research.

Figure 5 presents a keyword co-occurrence map illustrating the relationship between keywords and their applications.

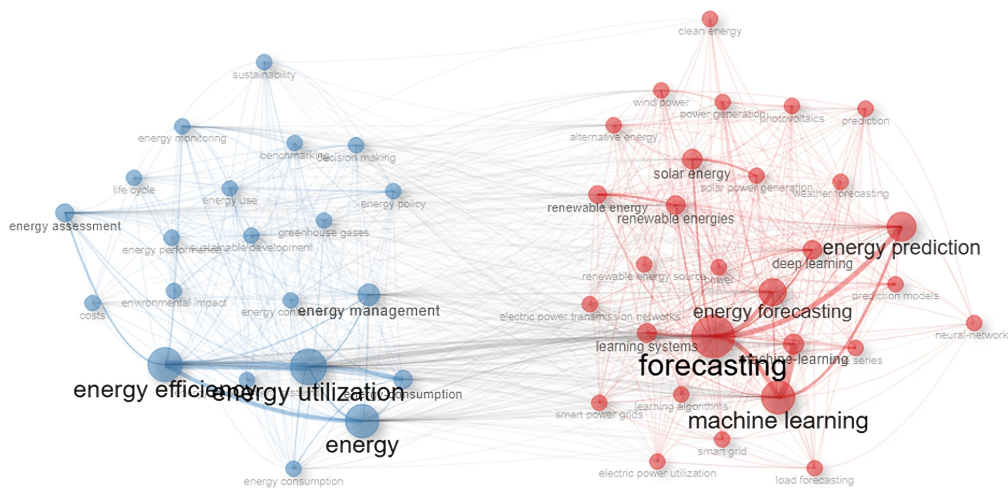


Figure 5. Keyword co-occurrence map.

According to **Figure 5**, the co-occurrence analysis identifies two distinct conceptual clusters that reflect a fundamental bifurcation in the energy literature between data-driven forecasting paradigms and strategic energy management and monitoring frameworks. Cluster 1, which is predominately focused on keywords such as energy forecasting, energy prediction, machine learning, deep learning, time series analysis, load forecasting, and

renewable energy, constitutes a technically oriented, model-driven research stream. Within this cluster, energy forecasting and machine learning are recognized as the most influential nodes, exhibiting strong connections to application-specific terms such as solar energy, wind power, photovoltaics, smart grids, and weather forecasting. This dense interconnectivity signifies a prevailing emphasis on predictive accuracy, algorithmic advancement, and short- to medium-term operational forecasting for renewable energy and power systems. In contrast, Cluster 2 is organized around broader strategic and systemic concepts, with energy monitoring, energy management, energy efficiency, and energy policy serving as central components. These terms are intricately linked to sustainability, energy consumption, decision-making processes, environmental impact, life cycle assessments, and greenhouse gas emissions. This indicates a research stream focused on long-term performance evaluation, policy assessment, and sustainability-oriented planning. The observed weaker direct connections between the clusters suggest that, although forecasting outputs are becoming increasingly accessible, their incorporation into strategic energy monitoring, policy formulation, and management frameworks remains limited. This separation highlights the conceptual gap that underpins the current review: the need to reconcile advanced forecasting methodologies with anticipatory, monitoring, and decision-support approaches to facilitate coherent, future-oriented governance of energy systems.

Figure 6 illustrates a thematic map showing the distinct structural dominance of machine learning-based forecasting in the landscape of energy research.

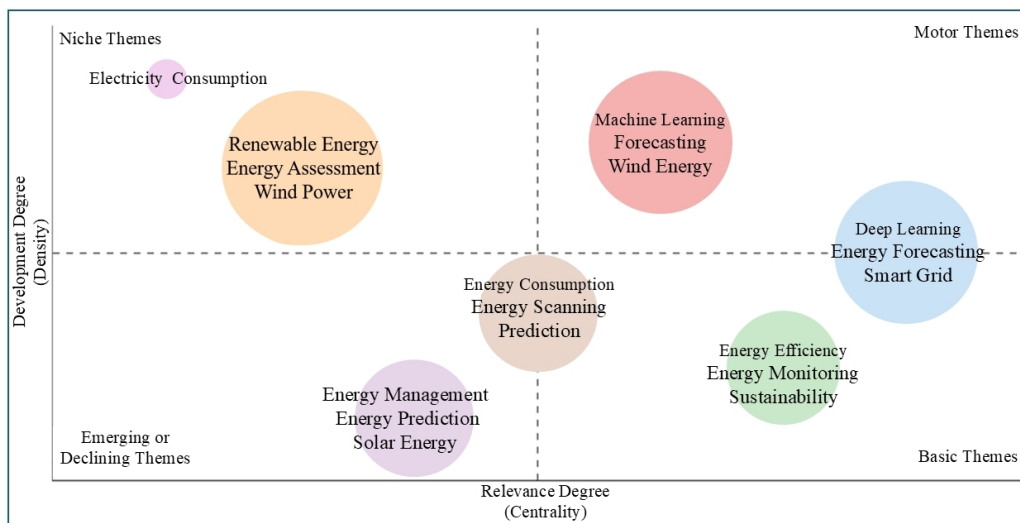


Figure 6. Thematic map and concepts diversity distribution.

According to **Figure 6**, the thematic map shows a clear structural dominance of machine learning-based forecasting in the energy research landscape. The cluster encompassing machine learning, forecasting, and wind energy is situated in the motor themes quadrant, signifying both high centrality and robust internal development. This positioning reflects the methodological maturity of these themes and their fundamental role in the field. Additionally, energy forecasting, deep learning, and smart grid are identified as highly central basic themes, further validating the significance of data-driven predictive paradigms. In contrast, themes associated with energy efficiency, monitoring, and sustainability occupy less densely developed positions, while broader strategic or foresight-oriented concepts are conspicuously absent from the motor quadrant. This structural imbalance underscores the predominant emphasis on predictive modeling over anticipatory and governance-oriented perspectives, thereby empirically supporting the necessity for the layered conceptual clarification proposed in this study. In general, data-driven forecasting paradigms predominantly characterize the energy research landscape, while broader anticipatory and strategic concepts remain comparatively less prominent. Furthermore, the thematic map illustrates a significant dominance of machine learning-based forecasting within this domain, which is positioned as a motor theme due to its high centrality and density. In contrast, themes related to sustainability and monitoring occupy fundamental yet less densely developed positions. Notably, broader anticipatory or foresight-related terms are absent from the motor quadrant. This structural disparity underscores the necessity for terminological clarification and nuanced

conceptual differentiation as proposed in this study.

The absence of, or low visibility of, various anticipatory and scanning-related terms in the bibliometric analysis does not imply that they are irrelevant. Instead, it points to the dominance of data-driven forecasting methods in energy research and underscores a conceptual gap that this review aims to address.

The analysis presented in **Figure 7a** illustrates a marked disparity in the global distribution of research publications, revealing a concentration of scholarly output primarily in Asia, North America, and certain regions of Europe. Notably, China is identified as the leading contributor to this body of work, followed by the United States and India. This trend indicates that large, rapidly growing energy markets are significantly influencing research, particularly in data-driven forecasting and renewable energy systems. Additionally, Western European nations—including the United Kingdom, Italy, Spain, and Germany—exhibit considerable contributions to this field, underscoring their longstanding commitment to research in energy transition and sustainability. In contrast, the contributions from Africa and portions of South America remain relatively limited, indicating potential regional disparities in research capacity and investment. Furthermore, Iran, Turkey, and Saudi Arabia emerge as notable contributors within the Middle East, reflecting an increasing engagement in energy forecasting and renewable energy research. Their involvement accentuates the emerging strategic significance of energy research for economies that are both developing and exporting energy resources, particularly concerning their diversification and sustainability initiatives.

