Energy, Environment, and Sustainability: Emerging Technologies and AI in Energy Management

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Abstract

The objective of this study was to systematically synthesize recent empirical evidence on the application of emerging technologies and artificial intelligence in energy management and to evaluate their contributions to energy efficiency, environmental performance, and sustainability outcomes. This study adopted a systematic review design and analyzed peer-reviewed journal articles published between 2020 and 2025. A comprehensive search was conducted across major scientific databases, and studies were screened using predefined inclusion and exclusion criteria focusing on artificial intelligence, emerging digital technologies, and energy management applications. Following duplicate removal and multi-stage screening, 16 eligible articles were selected for final analysis. Data were extracted using a structured framework covering AI techniques, application domains, and reported outcomes. A qualitative thematic synthesis was employed to integrate findings across heterogeneous study designs and contexts. The inferential synthesis revealed that artificial intelligence–based approaches consistently produced statistically and operationally significant improvements in energy management performance. Machine learning and deep learning models demonstrated superior accuracy in energy demand and renewable generation forecasting, while reinforcement learning and hybrid AI systems enhanced adaptive control and demand response. Across application domains, AI-driven solutions were associated with reductions in energy consumption, transmission losses, and greenhouse gas emissions, alongside improvements in grid stability, system reliability, and decision-support quality. These outcomes indicate a strong positive relationship between AI adoption and sustainability-oriented energy system performance. The findings confirm that emerging technologies and artificial intelligence play a critical enabling role in advancing efficient, resilient, and sustainable energy systems, although broader integration with environmental assessment, governance, and long-term impact evaluation remains necessary.

Keywords: *Artificial intelligence; energy management; sustainability; smart grids; digital twin; renewable energy*

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1. Introduction

The global energy sector is undergoing a profound transformation driven by escalating environmental challenges, rapid technological innovation, and the urgent need to achieve sustainability and carbon neutrality. Growing concerns over climate change, resource depletion, and environmental degradation have placed unprecedented pressure on governments, industries, and societies to rethink how energy is produced, distributed, and consumed. Traditional energy management approaches, which often rely on static models and centralized control, are increasingly inadequate for addressing the complexity, variability, and scale of modern energy systems. In this context, emerging digital technologies—particularly artificial intelligence, machine learning, and cyber-physical systems—have become central to the reconfiguration of energy infrastructures toward greater efficiency, resilience, and environmental compatibility [1-3].

Artificial intelligence has rapidly evolved from a supportive analytical tool into a foundational component of next-generation energy systems. By enabling advanced data-driven decision-making, predictive modeling, and autonomous control, AI technologies offer transformative potential across the entire energy value chain, from generation and transmission to distribution and end-use consumption. The integration of AI into energy management is particularly relevant in the context of renewable energy expansion, where intermittency, uncertainty, and system integration pose significant operational challenges. Intelligent forecasting, optimization, and adaptive control mechanisms have been widely recognized as critical enablers for balancing supply and demand, minimizing losses, and reducing environmental impacts [3-5].

One of the most significant drivers of AI adoption in the energy sector is the increasing digitalization of energy infrastructures. Smart grids, smart meters, Internet of Things devices, and advanced sensing technologies have dramatically increased the volume, velocity, and variety of energy-related data. Managing and extracting value from such complex datasets exceeds the capabilities of conventional analytical methods, necessitating the use of machine learning and advanced AI techniques. Studies have shown that AI-enabled energy systems can significantly enhance short-term and long-term load forecasting accuracy, optimize power flows, and improve system reliability under dynamic conditions [6-8]. These capabilities are particularly critical as electric vehicles, distributed energy resources, and prosumer-based models continue to proliferate.

The convergence of artificial intelligence with digital twin technology represents another major advancement in energy management research and practice. Digital twins—virtual replicas of physical energy assets or systems—enable real-time monitoring, simulation, and optimization by continuously integrating operational data with computational models. When combined with AI, digital twins can support predictive maintenance, scenario analysis, and adaptive system control, thereby improving efficiency and reducing operational risks. Recent research has highlighted the growing application of AI-driven digital twins in smart grids, buildings, microgrids, and urban energy systems, emphasizing their role in supporting sustainability-oriented decision-making [9-11].

