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Review

A Thematic Review of AI and ML in Sustainable Energy Policies for Developing Nations

Hassan Qudrat-Ullah

School of Administrative Studies, York University, Toronto, ON M3J 1P3, Canada; hassanq@yorku.ca

Abstract: The growing global energy demand and the pursuit of sustainability highlight the transformative potential of artificial intelligence (AI) and machine learning (ML) in energy systems. This thematic review explores their applications in energy generation, transmission, and consumption, emphasizing their role in optimizing renewable integration, enhancing operational efficiency, and enabling data-driven decision-making. By employing a thematic approach, this study categorizes and analyzes key challenges and opportunities, including economic considerations, technological advancements, and social implications. While AI/ML technologies offer significant benefits, their adoption in developing nations faces challenges, such as high upfront costs, skill shortages, and infrastructure limitations. Addressing these barriers through capacity building, international collaboration, and adaptive policies is critical to realizing the equitable and sustainable integration of AI/ML in energy systems.

Keywords: artificial intelligence (AI); machine learning (ML); energy systems; renewable energy integration; sustainable energy policies; developing nations; energy transition

Academic Editor: Piotr Kosowski

Received: 1 April 2025
Revised: 21 April 2025
Accepted: 25 April 2025
Published: 28 April 2025

Citation: Qudrat-Ullah, H. A Thematic Review of AI and ML in Sustainable Energy Policies for Developing Nations. *Energies* **2025**, *18*, 2239. https://doi.org/10.3390/en18092239

Correction Statement: This article has been republished with a minor change. The change does not affect the scientific content of the article and further details are available within the backmatter of the website version of this article.

1. Introduction

The global energy landscape is undergoing a significant transformation as nations confront growing energy demands, escalating environmental concerns, and the imperative for sustainable development. Challenges, such as climate change, resource depletion, and disparities in energy access, persist as critical barriers to achieving energy security and sustainability goals [1]. To address these issues, a global shift towards renewable energy sources has been initiated. However, this transition introduces complexities, including the intermittent nature of renewables and the need for intelligent management of increasingly dynamic energy systems. Recent advancements in artificial intelligence (AI) and machine learning (ML) have positioned these technologies as transformative tools, capable of enhancing the efficiency, reliability, and sustainability of energy systems [2,3].

Developing nations, which grapple with energy poverty, grid inefficiencies, and uneven access to reliable power, hold significant potential for benefiting from AI/ML integration. Despite being rich in renewable energy resources, these nations face formidable barriers, such as outdated infrastructure, limited technical expertise, and financial constraints [4,5]. AI and ML offer promising solutions to these challenges, providing capabilities for predictive analytics, real-time optimization, and seamless integration of renewable energy systems. This potential underscores the need for sustainable energy policies that leverage AI/ML technologies to address the unique energy needs of developing regions, foster economic development, and promote equitable access to energy [6].

The motivation for this research stems from the urgent need to explore innovative solutions for sustainable energy systems in developing nations, where the intersection of economic constraints and technological opportunities creates a fertile ground for transformative change. The application of AI and ML represents a paradigm shift in addressing these challenges. This thematic review aims to provide a comprehensive understanding of how AI and ML technologies are being applied to develop and implement sustainable energy policies tailored to the needs of developing nations [6].

The primary objective of this review is to analyze the transformative role of AI and ML in sustainable energy systems, with a particular focus on their applications in energy generation, transmission, and consumption. Specifically, this study highlights the potential of these technologies to integrate renewable resources, enhance energy efficiency, and provide innovative solutions to energy access challenges. The unique contributions of this review include:

- Categorizing and synthesizing key challenges and opportunities associated with AI/ML in energy systems, particularly in the context of developing nations.
- Offering insights into the technological, economic, and social implications of AI/ML integration.
- Proposing actionable strategies for policymakers, researchers, and industry leaders to scale the adoption of these technologies.

To achieve these goals, this review adopts a thematic approach, synthesizing evidence from the academic literature, case studies, and practical examples [7]. This approach facilitates an in-depth analysis of AI/ML applications, highlighting their potential to transform energy systems in regions with varying levels of technological maturity. By focusing on the unique challenges faced by developing nations, this review provides a nuanced perspective on the barriers to AI/ML adoption and identifies strategies to overcome them. The insights presented in this review aim to guide policymakers and stakeholders in leveraging AI/ML technologies to build resilient, adaptive, and sustainable energy systems. In doing so, this study contributes to the broader discourse on sustainable development and energy equity, offering a roadmap for integrating AI/ML into the energy policies of developing nations.

2. Review of Previous Work

This section critically examines the literature on sustainable energy planning, artificial intelligence (AI) applications, and energy transition strategies. The reviewed studies provide insights into the integration of renewable energy technologies, the role of AI in achieving sustainable development goals (SDGs), and region-specific energy planning [8]. This analysis identifies significant contributions from key works while highlighting the gaps and challenges that remain in achieving long-term sustainability objectives.

2.1. Artificial Intelligence and Sustainability

Artificial intelligence has emerged as a powerful tool for advancing sustainability across diverse sectors. Abdeldjalil et al. [9] and Kar et al. [10] provide systematic reviews emphasizing AI's capacity to enhance decision-making, optimize resource allocation, and improve efficiency in various domains. These studies highlight AI's potential in addressing global challenges, including climate change and resource scarcity. Nguyen and Patel [11] further explore AI's adaptability, particularly during the COVID-19 pandemic, where it played a critical role in modeling scenarios, predicting outcomes, and managing disruptions. However, the literature also emphasizes critical challenges, such as ethical concerns, unequal access to AI technologies, and the risk of exacerbating inequalities. Addressing these issues requires a balanced approach that ensures inclusivity and fairness in AI deployment.

Zhang (2024) [12] examine AI applications within the construction industry, providing a focused analysis of how AI aligns with SDGs. Their findings reveal AI's capability to reduce waste, enhance energy efficiency, and support sustainable urban development. Similarly, Massimo et al. [13] extend the analysis to demonstrate AI's role in transforming industrial practices, highlighting its potential to streamline processes and improve sustainability outcomes. These studies collectively underline the importance of integrating AI into policy frameworks to maximize its impact. Despite these advancements, the literature underscores the need for robust governance structures to mitigate risks and promote equitable AI adoption globally.

2.2. Regional Energy Transition Pathways

The transition to 100% renewable energy systems has garnered significant attention in both policy and academic discourse. Bogdanov et al. [14] present a comprehensive pathway for Japan's energy transition, offering a detailed analysis of technical feasibility, cost implications, and environmental benefits. Their work demonstrates that achieving a fully renewable system by 2050 is not only possible, but also economically advantageous. The Institute for Sustainable Energy Policies [15] builds on this foundation, focusing on Tokyo's metropolitan area and incorporating green recovery measures to address socio-economic challenges. Both studies highlight the necessity of robust policy support, public engagement, and international collaboration to achieve such ambitious goals.

In Europe, Crespo del Granado et al. [16] investigated energy transition pathways emphasizing the degree of regional cooperation and decentralization. Their findings underscore the importance of cohesive policies that harmonize national and regional objectives to overcome systemic inertia. Connolly et al. [17] contribute by providing a quantitative comparison of electricity, heating, and cooling sectors, demonstrating the need for integrated solutions to achieve decarbonization. These works collectively emphasize that, while technological innovation is critical, effective governance and stakeholder alignment are equally essential for successful energy transitions.

2.3. Case Studies: Galapagos Islands and Latin America

Localized studies on energy transition offer valuable lessons for implementing renewable energy solutions in unique socio-economic and environmental contexts. Clavijo Cevallos et al. [18] and Eras-Almeida et al. [19] focus on the Galapagos Islands, demonstrating the technical and economic feasibility of hybrid renewable energy systems. Their studies underscore the importance of addressing regional energy needs while preserving biodiversity and cultural heritage. Similarly, Icaza et al. [20] extend this focus to Ecuadorian heritage cities, showcasing the potential of systematic long-term planning to achieve 100% renewable energy targets by 2050. These localized examples highlight the need for tailored approaches that integrate community-specific challenges and opportunities.

Latin America's broader energy transition landscape is explored by Icaza-Alvarez et al. [21], who emphasize smart energy planning as a critical tool for decarbonization by 2050. Their findings reveal the significance of addressing political and technological challenges to ensure successful implementation. UN ECLAC and GET.transform [22] further complement these insights by outlining pathways for a just energy transition in the region, emphasizing equity and inclusion in planning processes. Together, these studies demonstrate the potential of regionally tailored strategies to bridge the gaps in energy access, reduce emissions, and foster sustainable development.

2.4. Broader Implications and Challenges

While significant progress has been made in the energy transition research, several challenges persist. The reviewed studies consistently highlight barriers, such as financial constraints, technological feasibility, and socio-political resistance. For example, the implementation of AI-driven solutions, as discussed by Abdeldjalil et al. [9] and Nguyen and

Patel [11], often faces resistance due to ethical concerns and limited infrastructure in developing regions. Similarly, regional energy transition studies, such as those by Bogdanov et al. [14] and Icaza-Alvarez et al. [21], reveal the critical need for robust policy frameworks and stakeholder alignment.

Moreover, the literature identifies the need for integrated approaches that combine technological innovation with inclusive policymaking and community engagement. The case studies from the Galapagos Islands and Latin America highlight the importance of localized planning to address unique challenges while leveraging regional strengths [23,24]. However, there remains a significant gap in understanding how to effectively scale localized solutions to meet global sustainability goals. Achieving these goals requires enhanced international cooperation, improved knowledge sharing, and the development of frameworks that integrate diverse disciplinary perspectives. This review study aims to contribute by addressing the gaps in interdisciplinary understanding, exploring strategies to foster equitable technological access, and analyzing socio-political barriers that hinder a just energy transition. Future research must further build on these insights to advance holistic and inclusive energy solutions globally.

3. Methodology

This study employed a thematic review methodology to systematically investigate the applications of artificial intelligence (AI) and machine learning (ML) in sustainable energy policies, particularly in the context of developing nations. This approach allows for the identification and synthesis of key themes and patterns across diverse literature, offering a structured understanding of the multifaceted role AI/ML plays in addressing critical energy challenges [7,25]. To enhance transparency and methodological rigor, this study incorporated relevant principles from the PRISMA framework [26], ensuring a systematic and comprehensive review process.