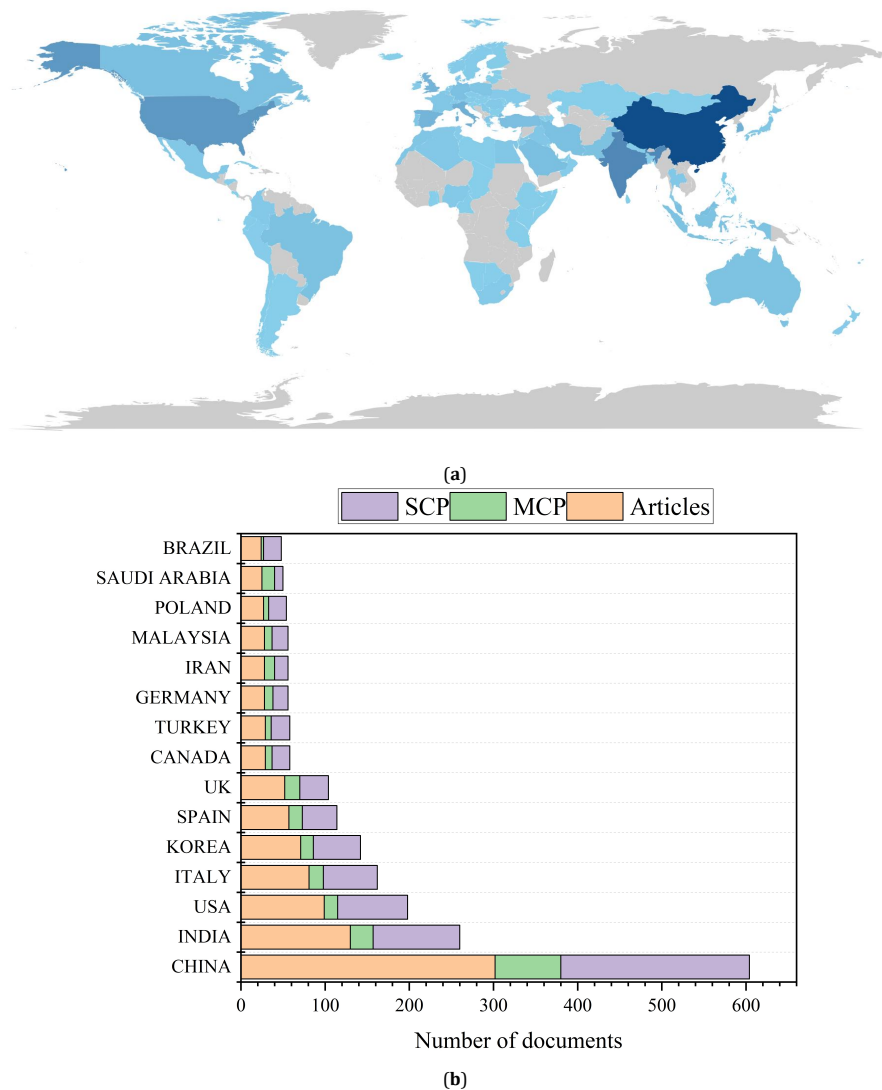


Figure 7. Global view (a) Global distribution of publications in energy forecasting research, (b) Country production by Single Country Publications (SCP) and Multi-Country Publications (MCP).

According to **Figure 7a**, the analysis of country-specific production indicates that SCP significantly outnumber MCP across almost all contributing nations, reflecting a predominantly domestic research focus in energy forecasting and related disciplines. China stands out as a leader in total research output, holding a substantial share of SCP, which underscores a highly autonomous and internally cohesive research ecosystem. The United States and India also demonstrate robust publication volumes; however, they similarly exhibit a pronounced predominance of SCP over MCP. This suggests that, although international collaboration exists, the primary impetus for research capacity remains rooted in national capabilities. European countries such as the United Kingdom, Italy, and Spain exhibit relatively higher proportions of MCP compared to Asian nations, suggesting a stronger integration into international research networks. This integration is likely supported by collaborative frameworks prevalent in Europe. In the Middle East, Iran demonstrates significant research output; however, it is characterized by a predominance of SCP, indicating limited international collaboration despite a developing domestic research capacity. Turkey presents a more balanced profile, though SCP still prevails, reflecting moderate rather than extensive global integration. Although Saudi Arabia produces fewer publications overall, it maintains a relatively notable share of MCP in its output, indicating a strategic reliance on international partnerships to enhance research visibility and capability. In summary, the SCP-MCP structure indicates that energy forecasting research remains predominantly nationally concentrated, with international collaboration playing a secondary yet increasingly significant role.

3.2. Conceptual Review and Terminology Analysis

3.2.1. Interpretation of Bibliometric Keyword Results

Energy forecasting is a vital element of power system operation and planning, with earlier research focusing on accurately predicting energy demand to enhance system reliability and economic efficiency [21]. Hyndman and Fan [22] evaluated the annual and weekly peak electricity demand distribution for South Australia since 2007, comparing it with actual demand data from the summer of 2007–2008. They forecasted demand distributions using temperature simulations, future economic scenarios, and residual bootstrapping techniques. Taylor and McSharry [23] evaluated short-term load-forecasting methods using real-world data from 10 European countries. They found that no single model consistently outperformed others, highlighting the need for model selection based on data characteristics and forecasting horizons. While the new alternative exponential smoothing method and periodic AR model performed poorly, the autoregressive integrated moving average (ARIMA) and principal component analysis (PCA) methods did well. The double seasonal Holt-Winters exponential smoothing method emerged as the best performer overall. Hippert et al. [24] provide one of the earliest comprehensive reviews of neural-network-based forecasting, demonstrating that machine learning techniques can better capture nonlinear relationships in electricity demand than traditional statistical models. Recent studies further expand this approach to renewable-rich energy systems. Benti et al. [25] demonstrate that traditional forecasting methods have limitations; therefore, machine learning (ML) and deep learning (DL) algorithms have become popular due to their capability to learn complex relationships from data and provide accurate predictions. Kumar et al. [26] utilize AI techniques like DL, ML, and neural networks to improve wind energy generation predictions. Their findings indicate a 15% increase in accuracy with the AI-based wind power forecasting (WPF) system compared to traditional methods, based on cross-validation using historical data. Mucomole et al. [27] systematize the parametric forecasting of solar energy and validate the estimates using machine learning models. They focused on studies with thorough analyses and validation while noting that interpolation models can effectively extrapolate over short scales, though significant investment is needed for land energy forecasting. Mosavi et al. [28] assert that hybrid machine learning (ML) models significantly enhance the accuracy, robustness, precision, and generalization capabilities of predictions in energy systems. This hybridization is especially effective for renewable energy systems, including solar, wind, and biofuels.

Table 5 provides a qualitative comparison of popular ML models for energy system forecasting applications, assessing model complexity, user-friendliness, accuracy, computational speed, and dataset type. It highlights the trade-offs between methodological sophistication and practical usability in energy forecasting and monitoring.

According to **Table 5**, traditional neural methodologies, such as Artificial Neural Networks (ANNs) and Multilayer Perceptrons (MLPs), achieve high predictive accuracy in energy forecasting. Nevertheless, these methodologies often encounter significant challenges related to model complexity and limited interpretability. Similarly,

Support Vector Machines (SVMs) and Wavelet Neural Networks (WNNs) achieve commendable accuracy; however, they are constrained by limited computational efficiency and lack user-friendliness, thereby limiting their applicability in large-scale or real-time energy-monitoring environments. In contrast, Decision Trees (DT) and Extreme Learning Machines (ELM) strike a favorable balance among accuracy, simplicity, and computational speed, making them suitable for exploratory energy assessment and monitoring. While deep learning and ensemble models offer improved performance in complex energy systems, they also introduce considerable complexity, exacerbating the gap between predictive accuracy and practical usability in strategic energy forecasting. Importantly, hybrid models present a promising solution by integrating high accuracy with improved efficiency and usability. Across all methodologies, there is a predominant reliance on historical datasets, underscoring the limitations of solely data-driven forecasting and highlighting the need to incorporate anticipatory, scanning-based approaches. These approaches are essential for effectively capturing emerging energy trends and systemic shifts. To further clarify these epistemological boundaries, **Figure 8** provides a conceptual mapping of statistical methods, machine learning, and foresight approaches, categorizing them by temporal horizon and reliance on historical data.

Table 5. Comparative study of ML models in energy systems [28].

ML Model	Complexity	User-Friendliness	Accuracy	Speed	Dataset Type
ANN	Reasonably high	Low	High	Reasonable	Historical
MLP	Reasonable	Reasonable	Reasonably high	High	Historical
ELM	Reasonable	Reasonably high	Reasonable	Reasonably high	Historical
SVM	Reasonably high	Low	High	Low	Historical
DT	Reasonable	Low	Reasonable	Reasonable	Historical
DL	High	Reasonable	High	Reasonable	Historical
Ensemble	High	Low	Reasonable	High	Historical
WNN	Reasonable	Low	High	Low	Historical
ANFIS	Reasonable	Reasonable	Reasonable	High	Historical
Hybrids	Reasonable	High	High	High	Historical

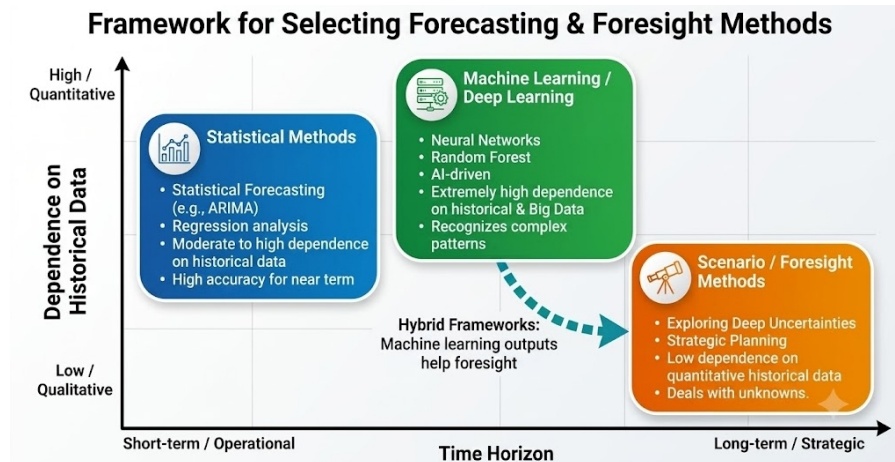


Figure 8. Conceptual mapping of anticipatory method classes against data dependence and time horizon.