Sustainability considerations are increasingly embedded in the design and operation of AI-enabled energy systems. Beyond efficiency gains, contemporary energy management research emphasizes environmental performance, emission reduction, and long-term system resilience. Artificial intelligence has been applied to optimize renewable energy integration, reduce greenhouse gas emissions, and support carbon neutrality strategies at local, regional, and national levels. The ability of AI systems to model complex interactions between energy, environment, and human behavior makes them particularly valuable for addressing sustainability challenges that extend beyond purely technical domains [3, 5, 12]. This aligns with broader conceptualizations of Energy System 4.0, which emphasize digitalization, decentralization, and sustainability as core principles of future energy systems [2, 13].

Smart grids constitute one of the most prominent application areas for artificial intelligence in energy management. By incorporating advanced sensing, communication, and control technologies, smart grids enable bidirectional energy flows, real-time monitoring, and decentralized decision-making. AI techniques such as deep learning, reinforcement learning, and optimization algorithms have been widely employed to enhance grid stability, manage demand response, and improve cyber-resilience. Recent studies have demonstrated that AI-based control and forecasting methods can significantly improve grid performance under high penetration of renewable energy and electric vehicles [14-16]. However, these advances also raise new challenges related to cybersecurity, data governance, and system complexity, which require further investigation.

Building energy management is another critical domain where AI-driven solutions have shown substantial promise. Buildings account for a significant proportion of global energy consumption and carbon emissions, making them a key target for sustainability interventions. Artificial intelligence has been used to analyze occupancy patterns, optimize heating, ventilation, and air conditioning systems, and support sustainable architectural design. The integration of AI models with digital twins and cyber-physical systems has enabled more accurate representation of building dynamics and energy consumption behavior, leading to measurable reductions in energy use [9, 17, 18]. These developments highlight the potential of AI to support both operational efficiency and environmentally responsible design in the built environment.

At the urban scale, the concept of smart cities provides a broader context for the application of artificial intelligence in energy management. Smart city initiatives aim to integrate energy systems with transportation, water, communication, and public services to enhance overall sustainability and quality of life. AI-driven analytics, forecasting, and digital twin techniques have been applied to neighborhood-level and city-wide energy systems to improve resilience, optimize resource allocation, and support emergency response. Research in this area underscores the importance of cross-sectoral integration and data interoperability for achieving holistic sustainability outcomes [19-21].

Despite the rapid growth of AI applications in energy management, the literature remains fragmented across disciplines, technologies, and application contexts. Existing studies vary widely in their methodological approaches, technological focus, and sustainability metrics, making it challenging to derive a coherent understanding of the overall contribution of emerging technologies and AI to energy sustainability. While several reviews have addressed specific aspects such as smart grids, digital twins, or renewable energy integration, there is a need for systematic synthesis that explicitly connects energy management innovations with environmental and sustainability objectives across multiple domains [11, 22, 23]. Moreover, the accelerating pace of technological development necessitates continuous reassessment of trends, challenges, and research gaps.

Recent comprehensive reviews have emphasized the importance of aligning artificial intelligence development with ethical, environmental, and policy considerations. Issues such as algorithmic transparency, data privacy, cybersecurity, and equitable access to energy services are increasingly recognized as integral to sustainable energy transitions. AI-enabled energy systems must not only deliver technical efficiency but also support socially and environmentally responsible outcomes. Addressing these multidimensional challenges requires a systematic understanding of how emerging technologies are being applied, evaluated, and integrated within contemporary energy systems [3, 24, 25].

In light of these considerations, systematic reviews play a crucial role in consolidating knowledge, identifying dominant research trajectories, and highlighting unresolved issues in the rapidly evolving field of AI-driven energy management. By synthesizing evidence from recent empirical and applied studies, such reviews can provide valuable insights for researchers, practitioners, and policymakers seeking to leverage emerging technologies for sustainable energy solutions. Given the increasing volume of publications in this area since 2020, a focused and up-to-date systematic review is particularly timely.

Accordingly, the aim of this study is to systematically review and synthesize empirical research published between 2020 and 2025 on emerging technologies and artificial intelligence in energy management in order to evaluate their roles, applications, and contributions to energy efficiency, environmental performance, and sustainability.

