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REVIEW

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Harnessing AI in renewable energy systems: driving environmental and socio-economic transformation

M. M. Mundu[1*], Mariam Basajja[2], Emmanuel Kweyu[3], V. S. Manjula[4] and Daniel Ejim Uti[5*]

*Correspondence:
M. M. Mundu
mundu.mustafa@kiu.ac.ug
Daniel Ejim Uti
daniel.ejimuti@kiu.ac.ug
[1]Department of Electrical, Telecommunication and Computer Engineering, Kampala International University, P. O. Box 20000, Kampala, Uganda
[2]Leiden University, Leiden 1011NC, Amsterdam, The Netherlands
[3]iLabAfrica, School of Computing and Engineering, Strathmore University, Nairobi P.O. Box 59857-00200, Nairobi, Kenya
[4]Department of Computer Science, Kampala International University, P. O. Box 20000, Kampala, Uganda
[5]Department of Research and Publications, Kampala International University, P.O. Box 20000, Kampala, Uganda

Abstract

The rapid expansion of renewable energy systems has intensified interest in Artificial Intelligence (AI) for improving forecasting, optimisation, and operational reliability. Yet despite growing technical advances, existing reviews focus narrowly on algorithmic performance and rarely integrate environmental, socio-economic, and governance dimensions, issues that are especially critical for low- and middle-income countries (LMICs), where data scarcity and institutional capacity constraints shape deployment outcomes. This creates an incomplete understanding of the opportunities and risks associated with AI-enabled renewable energy transitions. This study conducts a systematic review, following PRISMA guidelines, to synthesise evidence across four domains: technical integration, environmental impacts, socio-economic implications, and governance considerations. The review examines 113 studies spanning solar, wind, microgrids, storage management, and predictive maintenance. Findings show that while AI can enhance forecasting accuracy and system efficiency, these benefits are highly context-dependent and often derived from simulations rather than field deployments. The literature reveals underexplored risks, including the computational energy footprint of AI models, limited transferability to data-scarce regions, potential reinforcement of inequality in LMIC, and increasing concentration of technological power in corporate actors. Based on these, the paper proposes a cross-sectoral framework for responsible AI adoption in renewable energy and outlines priority actions for researchers, policymakers, and practitioners. These include rigorous reporting of model uncertainty and lifecycle impacts, strengthening data governance and local capacity, and validating AI tools in real-world low-resource contexts. The review concludes that AI can support sustainable energy transitions only when deployed within robust technical, institutional, and equity-oriented governance systems.

Keywords Artificial intelligence, Renewable energy systems, Grid optimization, Predictive maintenance, Energy access, Socioeconomic impacts, Environmental sustainability

Introduction

Background and context

The global transition toward low-carbon energy systems has significantly accelerated the deployment of renewable technologies such as solar, wind, hydro, and biomass [35, 66, 75]. While these resources are central to climate and energy security goals, their intermittent and decentralized nature introduces substantial forecasting, planning, and grid-integration challenges that traditional analytical tools struggle to manage. Addressing these complexities requires advanced approaches capable of modelling nonlinear patterns, managing uncertainty, and coordinating distributed energy resources at scale. Artificial Intelligence (AI) has thus emerged as a critical enabler, offering capabilities in forecasting, optimization, predictive maintenance, storage management, and real-time control that help manage variability and enhance the reliability of electricity supply (Márquez, [60]; Danish [27].

Although previous reviews highlight the technical potential of AI, they largely concentrate on algorithmic accuracy and system performance, with far less attention paid to environmental sustainability, socio-economic equity, governance, and the implications of deploying AI in low- and middle-income countries (LMICs). These omissions are significant because the integration of AI into renewable energy systems also introduces new risks such as algorithmic bias, opacity, high computational energy consumption, and the potential to automate or amplify existing inequalities that are rarely examined in a holistic, cross-disciplinary manner. Recent studies underscore that environmental considerations, including lifecycle impacts and the carbon footprint of AI models themselves, must be integrated into energy planning to strengthen accountability and sustainability [91, 111].

Persistent structural challenges also constrain the effective use of AI. Limited access to high-quality, domain-specific data reduces model generalizability across diverse climatic and infrastructural contexts. These gaps underscore the need for stronger data-sharing frameworks involving academia, industry, and regulatory bodies. Collaborative efforts to build open datasets, standardized benchmarks, and interoperable platforms are essential for real-world AI deployment in renewable systems [21]. By addressing these gaps, AI can support more reliable, context-appropriate renewable energy planning particularly in LMICs, where such innovations have high development value but where regulatory and infrastructural constraints remain significant.