As illustrated in **Figure 8**, anticipatory and forecasting methodologies occupy distinct spatial and epistemological positions when mapped against their temporal horizons and dependence on historical data. Statistical methods rely heavily on historical datasets, making them robust and accurate for short-term operational applications. In contrast, machine learning and deep learning models exhibit the greatest degree of data dependence, using extensive historical data to identify complex, non-linear patterns predominantly in short- to medium-term contexts. However, their retrospective nature limits their ability to address long-term structural changes or policy-driven disruptions independently. Conversely, scenario and foresight methodologies are situated within the long-term strategic domain and exhibit low dependence on quantitative historical data, instead concentrating on navigating deep uncertainties and exploring alternative future scenarios. Importantly, the conceptual bridge established by hybrid frameworks—where data-driven outputs from machine learning inform qualitative foresight processes—

underscores the complementary nature of these methodologies and highlights the necessity of a multi-layered anticipatory architecture.

Precise forecasting of wind speed is crucial for integrating volatile wind power into the grid, reducing the need for energy control, battery loading strategies, and reserve planning. ML models can predict wind speeds from seconds to hours, which is essential for energy grid balancing. The total power collected by wind turbines in a wind farm depends on factors such as location, hub height, and season. **Table 6** summarizes some papers in this field.

Table 6. Notable ML models in wind energy systems prediction.

Year	Reference	ML Model	Application
2017	Cornejo-Bueno et al. [29]	SVR, MLP and ELM, GPs, ERA-Interim reanalysis	Accurate prediction of Wind Power Ramp Events
2017	Mana et al. [30]	Hybrids of ANNs	Accurate wind power forecast
2018	Khosravi et al. [31]	MLP, SVR, fuzzy inference system, ANFIS, and group model of data handling	Prediction of wind speed data for Osorio wind farm
2018	Pandit and Infield [32]	Hybrid of GP	Predictive condition monitoring
2018	Sharifian et al. [33]	PSO, the Type-2 fuzzy NN	The wind power accurate forecasting
2021	Chandran et al. [34]	LSTM, GRU, and RNN	Short-term wind power forecasting
2022	Ren et al. [35]	Interval type-2 fuzzy	Short-term wind speed forecasting
2022	Alkesaiberi et al. [36]	GPR, SVR, Boosted trees, and Bagged trees	wind power forecasting for intermittency and variability of wind energy in smart grids
2022	Al-qaness et al. [37]	ANFIS, SVM, LSTM, and FFNN	Wind power forecasting
2022	Gu et al. [38]	FCM, WOA, ELM, and GMM	Short-term wind power forecasting for power grids
2022	Li et al. [39]	Hybrids of ANN, PSO, VMD, and Bi-LSTM	Typhoon wind speed prediction for turbines protection
2024	Hallgren et al. [40]	Random forest and hybrids of ANNs	Coastal wind speed prediction in offshore wind energy
2024	Bilgili and Gül [41]	Random Forest, Decision Trees, K-Nearest Neighbors, and XGBoost	Short-term wind turbine power generation forecasting
2022	Wen et al. [42]	KHC, SVD, and SVR	Wind power forecasting framework

Cornejo-Bueno et al. [29] evaluated various machine learning regression techniques to predict Wind Power Ramp Events (WPRES) using atmospheric reanalysis data. Their results showed that Multi-Layer Perceptron (MLP) models delivered strong predictive capability. Mana et al. [30] compared a standalone Artificial Neural Network (ANN) with a hybrid model using Supervisory Control and Data Acquisition (SCADA) data. While the hybrid model excelled at predicting high and low wind speeds, the standalone ANN performed better in medium ranges. Optimal outcomes were achieved at Numerical Weather Prediction heights of 100 m and 200 m. Khosravi et al. [31] developed models using a group method of data handling-type neural network, an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized by algorithms such as ant colony optimization, particle swarm optimization, and genetic algorithms, and a multilayer feed-forward neural network. The models factored in day, month, average air temperature, minimum and maximum temperatures, air pressure, wind speed, relative humidity, latitude, longitude, and top-of-atmosphere insolation, with the group method of data handling-type neural network proving to be the most effective. Pandit and Infield [32] applied a Gaussian Process algorithm to SCADA data for predictive condition monitoring. This approach estimated operational curves accurately, helping identify critical component failures and reduce maintenance costs. Sharifian et al. [33] proposed a fuzzy neural network model to forecast wind power under uncertain conditions using a particle swarm optimization algorithm. The model leverages neural network learning and fuzzy system expertise and was validated against a real wind farm. Chandran et al. [34] explore deep learning models for short-term wind power forecasting using time-series wind speed data. They evaluate Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) architectures across different forecasting horizons. The results show that these techniques effectively capture temporal dependencies in wind power generation, making them suitable for both existing and prospective wind farm sites for pre-installation assessments and operational forecasting. Ren et al. [35] conduct an interval type-2 fuzzy logic model for short-term wind speed forecasting that emphasizes accuracy while reducing model complexity. A two-stage fuzzy curve method is used to select the most informative input variables, followed by a Gaussian membership function with a variable center and recursive least squares parameter identification. Case studies from a wind farm in Colorado demonstrate that the proposed model outperforms type-1 and conventional type-2 fuzzy models, offering improved robustness and generalizability. Alkesaiberi et al. [36] develop ML models for wind power forecasting to tackle the variability of wind energy in smart grids. They use Bayesian optimization to enhance Gaussian Process Regression (GPR), Support Vector Regression (SVR), and ensemble models, incorporating lagged inputs and meteorological variables. Validation with real wind turbine data from France, Turkey, and Kaggle shows

that optimized GPR and ensemble models achieve superior forecasting performance, underscoring the importance of hyperparameter tuning and dynamic inputs for wind power predictions. Al-qaness et al. [37] propose an enhanced ANFIS framework for wind power forecasting, optimized using a modified Marine Predator Algorithm with mutation operators (MPAmu). This approach enhances parameter tuning and reduces the risk of premature convergence, thereby improving predictive accuracy. Validation with real wind turbine data from France indicates that the MPAmu-ANFIS model outperforms conventional ANFIS, various metaheuristic variants, and established machine learning models, such as SVM, Feedforward Neural Networks (FFNN), and LSTM networks. Gu et al. [38] highlighted that accurate short-term wind power forecasting is essential for the safe and efficient operation of power grids, particularly with large-scale wind energy integration. They introduced the FCM-WOA-ELM-GMM method, which enhances forecasting accuracy by using Fuzzy C-means (FCM) clustering to process meteorological and wind farm data. The Whale Optimization Algorithm (WOA) optimizes the input weights and hidden layer thresholds of the ELM, improving both speed and accuracy. Comparative analyses showed that the WOA-ELM model achieved the lowest RMSE values for 4-h, 24-h, and 72-h forecasting intervals, indicating superior accuracy across various conditions. Due to the highly variable and nonlinear nature of typhoon winds, their speed prediction is vital for optimizing wind power generation and protecting turbines. Li et al. [39] employ one-year wind data from a Chinese wind farm and introduce a hybrid model combining a physical model with an ANN approach. The proposed PSO-VMD-Bi-LSTM method decomposes wind speed data using Variational Mode Decomposition (VMD) and optimizes the Bi-LSTM model with Particle Swarm Optimization (PSO). The results show that Hybrids of ANN models is robust and accurate for predicting typhoon wind speeds, highlighting the potential of ANN-based methods for handling such complex forecasting tasks. Hallgren et al. [40] develop ML models to predict coastal wind speeds and occurrences of the low-level jet (LLJ) in offshore wind regions using ERA5 data and multi-year lidar data. Their models achieve about 5% RMSE reduction at turbine hub heights and improve LLJ detection, demonstrating the potential of ML in enhancing offshore wind resource characterization with limited direct observations. Bilgili and Gül [41] examine the use of machine learning algorithms for short-term forecasting of wind turbine power generation, using real-time SCADA and meteorological data. The study compares several models, including Random Forest, Decision Trees, K-Nearest Neighbors, and XGBoost. The results reveal that ensemble-based methods, particularly XGBoost, provide superior prediction accuracy and robustness, highlighting the effectiveness of data-driven machine learning approaches in wind energy forecasting and performance evaluation. Wen et al. [42] introduce a hybrid wind power forecasting framework that integrates spatial and temporal correlations among multiple wind turbines and plants. The approach utilizes an adaptive K-means–Hierarchical Clustering (KHC) methodology to capture time-varying wind patterns, followed by Singular Value Decomposition (SVD) to extract key power components. Also, a SVR model is then applied to these components, demonstrating enhanced short-term forecasting accuracy compared to conventional methods.