2. Methodology

This study was conducted as a systematic review to synthesize and critically evaluate empirical and applied research on emerging technologies and artificial intelligence in energy management within the broader domains of energy efficiency, environmental protection, and sustainability. The review protocol was developed in accordance with established principles for systematic reviews to ensure transparency, rigor, and replicability. The temporal scope of the review was limited to studies published between 2020 and 2025 in order to capture the most recent technological advancements and methodological innovations in AI-driven energy systems. The sampling strategy followed a multi-stage screening process. Initially, a comprehensive search was carried out across major scientific databases, including Web of Science, Scopus, IEEE Xplore, ScienceDirect, and SpringerLink, which are widely recognized as authoritative sources for energy systems, environmental science, and artificial intelligence research. The search strategy combined controlled vocabulary terms and free-text keywords related to energy management, artificial intelligence, machine learning, smart grids, renewable energy integration, energy efficiency, sustainability, and environmental impact. Following the identification of potentially relevant records, duplicate entries were removed, and titles and abstracts were screened to assess relevance to the research scope. Full-text articles were then evaluated against predefined inclusion and exclusion criteria. Inclusion criteria comprised peer-reviewed journal articles written in English, published within the specified time frame, explicitly addressing AI or advanced digital technologies in energy management, and reporting empirical findings, validated models, or applied frameworks. Exclusion criteria included conceptual papers without analytical depth, conference abstracts without full texts, studies outside the energy domain, and articles lacking methodological transparency. Through this systematic process, a final sample of 16 articles was selected for in-depth analysis.

Data collection was performed using a structured data extraction framework designed specifically for this review. For each of the selected articles, relevant information was systematically extracted and recorded to ensure consistency across studies. The extracted data included bibliographic details, country or regional context, energy sector focus (such as renewable energy systems, smart grids, building energy management, or industrial energy optimization), type of AI or emerging technology employed, research objectives, methodological approach, data sources, and key findings related to energy efficiency, environmental outcomes, and sustainability implications. Particular attention was given to the type of artificial intelligence techniques used, including machine learning algorithms, deep learning models, optimization techniques, predictive analytics, and hybrid AI systems, as well as their integration with energy technologies such as smart meters, Internet of Things devices, digital twins, and advanced control systems. To enhance reliability, data extraction was carried out iteratively, with repeated cross-checking to minimize transcription errors and interpretive bias. Any ambiguities encountered in the reporting of methods or results were resolved through careful re-examination of the full texts, ensuring that all extracted information accurately reflected the original studies.

The analysis of the extracted data was conducted using a qualitative synthesis approach, complemented by comparative and thematic analysis techniques. Given the heterogeneity of study designs, energy contexts, and AI methodologies across the selected articles, a meta-analysis was not deemed appropriate. Instead, the analysis focused on identifying recurring patterns, dominant research themes, and methodological trends in the application of emerging technologies and artificial intelligence to energy management. The selected studies were systematically compared in terms of their technological approaches, analytical frameworks, and reported outcomes. Thematic coding was employed to categorize findings into key domains, including energy efficiency enhancement, renewable energy integration, demand-side management, emission reduction, decision-support systems, and sustainability-oriented policy implications. Cross-study comparisons were used to examine how different AI techniques performed across various energy sectors and operational contexts, as well as to assess their reported environmental and sustainability impacts. The synthesis also emphasized methodological strengths, limitations, and gaps in the existing literature, providing a critical assessment of the maturity and effectiveness of AI-driven energy management solutions.