Relevance to SDGs and global challenges

Aligning AI-driven renewable energy innovations with global sustainability priorities is crucial, especially for SDG 13, which demands urgent responses to climate change and its socio-economic consequences [61]. Climate risks exacerbate poverty, displacement, and health burdens, linking SDG 13 directly to SDG 7 on clean energy access, SDG 8 on decent work, and broader commitments to human rights and equitable development [90, 100]. Even non-traditional sectors, such as sports, can contribute to climate mitigation and awareness, demonstrating the cross-cutting nature of sustainability challenges [38, 61, 100]. Coordinated action across governments, industry, academia, and communities is therefore required to embed sustainability into planning and operations at all levels.

AI is increasingly recognized as a driver of broader socio-environmental transformation beyond energy system optimization. It supports circular and low-carbon systems by improving production, logistics, infrastructure planning, and renewable integration [56]. AI advances SDG 7, SDG 11, and SDG 13 by strengthening energy access, urban sustainability, and climate resilience especially valuable in data-limited developing regions [78]. In environmental monitoring, AI enhances land-use mapping, biodiversity tracking, and climate-resilience modelling through remote sensing and automated assessment, contributing to transparency and climate justice [44]. When combined with IoT, blockchain, and edge computing, AI also enhances sustainability governance and infrastructure resilience [84]. Nevertheless, concerns about algorithmic bias, surveillance risks, and unequal access highlight the need for strong governance frameworks to ensure equitable AI deployment [44, 56].

This review therefore contributes a distinct perspective by synthesizing AI applications in renewable energy through an integrated environmental, socio-economic, and governance lens. It: (i) assesses the environmental implications of AI-enabled energy systems, including lifecycle impacts and AI model energy consumption; (ii) evaluates socio-economic opportunities and risks such as employment changes, energy-access implications, and digital inequality; and (iii) examines governance challenges around transparency, accountability, data rights, and the potential for AI to widen global disparities. By foregrounding these dimensions, the review extends beyond technical assessments to offer a holistic understanding of how AI can support—or complicate—equitable and sustainable energy transitions.

Particular emphasis is placed on LMIC contexts, where renewable energy expansion offers major development opportunities but where limitations in data availability, regulatory frameworks, and digital infrastructure hinder the effective use of AI. This focus aligns with SDG 7 (Affordable and Clean Energy), SDG 13 (Climate Action), and several cross-cutting goals concerning inequality, resilient infrastructure, and sustainable industrialization. The originality of this review therefore lies in its multidimensional synthesis of AI applications in renewable energy, integrating technological, environmental, socio-economic, and governance considerations—dimensions that existing literature often treats separately. By doing so, it provides a comprehensive foundation to support decision-making, policy formulation, and future research aimed at ensuring that AI contributes to just, inclusive, and sustainable energy futures.

Methodology of the literature review

Methodology

To ensure a rigorous and comprehensive synthesis of existing literature on the intersection of AI and renewable energy systems, this review adopted a systematic approach guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The methodological process followed four critical steps: identification, screening, eligibility assessment, and inclusion (Table 1).

Search strategy

A systematic search was conducted across major scholarly databases covering the period 2010 to March 2025. The start year (2010) was selected because the widespread adoption of machine learning and deep-learning methods in energy systems began around

Table 1 Summary of the methodological process

Step	Description	Output
Identification	Database search across (2010–2025)	672 records identified
Screening	Removal of duplicates and review of titles/abstracts	598 records screened; 178 eligible for full-text assessment
Eligibility	Full-text evaluation based on inclusion/exclusion criteria	113 studies meeting eligibility criteria
Inclusion	Final selection of studies for synthesis	113 studies included in review

this time. Search terms combined keywords related to "Artificial Intelligence," "Machine Learning," "Renewable Energy Systems," "Grid Optimization," "Energy Forecasting," "Predictive Maintenance," "Energy Access," and "Sustainable Development," using Boolean operators to refine the results.

Inclusion and exclusion criteria

The inclusion criteria for study selection required that publications focus on AI or machine learning applications in renewable energy systems, present empirical results, modelling approaches, frameworks, or systematic analyses, and address technological, environmental, socio-economic, or governance dimensions. Only peer-reviewed journal articles, conference proceedings, and English-language publications were considered. English-language publications were included because English remains the dominant language of AI, engineering, and energy systems research, and non-English coverage in technical databases is extremely limited. Studies were excluded if they lacked sufficient methodological detail, were purely conceptual commentaries, appeared as duplicate publications, or did not directly address renewable energy.