3.1. Literature Search Strategy

The literature search was conducted across multiple databases, including Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar, ensuring comprehensive coverage of peer-reviewed research. Search terms were iteratively developed, focusing on combinations of keywords, such as "artificial intelligence", "machine learning", "sustainable energy", and "developing nations".

3.2. Inclusion and Exclusion Criteria

To maintain focus and rigor, the following criteria guided the selection of studies:

(a) Inclusion Criteria:

- Peer-reviewed journal articles, conference proceedings, and book chapters.
- Publications from 2010 to 2025 to capture contemporary developments.
- Studies explicitly addressing AI/ML applications in energy systems or policies.
- Focus on developing nations or comparative analyses involving these regions.

(b) Exclusion Criteria:

- Non-peer-reviewed materials, such as editorials, opinions, and commentaries.
- Studies unrelated to energy systems or AI/ML applications.

3.3. Literature Selection Process

The selection process involved multiple steps, ensuring high-quality studies relevant to the research objectives:

1. **Database Search:** An initial search yielded 301 articles.

2. **Duplicate Removal:** After removing duplicates, 183 unique articles remained.
3. **Title and Abstract Screening:** A preliminary review identified 63 articles meeting the inclusion criteria.
4. **Full-Text Review:** Comprehensive evaluation of these articles resulted in 51 studies selected for quality assessment.
5. **Quality Assessment:** Using established criteria [25], studies were rated for relevance, rigor, and contribution. Only medium- and high-quality studies (42 in total) were included in the thematic analysis [27].

This rigorous process ensured that the final set of studies provided reliable and comprehensive insights into AI/ML applications in sustainable energy policies. By maintaining a systematic and transparent selection approach, this methodology minimized bias and ensured the inclusion of diverse perspectives. This comprehensive approach not only highlighted the breadth of the existing applications, but also revealed the gaps and opportunities for future research and policy innovation.

3.4. Thematic Analysis

The thematic analysis followed an inductive–deductive approach, allowing themes to emerge naturally from the data while aligning with this study's objectives [27]. A coding framework was iteratively developed and refined through a systematic engagement with the literature. This dual approach ensured a balanced integration of emergent insights and pre-existing knowledge, enhancing this study's relevance and rigor. The iterative process also facilitated the identification of nuanced patterns and relationships, providing a robust foundation for thematic categorization. Key themes identified are:

1. **Energy Generation:** Optimization of renewable energy production through AI/ML, enhancing energy forecasting and integration of renewables, like solar and wind [28,29].
2. **Energy Transmission and Distribution:** AI-enabled advancements in smart grids, improving reliability and operational efficiency [30,31].
3. **Energy Consumption and Demand Management:** Integration of AI/ML with IoT to improve energy efficiency and reduce wastage in residential and industrial sectors [32,33].
4. **Economic Implications:** Financial impacts and economic benefits, including cost savings and job creation, particularly in developing nations [34,35].
5. **Policy Development:** Role of AI in formulating and evaluating sustainable energy policies, enabling data-driven insights and real-time policy adjustments [36].

The themes were validated through iterative analysis and cross-referencing with secondary sources, providing a robust foundation for understanding the diverse applications of AI/ML in sustainable energy policies.

3.5. Methodological Flowchart

Figure 1 presents the methodological flowchart, illustrating the thematic review process from the database search to the synthesis of themes. This visual representation clarifies the structured and rigorous approach employed in this study. This thematic review methodology ensured a systematic, comprehensive, and transparent investigation of AI/ML applications in sustainable energy systems. The findings underscore the transformative potential of AI/ML in optimizing energy systems, driving economic growth, and supporting sustainable energy transitions in developing nations. This robust methodological foundation provides critical insights for decision-makers aiming to integrate AI/ML into energy policies effectively. Moreover, it highlights the importance of tailoring AI/ML solutions to address region-specific challenges and opportunities in developing contexts. By bridging technological advancements with policy frameworks, this study paves the way for more inclusive and impactful energy strategies.

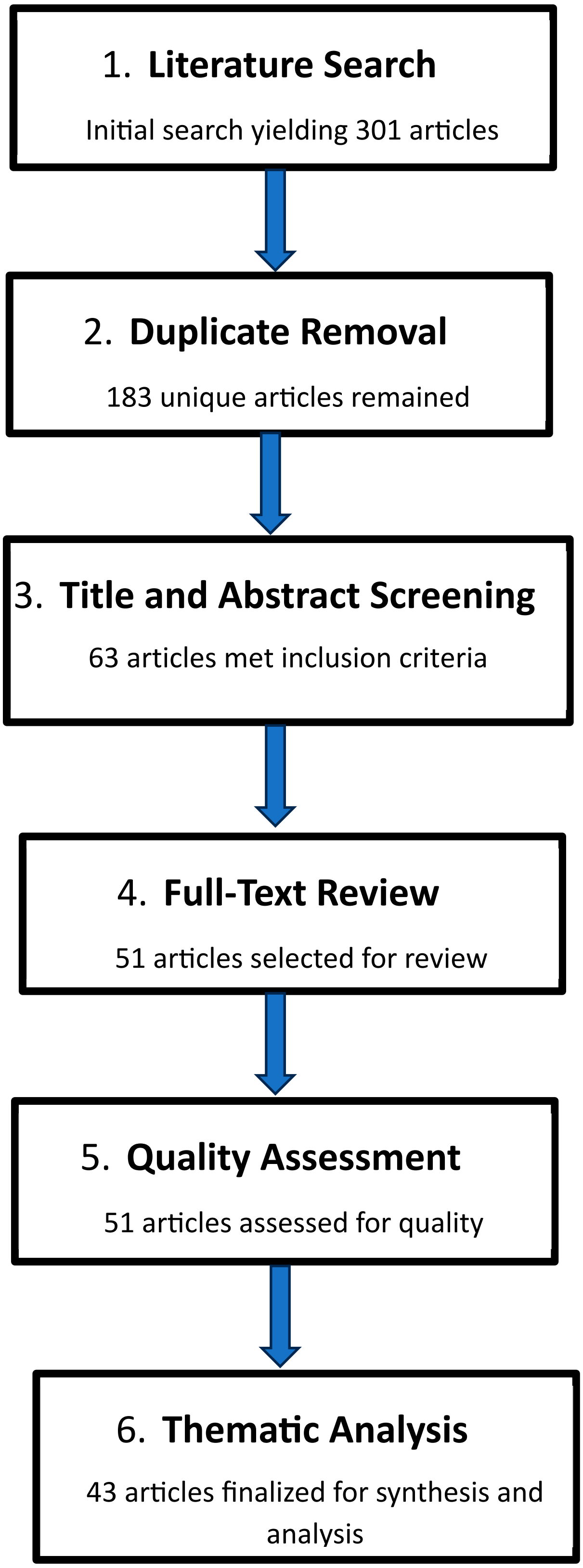

Figure 1. Methodological flowchart.

4. Transformative AI and ML Applications Across the Energy Spectrum

Artificial intelligence (AI) and machine learning (ML) are revolutionizing energy systems, enhancing efficiency, reliability, and sustainability across the entire energy spectrum. From optimizing renewable energy generation to improving energy transmission, distribution, and consumption management, these technologies are reshaping global energy landscapes. Their implementation in developed and developing nations alike has demonstrated significant cost savings, improved grid stability, and more sustainable energy practices. By leveraging predictive analytics, optimization algorithms, and real-time decision-making capabilities, AI and ML are key enablers in the transition to smarter, resilient, and sustainable energy systems. Table 1 illustrates key implementations of these technologies across various domains, countries, and their measurable impacts.

Table 1. AI and ML applications in sustainable energy in developing nations.

Domain	Country	AI/ML Application	Impact	Reference
Renewable Energy	India, South Africa	Wind turbine optimization	Annual savings of USD 10M (India) and USD 5M (South Africa)	[28,29]
Solar Energy	Ecuador	Hybrid energy system integration	Near 100% renewable reliance in the Galapagos Islands	[19]
Energy Transmission	Brazil, Kenya	Predictive grid maintenance	Saved USD 2M annually (Brazil) and improved grid efficiency by USD 3M (Kenya)	[29,37]
Energy Consumption	Mexico, Malaysia	AI-powered smart meters and demand–response	15% reduction in energy consumption (Mexico); USD 1.2M savings in pilot programs (Malaysia)	[21,32]

4.1. Energy Generation

AI and ML are transforming energy generation by enabling accurate forecasting, dynamic optimization, and efficient management of resources across renewable and non-renewable domains. In renewable energy, machine learning algorithms enhance wind and solar power generation by predicting weather patterns, solar radiation, and wind speeds with high accuracy. For example, AI models optimize wind turbine placement and operations, reducing curtailments and increasing efficiency, as demonstrated in India and South Africa, where such interventions resulted in annual savings of USD 10 million and USD 5 million, respectively [28,29,38]. These examples highlight the capacity of AI technologies to address critical efficiency challenges in renewable energy systems, even in regions with resource constraints.

Similarly, solar energy systems benefit from AI applications, like adaptive solar panel tracking systems and real-time weather data integration. These advancements have improved solar farm outputs by up to 20%, significantly boosting renewable energy contributions [9]. AI has also enabled advancements in hydropower, where predictive models balance energy generation with ecological needs by optimizing reservoir management and ensuring sustainability. Notably, in Ecuador's Galapagos Islands, AI-enabled hybrid systems integrate solar, wind, and bioenergy to achieve near 100% renewable reliance, minimizing the reliance on fossil fuels and reducing greenhouse gas emissions [19,39].

In addition to renewables, AI and ML improve the operational efficiency of conventional energy systems by optimizing fuel use and reducing emissions. For instance, hybrid systems combining renewable and non-renewable sources leverage AI algorithms to dynamically balance energy outputs, aligning production with fluctuating demand. These capabilities are particularly valuable in developing regions, where efficient resource allocation is critical for addressing energy access challenges and ensuring sustainability.

Such advancements underscore the versatility of AI/ML technologies in reshaping global energy generation landscapes.