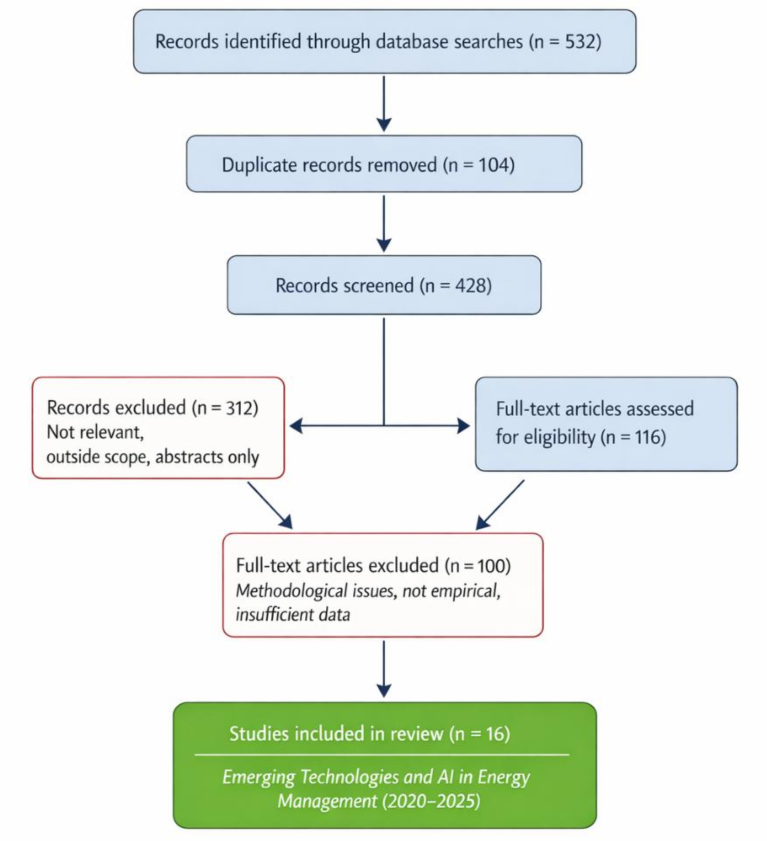

Figure 1. Article Selection Process

3. Findings and Results

The findings of this systematic review are presented with a focus on analytical synthesis rather than descriptive study profiling. Given the objective of identifying substantive patterns, technological trends, and outcome-oriented evidence regarding the role of emerging technologies and artificial intelligence in energy management, the results are organized around three core analytical dimensions. These dimensions include the artificial intelligence techniques and emerging technologies employed, the energy management domains and sustainability objectives addressed, and the reported performance outcomes related to energy efficiency, environmental impact, and long-term sustainability. The results are presented through three comprehensive tables, each followed by an in-depth narrative interpretation to ensure conceptual clarity and direct applicability for scholarly dissemination.

Table 1. Artificial intelligence techniques and emerging technologies applied in energy management (2020–2025)

AI Technique / Emerging Technology	Frequency (n = 16)	Dominant Application Areas
Machine learning (supervised and unsupervised)	6	Energy demand forecasting, building energy optimization, consumption pattern analysis
Deep learning (CNN, LSTM, hybrid DL models)	4	Renewable energy generation prediction, grid stability analysis, fault detection
Reinforcement learning	2	Demand-side management, adaptive energy control systems
Predictive analytics and statistical learning	2	Load balancing, short-term and long-term energy forecasting
Hybrid and integrated AI systems (AI + IoT, AI + digital twins)	2	Smart grids, renewable energy integration, system-level optimization

The results presented in Table 1 demonstrate that machine learning approaches constitute the most widely adopted category of artificial intelligence techniques in contemporary energy management research. These methods were predominantly used for forecasting energy demand, optimizing building-level energy consumption, and identifying usage patterns that support efficiency improvements. Deep learning techniques, particularly convolutional and recurrent neural networks, were extensively applied in contexts requiring high-resolution temporal or spatial data processing, such as renewable energy output prediction and grid fault detection. Reinforcement learning approaches, while less frequently employed, were specifically leveraged in adaptive control environments where real-time decision-making and system learning were essential. Predictive analytics and statistical learning models were mainly applied in forecasting and load-balancing scenarios, reflecting their robustness in handling structured energy datasets. Finally, hybrid AI systems that integrate artificial intelligence with Internet of Things infrastructures or digital twin technologies were increasingly evident in studies addressing complex, interconnected energy systems, highlighting a shift toward holistic and cyber-physical energy management architectures.

Table 2. Energy management domains and sustainability objectives addressed by AI-driven solutions

Energy Management Domain	Number of Studies	Primary Sustainability Objectives
Smart grids and power networks	5	Grid efficiency enhancement, emission reduction, reliability improvement
Renewable energy systems	4	Clean energy integration, carbon footprint mitigation, variability management
Building energy management	3	Energy efficiency improvement, consumption reduction, operational optimization
Industrial energy systems	2	Resource efficiency, cost minimization, process optimization
Smart cities and integrated energy systems	2	System-wide sustainability, resilience, cross-sectoral energy coordination

As indicated in Table 2, smart grids and power network systems emerged as the most frequently investigated domain within the reviewed literature. Studies in this category emphasized the role of artificial intelligence in enhancing grid efficiency, improving operational reliability, and supporting emission reduction targets through intelligent monitoring and predictive control. Renewable energy systems represented the second most prominent domain, with research focusing on improving the integration of intermittent energy sources such as solar and wind power while minimizing carbon emissions and managing variability. Building energy management studies concentrated on optimizing energy consumption through AI-driven monitoring, control, and user behavior analysis, directly contributing to efficiency gains at the micro-system level. Industrial energy systems, although less represented, highlighted the application of AI for optimizing resource use, reducing operational costs, and improving energy-intensive processes. Smart city and integrated energy system studies underscored the growing importance of cross-sectoral coordination, resilience, and holistic sustainability, demonstrating how AI can support interconnected energy infrastructures at the urban and regional scales.