Study selection process

The initial search yielded 672 records. After removing duplicates, 598 studies remained for title and abstract screening. Moreover, the total number of records identified is given by the sum of records from all database as shown in Eq. (1):

$$R = 672 \tag{1}$$

Following deduplication, $D = 74$ duplicate records were removed. The number of unique records remaining for screening is expressed in Eq. (2):

$$S = R - D = 672 - 74 = 598 \tag{2}$$

During the screening phase, the titles and abstracts of the $S = 598$ records were evaluated. Records that did not meet relevance criteria were excluded, totaling $E_s = 420$. The number of full-text articles assessed for eligibility is thus in Eq. (3):

$$F = S - E_s = 598 - 420 = 178 \tag{3}$$

In the eligibility phase, full-text articles were reviewed against inclusion criteria. A total of $E_f = 65$ articles were excluded for the following reasons: Non-renewable energy focus ($n = 27$), Insufficient AI content ($n = 18$), Methodological weaknesses ($n = 20$). The final number of studies included in the review is calculated as in Eq. (4):

$$I = F - E_f = 178 - 65 = 113 \tag{4}$$

Equation (5) below can summarize this process.

$$I = [(R - D)\ - E_s] - E_f = [(672 - 74)\ - 420] - 65 = 113 \tag{5}$$

This structured approach, outlined in Eq. (1) through (5), ensured that the review included only relevant, high-quality studies, thereby establishing a solid foundation for analyzing the role of AI in enhancing renewable energy systems. To enhance transparency, a PRISMA flow diagram summarizing the screening and selection process is provided in Fig. 1.

Data extraction and synthesis

A structured data extraction sheet was developed to capture key information from the selected studies, including the type of renewable energy system and AI technique employed, the primary objectives such as forecasting, optimization, or maintenance, as well as the associated environmental implications, socio-economic impacts, and governance or policy considerations. The data synthesis followed a mixed narrative–thematic approach, enabling the integration of both technical and non-technical dimensions and facilitating the identification of cross-cutting themes related to environmental sustainability, equity, and governance.

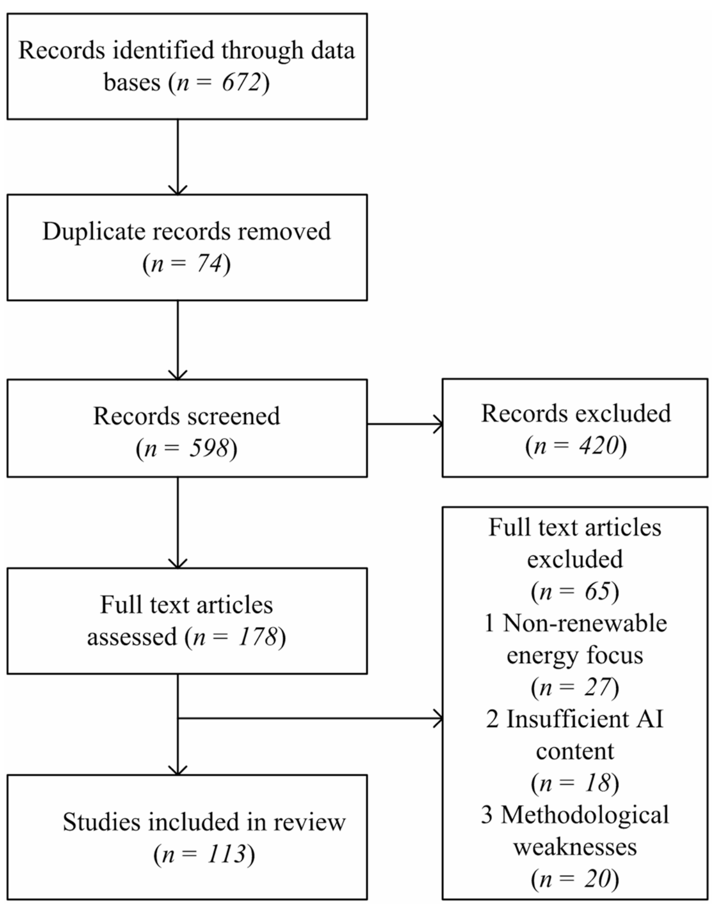

Fig. 1 Graphical PRISMA flow chart

AI integration in renewable energy systems

AI for renewable energy forecasting

AI-based forecasting techniques including LSTM networks, hybrid CNN–LSTM models, random forests, gradient boosting, SVR, and ANNs continue to demonstrate strong performance in predicting solar irradiance, wind speeds, and short-term power output [83, 107, 110, 112]; Feng et al., [15, 16, 37]; Shrimali & Shrimali [51]),. Deep learning approaches generally outperform classical statistical and traditional time-series methods because they capture nonlinearities and temporal dependencies more effectively, a trend consistently highlighted across the reviewed studies. For instance, Pasupuleti [83] shows that LSTM architectures yield substantial improvements in high-resolution temporal forecasting, while hybrid CNN–LSTM models improve both spatial and temporal feature extraction, supporting tasks such as load forecasting and fault detection [15] and enhancing demand-side management [22]. Ensemble and deep learning approaches have also proven effective for wind power forecasting and dynamic network reconfiguration [37].