4.2. Energy Transmission and Distribution

AI and ML are revolutionizing energy transmission and distribution systems by enhancing grid stability, reliability, and operational efficiency. Predictive maintenance systems powered by AI-driven analytics detect potential faults in grid networks, enabling utilities to take pre-emptive measures. For instance, real-time monitoring tools identify stress points and predict equipment failures, significantly reducing downtime and repair costs. Brazil's adoption of AI-powered grid management saved approximately USD 2 million annually through predictive maintenance, while Kenya's AI-driven load balancing improved operational efficiency by USD 3 million per year [29,37].

Reinforcement learning algorithms further optimize energy flow during peak loads, reducing transmission losses and enhancing overall grid performance. A notable example from Japan demonstrates how AI-enabled systems reduced transmission losses by 12%, improving grid efficiency under fluctuating demand conditions [14,39]. These innovations ensure the operational resilience of modern grids, enabling them to accommodate increasing shares of renewable energy while minimizing disruptions. Moreover, AI technologies support the integration of decentralized energy resources, such as microgrids, which expand energy access to underserved and remote areas.

The integration of AI into transmission and distribution systems fosters the development of smarter, more resilient grids capable of meeting the demands of a rapidly changing energy landscape. By reducing costs and improving operational efficiencies, these systems exemplify the scalability and transformative potential of AI technologies in energy networks. Success stories from developing nations highlight the feasibility of adopting AI-driven solutions to enhance grid reliability and energy accessibility on a global scale.

4.3. Energy Consumption and Demand Management

AI and ML technologies are driving transformative changes in energy consumption and demand management by empowering utilities and consumers to optimize usage patterns. Smart grids, combining IoT devices with ML algorithms, enable real-time monitoring, predictive load balancing, and efficient energy distribution [40]. In Mexico, the implementation of AI-powered smart meters led to a 15% reduction in energy consumption, illustrating the effectiveness of these systems in promoting energy efficiency [21]. By integrating AI-driven tools, energy providers can predict usage trends and adjust supply schedules to prevent inefficiencies and outages.

AI-driven demand–response systems analyze usage trends to optimize schedules for energy-intensive activities, improving grid reliability and enabling consumers to make informed energy decisions. In Malaysia, IoT-enabled smart homes with AI for demand–response reduced household energy bills by 15%, amounting to USD 1.2 million in savings during pilot programs [32]. Personalized AI tools further encourage behavioral changes by providing tailored recommendations, helping users adopt energy-saving habits [11]. These advancements align consumer behavior with broader sustainability goals, showcasing the societal benefits of AI-driven energy innovations.

By addressing rising energy demands through AI-empowered solutions, utilities achieve substantial energy savings and reduce operational costs. These innovations not only promote environmental sustainability but also improve energy access and affordability, particularly in developing nations. The growing adoption of AI technologies in demand management exemplifies their potential to drive large-scale energy transitions while enhancing consumer engagement.

4.4. Integrated Case Studies

Case Study 1: Kenya's Solar Energy Optimization: A pilot project in Kenya highlighted AI's/ML's transformative potential in renewable energy systems. By leveraging machine learning models to predict solar power generation, the project aligned energy production with demand schedules, significantly reducing shortages and enhancing grid reliability. This approach was particularly impactful in rural and underserved areas, where infrastructure gaps posed significant challenges. The scalability of AI-driven solar optimization underscores its value in achieving sustainable energy outcomes in diverse regional contexts [10].

Case Study 2: The Galapagos Islands' Renewable Energy Transformation: In the Galapagos Islands, AI-optimized hybrid energy systems integrate solar, wind, and bioenergy technologies to achieve near 100% renewable reliance. This system reduced greenhouse gas emissions and minimized diesel dependence, serving as a model for other island communities aiming to transition to renewable energy systems. These advancements illustrate AI's/ML's capacity to drive sustainable energy transitions in ecologically sensitive regions. The success of this project highlights the importance of integrating innovative technologies into conservation-focused energy strategies [19,20,41].

In summary, the integration of AI and ML technologies across the energy spectrum presents unprecedented opportunities to enhance efficiency, sustainability, and resilience. From optimizing renewable energy generation to improving transmission, distribution, and consumption management, these technologies are transforming energy landscapes globally. As demonstrated by examples from Kenya, the Galapagos Islands, and other regions, AI and ML bridge critical infrastructure gaps, accelerate renewable energy adoption, and empower stakeholders to achieve sustainable energy outcomes. Their widespread implementation holds immense promise for advancing energy equity and environmental sustainability worldwide.

5. Economic and Policy Implications of AI and ML

The application of artificial intelligence (AI) and machine learning (ML) in energy systems has emerged as a critical driver of innovation. These technologies offer significant economic benefits, including improved energy efficiency, optimized integration of renewables, and more effective demand-side management. Such advancements have the potential to lower operational costs, enhance system reliability, and facilitate a transition to more sustainable energy systems.

However, the adoption of AI/ML in developing countries poses unique economic and policy challenges. Limited access to funding, infrastructure deficits, and gaps in technical expertise often hinder the realization of these benefits. Furthermore, disparities in digital readiness across regions necessitate tailored policy approaches that consider local conditions, resource availability, and workforce readiness.

This section explores these economic and policy implications, framing the discussion within the context of cost–benefit analysis, financial constraints, and technology assessment.

5.1. Economic Considerations

Economic considerations play a pivotal role in the adoption and scaling of AI/ML technologies within energy systems, particularly in developing nations. These factors influence decisions around technology investment, workforce development, and long-term sustainability.

5.1.1. Cost–Benefit Analysis of AI/ML Deployment in Energy Systems

The implementation of AI and ML in energy systems provides the potential for significant economic benefits, including cost savings, improved operational efficiency, and enhanced reliability of energy infrastructure. A key factor in the widespread adoption of AI/ML technologies is the cost–benefit analysis, which involves comparing the initial investment costs with the long-term financial gains. For instance, AI-driven predictive maintenance systems in power grids have been shown to reduce operational costs by minimizing downtime and preventing equipment failures [29]. Similarly, AI-enhanced energy forecasting can optimize the integration of renewable energy into grids, reducing curtailment costs and improving grid stability.

In developing countries, the economic advantages of AI/ML are substantial but must be carefully weighed against upfront costs. In India, the deployment of AI for wind and solar forecasting has reportedly reduced curtailment losses, saving approximately USD 10 million annually [29]. However, the high initial investment in AI technologies, coupled with the need for skilled labor and robust infrastructure, poses challenges. Furthermore, the scalability of AI/ML solutions depends on the ability of countries to manage the financial burden of technology adoption while maintaining cost-effectiveness in energy generation, distribution, and consumption [28]. Balancing these upfront costs with the long-term benefits is critical to ensuring the sustainable adoption of AI/ML in developing nations' energy systems. AI also fosters economic inclusivity by reducing energy access costs and supporting entrepreneurship. By empowering small businesses in underprivileged communities, AI can help bridge economic disparities, promoting equitable growth and sustainable development. For example, AI-facilitated energy access in rural areas has enhanced socio-economic outcomes, such as improved education and healthcare, further incentivizing technological adoption.

5.1.2. Addressing Financial and Workforce Challenges in Developing Nations

While the economic benefits of AI/ML in energy systems are clear, the financial and workforce challenges in developing nations remain a significant barrier to widespread adoption. Many developing countries face budget constraints that make it difficult to invest in AI/ML technologies, which often require substantial upfront capital for the research, development, and infrastructure [37]. In addition, these technologies require a highly skilled workforce, which may not be readily available in low- and middle-income countries. Training programs and capacity-building initiatives are crucial for overcoming this challenge, ensuring that local communities can effectively manage and maintain AI-powered energy systems. Addressing these issues requires innovative financial strategies and tailored workforce development initiatives.

AI/ML technologies are reshaping energy economics by reducing operational costs, driving investments, and addressing energy inequalities [42]. Predictive analytics, for instance, have cut costs in solar and wind energy production by up to 20%, enabling broader adoption in resource-constrained settings [43]. However, despite these economic efficiencies, financial barriers persist. High upfront costs for infrastructure and limited access to international funding remain critical challenges [2,44]. For example, countries like South Africa and Kenya face challenges in scaling AI systems due to financial constraints and workforce shortages. Moreover, addressing the financial challenges in these countries involves tapping into international funding sources, public–private partnerships, and collaborative initiatives to share the financial burden. For example, global climate funds, development banks, and international organizations can provide financial support for the deployment of AI/ML systems in energy sectors, thus helping to bridge the financing gap [31].

Workforce challenges are another critical barrier. While automation raises concerns about job displacement, the integration of AI in renewable energy has created opportunities in data analysis, algorithm development, and system maintenance, offsetting potential job losses [4]. However, a lack of skilled professionals in developing countries limits the full-scale deployment of these technologies. Training programs and capacity-building initiatives are crucial to empowering local communities to manage and maintain AI-powered energy systems effectively [4,23,24]. Table 2 provides a detailed overview of the economic challenges faced by developing nations in deploying AI/ML technologies in energy systems. These initiatives are crucial to overcoming barriers and unlocking the full potential of AI/ML for energy development in these regions.

Table 2. Economic challenges of AI/ML in developing nations' energy systems.

Country	Economic Considerations
India	High upfront costs in technology and infrastructure; workforce development needed [29]
South Africa	Financial challenges in scaling AI across regions; investment in skilled workforce [28]
Brazil	Upfront capital investment required for AI technologies and sensors [45]
Kenya	Financial constraints in adopting AI-driven grid systems [37]
Bangladesh	Financial and workforce challenges; need for capacity building [31]
Malaysia	Need for training local technicians and developing infrastructure [32]
Chile	High initial costs; challenges with scaling AI solutions to rural areas [33]
Nigeria	Infrastructure challenges; reliance on international funding and partnerships [37]

5.2. Policy Development and Implementation

Policy frameworks are critical to fostering the integration of AI/ML in energy systems, balancing innovation with equitable access and sustainability. AI/ML technologies are revolutionizing energy policy by enabling data-driven decision-making and enhancing policy evaluation mechanisms. Natural language processing (NLP) tools, for instance, analyze policy documents to align them with climate goals, identifying execution gaps and enhancing transparency [7,46]. Such tools have been instrumental in Kenya and Bangladesh, where AI-driven systems have optimized energy consumption in rural areas, supported microgrid development, and improved resource allocation [37,47].