By synthesizing recent methodological advancements, it becomes apparent that addressing the inherent variability associated with wind energy through highly accurate, ML-driven predictive models is essential for the large-scale integration of wind power. Beyond achieving predictive accuracy, implementing these advanced forecasting techniques at the operational level empowers system operators to develop resilient demand response strategies. This, in turn, ensures the stability, flexibility, and reliability of contemporary smart grids amid variable weather conditions.

The economic and environmental benefits associated with solar photovoltaic (PV) technology as a renewable energy source have led to a marked increase in the deployment of PV panels in recent years. Enhanced computational power and the availability of extensive data have enabled ML models to deliver more accurate predictions. Given the importance of forecasting solar photovoltaic power output for energy-sector decision-makers, ML models are widely used. **Table 7** presents a selection of significant research studies in this domain.

Table 7. Notable ML models in solar energy systems prediction.

Year	Reference	ML Model	Application
2017	Hassan et al. [43]	Gradient boosting, RF and bagging	Modeling solar radiation
2017	Touati et al. [44]	Hybrid of MA, AR and ARMA modeling	Forecasting the output power of PV panels in environmental condition of Qatar.
2017	Voyant et al. [45]	linear quadratic estimation	Prediction of solar yields
2017	Voyant et al. [46]	Hybrid of multilayer perceptron	Forecasting of global radiation time series

Table 7. *Cont.*

Year	Reference	ML Model	Application
2018	Salcedo-Sanz et al. [47]	A hybrid CRO-ELM model.	Estimation of daily global solar radiation in Queensland, Australia.
2021	Huang et al. [48]	WPD, CNN, LSTM, and MLP	Short-term solar irradiance forecasting
2021	Ajith and Martínez-Ramón [49]	Multi-modal fusion network	Time series forecasting for global radiation: illuminating solar energy predictions
2022	Zhou et al. [50]	CART, RF, GBDT, CatBoost, LighGBM, and XGBoost	Solar irradiance forecast
2023	Neshat et al. [51]	MEMD, LSTM, and ADCMA	Short-term solar radiation forecasting
2023	Alizamir et al. [52]	MARS, ELM, KELM, VMD, and DELM	Daily solar radiation prediction
2025	Khayat et al. [53]	GRU, PSO, and XGBoost	Day-ahead photovoltaic generation forecasting in microgrids

Hassan et al. [43] developed ensemble models using gradient boosting, random forests (RF), and bagging to estimate solar radiation on hourly and daily scales. These models aim to generate synthetic radiation data to simulate solar energy system performance across different configurations. Touati et al. [44] studied the output power of photovoltaic panels in Qatar's extreme conditions, using a machine learning model to correlate factors such as irradiance, surface temperature, wind speed, humidity, and dust accumulation with power production. Voyant et al. [45] proposed models based on the Kalman filter for forecasting global radiation time series without the reliance on historical data. These methodologies were evaluated against various data-driven models with different time steps, using RMSE as the comparison metric. The findings indicated that the proposed model offered enhancements in predictive capabilities. Furthermore, Voyant et al. [46] introduced a method aimed at improving the understanding of uncertainty propagation within global radiation time series. In this study, a reliability index was defined to assess the validity of the predictions. The method was applied across several meteorological stations, with comparisons conducted utilizing the RMSE metric. The results demonstrated promising potential for successful application at these stations located in the Mediterranean region. Salcedo-Sanz et al. [47] investigated the prediction of global solar radiation at a specific location using a multilayer perceptron trained with extreme learning machines. A coral reefs optimization algorithm was employed to reduce significant predictive variables. The model was validated on data from Toledo, Spain, and demonstrated a lower average RMSE, indicating greater predictive accuracy than other machine learning techniques. Huang et al. [48] propose a multivariate deep learning framework for 1-h-ahead solar irradiance forecasting that integrates wavelet packet decomposition (WPD) with convolutional neural network (CNN), LSTM, and MLP architectures. The model incorporates multiple meteorological variables alongside irradiance time series to capture complex temporal and nonlinear dependencies. Validation using real datasets from multiple U.S. locations demonstrates superior accuracy compared to conventional neural and hybrid models. The results highlight the effectiveness of multi-branch hybrid structures for short-term solar energy forecasting. Ajith and Martínez-Ramón [49] propose a multi-modal deep learning approach for short-term solar irradiance forecasting by integrating infrared sky images with historical irradiance data. Their method extracts spatial and temporal features in parallel, enhancing performance in variable and cloudy conditions. Experimental results indicate significant reductions in forecasting error compared with traditional ML and DL models, especially at short horizons, suggesting strong potential for solar energy management and grid support. Neshat et al. [51] propose a hybrid deep learning framework that combines deep residual networks with gated recurrent architectures for one-hour-ahead solar radiation forecasting. This framework leverages advanced preprocessing and optimization techniques, including multivariate empirical mode decomposition (MEMD), gated LSTM, autoencoder-based outlier detection, and a differential covariance matrix adaptation (ADCM) hyperparameter tuner, to improve prediction accuracy. Benchmarking against various models demonstrates the superior performance of this approach, with real offshore buoy data showcasing its effectiveness in short-term solar irradiance prediction. Zhou et al. [50] evaluate multiple ML models for estimating solar photovoltaic resource potential across diverse climatic regions in China. Tree-based ensemble methods, particularly CatBoost, LightGBM, XGBoost, and Gradient Boosting Decision Tree (GBDT), demonstrate superior accuracy, stability, and computational efficiency compared to MLP and SVM. The results highlight the effectiveness of advanced ensemble learning techniques for large-scale solar energy resource assessment and PV system planning. Alizamir et al. [52] conduct a comprehensive evaluation of various artificial intelligence models for estimating daily solar radiation, aiming to support sustainable energy planning in developing regions. The research examines thirteen standalone and hybrid models, including Multivariate Adaptive Regression Splines (MARS), Extreme Learning Machine (ELM), Kernel Extreme Learning Machine (KELM), Variational Mode Decom-

position (VMD), and Deep Extreme Learning Machine (DELM). Models developed using meteorological data from two Iraqi stations demonstrate that the hybrid VMD-DELM model outperforms standalone methods, significantly reducing prediction errors. The results highlight the effectiveness of combining signal decomposition with deep learning to improve the accuracy of solar resource estimation, underscoring the role of advanced AI in renewable energy management and climate mitigation. Khayat et al. [53] introduce a hybrid forecasting model that combines Gated Recurrent Units (GRU) and XGBoost for day-ahead photovoltaic power generation in microgrids. This two-tier model captures temporal dependencies with GRU and refines nonlinear relationships using XGBoost, along with PSO for hyperparameter tuning. Validation under various weather conditions shows significant accuracy improvements over benchmark deep learning models, evidenced by low normalized Root Mean Square Error (nRMSE) and high R^2 values, highlighting its robustness for photovoltaic energy management and microgrid optimization.

Collectively, the ongoing advancement of deep learning and hybrid architectures in PV forecasting extends beyond merely reducing technical errors; it serves as a vital operational facilitator within the overarching energy transition. By effectively predicting real-time generation variances, these predictive models deliver the high-precision data necessary for the seamless alignment of supply and demand. As a result, this analytical framework underpins sophisticated demand response initiatives and ensures the operational reliability of decentralized smart grids.

3.2.2. Toward an Integrated Conceptual Framework for Anticipatory Energy Research

To address conceptual fragmentation and methodological conflation in anticipatory energy research, this section presents an integrated four-layer theoretical framework. This framework organizes anticipatory capacity into a hierarchical structure that is both complementary and cumulative: (1) Energy Monitoring, (2) Energy Scanning, (3) Energy Forecasting, and (4) Energy Foresight. Instead of viewing these methodologies as isolated paradigms, this integrated approach emphasizes how operational data, weak signals, quantitative models, and normative strategies interact dynamically through feed-forward and feedback mechanisms. The following subsections will detail the epistemological scope, methodological tools, and specific roles of each layer within the broader context of energy planning.