However, performance gains are sometimes marginal when datasets are noisy or limited, and model transferability remains a challenge due to region-specific climatological patterns an issue noted even in recent deep learning studies. Forecast accuracy remains strongly dependent on high-quality, granular meteorological and operational data. In LMICs, where such data are often sparse, researchers have increasingly relied on satellite imagery, data augmentation, and transfer learning [110, 112]. While promising, these strategies require careful calibration to avoid overfitting, biased predictions, or reduced generalizability. Overall, AI enhances forecasting accuracy, grid balancing, and resource scheduling, supporting more reliable integration of variable renewables and laying a foundation for intelligent, data-driven energy systems.

AI in operation, maintenance, and asset reliability

AI-driven predictive maintenance frameworks are increasingly central to renewable energy O&M, using vibration analysis, thermal imaging, SCADA data, and anomaly detection to identify early-stage equipment degradation. Studies report significant reliability gains, with Wada et al. (2024) showing reductions in unplanned downtime of up to 35% and energy output increases of 8.5%. Machine learning models including autoencoders, reinforcement learning systems, and fault-detection algorithms analyze large sensor datasets to detect wear in turbines, inverters, blades, and PV modules, improving maintenance scheduling and asset longevity [71]. Robotics integrated with AI further enhances inspection and repair: autonomous drones and crawling robots can identify defects and execute minor tasks, improving performance reliability by up to 25% and reducing labor risks [23].

Beyond maintenance, AI supports adaptive operational optimization by adjusting parameters such as panel tilt or turbine yaw in response to real-time environmental conditions, a capability noted by Dawodu et al. [79]. Cross-sector applications such as AI-driven defect detection in semiconductor manufacturing [50], infrastructure surveillance using autonomous drones [89], and AI-VI (AI–Visual Inspection) systems for mechanical component inspection [101] demonstrate the relevance of advanced visual inspection and classification techniques to renewable energy asset monitoring. Similarly, AI-enhanced non-destructive imaging improves defect detection in composite materials, contributing to higher precision and speed in industries where structural integrity is critical (Seçkin et al., [94]).

Despite clear benefits, the literature repeatedly revisits similar concepts, signaling a need for standardized evaluation metrics and consistent reporting. Implementation failures often stem from insufficient sensor coverage, noisy or incomplete data, and reliance on opaque "black-box" models that hinder operator trust. These concerns underscore the importance of explainable AI methods—such as SHAP values or attention mechanisms to improve transparency, interpretability, and the practical adoption of AI-driven O&M systems. Overall, AI's role in predictive maintenance, automated inspection, and operational optimization is pivotal for developing resilient, data-driven clean energy systems. To provide a holistic view of how AI is transforming operations and maintenance across sectors, Table 2 below summarizes the key AI methods employed and their corresponding benefits.

AI in energy storage optimization

AI plays an increasingly important role in storage scheduling, capacity planning, and battery health prediction, with reinforcement learning and machine learning models optimizing charging/discharging cycles and improving state-of-health estimation. Studies show that AI-driven storage control enhances system efficiency and resilience: Shen et al. [98] report efficiency gains of up to 28%, while Deep Reinforcement Learning (DRL) approaches such as (Deep Q-Networks) DQN and (Deep Deterministic Policy Gradient) DDPG support real-time, adaptive decision-making for load forecasting, fault prediction, and component lifetime extension [2, 3]. In simulated microgrids, DRL-based energy flow regulation achieves cost reductions of up to 14% [4].

Yet, many models still assume ideal operating conditions, failing to fully incorporate battery aging, thermal dynamics, or market variability. This aligns with concerns raised in the literature about instability when AI-controlled storage relies solely on historical data, especially under rapidly changing renewable penetration or climate-driven

Table 2 AI methods and benefits across sectors

Sector/Application	AI Method Used	Primary Benefits	References
Renewable Energy (Wind & Solar)	Predictive Maintenance using ML (e.g., regression, ANN)	Reduces unplanned downtime by 35%; improves output by 8.5%	Wada et al. (2024); Nayak et al. [71]
	Sensor Data Analysis and Fault Detection	Maximizes O&M efficiency; enhances asset reliability	Nayak et al. [71]
	Robotics and AI (autonomous inspection, anomaly detection)	Increases maintenance performance by up to 25%; lowers operational costs	Chinonyerem et al. [23]
	AI for adaptive energy production optimization	Improves energy yield under varying weather conditions	Dawodu et al. (2024)
Semiconductor Manufacturing	Deep Learning and Big Data Analytics	Enhances yield; improves quality control in chip production	Katari et al. [50]
Infrastructure (Roads)	Computer Vision + Autonomous Drones	Efficient defect detection and geolocation of road damage	Recalde et al. [89]
Manufacturing/Industrial QA	AI-VI (Vision Inspection with ML)	Automated real-time defect detection for springs and other small objects	Smitha & Jenifer [101]
Materials Engineering	AI-enhanced Non-Destructive Imaging (NDI) and Sensor Fusion	Higher accuracy and efficiency in internal defect identification of composite parts	Seçkin et al. (2025)

variability. Hybrid physical–ML models gaining support in works such as Arévalo et al. [11, 88] offer more robust alternatives by integrating domain knowledge with data-driven learning. Remaining implementation barriers include high computational costs, limited generalizability across contexts, and the need for real-world datasets to validate simulation-heavy research [2, 80].