AI also facilitates scenario planning and real-time monitoring, enabling adaptive policymaking that responds to dynamic challenges. Reinforcement learning models optimize energy distribution under fluctuating conditions, ensuring policies remain robust and effective [48]. Costa Rica's use of AI-enabled simulations for energy planning exemplifies how such tools can identify optimal pathways for renewable energy transitions [1,39,49]. Nevertheless, these advancements require robust regulatory frameworks to address ethical concerns such as data privacy, equitable access, and technology deployment. Policymakers must engage diverse stakeholders to ensure AI-driven policies reflect societal needs and foster trust. The dynamic nature of AI-driven systems demands policies that are both data-informed and adaptive.

5.2.1. Data-Driven Policymaking for Energy Equity and Access

AI and ML offer governments the ability to make data-driven decisions that can improve energy access and equity, particularly in developing countries where energy inequality remains a major challenge [50]. Through AI, policymakers can analyze vast amounts of data related to energy demand, resource availability, and socioeconomic factors to identify energy gaps and devise targeted policies [33]. By utilizing machine learning algorithms, policymakers can design more accurate energy models, forecast future energy demands, and plan energy infrastructure accordingly, ensuring that energy resources are distributed equitably across different regions and communities.

In countries like Kenya and Bangladesh, AI-driven tools have been used to optimize energy consumption in rural areas, enabling better resource allocation and supporting the development of microgrids. Such policies, informed by the real-time data, are essential to addressing energy poverty and fostering inclusivity in energy access [37]. Furthermore, AI can support the formulation of energy policies that align with sustainability goals, as it can assess the environmental and economic impact of different energy technologies, ensuring that policy decisions are backed by robust data.

5.2.2. Monitoring, Evaluation, and Adaptive Policies Using AI

The integration of AI and ML in policymaking also facilitates continuous monitoring and adaptive policy development. Traditional energy policies often face challenges in terms of flexibility, as they can be slow to respond to changing circumstances, such as shifts in energy demand, technological advances, or natural resource availability. AI enables the dynamic monitoring of energy systems, allowing for the real-time evaluation and adjustments to policy frameworks. Reinforcement learning models can optimize the energy distribution process in response to fluctuating conditions, ensuring that policies are continuously refined based on the actual performance data [31].

Furthermore, AI technologies can be used to evaluate the impact of energy policies on sustainability and social equity. For example, by using machine learning models to track energy consumption patterns and economic performance indicators, governments can determine whether policies are effectively addressing energy challenges, such as reducing emissions or improving energy access in underserved regions. In this context, AI acts as both a tool for policy evaluation and a means of ensuring that policies evolve in response to real-world outcomes [32].

The future of AI in energy policy development lies in its capacity to provide decision-makers with precise, data-backed insights that facilitate better governance and more sustainable energy management. As AI-driven solutions become more integrated into energy systems, policymakers must ensure that the resulting frameworks are inclusive, transparent, and adaptable to the rapidly changing landscape of global energy challenges.

5.3. Technology Assessment of AI/ML Applications in Energy Systems

The adoption of artificial intelligence (AI) and machine learning (ML) in energy systems requires a thorough evaluation of technical, economic, and contextual feasibility. A structured technology assessment can help ensure that these advanced solutions are suited to the unique challenges and opportunities of developing countries. This section conducts a technology assessment, incorporating a SWOT analysis to identify the key factors influencing AI/ML deployment in energy systems.

5.3.1. Technical Feasibility

The technical feasibility of AI/ML solutions is influenced by several critical factors. One such factor is algorithmic complexity. Advanced AI/ML techniques, such as reinforcement learning for grid optimization or convolutional neural networks for energy demand forecasting, require substantial computational resources. These demands can be a significant barrier for developing countries where digital infrastructure is still in its early stages [28]. The limited availability of computing power can hinder the effective implementation of these techniques, which require a robust digital ecosystem to function optimally.

In addition, AI/ML models rely on large datasets for training and validation. However, in many developing nations, challenges related to data collection, quality, and storage arise due to underdeveloped digital ecosystems [44]. Without proper data infrastructure, the training of AI/ML models becomes more difficult, which limits their effectiveness and application in these regions. Moreover, many existing energy systems in developing countries are not compatible with modern digital technologies. To integrate AI/ML solutions seamlessly, significant upgrades to legacy systems are often required, which can be costly and time-consuming, further complicating their adoption [44].

5.3.2. SWOT Analysis

A SWOT analysis is a valuable tool for evaluating the feasibility of AI/ML applications in developing countries. Table 3 below highlights the key factors influencing AI/ML deployment in energy systems, as identified through this analysis.

Table 3. SWOT analysis of technology assessment.

Strengths	Weaknesses	Opportunities	Threats
High potential for efficiency improvements	Dependence on high-quality data	Growing international collaborations	Ethical concerns (algorithmic bias, discriminatory outcomes)
Scalability for large-scale applications	Complexity of integrating AI with legacy systems	Global initiatives (e.g., IRENA) promoting sustainable practices	Cybersecurity risks
Improves energy management systems	Data availability issues, especially in developing countries	Knowledge sharing opportunities	
Optimizes grid operations and enhances demand prediction	Delayed deployment in regions with poor infrastructure		

5.3.3. Implications for Policymakers

The technology assessment highlights several key policy recommendations for promoting the effective use of AI/ML in energy systems. One important recommendation is to begin with incremental implementation. By starting with simpler AI/ML applications, such as demand forecasting, grid load balancing, or energy consumption optimization in specific sectors (e.g., residential or industrial), countries can build local capacity and demonstrate the value of these technologies in a manageable way [28]. These pilot projects can help policymakers identify practical challenges and tailor their implementation strategies accordingly, thus reducing resistance to change and allowing time for the necessary infrastructure to be put in place.

Another critical recommendation is to invest in data infrastructure tailored to the local context. Developing robust data ecosystems can enhance AI readiness by ensuring that sufficient and high-quality data are available for training and validation of AI models [44]. This can be achieved through government-supported initiatives, public–private partnerships, and international collaborations to improve data collection and management in energy sectors.

Furthermore, fostering public–private partnerships can provide a mechanism for sharing resources and expertise, facilitating the adoption of AI/ML technologies in developing countries [28]. Such collaborations can leverage the technical expertise of private sector firms while ensuring that the local context and needs of developing countries are met.

Finally, ensuring resilience and equity is crucial. Policymakers should establish cybersecurity frameworks and ethical guidelines to protect AI systems from threats and ensure that the benefits of AI are distributed equitably across society. Ethical considerations, such as preventing algorithmic bias and promoting transparency, should be integrated into AI deployment to mitigate potential risks of discrimination or unfair outcomes [51]. By addressing these considerations, policymakers can support the successful deployment of AI/ML technologies in energy systems, maximizing their potential for sustainable development.

5.4. A Dynamic Feedback-Based Energy Policy Framework

The evolving nature of global energy systems requires a dynamic approach to policy development, where AI and ML are integral components of decision-making. Policies must evolve continuously, driven by predictive analytics, scenario modeling, and real-time feedback, ensuring they remain responsive to challenges like climate change, fluctuating energy demands, and technological disruptions [52].

AI-enabled policy tools, such as digital twins and multi-objective optimization models, empower policymakers to simulate various scenarios and forecast the impact of proposed policies before implementation. This reduces risks, supports better resource allocation, and enhances resilience in energy systems [53,54]. By incorporating a dynamic framework, governments can respond swiftly to unforeseen changes while achieving long-term sustainability and equity goals.

System dynamics models provide a valuable framework for analyzing the feedback loops and complexities introduced by AI/ML in energy systems. These models illustrate how AI-driven efficiency gains can create reinforcing loops, stimulating investments in renewable technologies and generating socio-economic benefits. For instance, AI-enabled rural electrification has improved education and healthcare outcomes, further incentivizing technological adoption [55]. Figure 2 captures the interaction between AI efficiency, investment flows, and socio-economic development. At the same time, system dynamics models emphasize the importance of recognizing delays and unintended consequences, such as unequal benefit distribution and an over-reliance on automated systems. Integrating these models into policymaking ensures a nuanced understanding of AI's impacts, enabling efficient and equitable applications aligned with long-term sustainability goals [52,56].

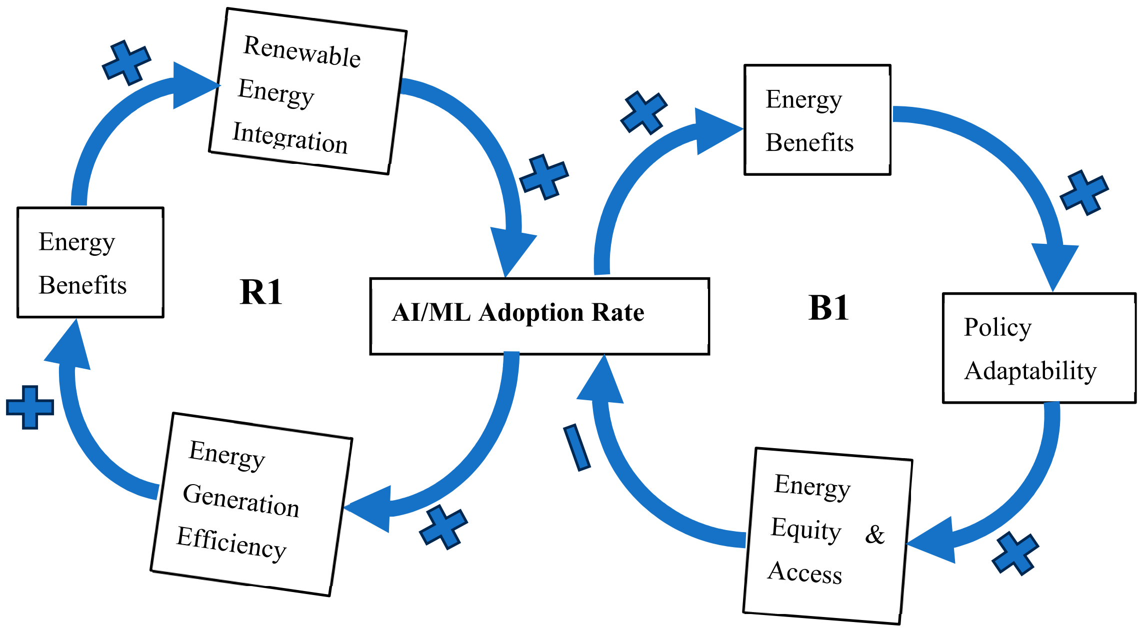

Figure 2. Dynamic feedback-based energy policy framework.