(1) Layer 1: Empirical Foundations through Energy Monitoring

Energy monitoring serves as the essential foundation for anticipatory energy research, emphasizing the systematic observation and measurement of energy flows, consumption patterns, and system performance in real-time. This process entails continuous data collection from sensors, smart meters, and metering infrastructure, thereby providing critical descriptive intelligence on the current state of energy systems [54]. In contrast to predictive or foresight-oriented approaches, monitoring does not seek to forecast future conditions; instead, it establishes an empirical baseline that facilitates the identification of deviations, trends, and anomalies [55]. Contemporary energy monitoring frameworks increasingly incorporate sophisticated data analytics to evaluate performance indicators, including load variability, peak demand, and efficiency metrics. This integration facilitates both operational optimization and the timely identification of anomalies [56]. Real-time observability is crucial not only for supporting short-term operational decision-making but also as a foundational element for advanced anticipatory activities, such as horizon scanning and forecasting. This approach ensures that future analyses are informed by a precise and high-resolution understanding of the system.

(2) Layer 2: Proactive Intelligence via Energy Scanning

Energy scanning constitutes the second layer of anticipatory energy research, progressing beyond real-time observation to facilitate the systematic identification of emerging trends, weak signals, drivers, and uncertainties that influence future energy systems. This approach is frequently operationalized through methodologies such as environmental scanning, horizon scanning, and strategic scanning. It effectively integrates qualitative and semi-quantitative methods to investigate technological, economic, regulatory, social, and ecological developments pertinent to the energy sector [57]. In contrast to energy monitoring, which concentrates on quantifiable system states, scanning prioritizes proactive awareness and anticipatory intelligence. This approach empowers stakeholders to identify potential disruptions before they become measurable phenomena [58]. In the field of energy research, scanning methodologies are routinely utilized to identify emerging renewable technologies, policy changes, market evolutions, and sustainability challenges. These activities play a crucial role in informing strategic planning and long-term decision-making. Techniques such as expert elicitation, Delphi surveys, literature reviews, patent analysis, and trend mapping are commonly employed to develop a proactive understanding of the energy landscape.

It is important to note that energy scanning does not seek to predict specific future outcomes; rather, it organizes uncertainty and expands the array of potential futures. This process serves as a vital link between descriptive monitoring and formal forecasting models. Therefore, this component establishes the conceptual and informational groundwork for robust energy foresight and forecasting frameworks [59].

(3) Layer 3: Quantitative Projections in Energy Forecasting

Energy forecasting represents the third layer of anticipatory energy research and serves as the most formalized and model-driven component within this field. This layer is concerned with predicting future energy demand, supply, generation, and system behavior through the application of quantitative models that are rooted in historical data, mathematical formulations, and statistical or computational techniques. Energy forecasting spans a diverse array of temporal scales, from short-term load forecasting to long-term projections that support infrastructure planning and the formulation of energy policies [60]. Energy forecasting encompasses a diverse range of temporal scales, ranging from short-term load forecasting to long-term projections. These projections are essential for supporting infrastructure planning and informing energy policy formulation [61]. Modern energy forecasting increasingly leverages sophisticated data-driven methodologies, encompassing machine learning, deep learning, and hybrid models. This approach is particularly pertinent for renewable energy sources such as wind and solar power, where system dynamics are highly nonlinear and heavily influenced by weather conditions [46,62]. While these methodologies exhibit high predictive accuracy, their efficacy is highly contingent on data availability, historical continuity, and the stability of the underlying system conditions. As a result, approaches that rely exclusively on forecasting may encounter difficulties in accounting for structural breaks, disruptive innovations, or policy-driven transformations that deviate from historical trends [63]. From an anticipatory standpoint, energy forecasting is most effective when situated within a comprehensive framework that incorporates insights from both monitoring and scanning layers. By merging empirical system data with forward-looking intelligence regarding emerging trends and uncertainties, forecasting models can be contextualized, interpreted, and subjected to stress-testing with greater efficacy. This layered approach mitigates the risk of excessive reliance on historical data and enhances the relevance of forecasting outputs for strategic energy planning and long-term decision-making.

(4) Layer 4: Strategic Navigation with Energy Foresight

Energy foresight constitutes the most advanced and integrative level of anticipatory energy research, synthesizing insights derived from monitoring, scanning, and forecasting to examine long-term systemic transformations within energy systems. In contrast to forecasting, which aims to estimate likely future states based on historical data, energy foresight intentionally addresses uncertainty, complexity, and alternative futures through structured exploratory and normative methodologies [64]. This dimension prioritizes strategic reflection over predictive accuracy, thereby facilitating decision-making in contexts characterized by profound uncertainty. Energy foresight typically employs a range of methodologies, including scenario development, backcasting, roadmapping, visioning, and participatory workshops, to explore plausible, probable, and desirable energy futures [65]. These methodologies are particularly pertinent for addressing energy transitions and decarbonization pathways. They become essential when future developments cannot be reliably extrapolated from historical trends [66]. Foresight processes encompass technological, economic, environmental, and societal dimensions, thereby enabling policymakers and stakeholders to evaluate trade-offs, identify strategic options, and enhance system resilience. Notably, energy foresight serves as the interpretative and strategic framework that contextualizes outputs derived from predictive models and scanning activities. The results of forecasting inform the assumptions underpinning various scenarios, while scanning activities uncover emerging drivers and wild cards that influence scenario narratives. Through this integrative function, foresight effectively connects quantitative evidence with qualitative judgment, transforming anticipatory knowledge into actionable insights for long-term energy planning and governance.

The four-layer framework presented in this study conceptualizes anticipatory energy research as a structured, cumulative process. The first layer, Energy Monitoring, delivers real-time and historical insights regarding system performance through various indicators and operational data. The second layer, Energy Scanning, broadens this perspective by identifying emerging trends, weak signals, and contextual factors that may impact future energy systems. The third layer, Energy Forecasting, translates the observed patterns into quantitative projections, providing estimates of future energy demand, supply, and system behavior based on specified assumptions. The final layer, Energy Foresight, synthesizes insights from the preceding layers to explore alternative futures, facilitate strategic dialogue, and inform long-term policy and planning. These layers do not operate in isolation; rather, they constitute

a complementary and hierarchical anticipatory architecture. Monitoring and forecasting are primarily data-driven, whereas scanning and foresight emphasize interpretative and strategic intelligence. The integration of these layers fosters more robust, transparent, and resilient energy decision-making, especially within the context of rapid technological advancements and significant uncertainty. **Table 8** summarizes these layers and their application.

Table 8. Comprehensive comparative framework of anticipatory energy research layers.

Layer	Primary Objective	Temporal Focus	Key Concepts & Terminology	Typical Methods	Main Outputs	Role in Energy Decision-Making
Layer 1: Energy Monitoring	Observe and track current system states	Short-term to present	Energy monitoring, tracking, assessment, indicators	Data collection, KPI analysis, dashboards, statistical summaries	Status reports, performance metrics	Operational control, compliance, system awareness
Layer 2: Energy Scanning	Identify emerging trends and weak signals	Medium- to long-term	Horizon scanning, environmental scanning, trend analysis, future watching	Literature surveillance, expert elicitation, Delphi, trend mapping	Identified drivers, uncertainties, early signals	Strategic awareness, risk identification
Layer 3: Energy Forecasting	Estimate future energy states	Short- to long-term	Energy forecasting, prediction, modeling, projection	Statistical models, ML/DL, hybrid models, scenario-based forecasting	Quantitative projections	Planning, investment analysis, policy support
Layer 4: Energy Foresight	Explore alternative and desirable futures	Long-term	Energy foresight, scenarios, backcasting, visioning	Scenario development, roadmapping, participatory methods	Plausible futures, strategic pathways	Long-term strategy, governance, transition planning

A key insight from this review is the common conflation of energy forecasting and energy foresight, especially in studies that employ machine learning and deep learning techniques. While these methods are often positioned as tools for predicting future energy systems, this study demonstrates that machine learning is fundamentally aligned with the forecasting layer. Because machine learning models derive patterns from historical data to yield probabilistic or deterministic predictions, they are inherently retrospective and reliant on the continuity of past structures. This makes them highly effective for short- to medium-term operational tasks, such as load forecasting and renewable energy generation estimation, but constrains their independent ability to address structural changes or disruptive technological advancements required for long-term energy planning. However, recognizing this ontological distinction does not preclude the integration of machine learning into foresight practices. On the contrary, as highlighted in recent policy foresight studies, there is a growing and valuable reliance on ML-supported hybrid structures. In these hybrid architectures, machine learning is not tasked with predicting a single definitive long-term future. Instead, it serves as a powerful analytical engine that processes massive datasets for horizon scanning or establishes rigorous quantitative boundary conditions. These data-driven inputs are subsequently integrated into qualitative foresight methodologies—such as scenario development, backcasting, and participatory visioning—to navigate deep uncertainty and normative sustainability goals. Treating machine learning solely as a foresight method may limit anticipatory capacity and reinforce established pathways in rapidly changing energy systems. However, when embedded within hybrid frameworks, ML acts as a complementary analytical tool that enriches, rather than replaces, energy scanning and foresight processes. Consequently, this study advocates for a layered framework in which monitoring and forecasting (including ML) provide robust empirical support, while scanning and foresight offer contextual interpretation and strategic guidance. Clearly defining these boundaries and acknowledging their hybrid intersections is essential for enhancing coherence in anticipatory energy research.