AI in microgrids, off-grid Systems, and energy access

Microgrids benefit significantly from AI-based demand prediction, optimal dispatch, fault detection, and intelligent control of distributed energy resources. Oudinga [80] notes that AI integration improves adaptability and responsiveness in decentralized networks, while advanced methods including reinforcement learning, multi-agent systems, and predictive modeling enhance energy dispatch, demand forecasting, and DER coordination [11, 88]. This contributes to greater reliability, particularly in renewable-dominant microgrids. AI also supports rural and off-grid electrification by stabilizing variable renewable supply and improving continuity of service [9].

However, several studies caution that the practical challenges of microgrid AI deployment are frequently understated. Some pilots have failed due to unreliable communication networks, intermittent sensor data, delays that destabilized control signals, or computational requirements exceeding local capacity issues consistent with broader concerns about high system complexity, model generalization limitations, and real-time control demands [2, 11]. These constraints highlight the importance of context-specific design, robust communication infrastructure, and empirical validation using field data before large-scale deployment of AI-driven microgrid control systems.

AI-driven forecasting, optimization, and control systems face several emerging risks that limit real-world reliability, including algorithmic bias where models trained on data-rich regions such as Europe systematically underpredict solar output in tropical climates, reinforcing existing energy inequities as well as the significant energy burden of training large deep-learning architectures, which can emit hundreds of kilograms of CO_2-equivalent when powered by non-renewable data centers. Over-reliance on black-box models further introduces operational vulnerabilities; for example, a wind farm received incorrect curtailment recommendations after an anomaly detector misclassified sensor noise as a failure, and the lack of interpretability tools hindered diagnosis. Real-world deployments also reveal a persistent gap between simulation and practice: AI controllers that perform well under ideal conditions often fail under intermittent connectivity, sensor outages, or weather variability, as seen in a microgrid pilot where a reinforcement learning controller destabilized operations during cloudy periods because it had been trained on unrealistically stable irradiance data.

Theoretical, practical, and policy implications

Theoretical contributions

AI models are advancing theory by providing new ways of representing nonlinear energy dynamics beyond traditional analytical methods. Hybrid physics–ML models are emerging as an important direction for improving robustness and generalizability. The reviewed work also shows a growing emphasis on explainable AI to ensure energy systems are trustworthy, interpretable, and auditable. Additionally, recent frameworks highlight the need to integrate environmental and socio-economic dimensions into AI modelling.

Practical applications

In practice, utilities are increasingly using AI-based forecasting to reduce reserve margins and operational costs. Predictive maintenance tools help extend equipment lifetimes, although their performance relies heavily on high-quality and consistent sensor data. AI-driven microgrid controllers support more stable off-grid systems but depend on strong communication networks and cybersecurity measures. Persistent implementation challenges such as data gaps, hardware limitations, and limited technical expertise remain significant barriers, especially in LMICs.

Policy and governance implications

Policy efforts should prioritize regulatory frameworks for algorithmic transparency, data privacy, and AI safety in energy systems. Incentives for green computing and low-carbon data centers are needed to address the environmental impacts of AI. National energy strategies should also include AI literacy and capacity-building programs to prevent widening digital divides. Finally, standardized reporting requirements for AI models covering performance, energy use, and uncertainty quantification would improve comparability and strengthen accountability.

Environmental impacts of AI-Driven renewable systems

Greenhouse gas emission reduction

AI is emerging as a transformative force in the global energy transition, particularly in reducing greenhouse gas emissions through the optimization of renewable energy systems. By enhancing the efficiency, reliability, and intelligence of renewable technologies, AI facilitates a systematic reduction in emissions both directly through improved system performance and indirectly by minimizing reliance on fossil fuel-based energy sources.

At the operational level, AI enables high-precision forecasting of solar irradiance and wind speed, allowing for more accurate and reliable energy production planning. This forecasting reduces dependence on carbon-intensive standby generators and improves overall grid stability (Daraojimba et al., 2023; Nnajiofor et al., [74]. Furthermore, AI-driven predictive maintenance and grid optimization help to detect faults early, coordinate loads, and dispatch renewable energy in a way that minimizes losses and maximizes output efficiency.

