AI

Article

AI in Energy: Overcoming Unforeseen Obstacles

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Abstract: Besides many sectors, artificial intelligence (AI) will drive energy sector transformation, offering new approaches to optimize energy systems' operation and reliability, ensuring techno-economic advantages. However, integrating AI into the energy sector is associated with unforeseen obstacles that might change optimistic approaches to dealing with AI integration. From a multidimensional perspective, these challenges are identified, categorized based on common dependency attributes, and finally, evaluated to align with the viable recommendations. A multidisciplinary approach is employed through the exhaustive literature to assess the main challenges facing the integration of AI into the energy sector. This study also provides insights and recommendations on overcoming these obstacles and highlights the potential benefits of successful integration. The findings suggest the need for a coordinated approach to overcome unforeseen obstacles and can serve as a valuable resource for policymakers, energy practitioners, and researchers looking to unlock the potential of AI in the energy sector.

Keywords: AI unforeseen obstacles; AI-empowered energy policy; computational intelligence; AI-integrated energy framework; energy sector; policy recommendations

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1. Introduction

AI initiatives date back many decades. AI history is linked with the inception of the computer "Electronic Numerical Integrator Additionally, Computer (ENIAC)" in 1946 [1]. Additionally, its earliest commercial application of AI was automating and speeding up mail processing using Optical Character Recognition (OCR) in 1970 by the US Postal Services [1]. In the early 1950s, with limited and expensive access to basic computers that could only execute commands (with no storing commands capability), the concept of computing machinery and intelligence was explored by Alan Turing [2]. Turning argued that by analyzing the available information and related reasons, humans can solve problems and make decisions, so by providing the inputs, why could machines not do the same thing?

The trend of computer development as a faster and cheaper machine with the capability of executing and storing more data from 1957 to 1974, while at the same time improving machine learning algorithms, can be called a flourishing period of AI endeavors [3]. After 1980, AI's ambitious development had been accountable for the development of correlative technologies (such as machine learning, deep learning, quantum computing, etc.), audacious investments, and inspiring the young generation to turn AI into the limelight of future technology. For instance, Japan's Fifth Generation Computer Project (FGCP), an industry research consortium, budgeted USD 400 million from 1982 to 1990 to revolutionize computer processing, implement logic programming, and improve artificial intelligence [4]. Long before AI's application at the student level was initiated as the basic AI logic programing take, it took over 40 years to become intelligence, intimately tied with great achievements in AI-flavored constructivism between 1980 and about 2017 [5]. A concise overview of the historical trends in intelligent computational and AI applications in the energy sector inspired by literature is presented in Figure 1.

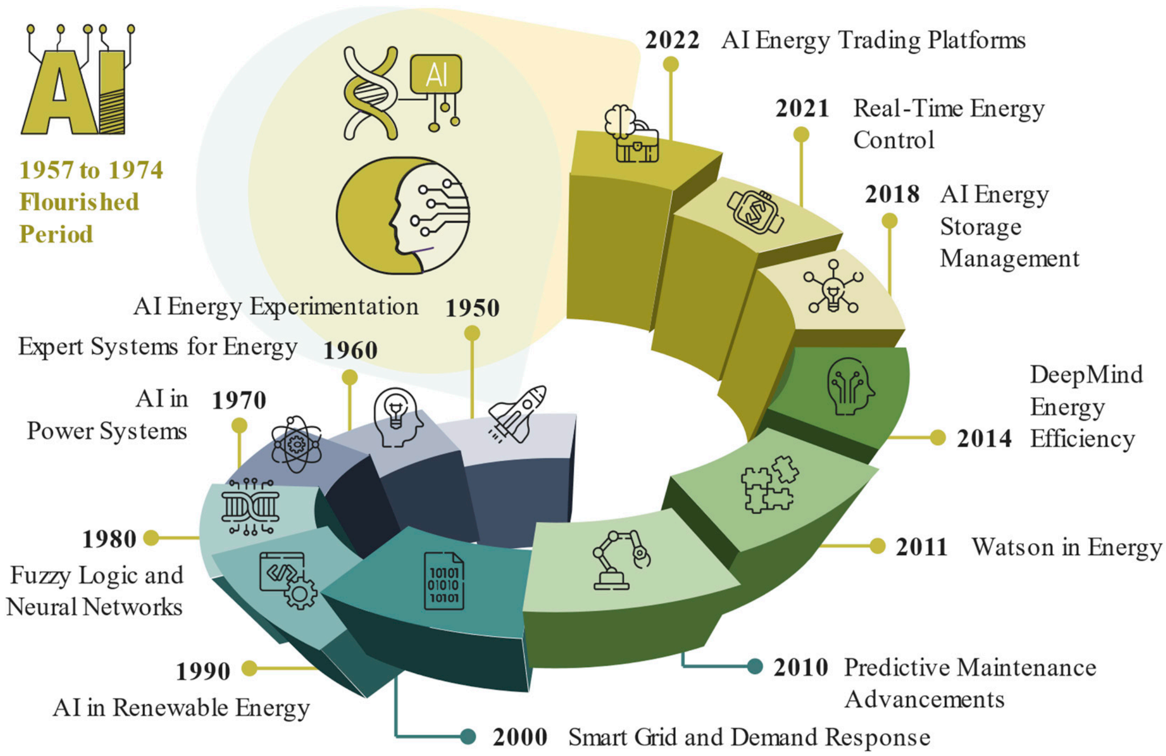

Figure 1. A tentative and historical perspective of AI deployment in energy sector from 1950 to 2022, using insights from [6–10].

- 1950: Early experimentation with AI in energy engineering.
- 1960: Development of expert systems for energy management.
- 1970: AI applications in power system control and optimization.
- 1980: Introduction of fuzzy logic and neural networks in energy systems.
- 1990: Integration of AI in renewable energy systems.
- 2000: Smart grid and demand response with AI integration.
- 2010: Advancements in predictive maintenance with machine learning.
- 2011: IBM's Watson aids energy management for buildings.
- 2014: Google's DeepMind applies AI for energy efficiency in data centers.
- 2018: AI-powered energy storage management systems.
- 2021: AI used for real-time monitoring and control of energy systems.
- 2022: AI-driven energy trading platforms and market analysis.

In the era of the fifth industry, technologies will move forward fast, impacting entire sectors, including the energy sector, and exposing new algorithms through the policy development process. Modern energy landscapes, besides integration with industry 4.0 to comply with industry 5.0 standards, emerge the concept of "man and machine", known as collaborative robots (cobots), aiming systems, and society integration in an agile and resilient manner with intelligent technologies [11]. Cobots, unlike conventional robots, are designed with kinematic and dynamic capabilities to cooperate with humans autonomously [12]. With all the advantages that robots have, there is the concern with taking peoples' jobs and changing the labor market. While cobots cannot replace the labor force, they can fill the gaps in society's aged populations. For example, it is reported that over 30% of Europeans will be over 65 by 2060 [13], which results in a high workforce demand. It has been reported that we should be careful about the increasing use of buzzwords such as industry 4.0+, 4.5, 6.0, and 7.0. While these terms may be prevalent in academic writing and grant applications, they do not necessarily help make practical business decisions or address the real technological challenges [14].

The technology value chain is an integral part of modern society. The industry revolution to the next revolution pushes society to be promoted with new challenges and opportunities. Industry 4.0 and 5.0 are considered technology-driven and value-driven ((1) human-centric: by promoting talents, diversity, and empowerment; (2) resiliency with flexible and adaptable technologies; and (3) sustainability: by ensuring substantiality requirements), respectively [14]. The modern technologies at the time of the fifth industry can be demonstrated with some challenges, such as the following [15]:

- Diverse values and acceptance among people.
- Measuring environmental and social value creation.
- Involving customers and enterprises across the value chain.
- Research spans multiple disciplines and complex systems.
- Innovation policy focused on ecosystems, agility, and outcomes.
- Need for productivity and substantial investments.

There is a limited body of research exploring the integration of AI into energy policies. The proposed framework addresses this gap by focusing on the techno-economic aspects and organizing them into eight key knowledge areas: data, technical, operational, knowledge-based, performance, tolerance, control and monitoring, and automation. By harmonizing these areas, the framework aims to achieve adaptability for AI implementation, enhance operational reliability, and accommodate scalability and future expansion. The comprehensive approach, encompassing the eight main categories of system robustness and their subcategories, ensures long-term sustainability in the energy sector.

This study aims to identify the energy sector's key challenges in adopting intelligent and smart technologies. A comprehensive literature review was conducted to find the relevant studies using meta-data and content analysis methodologies. The focus was on AI deployment in the energy sector, analyzed based on common strategic management [16] approaches: analogous estimation techniques, contingent response techniques, dependency determination techniques, expert judgment techniques, and brainstorming techniques [17]. This process resulted in an analogous outcome of expert insights regarding challenge exploration from various aspects. These challenges were then categorized based on expert judgment in a common-sense approach. It is important to note that this categorization can differ for various cases depending on the specific scenario conditions and requirements. This paper is organized into the following six sections: Section 2 reports the unseen challenges of AI in energy. AI integration requirements and challenges are discussed in Section 3. Data-driven modeling is addressed in Section 4. Section 5 is dedicated to Robotic Process Automation (RPA), followed by the AI-integrated energy policy developments in Section 6. Finally, the study's findings are concluded in Section 7.

2. Unseen Challenges of AI in Energy

Machine learning (ML) and AI in power systems are essential for advanced monitoring, control, operation, and integration of massive renewable energy, handling uncertainty and instability, adapting to changing conditions, and managing new aspects of smart grids [18]. However, these new approaches must also be incorporated into the legacy infrastructure and practices for machine learning methods that utilize flexibility and optimization. Today's integrated world with enormous amounts of data generation and exchanges requires robust infrastructures to discover helpful information from multidisciplinary information exchanges in various domains. The answer to this sophisticated and multidimensional requirement in the era of the industrial revolution is artificial intelligence (AI). Expeditiously, a tentative categorization of the challenges in Figure 2 will contribute to identifying key issues and prioritizing solutions based on their relevance to each category, thereby enabling the development of more focused and effective strategies for AI integration in energy systems.