3.2.3. Implications of Terminological Clarification in Anticipatory Energy Research

The systematic clarification of terminology presented in this review carries significant implications for energy policy formulation, strategic planning, and the design of energy research methodologies. By delineating the distinctions among monitoring, scanning, forecasting, and foresight, this study helps mitigate conceptual ambiguity and optimize the application of anticipatory approaches in energy systems analysis.

From a policy standpoint, this review elucidates the risks associated with conflating predictive accuracy with strategic insight in the realm of energy policy. Decisions concerning long-term decarbonization, infrastructure investments, and pathways for energy transition increasingly depend on quantitative models, including forecasting tools grounded in machine learning. While such tools can offer valuable projections for the short to medium term,

treating them as substitutes for strategic foresight may result in excessively deterministic policy decisions [67]. In contrast, energy foresight empowers policymakers to navigate profound uncertainties, examine alternative transition pathways, and assess the implications of disruptive technologies and societal evolution. By differentiating between forecasting and foresight, this approach enhances transparency in governance and ensures that analytical tools align with appropriate decision-making timelines. The outputs of forecasts should be interpreted as conditional inputs rather than absolute predictions, a vital distinction for long-term policy frameworks such as net-zero strategies and energy transition roadmaps [66].

To illustrate the operational risks associated with long-term energy planning, relying solely on data-driven ML forecasts without integrating strategic foresight exposes policy frameworks to two fundamental epistemological vulnerabilities: structural breaks [68] and path dependence [69]. The limitations of ML algorithms are primarily defined by their dependence on historical training data, which renders them ill-equipped to respond to sudden structural breaks and exogenous shocks. Notable examples of such shocks include the disruptions caused by the COVID-19 pandemic and the 2022 European energy crisis. During the 2020 lockdowns, ML and deep learning models trained on pre-pandemic data suffered significant declines in predictive accuracy. This deterioration occurred because the historical time-series datasets did not encompass scenarios analogous to global lockdowns, leading models to fail to predict the abrupt shift in demand from commercial and industrial sectors to residential loads [70,71]. Likewise, traditional ML models, which were optimized based on pre-2022 historical data, inaccurately anticipated stable trajectories for natural gas consumption and pricing, entirely overlooking the energy crisis of 2022 triggered by geopolitical supply disruptions, which constituted an “out-of-distribution” shock absent from the training datasets [72]. Given that machine learning relies on historical covariance, these models are incapable of quantifying the probability of unprecedented socio-political or public health disruptions. In contrast, strategic foresight and horizon scanning transcend these quantitative limitations by systematically monitoring emerging weak signals—such as geopolitical tensions and health policy discussions—and by employing exploratory scenario planning to enable planners to assess infrastructure resilience against low-probability, high-impact “black swan” events before they occur [73].

Furthermore, ML forecasting is highly susceptible to path dependence, often resorting to linear or incremental trend extrapolation from past data. This dependency becomes particularly problematic when modeling non-linear socio-technical transitions, such as the widespread adoption of electric vehicles (EVs). When initialized with early-stage historical adoption data, ML predictive models consistently underestimate future transformations in grid load because they overlook critical inflection points in S-curve adoption dynamics—the junctures at which technological penetration accelerates rapidly [74]. In contrast, technology-scanning methodologies eschew reliance solely on past numerical trends; they proactively track early qualitative indicators, including battery-cell cost-parity thresholds, supply chain constraints, and radical policy initiatives such as bans on combustion-engine vehicles. By identifying these socio-technical tipping points in advance, foresight methodologies empower planners to incorporate nonlinear, disruptive factors into long-term grid expansion strategies, thereby preventing significant infrastructure deficits [75].

This review emphasizes the critical need for the research community to align research questions, temporal scope, and methodological approaches effectively. The interchangeable use of terms such as energy forecasting, energy foresight, and energy scanning obscures significant epistemological distinctions. It may lead to methodological overreach, particularly when machine learning techniques are presented as tools for foresight. This study emphasizes the importance of firmly situating machine learning and deep learning within the forecasting layer, thereby encouraging researchers to adopt greater terminological precision and methodological reflexivity. Forecasting models are optimally designed for estimating future system states under stable conditions. In contrast, the processes of scanning and foresight are essential for analyzing emerging drivers, discontinuities, and normative objectives. By explicitly recognizing these distinctions, the study enhances the interpretability, reproducibility, and policy relevance of energy research, particularly within interdisciplinary contexts that encompass engineering, economics, and the social sciences [61,76].

This review suggests that integrating data-driven forecasting with foresight methodologies enhances anticipatory energy research. Machine learning-based forecasting can provide valuable quantitative insights, while foresight activities identify emerging variables and potential regime shifts. This combined approach creates a layered workflow where monitoring informs scanning, scanning shapes forecasting assumptions, and forecasting supports

scenario development. This integration addresses the limitations of data-driven models while emphasizing foresight's role as an interpretative strategic process, rather than solely a predictive one [77]. **Table 9** summarizes the key policy- and research-oriented implications derived from the proposed layered framework of anticipatory energy research.

Table 9. Implications of terminological clarification in anticipatory energy research.

Implication Domain	Key Issue	Main Insight from This Study	Practical Implications
Energy Policy & Strategic Planning	Congflation of forecasting and foresight	Forecasting tools, including machine learning, provide conditional predictions and cannot substitute foresight approaches that address deep uncertainty	Polymakers should use forecasting outputs as inputs to foresight and scenario processes rather than as deterministic decision tools
Long-term Energy Transitions	Path dependency in data-driven models	Over-reliance on historical data may underestimate disruptive transitions and policy-driven change	Strategic planning should integrate scanning and foresight methods to explore alternative decarbonization pathways
Research Design & Method Selection	Terminological ambiguity	Energy monitoring, scanning, forecasting, and foresight represent distinct anticipatory layers with different objectives and methods	Researchers should align terminology, methods, and time horizons explicitly to improve clarity and reproducibility
Role of Machine Learning	Misclassification of ML as foresight	Machine learning belongs to the forecasting layer and is epistemologically distinct from foresight	ML should support quantitative forecasting, not be framed as a foresight methodology
Integration of Methods	Fragmented anticipatory approaches	Data-driven and qualitative methods are complementary rather than competing	Hybrid workflows combining monitoring, scanning, forecasting, and foresight enhance anticipatory capacity
Policy-Science Interface	Limited interpretability of complex models	High predictive accuracy does not guarantee strategic relevance	Interpretative foresight frameworks are required to contextualize model outputs for policy use

Table 9 synthesizes key implications from the conceptual and bibliometric analyses by linking terminological clarifications to specific policy and research outcomes. It demonstrates that distinctions among monitoring, scanning, forecasting, and foresight are significant, influencing methodological selection, governance, and strategic energy planning. Also, **Table 9** highlights the risks of considering machine learning-based forecasting as a foresight tool, while also emphasizing the benefits of incorporating data-driven models into broader anticipatory frameworks. By organizing implications across policy, research design, and methodology, it provides a useful reference for aligning anticipatory tools with appropriate decision-making contexts.

3.2.4. Operationalizing the Framework: Practical Workflow and Application Scenario

To effectively bridge the gap between the proposed conceptual architecture and practical energy governance, this section outlines an operational workflow and a specific application scenario. The four layers are designed to function collaboratively rather than as disparate analytical silos, as illustrated schematically in **Figure 9**. This structured, iterative, and cumulative architecture facilitates a comprehensive approach to energy management.

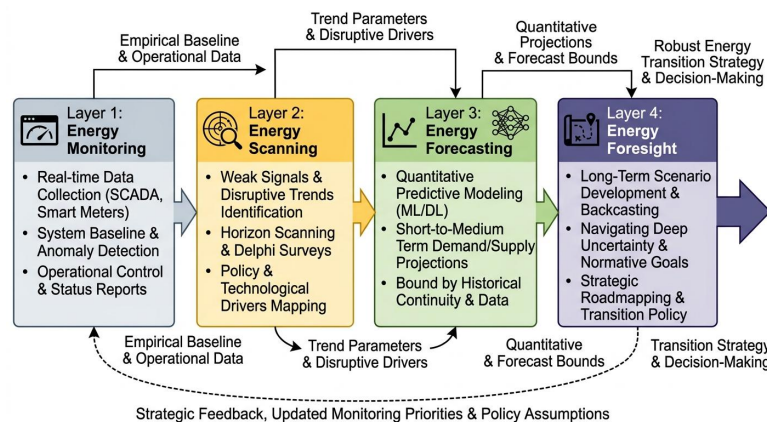


Figure 9. Operational workflow and decision pipeline of the four-layer anticipatory energy framework in regional transition planning.