Advanced machine learning and deep learning models play a pivotal role in analyzing large volumes of real-time energy data. These algorithms support dynamic control of energy flows, automated load balancing, and intelligent fault detection, all of which contribute to reduced energy waste and, consequently, lower emissions [108]. Such intelligent automation is central to scaling up intermittent renewable sources without sacrificing grid reliability.

In addition, AI has significantly enhanced the effectiveness of Life Cycle Assessments (LCAs) by offering accurate, data-rich insights into emissions over the entire operational lifetime of renewable systems. These AI-enhanced LCAs facilitate the identification of emission hotspots and opportunities for design or process optimization, ultimately promoting sustainable system design and deployment [13]. This not only supports emissions reductions but also improves accountability in energy planning and procurement.

The cumulative effect of these AI-enabled interventions is a marked reduction in both direct and indirect emissions those embedded in inefficiencies, redundancies, and overcapacity. As a result, AI is increasingly recognized as a vital enabler for achieving net-zero carbon targets and accelerating progress toward global climate goals.

However, several technical and ethical challenges must be addressed to maximize AI's potential in this domain. These include data variability, limited transparency of complex AI models (often referred to as "black-box" algorithms), and the need for robust real-time processing. Overcoming these barriers requires further research in explainable AI (XAI), reinforcement learning, and edge computing to ensure transparency, adaptability, and public trust in AI-based systems [108].

Complementing these technological advances, recent studies offer empirical evidence for the efficacy of AI-assisted emission reduction strategies across diverse geographic and policy contexts. For example, Virtual Power Plants (VPPs) which aggregate distributed energy resources using AI for intelligent dispatch have demonstrated remarkable environmental benefits. In Finland, AI-enabled VPPs have achieved GHG emission reductions ranging from 68% to 98% compared to conventional fossil-based balancing power sources [99]. These findings illustrate how coordinated, decentralized systems can deliver both grid flexibility and significant climate benefits.

The role of energy efficiency, long acknowledged as a cornerstone of emission mitigation, is now being amplified by AI-enabled systems that optimize building performance, appliance use, and industrial processes. As early as 1990, comparative studies identified energy efficiency as a major lever for long-term emission reductions across sectors and countries (Schwengels et al., [93]). Today, AI refines this potential by delivering real-time optimization and learning-based control mechanisms that minimize waste and align consumption with clean generation.

Additionally, the precision of emissions accounting is improving through AI-enhanced spatial and temporal analytics. A case study in Ontario, Canada showed that adopting a spatially and temporally sensitive methodology for calculating grid-related GHG emissions led to a 44% reduction in reported emissions for a commercial building, compared to conventional accounting methods [104]. These results underscore the importance of AI in improving both the accuracy and integrity of carbon assessments.

Moreover, cross-national case studies have identified diverse policy and design strategies for emissions reductions ranging from low-carbon neighborhood planning to behavior change incentives that benefit from AI-driven implementation and monitoring. AI's ability to simulate future scenarios, predict policy outcomes, and personalize user feedback strengthens the effectiveness and scalability of such initiatives [20].

Together, these findings highlight the central role of AI not only in improving the operational efficiency of renewable systems but also in amplifying the impact of broader emission reduction strategies. By coupling automation with precision analytics, AI opens a promising path toward cleaner, smarter, and more resilient energy systems one that aligns local actions with global climate ambitions.

To quantitatively assess the environmental benefits, such as greenhouse gas reductions from AI-optimized renewable energy systems, the following estimation model (Eq. (6)) can be applied.

$$GHG_{reduced} = E_{saved} \times EF \tag{6}$$

Where: $GHG_{reduced}$ is the estimated GHG reduction (kg CO_2e), E_{saved} is the energy saved from AI optimization (kWh) and EF is the emission factor (kg CO_2e/kWh), which varies by grid or region.

To further illustrate the quantitative impact of AI-driven optimizations in in solar and wind energy systems, particularly in terms of GHG emission reductions, Table 3 presents estimates derived from recent studies. These values were computed using the standard emission reduction model introduced above (Eq. (6)), which multiplies energy savings from AI-enhanced operations by region-specific emission factors.

Land and ecosystem use

AI is increasingly playing a transformative role in enhancing the sustainability and land-use efficiency of renewable energy systems. Through advanced algorithms and data-driven decision-making, AI optimizes the spatial layout, resource allocation, and operational efficiency of solar and wind energy farms, thereby minimizing the land footprint per unit of energy produced. For instance, AI models improve energy dispatch, grid integration, and reduce storage needs, effectively allowing renewable installations to generate more energy from the same or smaller land area [28]; Daraojimba et al., 2023). These enhancements not only increase technical efficiency but also reduce the demand for extensive land conversion a key contributor to ecosystem degradation.