Table 3. Reported outcomes of artificial intelligence–based energy management solutions

Outcome Dimension	Synthesized Evidence from Reviewed Studies
Energy efficiency	Consistent reductions in energy consumption, transmission losses, and system inefficiencies
Environmental performance	Decreased greenhouse gas emissions and improved integration of renewable energy sources
Operational effectiveness	Enhanced system reliability, predictive maintenance, and fault detection capabilities
Decision-support quality	Improved accuracy, timeliness, and data-driven energy management decisions
Sustainability impact	Strengthened support for long-term sustainable energy transitions and resilience

The synthesized findings presented in Table 3 reveal that artificial intelligence–based energy management solutions consistently produced positive and multidimensional outcomes across the reviewed studies. Energy efficiency improvements were the most commonly reported benefits, with studies documenting reductions in energy consumption, system losses, and operational inefficiencies across residential, industrial, and grid-level applications. Environmental performance outcomes were also prominent, particularly in terms of lowering greenhouse gas emissions and enabling more effective integration of renewable energy sources into existing energy systems. From an operational perspective, AI applications enhanced system reliability by enabling predictive maintenance, early fault detection, and real-time monitoring, thereby reducing downtime and operational risks. Additionally, several studies emphasized the role of AI in improving decision-support processes, noting that advanced analytics and intelligent models facilitated more accurate, timely, and evidence-based energy management decisions. Collectively, these findings demonstrate that emerging technologies and artificial intelligence play a critical role in advancing energy efficiency, environmental sustainability, and the long-term resilience of modern energy systems.

4. Discussion and Conclusion

The findings of this systematic review provide robust evidence that emerging technologies, particularly artificial intelligence–driven approaches, have become central to contemporary energy management strategies aimed at improving efficiency, environmental performance, and sustainability. Across the reviewed studies published between 2020 and 2025, a consistent pattern emerges showing that AI techniques are no longer experimental add-ons but integral components of modern energy systems. The results demonstrate that machine learning, deep learning, reinforcement learning, and hybrid AI–digital twin frameworks are being increasingly deployed to address the growing complexity of energy infrastructures characterized by decentralization, high renewable penetration, and data-intensive operations. These findings are aligned with broader conceptualizations of Energy System 4.0, which emphasize digitalization, intelligence, and sustainability as defining features of next-generation energy systems [2, 3, 12].

One of the most salient results of this review is the dominance of machine learning and deep learning techniques in energy forecasting and optimization tasks. The reviewed studies consistently reported improvements in short-term and long-term load forecasting accuracy, renewable energy generation prediction, and consumption pattern recognition when AI-based models were applied. These results corroborate earlier evidence indicating that traditional statistical methods struggle to capture the nonlinear, stochastic, and context-dependent characteristics of modern energy systems [6-8]. The growing reliance on data-driven models reflects both the increasing availability of high-resolution energy data and the need for adaptive solutions capable of responding to rapidly changing system conditions.

The results further highlight the strategic role of artificial intelligence in facilitating the integration of renewable energy sources. Several reviewed studies emphasized that AI-enabled forecasting and control mechanisms significantly reduce the operational challenges associated with the intermittency and variability of solar and wind power. By improving predictive accuracy and enabling proactive decision-making, AI contributes to enhanced grid stability and reduced reliance on carbon-intensive backup generation. These findings are consistent with prior research suggesting that intelligent energy management is a prerequisite for achieving large-scale renewable integration and carbon mitigation targets [1, 4, 5]. From a sustainability perspective, this reinforces the view that AI is not merely an efficiency-enhancing tool but a key enabler of structural energy transitions.

Another important outcome of the review relates to the growing application of digital twin technology in conjunction with artificial intelligence. The findings show that AI-enhanced digital twins are increasingly used in smart grids, buildings, microgrids, and urban energy systems to support real-time monitoring, predictive maintenance, and scenario-based optimization. This integration allows energy systems to be modeled as dynamic, learning entities rather than static infrastructures. Previous studies have argued that digital twins provide the necessary virtual environment for testing and optimizing sustainability-oriented interventions before physical implementation, thereby reducing costs and risks [9-11]. The present review extends this understanding by demonstrating that the added intelligence provided by AI substantially enhances the decision-support capabilities of digital twins in energy contexts.