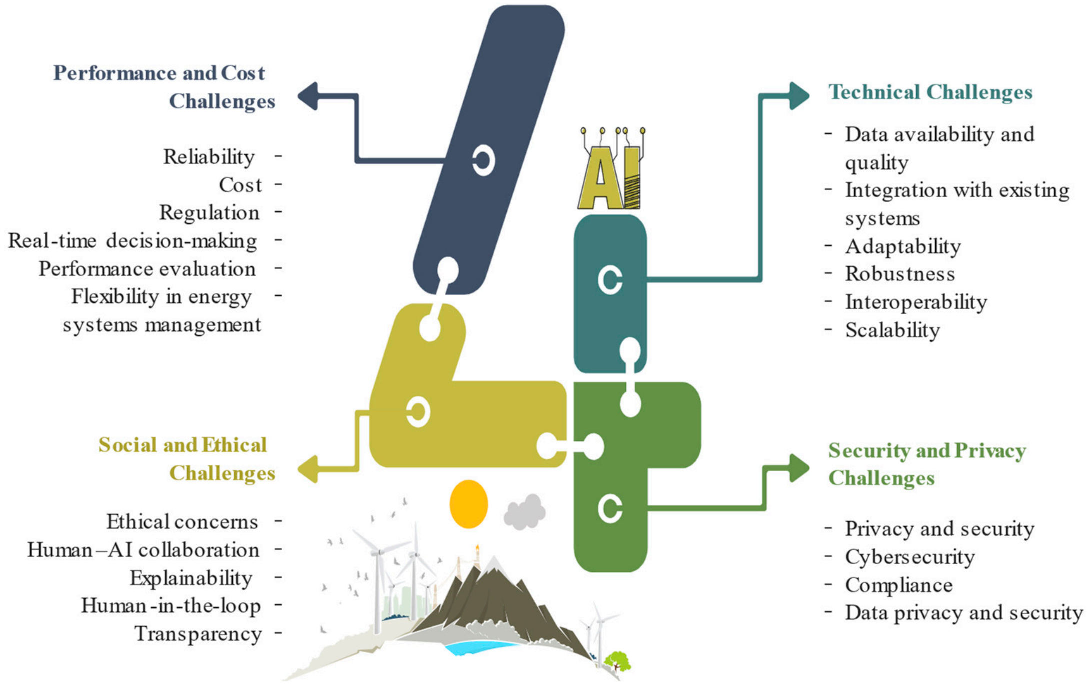

Figure 2. Classification of challenges related to AI integration in energy systems in a big picture in the context of the four main categories.

The integration of AI into the energy sector is associated with valuable lessons of success and failure, which primarily depend on data accuracy, algorithm selection, project management, integration with existing systems, monitoring and evaluation, stakeholder buy-in, expertise, budget, and resources, realistic expectations, and considerations of the ethical and social implications [19–22]. The visualization of the challenges' categories and factors with their interrelations and flow of variables is shown in Figures 3 and 4, which highlight the relationships among the main categories and their corresponding subcategories. The flow direction in Figure 4 provides valuable insights into the intricate interdependencies among these variables.

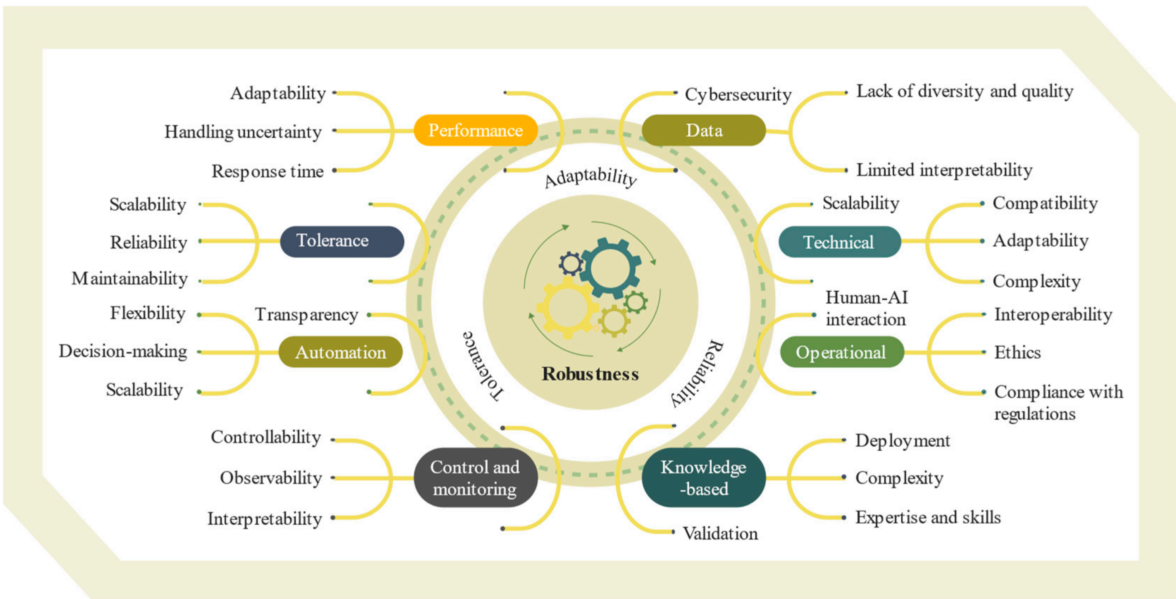

Figure 3. AI application in the energy systems' main challenges and their related factors.

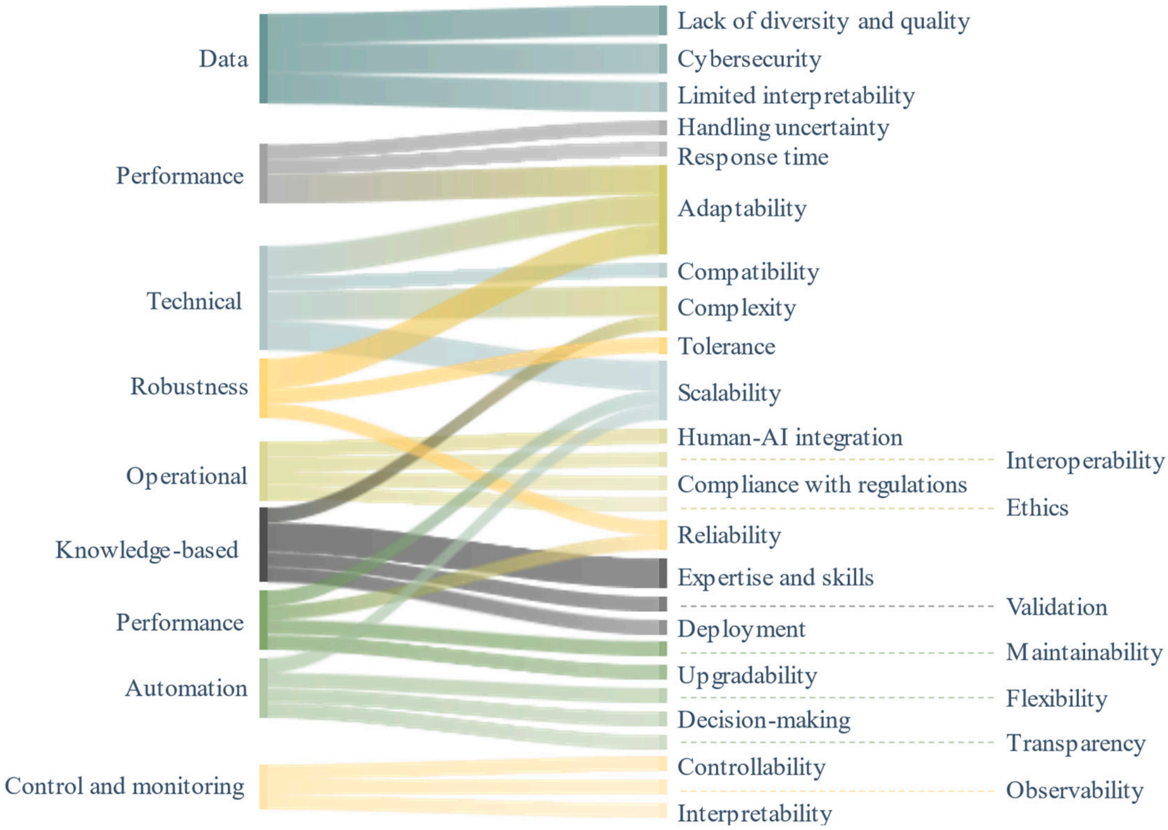

Figure 4. AI application in the energy systems' main challenges relationship map from a diverse perspective (animated online version link of this figure is given in the Supplementary Materials Section).

As the world increasingly relies on intelligence technologies to solve complex problems, several factors come into play when considering implementing AI in various industries, especially the energy sector. Among these factors, complexity, circumstance, and crucialness contribute to AI's overall impact and successful deployment in energy projects. Mainly, complexity arises from integrating AI technologies with existing infrastructures, often requiring high data availability with high-quality levels. This can pose challenges as implementers strive to use AI optimally while preserving human expertise. A medium level of human–AI collaboration and explainability is necessary to ensure that individuals can understand and trust the outputs of these techniques. Furthermore, a medium degree of flexibility is crucial for effective energy systems management, which may involve adapting to fluctuating demands or incorporating new energy resources. Despite the low emphasis on human-in-the-loop and performance evaluations, these factors remain relevant for creating more robust and reliable AI strategies.

The circumstances surrounding AI implementation often dictate the level of success and acceptance in various industries. High data availability and quality, privacy, security, and integration with new and existing setups are all essential aspects to be addressed. High cost and investment requirements can be a barrier for some utilities, making scalability a significant concern. While human–AI collaboration, explainability, human-in-the-loop, and performance evaluations are given medium to low priority, they still contribute to the overall success of AI strategies in diverse settings.