The operationalization of this framework commences with Layer 1 (Energy Monitoring), in which continuous, real-time data collection establishes an empirical baseline of current system performance and operational parameters. Building on this empirical foundation, Layer 2 (Energy Scanning) undertakes ongoing horizon scanning to identify structural discontinuities, weak signals, and external drivers—such as regulatory changes and emerging technologies—outside historical datasets. Layer 3 (Energy Forecasting) subsequently employs quantitative models, including ML and DL architectures, to produce deterministic or probabilistic predictions from baseline monitoring data while remaining constrained by trend parameters established in Layer 2. Lastly, Layer 4 (Energy Foresight) integrates these quantitative model outputs with qualitative contextual drivers to develop plausible scenarios, backcasting roadmaps, and policy stress tests. Importantly, insights generated in Layer 4 continuously feedback into the lower layers, refining monitoring priorities and updating model assumptions over time.

To illustrate the practical application of this integrated workflow, consider a hypothetical scenario involving a regional energy planning authority responsible for managing the transition to an 80% renewable energy grid by 2040 amidst significant technological and regulatory uncertainty. In Layer 1, advanced smart meter infrastructure and SCADA systems continuously gather data on solar and wind variability, grid frequency, and demand patterns, thereby establishing an accurate physical baseline for operational control [78]. Concurrently, Layer 2 facilitates systematic horizon scanning to identify emerging weak signals [79], such as the nascent commercialization of sodium-ion battery storage, forthcoming amendments to carbon tax policies, or potential supply chain disruptions regarding critical minerals [80]. These qualitative insights directly inform Layer 3, where data-driven machine learning models, including hybrid LSTM-XGBoost frameworks, analyze historical meteorological data and operational load patterns to forecast short- and medium-term generation profiles, thereby optimizing day-ahead dispatch and storage management [81]. However, recognizing the limitations of statistical ML models in extrapolating extreme events or structural policy changes by 2040, planners proceed to Layer 4 to implement participatory scenario development and backcasting [82]. In this phase, decision-makers formulate alternative long-term transition strategies—such as “Accelerated Electrification,” “Resource Constraints,” or “Decentralized Hydrogen”—where quantitative forecasts from Layer 3 serve as foundational boundary conditions and the weak signals identified in Layer 2 act as drivers for stress-testing. By integrating all four layers into a cohesive decision-making framework, energy authorities can circumvent the common pitfall of interpreting retrospective machine learning forecasts as long-term strategic policy, thereby ensuring that foresight remains both visionary and empirically substantiated.

The proposed four-layer framework not only presents a theoretical taxonomy but also operationalizes essential engineering and management functions within contemporary power systems. At the foundational level, Layer 1 (Monitoring) utilizes advanced SCADA architectures and smart metering technologies to capture high-frequency operational states across decentralized smart grids [83]. These real-time empirical data streams are subsequently integrated into Layer 3 (Forecasting), where short-term machine learning models effectively address the spatiotemporal intermittency of renewable energy generation. Specifically, precise photovoltaic forecasting and wind energy integration depend on these predictive systems to model solar irradiance patterns and wind power fluctuations, thereby alleviating grid instability [84]. Importantly, the forecasts generated in Layer 3 activate dynamic demand response mechanisms, facilitating automated load management and peak shaving to ensure real-time balance between supply and demand [85]. Furthermore, by bridging these short-term operational layers (1 and 3) with strategic horizon scanning and long-term foresight (Layers 2 and 4), grid operators are equipped to anticipate structural vulnerabilities, assess future energy storage requirements, and synchronize daily grid operations with long-term decarbonization objectives.

In addition to the operational dynamics of the grid, the predictive capabilities of Layer 3 (Energy Forecasting) are of significant importance at both the macroeconomic and national policy levels. Recent literature underscores the prevailing efficacy of data-driven methodologies within contemporary energy transition research. Advanced machine learning algorithms have been employed to analyze intricate energy-environmental interactions. For instance, recent studies have utilized the Causal Direction from Dependency (D2C) machine learning algorithm to ascertain predictive causal relationships among renewable energy production, economic growth, and CO₂ emissions across key global economies, such as China, India, and the United States. This methodological approach has successfully facilitated the forecasting of near-term emission trajectories [86]. Similarly, the integration of traditional time-series analyses with advanced machine learning-driven direct-to-consumer methodologies has been effectively employed to analyze historical data in Russia, thereby elucidating the causal relationship between energy

consumption, external GDP shocks, and carbon emissions. This hybrid methodology offers quantitative justification for long-term structural investments in alternative energy sources [87]. These applications serve as exemplary illustrations of the operational efficacy of quantitative forecasting within our framework, demonstrating how machine learning can effectively unearth causal relationships from historical datasets to inform both micro-level grid management and macro-level sustainability policies.

3.2.5. Retrospective Framework Validation through Diverse Historical Policy Analyses

Although the preceding hypothetical scenario demonstrates the potential application of the four-layer framework in regional planning, a theoretical framework of this scope necessitates substantial empirical validation across a variety of real-world contexts. To thoroughly establish the operational effectiveness of the proposed taxonomy, this section will retrospectively apply the framework to an analysis of three significant historical failures in energy policy. The first case is the 2021 Texas power grid crisis during Winter Storm Uri, which exemplifies the effects of climatic extremes. The second case is the 2022 European Energy Crisis, characterized by geopolitical shocks. The third case involves the 2011 Fukushima Daiichi Nuclear Disaster, which represents black-swan structural shifts. These examples illustrate that an exclusive reliance on foundational predictive layers can result in systemic collapse. In contrast, integrating scanning and foresight approaches significantly enhances structural resilience against extreme, out-of-distribution disruptions across diverse operational environments.

(1) Climatic Extremes: The 2021 Texas Power Grid Crisis

Prior to the 2021 crisis, the Electric Reliability Council of Texas (ERCOT) relied heavily on foundational operational layers [88]. In Layer 1 (Energy Monitoring), advanced smart meter infrastructure, along with SCADA systems, continuously collected baseline data on operational load patterns. In Layer 3 (Energy Forecasting), quantitative and machine learning-driven predictive models utilized decades of historical meteorological data to accurately forecast standard winter generation profiles and optimize dispatch mechanisms. However, due to the lack of integration with Layer 2 (Energy Scanning), these predictive models did not identify emerging nonlinear weak signals beyond traditional load datasets, such as Arctic amplification and alterations in the polar vortex [89]. As a result, when the unprecedented freeze occurred, an event not represented in the models' historical training data, the models catastrophically failed in their forecasts [90]. Had Layer 4 (Energy Foresight) been effectively operationalized to synthesize Layer 2 scanning signals into extreme, low-probability "worst-case" scenarios, decision-makers could have conducted backcasting and policy stress tests prior to the event. Rather than aiming for exact algorithmic predictive accuracy, this approach to strategic foresight would have facilitated proactive interventions, such as the mandated winterization of natural gas and wind infrastructure. This historical analysis underscores empirical evidence that while data-driven monitoring and forecasting (Layers 1 and 3) are essential for baseline operational efficiency, they must be complemented by continuous scanning and strategic foresight (Layers 2 and 4) to navigate extreme uncertainties and prevent systemic failures in real-world energy systems.

(2) Geopolitical Shocks: The 2022 European Energy Crisis

Prior to 2022, European energy governance was predominantly based on a multi-layered framework [91]. In Layer 1 (Energy Monitoring), ongoing data streams were employed to monitor cross-border pipeline flows, liquefied natural gas (LNG) imports, and real-time market pricing. Layer 3 (Energy Forecasting) involved the utilization of econometric and machine learning-driven predictive models, which analyzed decades of historical market data to accurately forecast baseline gas demand and pricing under the assumption of stable commercial trajectories. However, the lack of integration of these predictive models with Layer 2 (Energy Scanning) prevented the identification of systemic weak signals that extended beyond traditional economic datasets, including increasing infrastructural dependencies and adversarial geopolitical influences. As a result, when the structural cessation of pipeline supplies transpired—an unprecedented out-of-distribution shock devoid of historical statistical significance—the solely data-driven forecasts failed catastrophically [92]. Had Layer 4 (Energy Foresight) been operationalized to consolidate Layer 2 scanning signals into exploratory, low-probability "worst-case" disruption scenarios, decision-makers would have had the opportunity to implement policy stress tests and engage in diversification backcasting prior to the crisis. Rather than presuming market continuity, such strategic foresight could have propelled proactive structural interventions, including expedited LNG terminal deployment, binding storage mandates, and vigorous grid electrification initiatives. This historical policy analysis demonstrates that while economic monitoring and forecasting (Layers 1 and 3) are vital for short-term market optimization, they must be supported by overarching

continuous scanning and strategic foresight (Layers 2 and 4) to navigate geopolitical volatility and avert systemic energy shortages effectively.