A Causal Loop Diagram (CLD)-based dynamic model, as shown in Figure 2, can further aid policy development by visualizing interactions between key variables in feedback loops [57]. These variables—such as AI/ML adoption, energy generation efficiency, renewable energy integration, policy adaptability, energy equity, and economic benefits—interact in both reinforcing (positive) and balancing (negative) feedback loops, which are essential for driving system-wide change [52].

For instance, a positive feedback loop may amplify desirable outcomes, like how improved AI-driven forecasting enhances renewable energy adoption by increasing grid reliability and reducing costs. Figure 2 shows how AI adoption leads to better forecasting, thereby fostering further integration of AI into the system (Reinforcing Loop R1). This is consistent with the dynamics discussed by [52], where reinforcing loops accelerate growth and innovation within systems.

In contrast, negative feedback loops help stabilize the system, such as the need for regulatory interventions to prevent the over-reliance on certain technologies or mitigate inequality in access [53,56]. In Figure 2, the balancing loop (B1) highlights challenges such as high initial costs, especially in resource-limited regions, which necessitate targeted policy measures. As noted by [57], balancing loops are essential for maintaining system equilibrium and ensuring that excessive growth or technological dependence is curtailed.

Key variables are:

- AI/ML Adoption Rate: Influenced by factors like investment, workforce readiness, and incentives.
- Energy Generation Efficiency: Enhanced through AI-driven optimization.
- Renewable Energy Integration: Dependent on grid stability and technological readiness.
- Policy Adaptability: Enabled by real-time analytics for continuous improvements.
- Energy Equity and Access: Shaped by data-driven, inclusive policies.
- Economic Benefits: Driven by efficiency gains and cost reductions.

By visualizing these feedback loops, policymakers can better anticipate system-wide impacts, identify leverage points for intervention, and design adaptive policies that balance innovation, equity, and long-term sustainability.

5.5. Interdisciplinary and Ethical Synergies

The intersection of AI, energy, and policy invites interdisciplinary collaboration to address multifaceted challenges. Combining the qualitative research on socio-political dynamics with quantitative methods, like econometric modeling, informs cost-effective strategies and scalable solutions [48]. For example, hybrid studies integrating techno-economic analyses with policy reviews have successfully guided renewable energy initiatives in Sub-Saharan Africa [2]. These approaches bridge theory and practice, fostering evidence-based policymaking that balances innovation with inclusivity.

Moreover, interdisciplinary collaboration ensures that ethical AI frameworks prioritize fairness, transparency, and cultural sensitivity. Ethical considerations in AI deployment are paramount, particularly in energy systems, where decisions can disproportionately impact marginalized communities. For example, fairness in AI algorithms must ensure equitable access to energy resources and avoid reinforcing existing social inequalities [58]. Transparency in AI processes, including clear documentation and open source models where feasible, builds trust among stakeholders and encourages accountability [59]. These principles are critical in the energy sector, where ethical AI can address energy justice by ensuring equitable distribution and avoiding biases that can harm underserved populations [51].

Engaging diverse perspectives enhances the design and implementation of policies that address societal needs. Including stakeholders from various disciplines, such as social scientists, ethicists, engineers, and policymakers, helps to develop AI systems that are culturally sensitive and aligned with local values [60]. For instance, integrating local knowledge can improve the acceptance of AI-driven energy projects in indigenous and rural communities, ensuring solutions are both effective and respectful of cultural traditions. A lifecycle approach to AI ethics further ensures that ethical considerations are embedded throughout the development and deployment stages, addressing issues like transparency, fairness, and inclusivity [61]. Ethical AI frameworks also emphasize the importance of avoiding algorithmic biases, which can result in discriminatory outcomes [62]. By adopting fairness metrics and regular audits of AI systems, developers can mitigate the risk of systemic biases that might otherwise exclude certain groups from the benefits of renewable energy advancements.

Such interdisciplinary and inclusive approaches are essential for achieving sustainable energy transitions that benefit all communities [49]. By embedding ethical principles into AI systems, developers can ensure that these technologies enhance social equity and reduce disparities. Ethical AI systems also foster long-term trust among stakeholders by promoting transparency and accountability. This trust is crucial for the widespread adoption and successful integration of AI-driven energy solutions. Additionally, incorporating ethical frameworks strengthens the sustainability of energy systems, making them more resilient and impactful [62,63].

6. Comparative Analysis with Developed Nations

The adoption of artificial intelligence (AI) and machine learning (ML) in the energy sector exhibits notable differences between developed and developing nations. These differences stem from variations in technological infrastructure, economic capacity, policy frameworks, and societal needs. This section provides an in-depth comparative analysis, highlighting the key technological, economic, and policy dimensions that distinguish these regions.

6.1. Technological Advancements and Applications

Developed nations, with advanced infrastructure and robust research ecosystems, have leveraged AI/ML to optimize energy systems comprehensively. For example, countries like Germany and the United States employ AI-powered smart grids to manage fluctuating renewable energy sources effectively, ensuring grid stability and reducing transmission losses [33,40]. Similarly, AI-driven demand–response systems are prevalent in these nations, enabling utilities to balance loads dynamically while fostering energy conservation in residential and industrial sectors [29].

In contrast, developing nations, such as India, Kenya, and Bangladesh, focus on cost-effective implementations of AI/ML technologies. These include predictive maintenance for energy grids and AI-enhanced microgrid systems, which are more suited to their resource-constrained environments [37]. While the technological capabilities in these nations are expanding, the focus remains on addressing basic energy access challenges, reducing costs, and ensuring reliability.

Despite these differences, there is significant potential for knowledge exchange between regions. For instance, the localized AI models used in developing nations to optimize renewable energy in remote areas could inspire scalable solutions for rural regions in developed countries. Conversely, advanced smart grid technologies and high-capacity data centers in developed nations could be adapted to enhance efficiency in urban centers of developing countries.

Technological advancements in developed and developing nations reveal a complementary dynamic, where localized solutions and global innovations can mutually inform future strategies. The key lies in tailoring these technologies to address region-specific energy challenges while fostering global collaboration.

6.2. Economic and Policy Dimensions

Economic factors play a pivotal role in shaping the adoption of AI/ML in the energy sectors of developed and developing nations. Developed countries benefit from greater financial resources, enabling large-scale investments in AI technologies, workforce training, and policy support. For example, the European Union's Green Deal provides substantial funding for AI-driven energy projects, fostering innovation while meeting the sustainability goals [28,64].

In developing nations, financial constraints often limit the scale of AI/ML deployments. However, international funding sources, such as the Green Climate Fund and partnerships with global organizations, have facilitated notable advancements in countries like Brazil and South Africa [31]. Policy frameworks in these nations often prioritize accessibility and cost-effectiveness, focusing on bridging the energy gap in underserved communities while fostering gradual integration of AI/ML technologies.

From a policy perspective, developed nations emphasize long-term sustainability and innovation. For instance, the United States has implemented tax incentives for companies adopting AI in renewable energy systems [29]. On the other hand, developing nations are adopting adaptive policies that align with their socio-economic realities, such as subsidizing AI-enabled renewable projects in rural areas to encourage adoption and community engagement [37].

Economic and policy considerations underscore the necessity of tailored approaches to AI/ML adoption in energy systems. By addressing financial disparities and fostering inclusive policy development, nations can collectively advance towards global energy sustainability.

Overall, this comparative analysis highlights the multifaceted role of AI/ML in energy systems across diverse regional contexts. While developed nations lead in innovation and large-scale deployment, developing nations are making strides through resourceful, localized applications. Bridging the gap between these regions requires fostering international collaboration, knowledge sharing, and equitable access to technology and funding. By leveraging the unique strengths of each region, AI/ML can become a universal driver of sustainable energy transformation.

7. Challenges and Barriers

While AI and ML hold transformative potential for sustainable energy policies, several challenges and barriers impede their implementation. These challenges span technological limitations, infrastructure inadequacies, regulatory gaps, and social acceptance issues, each of which requires careful consideration to ensure equitable and effective policy deployment. Addressing these barriers is crucial for harnessing the full potential of AI and ML in energy systems and ensuring that these technologies contribute to global sustainability goals in a fair and effective manner.

7.1. Technological and Infrastructure Barriers

The integration of AI and ML in energy systems is often hindered by poor data quality, insufficient computational resources, and infrastructure constraints. High-quality, real-time data are crucial for predictive modeling and decision-making; however, data availability is often fragmented, inconsistent, or siloed, especially in developing regions [65]. The lack of comprehensive datasets is a significant obstacle, as it restricts AI algorithms' ability to make accurate predictions regarding energy generation, consumption, and distribution.

Additionally, data often come from diverse and incompatible sources, further complicating efforts to establish a unified system for AI-driven energy management.

In addition to the data challenges, the computational resources required for training advanced AI models—such as neural networks and reinforcement learning algorithms—are substantial. These resources, including high-performance computing clusters and energy-efficient processors, may not be accessible to all governments or institutions, especially in resource-limited settings [3]. Even where such resources exist, they are often inefficiently distributed, with a concentration of computational power in urban centers and research institutions, leaving rural areas and smaller energy utilities underserved. As a result, AI/ML adoption remains skewed towards a few well-resourced areas, exacerbating inequality in energy access and policy implementation.

Moreover, the existing energy grids often lack the digital infrastructure necessary to implement AI-based solutions, such as advanced sensors, IoT devices, and edge computing systems. Traditional energy grids are typically built for linear, predictable energy flow, and their limited capacity to incorporate decentralized and variable renewable energy sources requires a major overhaul to accommodate the complex requirements of AI systems. In particular, integrating real-time data feeds into AI-powered solutions demands more sophisticated grid infrastructure capable of high-speed data transmission and secure data storage. These infrastructure upgrades may require considerable investments, which many developing nations may not be able to afford without international support.