Crucialness is critical in ensuring AI systems' responsible and effective implementation. High priority is given to privacy and security, explainability, reliability, regulation, and scalability. These aspects ensure that AI approaches are technically sound and conform to ethical and legal standards. Human-in-the-loop, ethical concerns, cybersecurity, and transparency are also important and considered medium priorities, as they help build trust and confidence in AI systems. Human–AI collaboration, data availability, quality, integration with existing systems, cost and investment, and performance evaluation are regarded as low-priority factors, but they still contribute to the overall impact of AI on society through optimum energy systems' operation. Ultimately, transforming from a parameter-based model to a data-driven model poses numerous challenges in Triple-C (complexity, circumstance, and crucialness), which are addressed in Figure 5.

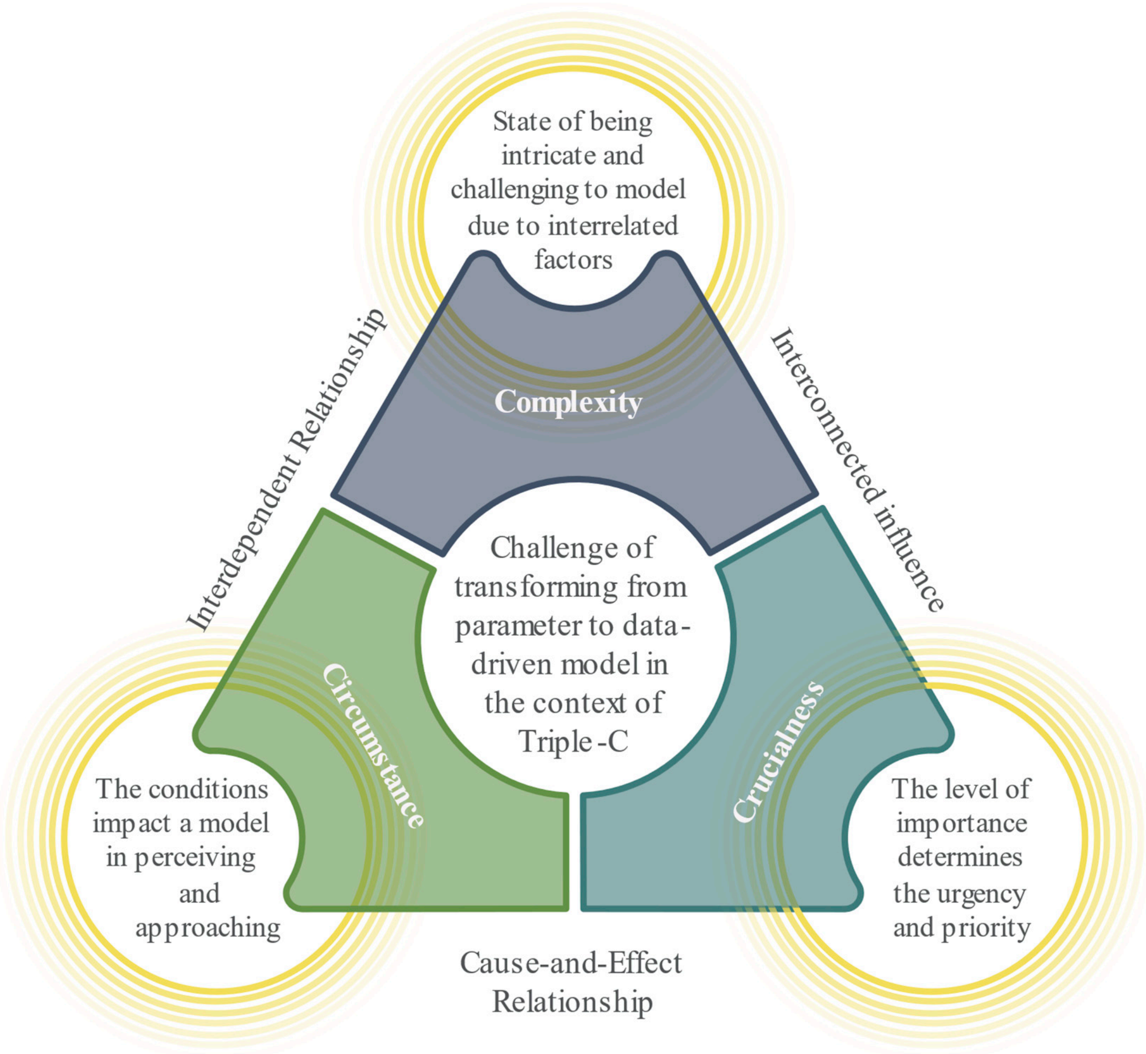

Figure 5. Observing the challenges of transforming from a parameter-based model to a data-driven based in the context of Triple-C (complexity, circumstance, and crucialness).

The relationships between complexity, circumstance, and crucialness provide valuable insights into the challenges and opportunities of implementing AI systems across various industries (Figure 6). Addressing these factors can help ensure the successful adoption of AI technologies while maximizing their benefits and minimizing the potential risks. By considering the impact of these factors on AI strategies' development and deployment, stakeholders can better understand the implications of AI in their respective fields (from energy planning to generation, transmission, and distribution), and make more informed decisions about their adoption and deployment. Investigating the challenges of transitioning from a parameter-based model to a data-driven model in the context of Triple-C (complexity, circumstance, and crucialness) across various scenarios and situations is explored in Table 1.

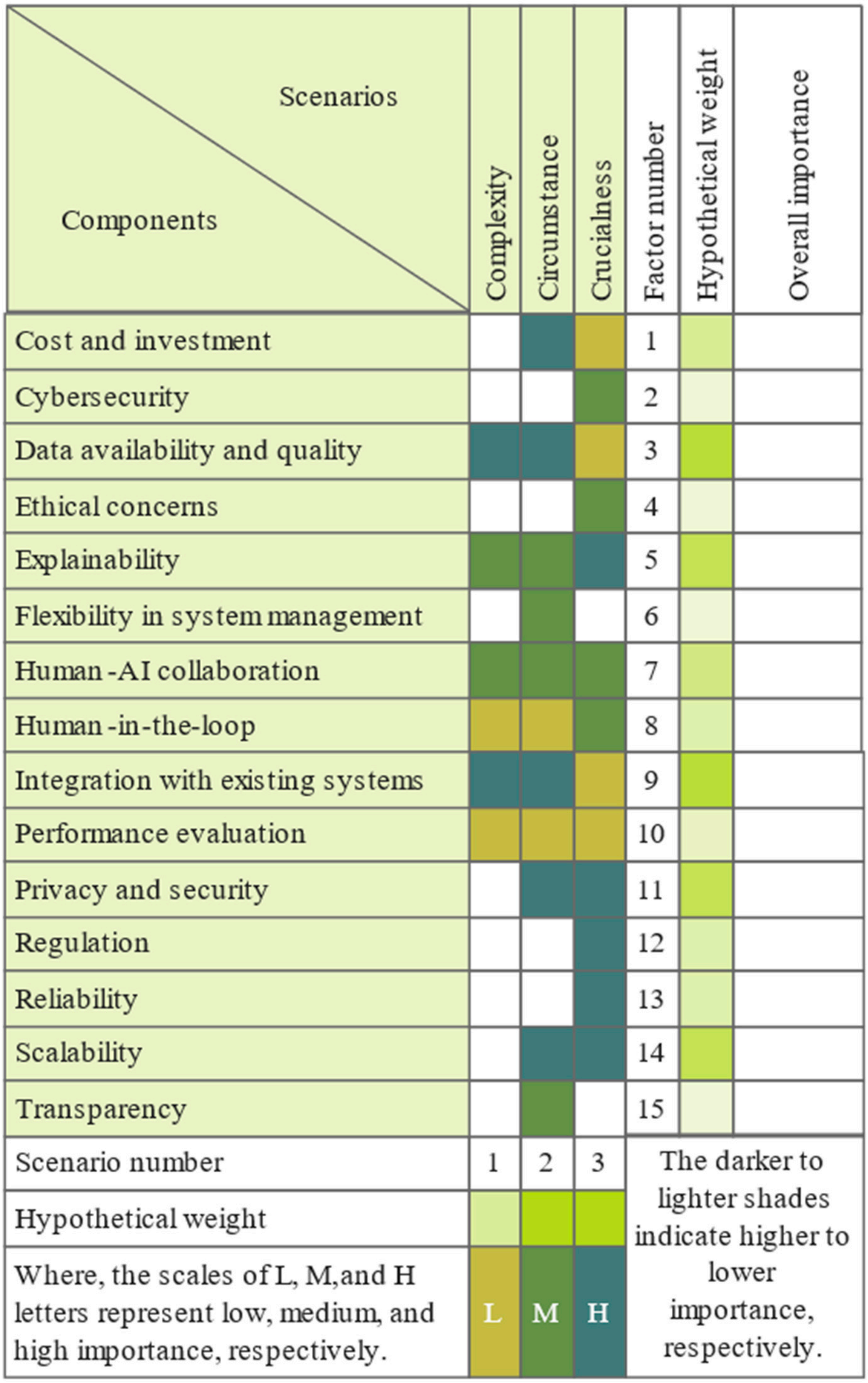

Figure 6. Exploring the challenges of transforming from a parameter-based model to a data-driven model in the context of Triple-C (complexity, circumstance, and crucialness) within a range of hypothetical scenarios.

Table 1. Summary of key challenges in integrating AI into energy systems [19–22].