In addition, machine learning tools are used for comprehensive lifecycle assessments (LCA) of renewable energy projects, taking into account material inputs, emissions, and land-use impacts across the entire value chain [13]. These AI-driven LCA frameworks

Table 3 GHG reduction estimates from studies using AI in Solar/Wind optimization

Study/Source	Context	AI application	GHG reduction estimate	Findings
Sillman et al. [99]	Finland	AI-assisted Virtual Power Plants (VPPs) for balancing grid power	68–98% reduction	Aggregated distributed resources to replace fossil-based grid balancing systems.
St-Jacques et al. [104]	Ontario, Canada	Spatial and temporal GHG estimation using smart data analytics	44% reduction (case study)	AI-enhanced emissions accounting revealed more accurate and lower GHG totals.
Daraojimba et al. (2023)	General/ Multiple Regions	AI in solar and wind forecasting and integration	Indirect but significant	Improved grid reliability and decreased fossil fuel standby requirements.
Ukoba et al. [108]	Nigeria/ Developing Country Context	Machine learning for fault detection, load forecasting, and energy flow control	Not quantified but impactful	Enhanced efficiency and reduced energy waste imply lower system-level emissions.
Bassey et al. [13]	General	AI-driven life cycle assessments (LCA) for renewables	Lifecycle GHG savings identified	Enabled optimization across full system life cycle, reducing embodied emissions.
Campbell et al. [20]	International case studies	AI-supported emissions reduction strategy design and evaluation	Context-specific reductions	Enabled evidence-based emission mitigation through adaptive energy planning.
Schwengels et al. (1990)	Cross-country historical analysis	Early recognition of energy efficiency's climate role (pre-AI)	Projected significant reductions	Laid groundwork for AI-enabled efficiency optimization across sectors.

Some studies (e.g., Daraojimba et al., 2023 and Ukoba et al., [108] do not provide direct GHG percentage reductions but demonstrate strong evidence of emissions decline through efficiency improvements and fossil fuel displacement help project developers and policymakers make informed decisions that balance energy outputs with environmental and land-use considerations.

Furthermore, AI plays a pivotal role in the design and management of hybrid renewable energy systems integrating solar, wind, and biomass sources which improves system resilience while reducing land-use pressure by consolidating infrastructure and energy generation [48]. These systems enable a diversified energy portfolio while making optimal use of land resources, often in areas with competing environmental and human needs.

However, land use in the context of energy infrastructure remains a complex issue that extends beyond technical optimization. Decisions about where and how to deploy renewable energy systems often involve significant trade-offs between human development goals and the preservation of ecosystem services and biodiversity. According to DeFries et al. [29], land-use decisions must carefully consider both immediate socio-economic needs and the long-term integrity of ecosystem functions, such as hydrological balance, climate regulation, and biodiversity conservation. These trade-offs are particularly significant in ecologically sensitive or biodiversity-rich areas, where energy infrastructure can fragment habitats or disrupt ecosystem processes (DeFries et al., 2013).

To navigate these complexities, systematic conservation planning and ecosystem service modeling are increasingly used to identify optimal land-use scenarios, which attempt to balance energy development with environmental stewardship [36, 72]. While such modeling often reveals synergies such as areas that are both suitable for renewable energy and low in biodiversity conflict it also highlights potential conflicts, particularly where energy development may compromise provisioning services or alter landscape-level ecological dynamics [36, 72].

As emphasized by DeFries et al. [29], advancing quantitative knowledge about how different land-use changes affect ecosystems is essential for making decisions that are both sustainable and socially acceptable. When integrated with AI-driven energy planning tools, such ecological data can inform more robust, adaptive, and defensible land-use strategies. This integration allows energy developers, conservationists, and policymakers to jointly identify zones for low-impact energy development and to design mitigation strategies that preserve essential ecosystem services.

In conclusion, while AI significantly enhances the efficiency and spatial precision of renewable energy systems, its integration with ecological knowledge and land-use planning is vital to ensure that energy transitions do not come at the expense of biodiversity and long-term environmental sustainability. The synergy between AI-enabled optimization and ecosystem-based land-use planning represents a promising pathway toward reconciling the twin goals of clean energy and ecological resilience.