Addressing these technological and infrastructure challenges requires coordinated efforts at multiple levels. Governments should prioritize investments in digital infrastructure, such as the installation of smart meters, IoT-enabled sensors, and data storage systems. At the same time, standardized frameworks for data collection, sharing, and governance should be developed to ensure that AI models have access to reliable, high-quality data across different energy sectors. International collaboration and public–private partnerships will also be essential in overcoming infrastructure limitations, providing funding, and facilitating technology transfer [66]. By building resilient, future-proof infrastructure and fostering data interoperability, the barriers to AI/ML deployment can be mitigated, enabling the equitable benefits of these technologies across regions.

7.2. Regulatory and Social Challenges

The adoption of AI and ML in energy policy is also constrained by the absence of comprehensive regulatory frameworks and the need to address ethical considerations. Many jurisdictions, particularly in developing nations, lack clear guidelines for using AI in decision-making processes, creating uncertainties about accountability, data privacy, and transparency [67]. Without well-defined regulatory structures, governments and energy providers may hesitate to implement AI/ML solutions for fear of legal challenges or compliance issues. This regulatory vacuum can delay the deployment of innovative technologies and limit their scalability, especially in regions where regulatory clarity is required for cross-border energy transactions or the implementation of large-scale energy projects.

Moreover, the application of AI in energy policymaking raises a host of ethical challenges. One major concern is the potential for biases in AI algorithms, which could lead to unfair outcomes, such as inequitable access to energy or the exacerbation of existing social inequalities [62]. For instance, algorithms trained on historical data might unintentionally favor certain geographic areas or demographic groups, leaving marginalized communities at a disadvantage. Additionally, AI systems are sometimes seen as “black boxes” with decision-making processes that are not easily interpretable. This opacity raises concerns about accountability and the ability of affected populations to challenge decisions made by AI systems.

Public resistance to AI technologies further complicates the regulatory landscape. Concerns about privacy, surveillance, and job displacement are common, particularly in regions where the workforce may be adversely impacted by automation [62]. For example, AI-based energy management systems may reduce the need for human labor in certain energy sectors, prompting fears about unemployment and the social implications of widespread automation. This resistance is especially pronounced in developing countries, where technology adoption often encounters cultural and societal barriers. A lack of public understanding of AI's potential benefits also leads to skepticism about its role in energy policy.

Overcoming these regulatory and social challenges requires a multi-faceted approach. Governments must establish robust regulatory frameworks that prioritize transparency, fairness, and accountability in the use of AI/ML technologies. These frameworks should address key concerns, including data privacy, algorithmic transparency, and the equitable distribution of benefits. In addition, ethical AI development must be encouraged through collaboration between governments, private companies, and civil society organizations. Public engagement campaigns and educational initiatives are essential to foster understanding and trust in AI-driven energy solutions, emphasizing their potential to improve quality of life and support sustainable development.

Furthermore, incorporating a stakeholder-driven approach to AI deployment can help mitigate social resistance. Engaging local communities in the planning and implementation of AI technologies can reduce fears and ensure that the needs and values of affected populations are taken into account. Policymakers should also consider providing training and reskilling programs to prepare the workforce for the changes brought by AI, ensuring that workers can transition into new roles in the AI-powered energy sector.

7.3. Cultural and Institutional Barriers to AI/ML Adoption

The successful adoption of AI and ML technologies in energy systems in developing countries is often hindered by various cultural and institutional barriers. These challenges need to be addressed to ensure the effective implementation of AI-driven solutions.

- **Cultural** Resistance: Cultural factors, such as the mistrust of technology, fear of social disruption, and resistance to change, are common in many developing countries. The reluctance to embrace AI technologies can stem from a lack of understanding or misconceptions about their benefits. In particular, there is often an attachment to traditional ways of managing energy systems, which can create resistance to new technological approaches.

Concerns about job displacement due to automation, as well as fears that AI might exacerbate existing inequalities, can lead to public opposition. Additionally, skepticism towards foreign technology or interventions—especially when AI solutions are driven by external corporations—can further fuel resistance. Therefore, public engagement and education campaigns are crucial to building trust and understanding, highlighting the potential of AI in improving energy systems by increasing efficiency and reducing costs [68].

- **Institutional Challenges:** Weak institutional frameworks and governance structures present significant barriers to the adoption of AI in developing countries. Many governments in these regions face difficulties in establishing clear policies for the integration of AI technologies in energy systems, which results in regulatory uncertainties and delays. Without well-defined legal and regulatory frameworks, AI projects may be delayed or abandoned due to concerns over data privacy, accountability, and compliance.

In addition to the regulatory challenges, there is often a lack of skilled personnel to manage the implementation of AI technologies. Many developing countries suffer from a shortage of local experts in fields such as data science, energy policy, and AI systems management. This limits the ability of local institutions to oversee AI-driven energy solutions and necessitates reliance on foreign expertise, which can be expensive and slow down the process of adoption.

Bureaucratic inefficiencies, such as slow decision-making processes and a lack of coordination between stakeholders, further exacerbate the challenges of implementing AI in energy systems. These institutional barriers can significantly hinder the timely and effective deployment of AI/ML solutions [69].

- **Strategies for Overcoming Barriers**: To overcome these cultural and institutional barriers, policymakers need to focus on both local capacity building and fostering collaboration among key stakeholders. Public–private partnerships (PPPs) can be particularly effective in bridging the gap between technology providers and local institutions. These partnerships allow for the alignment of AI solutions with the needs of the local context, ensuring that they are culturally appropriate and institutionally feasible [66,69,70].

Strengthening governance structures is another critical step in overcoming institutional barriers. Governments should work on creating clear, transparent regulatory frameworks that provide guidance on AI integration while addressing concerns related to data privacy, security, and ethical considerations. Additionally, investing in human capital development through training programs and educational initiatives will help build a local workforce capable of managing AI technologies [71].

Engaging communities and local stakeholders in the planning and decision-making processes can also help reduce cultural resistance. By incorporating local input and ensuring that AI systems are designed with cultural sensitivities in mind, governments and organizations can build trust and facilitate greater acceptance of AI technologies. Public awareness campaigns that emphasize the long-term benefits of AI for energy efficiency, cost reduction, and environmental sustainability will also play a key role in shifting public perception [68,71].

In conclusion, while cultural and institutional barriers pose significant challenges to AI adoption in developing countries, a concerted effort to address these issues through capacity building, effective governance, and stakeholder engagement can lead to successful AI integration into energy systems.

8. Future Research Directions and Recommendations

The integration of artificial intelligence (AI) and machine learning (ML) in energy systems holds immense potential to reshape the global energy landscape. However, unlocking this potential requires addressing critical implementation challenges, sustained innovation, strategic capacity building, and robust international collaboration. This section outlines key future directions and actionable recommendations for advancing AI/ML-driven energy sustainability while tackling barriers to adoption.

8.1. Advancing AI/ML for Energy Sustainability

AI and ML innovations are crucial for addressing energy sustainability challenges, particularly in resource-constrained environments. Open source AI tools, such as TensorFlow (version: 2.19.0) and PyTorch (version: 2.7.0), enable local innovators to develop tailored solutions for renewable energy forecasting, microgrid optimization, and demand-side management. However, widespread adoption faces significant obstacles.

- **Political Resistance**: Political resistance remains a critical barrier to the integration of advanced AI/ML technologies. Entrenched interests, alongside the inertia of existing energy policies, often slow down the adoption of innovative solutions. Addressing this resistance requires sustained advocacy and the demonstration of the socioeconomic benefits of AI-driven approaches.
- **Data Governance and Infrastructure:** A lack of access to high-quality, region-specific datasets and inadequate infrastructure limits the capacity to implement AI/ML technologies effectively. Improving data governance through regional initiatives and fostering open data-sharing agreements can mitigate these challenges. Additionally, investing in robust, scalable infrastructure is critical to supporting the deployment of AI models in both urban and rural areas.
- **Technical Innovations:** To enhance scalability and accessibility, the researchers should focus on developing lightweight, energy-efficient AI models that can operate effectively on low-power devices. This innovation is particularly vital for remote regions with limited computational resources. Furthermore, integrating AI with blockchain technologies can foster transparency and accountability in energy trading and carbon credit systems. By creating centralized platforms for sharing datasets, algorithms, and case studies, stakeholders can accelerate innovation and ensure equitable access to AI/ML solutions across economic regions. Advancing AI/ML for energy sustainability requires innovation that addresses these barriers while ensuring adaptability to diverse regional contexts. The ongoing commitment to these priorities will play a pivotal role in global energy transitions.

8.2. Capacity Building, Collaboration, and Future Work

Building local capacity and fostering international collaboration are essential for the successful integration of AI/ML in energy systems. Skill gaps, particularly in developing nations, limit the ability to design, deploy, and sustain advanced energy technologies. While initiatives such as the African AI Energy Training Network have demonstrated success in reducing these gaps, more work is needed:

- **Training and Capacity Building:** Universities, research institutions, and industry leaders should collaborate to design curricula and certification programs that focus on AI/ML applications in energy. These programs must emphasize hands-on training, practical projects, and interdisciplinary learning to equip individuals with the skills necessary to address real-world energy challenges. Developing specialized training initiatives tailored to local energy needs can empower communities to adopt and sustain AI-driven solutions.
- **International Collaboration:** International partnerships enhance capacity-building efforts by facilitating knowledge exchange and resource sharing. Developed nations, with their advanced technological ecosystems, can provide mentorship, funding, and technical expertise to support AI/ML adoption in developing regions. Collaborative platforms that bring together governments, academia, private industry, and non-governmental organizations play a vital role in enabling joint research projects, pilot programs, and policy development.
- **Future Work:** Future research should explore the integration of AI/ML with emerging technologies, such as the Internet of Things (IoT) and distributed energy systems, particularly in rural and underserved regions. Investigating the interplay between social, cultural, and institutional factors and AI/ML adoption will provide valuable insights for overcoming resistance and fostering inclusive energy transitions. Additionally, pilot programs that test scalable AI-driven solutions in diverse contexts will be critical for demonstrating their adaptability and effectiveness.