Smart grids emerged as the most extensively studied application domain, reflecting their central role in modern energy ecosystems. The reviewed results indicate that AI-based solutions contribute to improved grid efficiency, reliability, and resilience through demand response optimization, fault detection, and adaptive control. These findings are strongly supported by previous literature emphasizing that smart grids require intelligent coordination mechanisms to manage bidirectional power flows, distributed energy resources, and prosumer participation [14, 15, 21]. Moreover, the increasing emphasis on cyber-resilience and secure data management within AI-enabled grids highlights the evolving nature of sustainability, which now encompasses not only environmental but also operational and digital security dimensions [16, 24].

The review also underscores the significant contribution of artificial intelligence to building energy management and sustainable architecture. The findings show that AI-driven control systems, occupancy-aware models, and predictive analytics lead to measurable reductions in energy consumption and emissions in residential and commercial buildings. These outcomes align closely with earlier studies that identified buildings as critical leverage points for achieving sustainability goals due to their substantial share of global energy use [9, 17, 18]. Importantly, the reviewed evidence suggests that AI not only optimizes operational performance but also informs design-stage decisions, thereby embedding sustainability considerations throughout the building lifecycle.

At a broader system level, the findings indicate that AI-enabled energy management increasingly supports integrated and cross-sectoral sustainability objectives, particularly in smart city contexts. Studies focusing on urban and neighborhood-scale energy systems demonstrated that AI-driven analytics and digital twins enhance resilience, optimize resource allocation, and improve emergency response capabilities. These results resonate with prior research advocating for holistic, data-driven approaches to urban sustainability that transcend sectoral silos [19, 20, 26]. The convergence of energy, mobility, water, and communication systems within AI-enabled smart cities reflects a shift toward systemic sustainability thinking.

Despite these advances, the findings also reveal persistent challenges and gaps in the literature. While many studies reported technical performance improvements, fewer provided comprehensive evaluations of long-term environmental impacts, social implications, or policy alignment. This observation echoes earlier critiques that AI-driven energy research often prioritizes algorithmic performance over broader sustainability assessment [3, 22, 23]. Furthermore, issues related to data quality, interoperability, and ethical governance remain underexplored, despite their relevance for large-scale deployment of AI in energy systems. The present review thus reinforces calls for more integrative research frameworks that connect technological innovation with environmental, social, and institutional dimensions of sustainability.

Overall, the discussion of results confirms that emerging technologies and artificial intelligence are reshaping energy management in ways that are fundamentally aligned with sustainability imperatives. By enabling more efficient, resilient, and adaptive energy systems, AI contributes directly to energy transition goals. At the same time, the findings suggest that realizing the full sustainability potential of AI requires moving beyond isolated technical applications toward coordinated, system-level strategies informed by interdisciplinary research and policy engagement.

Despite the comprehensive scope of this systematic review, several limitations should be acknowledged. First, the review was restricted to articles published between 2020 and 2025, which, while ensuring topical relevance, may have excluded earlier foundational studies that shaped current AI applications in energy management. Second, only peer-reviewed journal articles written in English were included, potentially limiting the representation of relevant research published in other languages or non-journal formats. Third, the heterogeneity of methodologies, application contexts, and evaluation metrics across the selected studies constrained the ability to perform quantitative meta-analysis, necessitating a qualitative synthesis approach. Finally, the reliance on reported outcomes in the reviewed studies may introduce publication bias, as unsuccessful or null results are less likely to be published.

Future research should place greater emphasis on longitudinal and large-scale empirical evaluations of AI-driven energy management systems to assess their long-term environmental, economic, and social impacts. There is also a need for more interdisciplinary studies that integrate technical AI development with policy analysis, behavioral research, and sustainability assessment frameworks. Additionally, future work should address ethical, governance, and data-related challenges, including transparency, cybersecurity, and equitable access to AI-enabled energy services. Expanding research beyond single-sector applications toward integrated, cross-sectoral energy systems would further enhance understanding of AI's role in systemic sustainability transitions.

From a practical perspective, energy stakeholders should prioritize the integration of AI solutions within broader sustainability strategies rather than adopting isolated technological interventions. Practitioners are encouraged to invest in data infrastructure, interoperability standards, and workforce training to support effective AI deployment. Policymakers and industry leaders should also foster collaborative platforms that bring together technology developers, energy operators, and sustainability experts to ensure that AI-driven energy management solutions are aligned with environmental goals, regulatory frameworks, and societal needs.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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