No.	Challenge	Details
1	Data availability and quality	The availability and quality of data are critical factors for the successful implementation of AI-based systems in energy systems. These systems rely on large amounts of data for training and testing, and the data must be in a specific format and series. Inadequate or low-quality data can lead to poor results and inaccurate predictions, making it essential to have a robust data collection and preprocessing strategy in place.
2	Privacy and security	Using AI in energy systems raises concerns about protecting sensitive energy consumption and production information. This information can be collected and stored to identify patterns and make predictions, but it also creates a risk of data breaches and unauthorized access. Robust security measures such as encryption and secure data storage must be implemented to mitigate these risks.
3	Explainability	One of the challenges of AI systems is their lack of interpretability and understandability. This can make explaining their decision-making process to stakeholders challenging, particularly in critical decision-making tasks involving safety or compliance. To address this challenge, developing transparent AI systems that non-technical stakeholders can easily understand is essential.
4	Reliability	AI systems may not always produce reliable results, especially if they are not properly trained or if the data used to train them do not represent real-world conditions. To ensure the reliability of AI systems, it is essential to thoroughly test them and validate their results before deploying them in production.
5	Integration with existing systems	Integrating AI systems into existing energy systems can be a complex process that requires significant changes to existing infrastructure, such as hardware and software, as well as business processes and workflows. To ensure successful integration, it is essential to thoroughly understand the existing energy systems and plan for the integration of AI systems accordingly.
6	Cost	Developing and implementing AI systems can be expensive, which may not be feasible for some energy companies or organizations. It is essential to consider these systems' costs and benefits carefully and prioritize investments in areas that will have the greatest impact.
7	Regulation	The lack of regulation and standards for the use of AI in energy systems can make it difficult for organizations to ensure compliance with the legal and ethical requirements. It is essential to stay informed about regulatory developments and work with regulators to establish the best practices for using AI in energy systems.
8	Scalability	AI systems may not be able to handle large-scale energy systems and the complexity and variability of real-world energy systems. To ensure that AI systems can scale to handle large-scale energy systems, developing AI systems that can scale and test them under realistic conditions is essential.
9	Human-in-the-loop	To ensure that AI systems complement and enhance human decision-making rather than replace it. Incorporating human oversight into the decision-making process or providing human operators with tools to verify and correct AI-generated decisions is essential.

Table 1. *Cont.*

No.	Challenge	Details
10	Ethical concerns	Using AI in energy systems may raise ethical concerns, such as potential bias in decision-making and the displacement of human workers. It is essential to develop and implement ethical guidelines for using AI in energy systems and to ensure that the potential risks and impacts of AI systems are carefully considered.
11	Cybersecurity	Ensuring that AI systems are protected from cyber-attacks and unauthorized access is crucial for the security and integrity of energy systems. This can include implementing robust security measures, such as secure data storage and encryption, as well as regular security audits and vulnerability assessments. Additionally, it is vital to develop and implement incident response plans to address any potential security breaches or vulnerabilities.
12	Adaptability	As energy markets and regulations are constantly evolving, AI systems need to have the ability to adapt to these changes to remain effective and efficient. This may require regular updates and adjustments to the AI system and the development of methods for detecting and responding to changes in the energy market or regulatory environment.
13	Transparency	AI systems must be transparent in their decision-making processes. This can be achieved by providing clear explanations of the logic and reasoning behind a decision and making the system's underlying data and algorithms available for review. This is also important for ensuring compliance with regulations and ethical guidelines.
14	Human–AI collaboration	For AI systems to be effective in energy systems, they must be able to work effectively with human operators and decision-makers. This may require the development of interfaces and tools that allow for accessible communication and collaboration between humans and AI systems.
15	Real-time decision making	Energy systems often require real-time decision-making, such as responding to energy demand or supply changes. AI systems must be able to make decisions quickly and accurately in real-time to be effective in these systems.
16	Performance evaluation	To ensure that AI systems perform well, evaluating their performance using appropriate metrics is essential. This may include metrics such as accuracy, efficiency, and scalability.
17	Scalability	As energy systems often have to handle large-scale operations, AI systems must also be able to scale to handle these operations. This may require the development of methods for distributed computing and parallel processing.
18	Robustness	Energy systems are often subject to uncertainty and variability, such as changes in weather or equipment failure. AI systems must handle these uncertainties and variabilities to be effective in these systems.
19	Interoperability	AI systems must be able to work with other systems and technologies, such as energy management systems or sensor networks. This requires the development of methods for integrating AI systems with other systems and technologies.

Table 1. *Cont.*

No.	Challenge	Details
20	Data privacy and security	Ensuring that sensitive information and data generated by energy systems are protected from unauthorized access, use, or disclosure is a significant challenge in integrating AI into energy systems. This includes protecting data from cyberattacks and ensuring that data are used in a way that complies with regulations such as the General Data Protection Regulation (GDPR).
21	Compliance	Energy systems must comply with various regulations and standards, such as those related to safety and environmental protection. Integrating AI into energy systems can introduce new complexities and challenges in ensuring compliance with these regulations.
22	Human–AI collaboration	Ensuring that AI systems work seamlessly with human operators and decision-makers is a significant challenge in integrating AI into energy systems. This includes developing interfaces and workflows that allow human operators to understand and interact with AI systems easily and ensuring that AI systems consider human preferences and constraints when making decisions.
23	Explainability	One of the challenges in integrating AI into energy systems is the ability of humans to understand and explain how AI systems make decisions. This is important for building trust in AI systems as well as ensuring that AI systems are used in a way that is fair and transparent.
24	Human-in-the-loop	Ensuring that human operators and decision-makers can intervene in the decision-making process of AI systems is an important challenge in integrating AI into energy systems. This is necessary to ensure that AI systems are used in a safe, fair, and transparent way, and to allow human operators to take into account factors that the AI system may not capture.
25	Flexibility in energy systems management	Energy systems are complex and dynamic, and integrating AI into these systems can introduce new challenges in terms of flexibility and adaptability. This includes ensuring that AI systems can adapt to changing conditions and respond to unexpected events and that AI systems can work seamlessly with other systems and devices in the energy ecosystem.

Integrating AI into energy systems presents various challenges, as documented in the literature. Ensuring seamless integration with new or existing energy systems remains a concern, necessitating compatibility with legacy infrastructure and processes. This section addresses the most significant challenges encountered across diverse scenarios and under different circumstances. An exhaustive list of these challenges is discussed in Table 1.

However, the improper use of machine learning, even when prerequisites are available, can still lead to undesired results. This highlights the importance of thoroughly understanding the underlying models and deploying the appropriate tools and techniques to ensure the efficacy of machine learning applications. Data quality plays a crucial role in achieving accurate and reliable outcomes. Utilizing high-quality datasets helps minimize errors and biases while enhancing the overall performance of machine learning algorithms. To avoid undesired results, it is essential for practitioners to carefully consider the choice of models, techniques, and data sources while also closely monitoring the implementation process to ensure that the machine learning systems perform as intended. According to [23], in some cases, optimizing neural networks can be challenging due to several factors, such as ill-conditioning of the Hessian matrix, local minima and saddle points, cliffs, exploding gradients, deep computational graphs, and the theoretical limits of optimization. These challenges can arise even when optimizing convex functions, making it difficult to find deep models. Hypothetical results also show difficulties in the performance of off-limit algorithms, but they are not necessarily applicable in practical applications where neural networks are used. The goal is not to find the exact minimum of a function but to reduce its value enough to obtain a reasonable generalization error limit.

3. AI Integration Requirement and Conundrum

Artificial intelligence (AI) is a field of computer science established in the 1950s to study the phenomenon of intelligence using computers to simulate human thought processes, reaching a scientific understanding of intelligence using the logical operations of computers for a better understanding and performance of the human mind [24]. Computational intelligence was born in the twentieth century to enable computers to simulate humans' learning with decision-making capabilities and become a game-changer in today's life [25]. Numerical modeling and analysis are carried out without considering factors such as the accuracy and dependence of the model. A numerical concept of 4E (energy, exergy, environment, and economics) was implemented to analyze a hybrid waste-to-energy system to reduce emissions pollution and level the cost of electricity production [26].

A new blueprint is depicted in Figure 7, which indicates that DS makes the foundation for the analysis and interpretation of data, while AI and ML use these data to inform and direct energy policy decisions at diverse levels with an interlinked and overlapping correlation. Data science (DS) bestows a broad range of tasks, including classification, regression, association analysis, clustering, anomaly detection, recommendation engines, feature selection, time-series forecasting, deep learning, text mining, etc. AI and ML are limited to specific applications within desired landscapes [27]. Generalizing these three levels with close interdependency remains a challenge. Data science establishes the first step in developing energy policies for AI and ML through data collection and analysis in a big scheme. AI uses that data to automate tasks and create smart energy production, transmission, and distribution systems, and ML uses AI to implement self-learning algorithms and predict energy consumption patterns, market trends, and system performance [28]. AI and ML are built on top of DS and use the data to identify patterns, make predictions, and imagine a blueprint [25] that enables policymakers to make informed decisions on system setup based on a technical and circular economy foundation at the national, regional, and local levels.

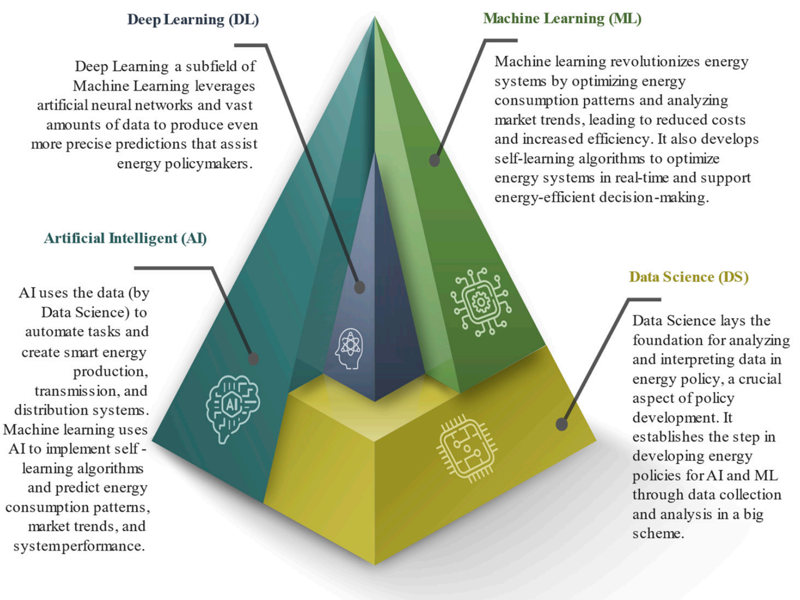

Figure 7. The proposed blueprint for utilizing DS, AI, and ML to inform energy policy decisions at diverse levels [26–28].