The future of AI/ML in energy systems depends on a collective effort to foster innovation, build capacity, and establish robust international partnerships. By addressing existing disparities and promoting equitable access to advanced technologies, stakeholders can advance energy sustainability and create resilient global energy systems. Such efforts require not only technological advancements, but also a commitment to inclusive policies that bridge gaps between developed and developing nations. Emphasizing sustainability and equity in these initiatives will ensure that the benefits of AI/ML integration extend across all socioeconomic and geographic boundaries.

9. Conclusions

This thematic review highlights the transformative potential of AI and ML technologies in fostering sustainable energy systems globally. By improving efficiency in energy generation, optimizing grid operations, enhancing demand management, and facilitating renewable energy integration, AI and ML are pivotal to addressing the pressing challenges of energy sustainability. This review underscores the tangible impact of AI-driven solutions, including cost reductions seen in renewable energy forecasting and improvements in grid reliability. Furthermore, it highlights the differences in AI adoption between developed and developing nations, showing that while developed nations have made substantial progress, there are valuable lessons and scalable models that can be applied to the unique challenges faced by developing countries, promoting broader and more equitable global adoption.

However, significant barriers to the widespread adoption of AI/ML in energy systems remain, particularly regarding upfront costs, skilled workforce shortages, and inadequate infrastructure in developing nations. These challenges call for a strategic approach that blends technological innovation with policy initiatives, capacity building, and financial mechanisms to enable equitable access to AI/ML solutions across regions.

The integration of AI/ML into sustainable energy policies is now more of a necessity than an option. Decision-makers must prioritize these technologies to drive long-term energy transformation. The key is not only fostering technological adoption but also creating supportive ecosystems through public–private partnerships, innovative financing models, and international collaboration. Based on this comprehensive thematic review, here are some unique insights for decision-makers:

- AI-driven solutions can significantly reduce operational costs and improve the efficiency of energy systems. For example, predictive maintenance and energy forecasting have been shown to save millions in repair costs and reduce energy curtailment [29]. Governments should incentivize AI adoption by creating subsidies or tax incentives for energy companies to integrate such technologies.
- Investing in open source AI tools can lower the barriers for developing nations, enabling them to access advanced energy solutions without substantial upfront investment. Promoting open source platforms should be a key priority for policymakers to democratize access to AI technologies.
- Scalable models and adaptive AI systems should be developed to account for the varying energy needs of both developed and developing nations. AI technologies should be tailored to local contexts, such as climate, energy infrastructure, and socioeconomic factors, to ensure a successful and sustainable implementation in diverse regions.
- Cross-border collaborations and international partnerships are critical for knowledge-sharing and resource mobilization. Decision-makers should create frameworks that encourage international cooperation to foster innovation in AI-driven energy solutions and expand access to capital for technology adoption.
- Capacity building is essential for the long-term success of AI/ML integration. Governments should invest in training programs to upskill local workforces in developing

nations, equipping them with the expertise to manage, maintain, and optimize AI-powered energy systems effectively.

- Policy frameworks must evolve to support the dynamic nature of AI technologies. The rapid pace of AI/ML advancements necessitates adaptive and flexible energy policies that can quickly integrate new technological developments while ensuring they align with sustainability goals and equity principles.
- Public–private partnerships (PPPs) should be leveraged to reduce the financial burden on developing countries. Governments should seek international funding, development bank support, and private sector investment to scale AI/ML applications in energy systems, particularly in rural and underserved areas.

Future work should focus on extending AI/ML applications to sectors such as water management and climate adaptation, exploring their synergies with energy systems. It is also essential to examine the long-term policy implications of AI/ML integration, ensuring that social equity and environmental sustainability remain at the forefront of technological advancement.

Decision-makers must act decisively to prioritize AI-driven energy solutions, foster global collaborations, and create adaptive policies. By addressing barriers, investing in open source development, and promoting capacity building, stakeholders can drive a global transition to sustainable, resilient, and equitable energy systems. The future of AI/ML in energy systems depends on a collective effort to foster innovation, build capacity, and establish robust international partnerships. By addressing the existing disparities and promoting equitable access to advanced technologies, stakeholders can advance energy sustainability and create resilient global energy systems.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

References

1. International Energy Agency (IEA). World Energy Outlook 2023: Energy and Sustainability. 2023. Available online: https://www.iea.org/reports/world-energy-outlook-2023 (accessed on 19 April 2025).
2. Mhlanga, D. Artificial intelligence and machine learning for energy consumption and production in emerging markets: A review. *Energies* **2023**, *16*, 745. [CrossRef]
3. Pimenow, S.; Pimenowa, O.; Prus, P. Challenges of artificial intelligence development in the context of energy consumption and impact on climate change. *Energies* **2024**, *17*, 5965. [CrossRef]
4. Fasesin, K.; Oladinni, A.; Emezirinwune, M.U.; Oba-Sulaiman, Z.; Abdulsalam, K.A. Renewable energy in developing countries: Challenges, opportunities, and policy recommendations for innovative funding. *Adeleke Univ. J. Sci.* **2024**, *3*, 120–129.
5. Walczewski, M.J.; Wöhrle, H. Prediction of electricity generation using onshore wind and solar energy in Germany. *Energies* **2024**, *17*, 844. [CrossRef]
6. Falcone, P.M. Sustainable energy policies in developing countries: A review of challenges and opportunities. *Energies* **2023**, *16*, 6682. [CrossRef]
7. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]
8. Persello, C.; Wegner, J.D.; Hänsch, R.; Tuia, D.; Ghamisi, P.; Koeva, M.; Camps-Valls, G. Deep learning and Earth observation to support the sustainable development goals. *arXiv* **2021**, arXiv:2112.11367.
9. Abdeldjalil, C.; Mohammed, K.; Asma, O. Digitalization and sustainable development: A literature review focused on artificial intelligence (2019–2024). *J. Law Sustain. Dev.* **2024**, *12*, e4155. [CrossRef]
10. Kar, A.K.; Choudhary, S.K.; Singh, V.K. How can artificial intelligence impact sustainability: A systematic literature review. *J. Clean. Prod.* **2022**, *376*, 134120. [CrossRef]
11. Năstasă, A.; Dumitra, T.-C.; Grigorescu, A. Artificial intelligence and sustainable development during the pandemic: An overview of the scientific debates. *Heliyon* **2024**, *10*, e30412. [CrossRef]
12. Zhang, E.; Pasternak, S.; Brown, A.J. Considerations for embedding equity in the energy transition. *Clim. Energy* **2024**, *41*, 1–10. [CrossRef]

13. Massimo, R.; Yigitcanlar, T.; Hon, C.; Teo, M. Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. *Sustain. Cities Soc.* **2024**, *108*, 105499. [CrossRef]
14. Bogdanov, D.; Oyewo, A.S.; Mensah, T.N.O.; Nishida, Y.; Saito, T.; Aikawa, T.; Kimura, S.; Gagnebin, M.; Pescia, D.; Shimoyama, T.; et al. Energy transition for Japan: Pathways towards a 100% renewable energy system in 2050. *IET Renew. Power Gener.* **2023**, *17*, 317–329. [CrossRef]
15. Institute for Sustainable Energy Policies. 100% Renewable Energy Scenario in Tokyo Metropolitan Area with Green Recovery by 2050. 2021. Available online: https://www.isep.or.jp/en/1161/ (accessed on 19 April 2025).
16. Crespo del Granado, P.; Resch, G.; Holz, F.; Welisch, M.; Geipel, J.; Hartner, M.; Forthuber, S.; Sensfuss, F.; Olmos, L.; Bernath, C.; et al. Energy transition pathways to a low-carbon Europe in 2050: The degree of cooperation and the level of decentralization. *Econ. Energy Environ. Policy* **2020**, *9*, 65–82. [CrossRef]
17. Connolly, D. Heat Roadmap Europe: Quantitative comparison between the electricity, heating, and cooling sectors for different European countries. *Energy* **2014**, *65*, 203–215. [CrossRef]
18. Clavijo Cevallos, M.P.; Calo Chicaiza, L.A.; Donoso Veliz, A.P.; Navas Martínez, P.E. Relation of the efficiency and energy potential of the Galapagos Islands through the use of renewable energies. *J. Energy Environ. Chem. Eng.* **2023**, *8*, 59–67. [CrossRef]
19. Eras-Almeida, A.A.; Egido-Aguilera, M.A.; Blechinger, P.; Berendes, S.; Caamaño, E.; García-Alcalde, E. Decarbonizing the Galapagos Islands: Techno-economic perspectives for the hybrid renewable mini-grid Baltra–Santa Cruz. *Sustainability* **2020**, *12*, 2282. [CrossRef]
20. Icaza-Alvarez, D.; Galan-Hernandez, N.D.; Orozco-Guillen, E.E.; Jurado, F. Smart energy planning in the midst of a technological and political change towards a 100% renewable system in Mexico by 2050. *Energies* **2023**, *16*, 7121. [CrossRef]
21. Icaza-Alvarez, D.; Jurado, F.; Tostado-Véliz, M. Smart energy planning for the decarbonization of Latin America and the Caribbean in 2050. *Energy Rep.* **2024**, *11*, 6160–6185. [CrossRef]
22. UN ECLAC & GET.transform. Pathways to Sustainable Planning for a Just Energy Transition in Latin America and the Caribbean. 2023. Available online: https://www.get-transform.eu/pathways-to-sustainable-planning-for-a-just-energy-transition-in-latin-america-and-the-caribbean/ (accessed on 19 April 2025).
23. Ortiz Nuques, M.I.; AI-Powered Ocean Protection and Sustainable Trade: The Galapagos Islands as A Case Study. Harv. *Int. Law J.* 2024. Available online: https://journals.law.harvard.edu/ilj/2024/05/ai-powered-ocean-protection-and-sustainable-trade-the-galapagos-islands-as-a-case-study/ (accessed on 19 April 2025).
24. Prabhakaran, V.; Qadri, R.; Hutchinson, B. Cultural incongruencies in artificial intelligence. *arXiv* **2022**, arXiv:2211.13069.
25. Nowell, L.S.; Norris, J.M.; White, D.E.; Moules, N.J. Thematic analysis: Striving to meet the trustworthiness criteria. *Int. J. Qual. Methods* **2017**, *16*, 1609406917733847. [CrossRef]
26. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; The PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Med.* **2009**, *6*, e1000097. [CrossRef] [PubMed]
27. Fereday, J.; Muir-Cochrane, E. Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *Int. J. Qual. Methods* **2006**, *5*, 80–92. [CrossRef]
28. Alazemi, T.; Darwish, M.; Radi, M. Renewable energy sources integration via machine learning modelling: A systematic literature review. *Heliyon* **2024**, *10*, e26088. [CrossRef]
29. Shoaei, M.; Noorollahi, Y.; Hajinezhad, A.; Moosavian, S.F. A review of the applications of artificial intelligence in renewable energy systems: An approach-based study. *Energy Convers. Manag.* **2024**, *306*, 118207. [CrossRef]
30. Asensio, F.J.; San Martín, J.I.; Zamora, I.; Saldaña, G.; Oñederra, O. Analysis of electrochemical and thermal models and modeling techniques for polymer electrolyte membrane fuel cells. *Renew. Sustain. Energy Rev.* **2019**, *113*, 109283. [CrossRef]
31. Jiao, J. Application and prospect of artificial intelligence in smart grid. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *510*, 022012. [CrossRef]
32. Ali, A.N.F.; Sulaima, M.F.; Razak, I.A.W.A.; Abdul Kadir, A.F. Artificial intelligence application in demand response: Advantages, issues, status, and challenges. *IEEE Access* **2023**, *11*, 16907–16922. [CrossRef]
33. Mugalakhod, S.; Nirmanik, S.M. AI driven smart homes energy efficiency and model. *Int. J. Res. Appl. Sci. Eng. Technol.* **2022**, *10*, 461–465. [CrossRef]
34. Chen, C.; Hu, Y.; Karuppiah, M.; Kumar, P.M. Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101358. [CrossRef]
35. Sun, S.; Yang, Q.; Ma, J.; Ferré, A.J.; Yan, W. Hierarchical planning of PEV charging facilities and DGs under transportation-power network couplings. *Renew. Energy* **2020**, *150*, 356–369. [CrossRef]
36. Zhang, X.; Khan, K.; Shao, X.; Oprean-Stan, C.; Zhang, Q. The rising role of artificial intelligence in renewable energy development in China. *Energy Econ.* **2024**, *132*, 107489. [CrossRef]
37. McCauley, D.; Ramasar, V.; Heffron, R.J.; Sovacool, B.K.; Mebratu, D.; Mundaca, L. Energy justice in the transition to low carbon energy systems: Exploring key themes in interdisciplinary research. *Appl. Energy* **2019**, *233–234*, 916–921. [CrossRef]