(3) Black Swan Shifts: The 2011 Fukushima Daiichi Nuclear Disaster

Prior to 2011, nuclear safety and risk assessment regulation was fundamentally based on a layered framework [93]. In Layer 1 (Energy Monitoring), real-time sensor networks were employed to monitor seismic activity continuously, cooling water levels, and reactor operational parameters. Layer 3 (Energy Forecasting) utilized probabilistic risk assessment and statistical modeling, leveraging bounded historical records of seismic frequency and tsunami heights to establish safe engineering thresholds. Nonetheless, the lack of integration with Layer 2 (Energy Scanning) in these predictive safety models prevented them from adequately capturing macro-systemic environmental changes and tail-end historical anomalies beyond standard observation windows. As a result, when the compounding earthquake-tsunami sequence occurred, a quintessential “black swan” event not accounted for in conventional frequency-duration models, the stationary predictive frameworks exhibited significant epistemological limitations [94]. Had Layer 4 (Energy Foresight) been effectively operationalized to synthesize insights from scanning processes into scenarios that account for non-stationarity and extreme cases, decision-makers would likely have reconsidered the assumption of historical statistical stationarity. The implementation of strategic foresight would have required precautionary stress tests and backcasting protocols, necessitating structural safeguards, such as relocating emergency generators above historically established wave ceilings, regardless of standard cost-benefit analyses. This historical policy analysis empirically substantiates that while real-time monitoring and probabilistic forecasting (Layers 1 and 3) are critical for operational safety during normal conditions, these must be systematically governed by long-term scanning and strategic foresight (Layers 2 and 4) to safeguard critical energy infrastructure against substantial environmental uncertainties.

3.2.6. Synthesis of Core Definitions and Conceptual Boundaries

To remove conceptual ambiguity and create a unified baseline for anticipatory energy research, the operational and theoretical boundaries of the proposed framework must be synthesized into a cohesive continuum. At the foundational level, Energy Monitoring (Layer 1) involves the continuous, real-time capture and visualization of the physical states of power systems using empirical data streams. For example, advanced SCADA systems consistently measure wind turbine rotor speeds or real-time irradiance levels at solar energy facilities. This layer provides immediate operational visibility and establishes an empirical baseline essential for higher-level analyses. Building upon this fundamental framework, Energy Scanning (Layer 2) transcends routine operational data by systematically tracking external drivers, policy changes, and weak signals that fall outside of historical datasets. In the realm of renewable energy, this encompasses identifying potential structural discontinuities before they emerge as quantitative trends. For instance, it involves monitoring the early commercialization of next-generation perovskite solar cells or the preliminary regulatory changes concerning the zoning of offshore wind farms. Building upon the empirical baselines and contextual drivers established in the foundational layers, Energy Forecasting (Layer 3) undertakes the quantitative, probabilistic, or deterministic modeling of future energy supply, demand, and generation profiles. This layer employs statistical and ML methodologies, such as LSTM networks and XGBoost, while assuming structural continuity to project short- to medium-term outcomes. For instance, forecasting models analyze historical wind speed datasets alongside real-time meteorological inputs to predict day-ahead wind power ramp events, or use satellite cloud-tracking data to forecast abrupt declines in photovoltaic generation. The data-driven extrapolation conducted in this layer is explicitly limited to operational horizons. It is crucial for optimizing immediate grid operations, dynamic demand response, and automated integration of renewable energy sources. Finally, recognizing the intrinsic limitations of statistical extrapolation in contexts characterized by deep uncertainty, Energy Foresight (Layer 4) engages in qualitative and hybrid exploration of multiple, plausible, and desirable long-term transition pathways. Rather than pursuing a singular deterministic outcome—a primary focus of forecasting—foresight employs normative methodologies such as scenario planning, participatory visioning, and backcasting. In practice, Layer 4 uses quantitative outputs from Layer 3, including projected baseline generation capacities for regional wind and solar fleets, as boundary conditions for stress-testing future policy scenarios. This approach enables decision-makers to assess complex, long-term objectives, such as the strategic feasibility of achieving a 100% renewable grid by 2050, within the context of evolving geopolitical landscapes and extreme climate conditions. Collectively, these interrelated layers ensure that anticipatory energy research effectively connects real-time data

monitoring with long-term strategic governance.

4. Conclusions

This study addresses an important challenge in energy research: the inconsistent terminology surrounding energy monitoring, scanning, forecasting, and foresight. This systematic review and bibliometric analysis present a structured synthesis of these concepts as defined in contemporary literature. The key contribution is a four-layer framework that clarifies these concepts' boundaries and highlights their complementary roles: energy monitoring for real-time awareness, energy scanning for identifying trends, energy forecasting for predictive modeling, and energy foresight for long-term strategic decision-making. This structure shows that the effectiveness of anticipatory methods in energy research depends on their integrated application across various temporal scales and contexts.

A key finding of this review concerns the positioning of machine learning and deep learning methodologies within energy research. While these techniques are increasingly used, they align more with forecasting than with foresight. Their reliance on historical data makes them effective for short- to medium-term predictions, particularly in wind and solar energy. However, this dependence limits their ability to address structural changes, policy discontinuities, and transformative transitions in energy systems. By situating machine learning within the forecasting domain, this study challenges the tendency to equate data-driven predictions with foresight and underscores the need for precise terminology.

The bibliometric analysis identifies a conceptual divergence in the literature between two research paradigms: data-intensive, model-driven approaches and system-oriented, policy-focused studies. The former prioritizes predictive accuracy and operational optimization, while the latter emphasizes energy efficiency, sustainability, governance, and long-term planning. Bridging these streams requires intentional methodological integration, where forecasting outputs inform, rather than replace, scanning and foresight activities. This approach enhances interpretability, reduces path dependence, and strengthens strategic decision-making in the context of energy transitions.

The findings presented have significant practical implications for both energy policy and research methodologies. It is recommended that policymakers regard forecasting results as conditional inputs rather than deterministic projections, especially when developing long-term transition strategies. Furthermore, for researchers, the clarified terminological framework guides aligning research inquiries, time frames, and methodologies, thereby enhancing transparency, reproducibility, and communication across disciplines.

Finally, the constraints of this study should be acknowledged. Firstly, the review primarily relies on peer-reviewed journal articles indexed in the Scopus database. While this approach is extensive, the reliance on a single database introduces the possibility of selection bias, as it excludes grey literature, governmental policy documents, and relevant articles that are exclusively indexed in other databases such as Web of Science, IEEE Xplore, and AIAA. Secondly, the selected timeframe of 2015 to 2025, although intentionally designed to comprehensively capture current energy transitions and recent advancements in machine learning, including those relevant to contemporary energy transitions, such as those emerging post-Paris Agreement, sufficiently, inherently omits foundational foresight studies and historical energy scenarios developed before 2015. Thirdly, this study prioritizes conceptual and methodological interpretations over empirical assessments of forecasting performance. Furthermore, the intentional exclusion of highly technical, model-centric studies to maintain conceptual coherence may have led to the omission of critical insights from specific fields of application.

Future research may build upon this work in several notable directions. To address the aforementioned limitations in search strategies, subsequent studies should implement multi-database approaches and incorporate grey literature to capture a broader spectrum of industry and policy foresight. Conducting longitudinal bibliometric studies over an extended historical timeframe could yield valuable insights into the long-term evolution of anticipatory terminology. Furthermore, empirical research is essential for assessing hybrid anticipatory workflows that integrate monitoring, scanning, forecasting, and foresight in real-world energy planning contexts. A deeper investigation into how foresight processes may systematically incorporate outputs from machine learning models while preserving their exploratory nature would also be highly advantageous. Finally, broadening this terminological analysis to include cross-sectoral domains, such as water-energy-food systems and climate-energy governance, could significantly enhance the generalizability and impact of the proposed framework.

Supplementary Materials

The following supporting information can be downloaded at: <https://ojs.ukscip.com/uploads/2/asset-file/2026/09/NEEA-100528-Supplementary-Materials.zip>.

Author Contributions

Conceptualization, M.Z. and S.M.Y.; methodology, F.G.; software, F.G. and M.P.; validation, P.K. and F.G.; formal analysis, F.G.; investigation, F.G. and M.P.; resources, M.P. and P.K.; data curation, F.G.; writing—original draft preparation, F.G., P.K. and M.P.; writing—review and editing, F.G. and S.M.Y.; visualization, P.K., M.P. and F.G.; supervision, M.Z. and S.M.Y.; project administration, M.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this work, the authors used Gemini and Grammarly solely for language editing, grammar correction, and proofreading to improve clarity and readability of the manuscript. No AI tools were used for generating scientific ideas, data analysis, result interpretation, or preparing scientific content. The authors reviewed and edited the output generated by these tools and took full responsibility for the content of the published article.

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