Data science (DS) lays the foundation for analyzing and interpreting data in energy policy, which is a crucial aspect of policy development. Artificial intelligence (AI) and ML build upon this foundation by using data to identify patterns and make predictions [29]. These insights and predictions inform energy policy decisions at various levels, including the national, regional, and local levels, and drive initiatives that prioritize energy efficiency, promote the adoption of renewable energy sources, and reduce greenhouse gas emissions. Furthermore, deep learning (DL), a subfield of ML, leverages artificial neural networks and vast amounts of data to produce even more precise predictions that assist energy policy-makers [30]. However, distinguishing these interrelated categorizations can be challenging. Nonetheless, a conceptual blueprint in Table 2, which is specific to the energy engineering discipline in the context of policy development, provides a mainstream conception.

Table 2. Contribution of DS, AI, and ML in shaping energy policy from a macro perspective.

Domain	The Main Contribution from a Macro Perspective
Data Science (DS)	• Collection and organization of large energy-related datasets. • Development of data management and storage systems. • Analysis of energy consumption patterns and forecasting. • Predictive modeling and optimization of energy systems.
Artificial Intelligence (AI)	• Automation of routine tasks in energy production, transmission, and distribution. • Development of smart energy systems. • Implementation of AI-powered energy management systems. • Predictive maintenance and fault detection in energy systems.
Machine Learning (MS)	• Predictive modeling and optimization of energy consumption patterns. • Prediction and analysis of energy market trends. • Implementation of self-learning algorithms in energy systems. • Development of energy-efficient decision-making systems.

The literature [31–35] indicates that experts and professionals face challenges in their decision-making processes due to the surfeit of advancements and strategic modifications in integrating AI into energy systems that utilize data-driven models instead of system parameter-based models. This poses a challenge in singling out the critical aspect for a feasible policy decision amidst a labyrinth of multidisciplinary factors such as technical, technological, social, political, environmental, ecological, economic, institutional, and global limitations.

4. Data-Driven Modeling

Incorporating machine learning into energy policies requires accurate, data-driven models and appropriate datasets. Breaking down the policy processes into manageable portions allows for better data analysis and dataset creation. The high volume and variability of smart grid data pose challenges for AI algorithms, requiring improved robustness, adaptiveness, and online processing [36]. Data-driven models identify patterns in historical data without prior knowledge of system dynamics, while parameter-based models rely on mathematical equations and system knowledge [37]. Data-driven models offer advantages such as automatic pattern learning, high accuracy potential, and improvement over time with new data. However, they have limitations, such as overfitting susceptibility, data quality sensitivity, and interpretation difficulties [38–40].

Data are a critical component in machine learning and analytics, undergoing multiple processing stages to ensure quality and usability, yet the term Big Data remains conceptually vague, despite its popularity in academia and industry [41,42]. The stages of data processing include data collection, which involves gathering raw data from multiple sources such as web scraping, APIs, surveys, and databases. Data cleansing removes inconsistencies, duplicates, and handles missing values to improve data quality. Data labeling annotates or tags data with relevant labels for supervised learning tasks, while data augmentation creates new or modified instances of data to expand and diversify the dataset, improving model performance [43]. Data encoding transforms data into machine-readable formats, such as one-hot encoding and label encoding. Feature extraction extracts the essential characteristics from the raw data to represent and summarize it [44]. Feature scaling standardizes and normalizes data features to ensure equal contribution to model training, and feature engineering creates new features or transformations to enhance the dataset's predictive power [45]. Data imputation fills in missing values with estimates based on existing data, and data integration combines datasets from multiple sources to create a unified dataset.

Dimensionality reduction reduces the number of features while maintaining the most relevant information. Data anonymization protects the sensitive information in datasets through techniques such as data masking and generalization [44]. Data splitting divides the dataset into training, validation, and testing subsets to evaluate the model's performance, and data shuffling rearranges the order of data samples to prevent bias in the model training process [45]. Data versioning tracks change and maintain historical records of datasets for reproducibility and auditing purposes [46]. Data storage manages data storage in various forms, such as cloud storage, local storage, and databases. Data validation ensures data correctness and consistency using statistical tests, visualizations, and outlier detection. Lastly, data monitoring observes the data pipeline for performance metrics, real-time monitoring, and notifications to maintain data quality and integrity [44].

5. Robotic Process Automation (RPA)

Computational intelligence and data science have the potential to contribute to policy development processes and improve the operational efficiency and performance of energy systems through the implementation of Robotic Process Automation (RPA) and other forms of automation. However, there are concerns regarding these solutions' integration and smooth operation [47,48], as elaborated in Figure 8. The application of RPA technologies in the energy sector is increasing to automate repetitive and manual tasks, reduce labor and machinery costs, and improve accuracy, efficiency, satisfaction, and speed [49]. Autonomous complexity in energy systems refers to the degree of automation and the level of interdependence between human operators and autonomous systems in a power plant setup [48]. RPA creates software bots to perform tasks by mimicking human actions and interacting with existing software systems. The future direction of RPA in energy is expected to grow with a focus on integrating RPA with other technologies, such as AI and IoT, to create advanced automation solutions [50]. Energy utilities aim to continue to use RPA to streamline processes, reduce costs, and improve customer satisfaction. Given the significance of RPA in the energy sector, deploying this technology necessitates the mitigation of complexities that may hinder its implementation. An exhaustive examination of the potential complexities associated with the performance of RPA in the energy sector is presented in Figure 8.

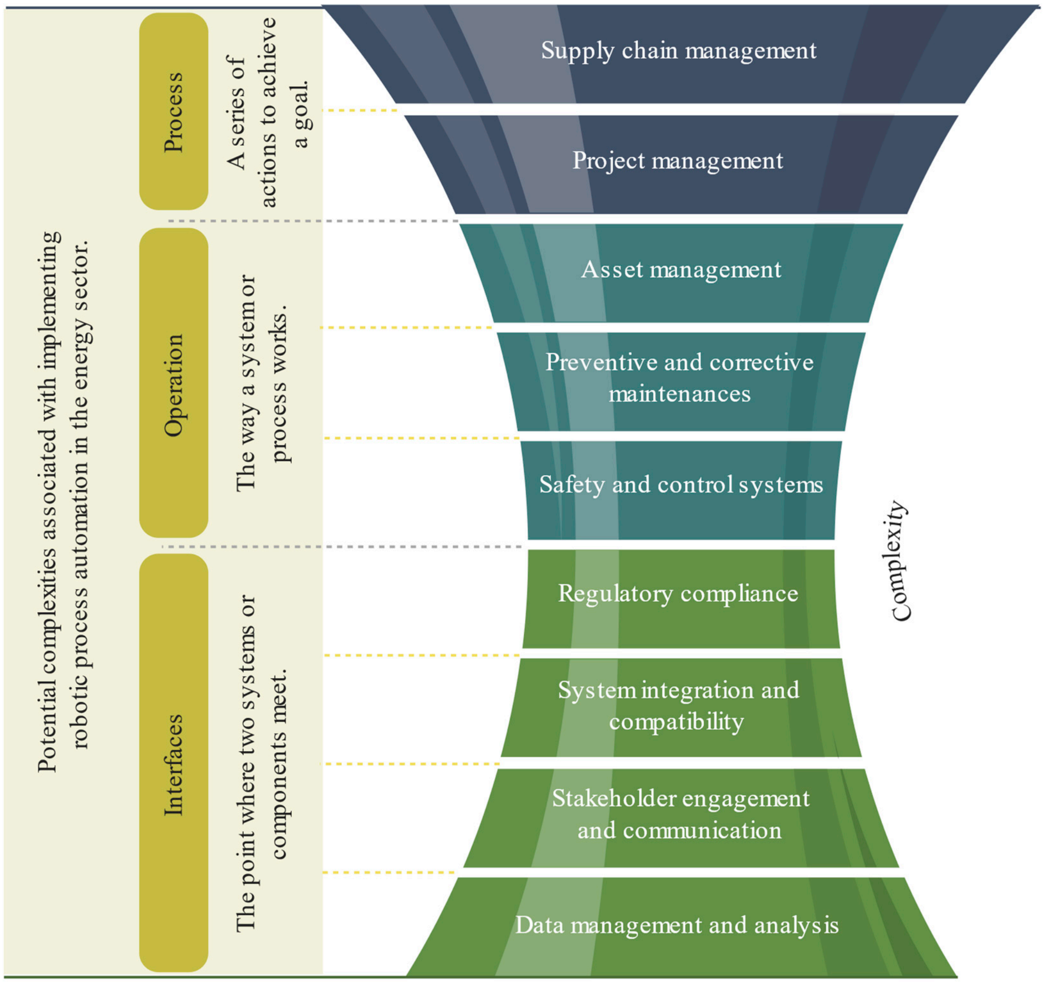

Figure 8. Potential complexities of autonomy associated with implementing RPA in the energy sector.

Autonomy is an automation system's ability to complete a cognitive task without human intervention, emerging from the aggregation of autonomous tasks in a perception/situational awareness/decision-making/action chain [47]. The coexistence of multiple autonomous systems may require human intervention, with technological barriers of complexity, adaption, and interactions with autonomous systems and operators [51].

6. AI-Integrated Energy Policy Development

With an increasing demand for collecting, exploring, and analyzing big data, AI is prioritized in handling these big datasets and automated operations, which is versatile in terms of numerous applications within various platforms. Adequate energy supply and demand planning are linked with analyzing enormous amounts of past data to respond to current demand efficiently and predict future growth patterns optimally. Balancing supply and demand through optimization of efficiencies and minimizing losses can be achieved by combining domain expertise (technical, technological, economic, institutional, social, etc.) [16] and scientific methodologies (mathematics, statistics, algorithms, etc.) backed by technological innovations (coding, processing, operating, etc.) called data science, a central part of an AI platform.