38. Budiarso; Warjito; Lubis, M.N.; Adanta, D. Performance of a low cost spoon-based Turgo turbine for pico hydro installation. *Energy Procedia* **2019**, *156*, 447–451. [CrossRef]
39. Danish, M.S.S.; Senjyu, T. AI-Enabled Energy Policy for a Sustainable Future. *Sustainability* **2023**, *15*, 7643. [CrossRef]
40. Beemkumar, N.; Chaudhary, C.; Doda, D.K.; Kumar, S. Review on smart grids and renewable integration: An artificial intelligence-powered perspective. *Multidiscip. Rev.* **2024**, *6*, 2023ss070. [CrossRef]
41. Hu, J.-L.; Bui, N.H.B. The future design of smart energy systems with energy flexumers: A constructive literature review. *Energies* **2024**, *17*, 2039. [CrossRef]
42. Jiao, Z.; Zhang, C.; Li, W. Artificial intelligence in energy economics research: A bibliometric review. *Energies* **2025**, *18*, 434. [CrossRef]
43. Khan, P.W.; Kim, Y.; Byun, Y.-C.; Lee, S.-J. Influencing factors evaluation of machine learning-based energy consumption prediction. *Energies* **2021**, *14*, 7167. [CrossRef]
44. Agajie, T.F.; Ali, A.; Fopah-Lele, A.; Amoussou, I.; Khan, B.; Rodríguez Velasco, C.L.; Tanyi, E. A comprehensive review on techno-economic analysis and optimal sizing of hybrid renewable energy sources with energy storage systems. *Energies* **2023**, *16*, 642. [CrossRef]
45. Jain, V.; Mitra, A. Ethical implications of artificial intelligence in promoting sustainable clean energy solutions. In *Handbook of Research on AI and Ethics in Sustainable Energy Systems*; IGI Global: Hershey, PA, USA, 2024; pp. 96–118. [CrossRef]
46. Rashidi, S. Applications of machine learning techniques in energy systems integrated with phase change materials: A concise review. *Eng. Anal. Bound. Elem.* **2023**, *150*, 237–245. [CrossRef]
47. Gómez-Ramírez, G.A.; Meza, C.; Mora-Jiménez, G.; Rojas Morales, J.R.; García-Santander, L. The Central American power system: Achievements, challenges, and opportunities for a green transition. *Energies* **2023**, *16*, 4328. [CrossRef]
48. Li, L.; Wen, J.; Li, Y.; Mu, Z. Supply chain challenges and energy insecurity: The role of AI in facilitating renewable energy transition. *Energy Econ.* **2025**, *144*, 108378. [CrossRef]
49. García Sánchez, D.; Avendaño Leadem, D. Energy transition and path dependence: The case of Costa Rica. *Rev. Geográfica De América Central* **2021**, *61*, 1–25. [CrossRef]
50. Elomari, Y.; Mateu, C.; Marín-Genescà, M.; Boer, D. A data-driven framework for designing a renewable energy community based on the integration of machine learning model with life cycle assessment and life cycle cost parameters. *Appl. Energy* **2024**, *358*, 122619. [CrossRef]
51. Noorman, M.; Apráez, B.E.; Lavrijssen, S. AI and energy justice. *Energies* **2023**, *16*, 2110. [CrossRef]
52. Sterman, J.D. *Business Dynamics: Systems Thinking and Modeling for a Complex World*; Irwin McGraw-Hill: Irvine, CA, USA, 2000.
53. Qudrat-Ullah, H. *Systems Thinking for Sustainability Education in Business Schools*; Springer: New York, NY, USA, 2024.
54. Qudrat-Ullah, H.; Karakul, M. Modelling for policy assessment in the electricity supply sector of Pakistan. *Int. J. Energy Sect. Manag.* **2007**, *1*, 240–256. [CrossRef]
55. Qudrat-Ullah, H. *Exploring the Dynamics of Renewable Energy and Sustainable Development in Africa: A Cross-Country and Interdisciplinary Approach*; Springer: Cham, Switzerland, 2023; Available online: https://link.springer.com/book/10.1007/978-3-031-48528-2 (accessed on 19 April 2025).
56. Qudrat-Ullah, H. *The Physics of Stocks and Flows of Energy Systems*; Springer: New York, NY, USA, 2016.
57. Senge, P.M. *The Fifth Discipline: The Art and Practice of the Learning Organization*; Doubleday: New York, NY, USA, 1990.
58. Floridi, L.; Cowls, J.; Beltrametti, M.; Chatila, R.; Chazerand, P.; Dignum, V.; Luetge, C.; Madelin, R.; Pagallo, U.; Rossi, F.; et al. AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds Mach.* **2021**, *28*, 689–707. [CrossRef]
59. Jobin, A.; Ienca, M.; Vayena, E. The global landscape of AI ethics guidelines. *Nat. Mach. Intell.* **2019**, *1*, 389–399. [CrossRef]
60. Whittlestone, J.; Nyrup, R.; Alexandrova, A.; Cave, S. The role and limits of principles in AI ethics: Towards a focus on tensions. In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, San Jose, CA, USA, 27–28 January 2019; pp. 195–200. [CrossRef]
61. El-Haber, G.; Devillers, R.; Zamyatin, A. Ethical considerations in AI deployment for energy systems: A lifecycle approach. *Energies* **2024**, *17*, 587. [CrossRef]
62. Binns, R. Algorithmic accountability and public sector AI adoption. *AI Soc.* **2018**, *33*, 231–243.
63. Grote, T.; Berens, P. On the ethics of algorithmic decision-making in healthcare. *J. Med. Ethics* **2020**, *46*, 205–211. [CrossRef] [PubMed]
64. International Energy Agency. Spain 2021: Energy Policy Review. 2021. Available online: https://www.iea.org/reports/spain-2021 (accessed on 19 April 2025).
65. Manandhar, P.; Rafiq, H.; Rodriguez-Ubinas, E. Current status, challenges, and prospects of data-driven urban energy modeling: A review of machine learning methods. *Energy Rep.* **2023**, *9*, 2757–2776. [CrossRef]
66. International Finance Corporation. (n.d.) Public-Private Partnerships in Power. Available online: https://www.ifc.org/en/what-we-do/sector-expertise/public-private-partnerships/power (accessed on 19 April 2025).

67. Veale, M.; Binns, R.; Edwards, L. Algorithms that remember: Model inversion attacks and data protection law. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2018**, *376*, 20180083. [CrossRef]
68. United Nations. Public-Private Partnerships can Bring Affordable Clean Energy to Poor. *UN News*. 2011. Available online: https://news.un.org/en/story/2011/06/377152 (accessed on 19 April 2025).
69. Rongé, A.; Shastry, V.; Kamau, A. *Public-Private Partnerships in the African Energy Sector*; Center on Global Energy Policy at Columbia University SIPA: New York, NY, USA, 2024. Available online: https://www.energypolicy.columbia.edu/publications/public-private-partnerships-in-the-african-energy-sector/ (accessed on 19 April 2025).
70. Fleta-Asín, J.; Muñoz, F. Renewable energy public–private partnerships in developing countries: Determinants of private investment. *Sustain. Dev.* **2021**, *29*, 653–670. [CrossRef]
71. United Nations Development Programme. How UNDP Catalyzes Innovative Public-Private Partnerships that Reduce Carbon Emissions. UNDP Energy Blog. 8 February 2023. Available online: https://www.undp.org/energy/blog/how-undp-catalyzes-innovative-public-private-partnerships-reduce-carbon-emissions (accessed on 19 April 2025).