The coordinate systems of AI application in the energy sector to optimize and automate the system and energy policy objectives to ensure standardized methods for a reliable techno-economic operation closely cross each other based on their goals from application perspectives [52]. This common point will enable policymakers to utilize AI optimally by shaping an integrated roadmap based on emerging dual optimization factors for a single purpose [53]. Tackling AI limitations in energy system applications requires a harmonious approach that optimizes energy management implementation in policy development in terms of a course of action [54]. Followed by human resources' capacity building to empower humans to collaborate with cobots and humanoids, achieving the organizational goals. With real-time access to stakeholders' information at different hierarchy levels, privacy and its ethics are more crucial than before, which was not considerably addressed in the previous energy policies [55]. So, it warns policymakers to strictly consider this concern along the policy development journey from development to update. For example, using drones to conduct preventive or corrective maintenance of transmission lines or wind turbines.

Many interdisciplinary terms are used interchangeably in various knowledge domains in the context of energy policy development. The two main shortcomings demonstrate this. The terminology of specific terms represents particular quantitative and qualitative attributes for the specific domain usage. The mostly interchangeably use of such terminology in any other than the particular domain can be confusing and misleading. On the other hand, non-observing the terminology and disordered usage of their hierarchy can contribute to the misunderstanding of the policy in implementation by experts from different domains. Such problems can be found in energy policies, which are poorly coordinated among different stakeholders and experts or are less focused on policy terminology. Most rely on the technical aspects since policy development is a collaborative and high-endeavor task for a vital outcome within feedback look of revision and update. The existing policies have the opportunity to be polished and standardized for interdisciplinary domains, better understanding, and effective deployment. So, an essential hierarchical presentation of the critical terms of professional and methodological are listed below [56,57]:

- Paradigm: from a philosophical framework to an idea, linking conceptual phenomena to real-world life.
- Framework: from assumptions to hypotheses, linking models and methods to define parameters' relationships, characteristics, behavior, etc., in a big image.
- Model: from a general to descriptive representation of any framework with details of operations, performances, mechanisms, etc.

AI enables policies to have a black-box operation mechanism and tools with feedback flow for better performances, ensuring high forecasting accuracy and viable applications. The literature suggests a multifaceted approach to dealing with the complexity of energy and environmental sustainability, encompassing the technical, technological, economic, social, institutional, and political dimensions [,[58]]. Building upon this idea, Figure 9 investigates the factors influencing energy policy development and achieving sustainable development goals, categorized into various dimensions.

As the primary focus of this study is on the AI challenges in the development of energy systems, the energy policy development process is briefly introduced in Figure 10. This illustration highlights the hierarchy of formulation, levels of the process, methodologies, indices, and the main building blocks, providing a comprehensive overview as a reference.

From a technical policy perspective, resilience relies on cogitating and critiquing, dealing with a persistent flow of decision-making [59] that is controlled by the policy indicators for self-organizing, learning, adapting, and maintaining inertia, ensuring long-run system sustainability [60]. At regional and national levels, energy policies can be developed to incentivize energy efficiency, promote renewable energy technologies, reduce greenhouse gas emissions, etc. Regional levels can be tailored to address specific energy challenges, e.g., access to energy, energy security, etc. [61]. Additionally, at the local level, energy policies can be designed to support energy conservation, encourage the development of sustainable energy infrastructure, etc.

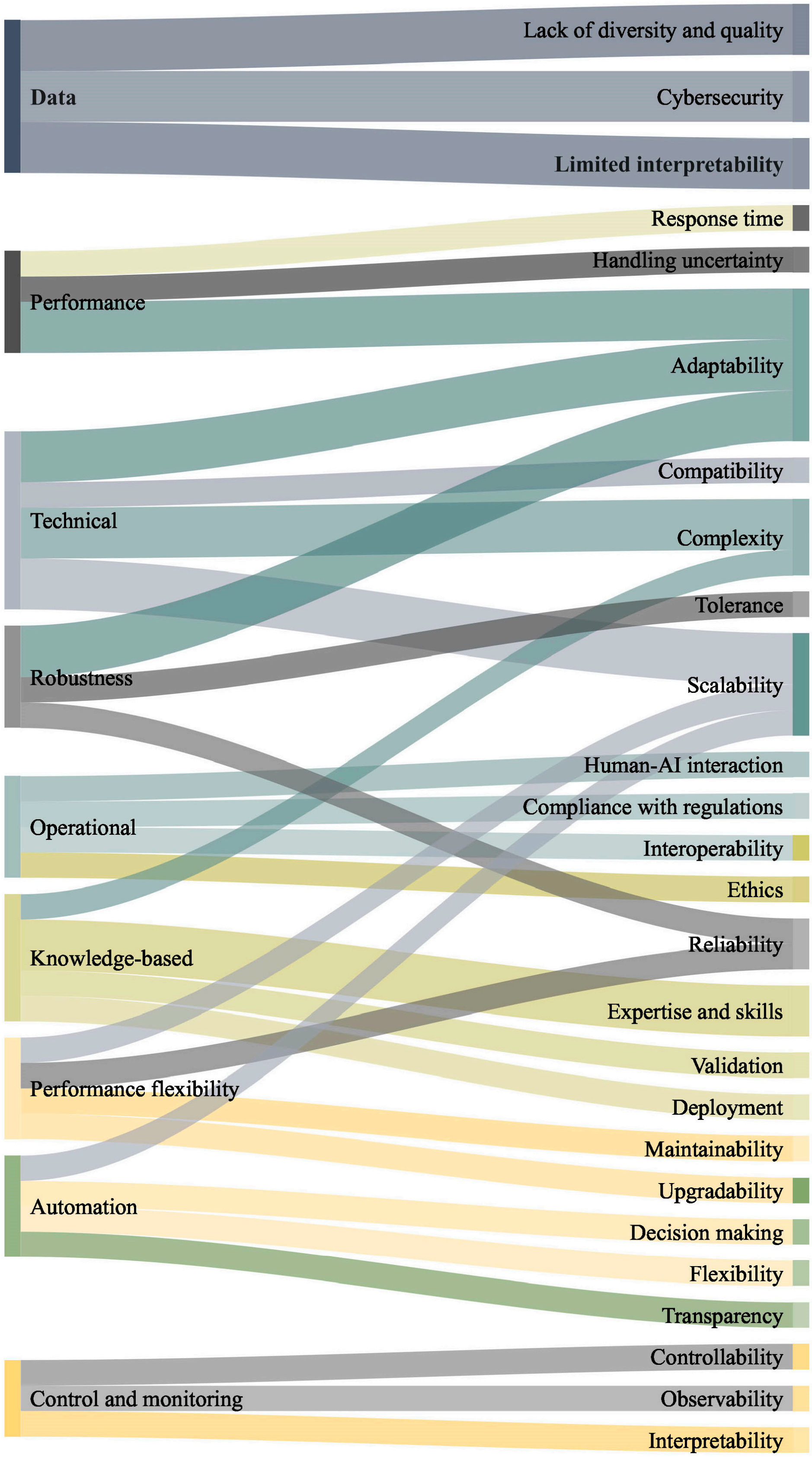

Figure 9. The most influential factors in energy policy development with the integration of AI strategies (animated online version link of this figure is given in the Supplementary Materials Section).

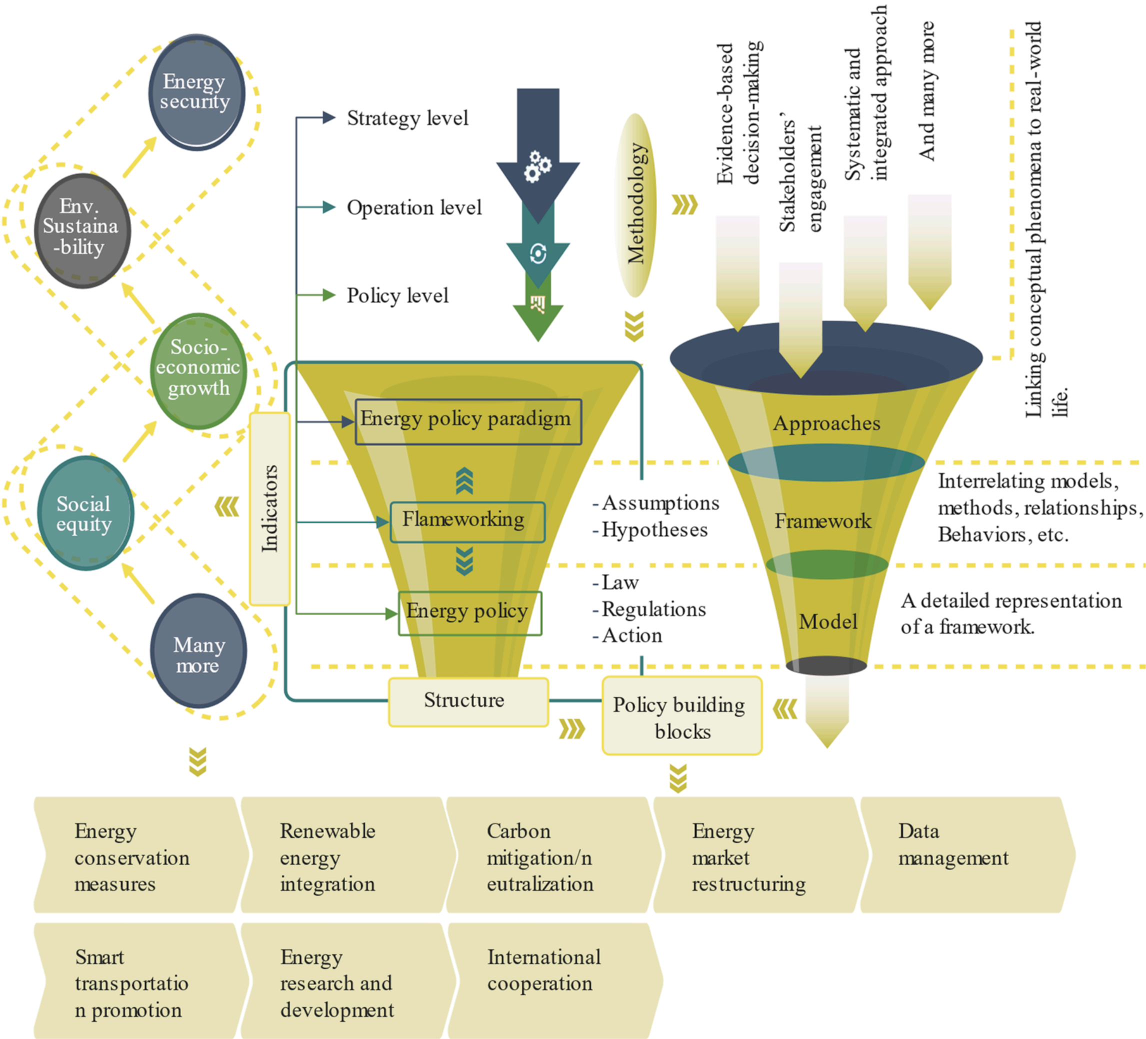

Figure 10. Overview of energy policy development hierarchy and building blocks.

7. Conclusions

AI is poised to revolutionize the energy sector by offering innovative solutions to optimize system operations and improve reliability while ensuring techno-economic advantages. These advantages result in improved efficiency, optimized demand balancing and forecasting, enhanced system stability and reliability through optimal preventive and corrective maintenance, high-yield economic operation, proper unit commitments, and demand–supply control that can achieve market optimization. Streamlining decision-making processes and reducing operational and capital expenses contribute to a more cost-effective energy sector. Lastly, enhanced cybersecurity is ensured through data-driven solutions, making the energy systems economically viable, accessible, and sustainable. However, the successful integration of AI into the energy sector comes with its share of unforeseen obstacles, which may alter the optimism surrounding the adoption of AI. This study explores, identifies, categorizes, and evaluates the challenges from a multidimensional perspective and provides a detailed roadmap. Shedding light on the main challenges facing the integration of AI in the energy sector suggests that a coordinated approach is essential to overcome these unforeseen challenges and can serve as a valuable resource for policymakers, energy practitioners, and researchers looking to unlock the full potential of AI in the energy sector. Meanwhile, a novel policy development and implementation framework is proposed, which aims to contribute to a more efficient, resilient, and sustainable future.

Supplementary Materials: The following supporting information can be downloaded at: https://github.com/mirsayedshah/AI-in-Energy-Overcoming-Unforeseen-Obstacles.git (accessed on 8 March 2023): Animated versions of Figures 4 and 9, along with their HTML code for easy understanding and observation of the utilized weights. These animations can be adapted for various purposes, making it easier to interpret and analyze the data in the figures. The repository contains animated versions of Figures 4 and 9, which help visualize the relationships and weights between various challenges in AI applications for energy systems and factors in energy policy development with AI integration. The accompanying HTML code allows for easy modification and adaptation for other purposes or datasets. Using these resources can enhance understanding of the data and tailor these visualizations for related research or projects.

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References

1. Kubassova, O.; Shaikh, F.; Melus, C.; Mahler, M. History, Current Status, and Future Directions of Artificial Intelligence. In *Precision Medicine and Artificial Intelligence*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 1–38. ISBN 978-0-12-820239-5.
2. Turing, A.M. Computing Machinery and Intelligence. In *Parsing the Turing Test: Philosophical and Methodological Issues in the Quest for the Thinking Computer*; Epstein, R., Roberts, G., Beber, G., Eds.; Springer: Dordrecht, The Netherlands, 2009; pp. 23–65, ISBN 978-1-4020-6710-5.
3. Anyoha, R. The History of Artificial Intelligence. *Sci. News*. 2017. Available online: https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/ (accessed on 12 February 2023).
4. Odagiri, H.; Nakamura, Y.; Shibuya, M. Research Consortia as a Vehicle for Basic Research: The Case of a Fifth Generation Computer Project in Japan. *Res. Policy* **1997**, *26*, 191–207. [CrossRef]
5. Kahn, K.; Winters, N. Constructionism and AI: A History and Possible Futures. *Br. J. Educ. Technol.* **2021**, *52*, 1130–1142. [CrossRef]
6. Kazim, E.; Koshiyama, A.S. A High-Level Overview of AI Ethics. *Patterns* **2021**, *2*, 100314. [CrossRef] [PubMed]
7. Southworth, J.; Migliaccio, K.; Glover, J.; Glover, J.; Reed, D.; McCarty, C.; Brendemuhl, J.; Thomas, A. Developing a Model for AI Across the Curriculum: Transforming the Higher Education Landscape via Innovation in AI Literacy. *Comput. Educ. Artif. Intell.* **2023**, *4*, 100127. [CrossRef]
8. Gendron, J.; Maduro, R. 6—The Role of Inference in AI: Start S.M.A.L.L. with Mindful Modeling☆☆ S.M.A.L.L. Is an Acronym for Specific-Mindful-Attainable-Limited-Lucid. In *AI Assurance*; Batarseh, F.A., Freeman, L.J., Eds.; Academic Press: Cambridge, MA, USA, 2023; pp. 185–229. ISBN 978-0-323-91919-7.
9. Saha, S.; Gan, Z.; Cheng, L.; Gao, J.; Kafka, O.L.; Xie, X.; Li, H.; Tajdari, M.; Kim, H.A.; Liu, W.K. Hierarchical Deep Learning Neural Network (HiDeNN): An Artificial Intelligence (AI) Framework for Computational Science and Engineering. *Comput. Methods Appl. Mech. Eng.* **2021**, *373*, 113452. [CrossRef]
10. Toosi, A.; Bottino, A.G.; Saboury, B.; Siegel, E.; Rahmim, A. A Brief History of AI: How to Prevent Another Winter (A Critical Review). *PET Clin.* **2021**, *16*, 449–469. [CrossRef]
11. Huang, S.; Wang, B.; Li, X.; Zheng, P.; Mourtzis, D.; Wang, L. Industry 5.0 and Society 5.0—Comparison, Complementation and Co-Evolution. *J. Manuf. Syst.* **2022**, *64*, 424–428. [CrossRef]
12. Rossato, C.; Pluchino, P.; Cellini, N.; Jacucci, G.; Spagnolli, A.; Gamberini, L. Facing with Collaborative Robots: The Subjective Experience in Senior and Younger Workers. *Cyberpsychology Behav. Soc. Netw.* **2021**, *24*, 349–356. [CrossRef]
13. Biton, A.; Shoval, S.; Lerman, Y. The Use of Cobots for Disabled and Older Adults. *IFAC-Pap.* **2022**, *55*, 96–101. [CrossRef]
14. Xu, X.; Lu, Y.; Vogel-Heuser, B.; Wang, L. Industry 4.0 and Industry 5.0—Inception, Conception and Perception. *J. Manuf. Syst.* **2021**, *61*, 530–535. [CrossRef]
15. Breque, M.; Nul, L.D.; Petridis, A. *Industry 5.0: Towards a Sustainable, Human Centric and Resilient European Industry*; European Commission: Brussels, Belgium; Directorate General for Research and Innovation: Brussels, Belgium, 2021; ISBN 978-92-76-25308-2.
16. Danish, M.S.S.; Senjyu, T.; Zaheb, H.; Sabory, N.R.; Ibrahimi, A.M.; Matayoshi, H. A Novel Transdisciplinary Paradigm for Municipal Solid Waste to Energy. *J. Clean. Prod.* **2019**, *233*, 880–892. [CrossRef]

17. Danish, S.M.S.; Zaheb, H.; Sabori, N.R.; Karimy, H.; Faiq, A.B.; Fedayi, H.; Senjyu, T. The Road Ahead for Municipal Solid Waste Management in the 21st Century: A Novel-Standardized Simulated Paradigm. In *IOP Conference Series: Earth and Environmental Science, Proceedings of the 2019 3rd International Conference on Energy and Environmental Science, Seoul, Republic of Korea, 26–29 June 2019*; IOP Publishing: Seoul, Republic of Korea, 2019; Volume 291, p. 012009.
18. Dobbe, R.; Hidalgo-Gonzalez, P.; Karagiannopoulos, S.; Henriquez-Auba, R.; Hug, G.; Callaway, D.S.; Tomlin, C.J. Learning to Control in Power Systems: Design and Analysis Guidelines for Concrete Safety Problems. *Electr. Power Syst. Res.* **2020**, *189*, 106615. [CrossRef]
19. Mortier, T. Why Artificial Intelligence Is a Game-Changer for Renewable Energy. Available online: https://www.ey.com/en_gl/power-utilities/why-artificial-intelligence-is-a-game-changer-for-renewable-energy (accessed on 6 October 2022).
20. Nix, A.; Decker, S.; Wolf, C. Enron and the California Energy Crisis: The Role of Networks in Enabling Organizational Corruption. *Bus. Hist. Rev.* **2021**, *95*, 765–802. [CrossRef]
21. Szczepaniuk, H.; Szczepaniuk, E.K. Applications of Artificial Intelligence Algorithms in the Energy Sector. *Energies* **2023**, *16*, 347. [CrossRef]
22. Gillan, S.; Martin, J.D. Corporate Governance Post-Enron: Effective Reforms, or Closing the Stable Door? *J. Corp. Financ.* **2007**, *13*, 929–958. [CrossRef]
23. Danish, M.S.S.; Senjyu, T. AI-Enabled Energy Policy for a Sustainable Future. *Sustainability* **2023**, *15*, 7643. [CrossRef]
24. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; The MIT Press: Cambridge, MA, USA, 2016; ISBN 978-0-262-03561-3.
25. Brey, P.; Søraker, J.H. Philosophy of Computing and Information Technology. In *Philosophy of Technology and Engineering Sciences*; Elsevier: Amsterdam, The Netherlands, 2009; pp. 1341–1407. ISBN 978-0-444-51667-1.
26. Entezari, A.; Aslani, A.; Zahedi, R.; Noorollahi, Y. Artificial Intelligence and Machine Learning in Energy Systems: A Bibliographic Perspective. *Energy Strategy Rev.* **2023**, *45*, 101017. [CrossRef]
27. Carneiro, M.L.N.M.; Gomes, M.S.P. Energy, Exergy, Environmental and Economic Analysis of Hybrid Waste-to-Energy Plants. *Energy Convers. Manag.* **2019**, *179*, 397–417. [CrossRef]
28. Kotu, V.; Deshpande, B. Chapter 1: Introduction. In *Data Science*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 1–18, ISBN 978-0-12-814761-0.
29. Sandeep, S.R.; Ahamad, S.; Saxena, D.; Srivastava, K.; Jaiswal, S.; Bora, A. To Understand the Relationship between Machine Learning and Artificial Intelligence in Large and Diversified Business Organisations. *Mater. Today Proc.* **2022**, *56*, 2082–2086. [CrossRef]
30. Valle-Cruz, D.; Criado, J.I.; Sandoval-Almazán, R.; Ruvalcaba-Gomez, E.A. Assessing the Public Policy-Cycle Framework in the Age of Artificial Intelligence: From Agenda-Setting to Policy Evaluation. *Gov. Inf. Q.* **2020**, *37*, 101509. [CrossRef]
31. Runge, J.; Zmeureanu, R. Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review. *Energies* **2019**, *12*, 3254. [CrossRef]
32. Liu, Z.; Sun, Y.; Xing, C.; Liu, J.; He, Y.; Zhou, Y.; Zhang, G. Artificial Intelligence Powered Large-Scale Renewable Integrations in Multi-Energy Systems for Carbon Neutrality Transition: Challenges and Future Perspectives. *Energy AI* **2022**, *10*, 100195. [CrossRef]
33. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H. Artificial Intelligence in Sustainable Energy Industry: Status Quo, Challenges and Opportunities. *J. Clean. Prod.* **2021**, *289*, 125834. [CrossRef]
34. Feng, C.; Liu, Y.; Zhang, J. A Taxonomical Review on Recent Artificial Intelligence Applications to PV Integration into Power Grids. *Int. J. Electr. Power Energy Syst.* **2021**, *132*, 107176. [CrossRef]
35. Yildizbasi, A. Blockchain and Renewable Energy: Integration Challenges in Circular Economy Era. *Renew. Energy* **2021**, *176*, 183–197. [CrossRef]
36. Integration of Energy Storage System and Renewable Energy Sources Based on Artificial Intelligence: An Overview | Elsevier Enhanced Reader. Available online: https://reader.elsevier.com/reader/sd/pii/S2352152X21005387?token=488B12E6AF8C359D4EC639E3C3D809949BF792C332BBAB06FA60E0E37A466E8E39B893FF36EB11FCC56D4BA4D4559A91&originRegion=us-east-1&originCreation=20230129131700 (accessed on 29 January 2023).
37. Omitaomu, O.A.; Niu, H. Artificial Intelligence Techniques in Smart Grid: A Survey. *Smart Cities* **2021**, *4*, 548–568. [CrossRef]
38. Danish, M.S.S.; Senjyu, T. Shaping the Future of Sustainable Energy through AI-Enabled Circular Economy Policies. *Circ. Econ.* **2023**, *in press*. [CrossRef]
39. Pai, P.-F.; Chen, T.-C. Rough Set Theory with Discriminant Analysis in Analyzing Electricity Loads. *Expert Syst. Appl.* **2009**, *36*, 8799–8806. [CrossRef]
40. Busari, G.A.; Lim, D.H. Crude Oil Price Prediction: A Comparison between AdaBoost-LSTM and AdaBoost-GRU for Improving Forecasting Performance. *Comput. Chem. Eng.* **2021**, *155*, 107513. [CrossRef]
41. Shi, Z.; Zhu, J.; Wei, H. SARSA-Based Delay-Aware Route Selection for SDN-Enabled Wireless-PLC Power Distribution IoT. *Alex. Eng. J.* **2022**, *61*, 5795–5803. [CrossRef]
42. De Mauro, A.; Greco, M.; Grimaldi, M. What Is Big Data? A Consensual Definition and a Review of Key Research Topics. *AIP Conf. Proc.* **2015**, *1644*, 97–104. [CrossRef]
43. Ball, G.H. Data Analysis in the Social Sciences: What about the Details? In Proceedings of the November 30–December 1, 1965, Fall Joint Computer Conference, Part I; Association for Computing Machinery: New York, NY, USA, 1965; pp. 533–559.
44. Danish, M.S.S. AI and Expert Insights for Sustainable Energy Future. *Energies* **2023**, *16*, 3309. [CrossRef]

45. Lopez-Arevalo, I.; Aldana-Bobadilla, E.; Molina-Villegas, A.; Galeana-Zapién, H.; Muñiz-Sanchez, V.; Gausin-Valle, S. A Memory-Efficient Encoding Method for Processing Mixed-Type Data on Machine Learning. *Entropy* **2020**, *22*, 1391. [CrossRef]
46. Zhao, L.; Chen, Z.; Yang, Z.; Hu, Y.; Obaidat, M.S. Local Similarity Imputation Based on Fast Clustering for Incomplete Data in Cyber-Physical Systems. *IEEE Syst. J.* **2018**, *12*, 1610–1620. [CrossRef]
47. Danish, M.S.S.; Zahra, N.; Senjyu, T. AI-Coherent Data-Driven Forecasting Model for a Combined Cycle Power Plant. *Energy Convers. Manag.* 2023, *in press*. [CrossRef]
48. Borghesan, F.; Zagorowska, M.; Mercangöz, M. Unmanned and Autonomous Systems: Future of Automation in Process and Energy Industries. *IFAC-Pap.* **2022**, *55*, 875–882. [CrossRef]
49. Kim, J.; Lee, D.; Yang, J.; Lee, S. Conceptual Design of Autonomous Emergency Operation System for Nuclear Power Plants and Its Prototype. *Nucl. Eng. Technol.* **2020**, *52*, 308–322. [CrossRef]
50. Kumar, K.; Shah, R.; Kumar, N.; Singh, R.P. Application of Robotic Process Automation. In *Applications of Artificial Intelligence in Engineering*; Gao, X.-Z., Kumar, R., Srivastava, S., Soni, B.P., Eds.; Springer: Singapore, 2021; pp. 929–937.
51. George, A.; Ali, M.; Papakostas, N. Utilising Robotic Process Automation Technologies for Streamlining the Additive Manufacturing Design Workflow. *CIRP Ann.* **2021**, *70*, 119–122. [CrossRef]
52. Harrison, R.; Vera, D.; Ahmad, B. Towards the Realization of Dynamically Adaptable Manufacturing Automation Systems. *Philos. Trans. R. Soc. Math. Phys. Eng. Sci.* **2021**, *379*, 20200365. [CrossRef]
53. Samuel, O.; Javaid, N.; Khalid, A.; Khan, W.Z.; Aalsalem, M.Y.; Afzal, M.K.; Kim, B.-S. Towards Real-Time Energy Management of Multi-Microgrid Using a Deep Convolution Neural Network and Cooperative Game Approach. *IEEE Access* **2020**, *8*, 161377–161395. [CrossRef]
54. Ghobakhloo, M.; Iranmanesh, M.; Morales, M.E.; Nilashi, M.; Amran, A. Actions and Approaches for Enabling Industry 5.0-Driven Sustainable Industrial Transformation: A Strategy Roadmap. *Corp. Soc. Responsib. Environ. Manag.* **2022**, *30*, 1473–1494. [CrossRef]
55. Danish, M.S.S.; Zaheb, H.; Sabory, N.R.; Tomonobu, S.; Ahmadi, M.; Sadat, S.H. *Empowering Developing Nations and Sustainable Development: Case Studies and Synthesis*, 1st ed.; REPA—Research and Education Promotion Association: Naha, Japan, 2020; ISBN 978-4-910361-20-8.
56. Riva, G.; Wiederhold, B.K. Human–Robot Confluence: Toward a Humane Robotics. *Cyberpsychology Behav. Soc. Netw.* **2021**, *24*, 291–293. [CrossRef]
57. Danish, M.S.S.; Sabory, N.R.; Ibrahimi, A.M.; Senjyu, T.; Ahadi, M.H.; Stanikzai, M.Z. A Concise Overview of Energy Development Within Sustainability Requirements. In *Sustainability Outreach in Developing Countries*; Danish, M.S.S., Senjyu, T., Sabory, N.R., Eds.; Springer: Singapore, 2021; pp. 15–27. ISBN 9789811571794.
58. Danish, M.S.S.; Matayoshi, H.; Howlader, H.O.R.; Chakraborty, S.; Mandal, P.; Senjyu, T. Microgrid Planning and Design: Resilience to Sustainability. In Proceedings of the 2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia), Bangkok, Thailand, 19–23 March 2019; IEEE: Bangkok, Thailand, 2019; pp. 253–258.
59. Danish, M.S.S.; Senjyu, T.; Faisal, N.; Stannikzai, M.Z.; Nazari, A.M.; Vargas-Hernández, J.G. A Review on Environmental-Friendly Energy Multidisciplinary Exposition from Goals to Action. *J. Environ. Sci. Revolut.* **2021**, *2*, 1–9. [CrossRef]
60. Folke, C.; Carpenter, S.; Walker, B.; Scheffer, M.; Elmqvist, T.; Gunderson, L.; Holling, C.S. Regime Shifts, Resilience, and Biodiversity in Ecosystem Management. *Annu. Rev. Ecol. Evol. Syst.* **2004**, *35*, 557–581. [CrossRef]
61. Vargas-Hernández, J.G.; Danish, M.S.S. System of Green Resilience Eco-Oriented Land Uses in Urban Socio-Ecosystems. In *Eco-Friendly Energy Processes and Technologies for Achieving Sustainable Development*; Danish, M.S.S., Senjyu, T.S., Eds.; Advances in Environmental Engineering and Green Technologies; IGI Global: Hershey, PA, USA, 2021; pp. 1–23, ISBN 978-1-79984-915-5.