Water-energy systems

AI is playing an increasingly transformative role in advancing environmentally sustainable technologies, particularly in water and energy systems. In desalination and water treatment, AI enhances system performance, enabling smarter control, reduced energy demand, and improved water quality. AI-powered models have achieved up to 50% energy savings while minimizing operational downtime and maximizing water recovery, contributing to the viability of water reclamation solutions in water-stressed regions [7, 45]. In Fig. 2 for the conceptual model of the AI-enabled water-energy nexus, AI tools

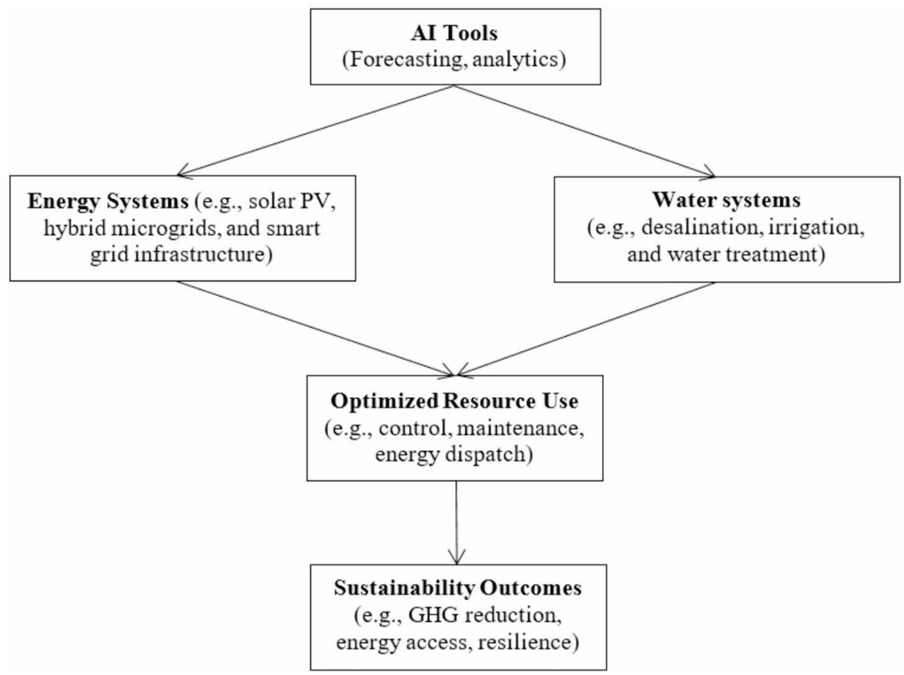

Fig. 2 AI –enabled Water Energy Nexus For Sustainable Resource Management

enhance both water systems (e.g., desalination, irrigation) and energy systems (e.g., solar, microgrids), leading to optimized resource use and sustainability outcomes such as improved water efficiency, energy savings, and reduced emissions.

Moreover, solar-powered desalination methods such as photovoltaic (PV)-driven reverse osmosis, solar thermal distillation, and solar stills are increasingly recognized as sustainable alternatives to conventional fossil-fuel-based technologies. Despite their potential, these methods still face obstacles such as high capital investment and variability in solar energy supply. AI contributes significantly here by supporting strategic planning of desalination infrastructure, optimizing location, capacity, and technology selection through predictive modeling and multi-criteria decision tools [68]; AlZu'bi et al., [10]; Nnamchi et al., [76]. These advances enhance both economic feasibility and environmental resilience of water systems, particularly in climate-vulnerable and arid regions.

Across the broader water-energy systems, AI-driven renewable energy systems facilitate integrated solutions for efficiency and climate resilience. Machine learning algorithms enhance solar power generation and smart grid management, resulting in improved energy yield and reduced system losses [108, 110]. In thermal and hybrid systems, this also leads to reduced water consumption critical in areas dependent on water-intensive cooling technologies.

In agriculture, AI-driven precision technologies including smart sensors, Internet-of-Things (IoT) devices, and drone-based imaging enable real-time irrigation adjustments and soil moisture monitoring. These innovations significantly enhance water use efficiency and improve crop productivity in water-scarce environments (Chithra et al., [24]). The integration of AI and blockchain technologies is also emerging as a powerful approach to increase transparency, traceability, and accountability in water use, especially under dynamic climate pressures [55].

Beyond direct applications in water and energy systems, AI plays a pivotal role in supporting broader environmental and climate governance. It aids climate modeling, improves pollution detection, and facilitates renewable energy deployment, ultimately contributing to enhanced sustainability [6, 49]. AI systems have demonstrated potential to boost energy efficiency by 25–35% and reduce resource waste by up to 30%, offering measurable gains in operational sustainability (Audiah et al., 2024; Oviedo-Bayas et al., [81]. In parallel, AI is being deployed in biodiversity monitoring and water resource management, expanding its influence across ecosystem-level sustainability strategies [49].

Nevertheless, several critical challenges must be addressed to unlock AI's full potential in environmental systems. These include concerns over data quality, model transparency, and algorithmic fairness, as well as the high energy consumption and infrastructural requirements associated with large-scale AI deployment [6, 49, 81]. Advancements in explainable AI and the integration of physics-based and data-driven models offer promising pathways to overcome these barriers while reinforcing trust and accountability in AI-enabled environmental governance [49]; Audiah et al., 2024).

Thematic synthesis of AI integration in renewable energy systems

Technical integration of AI in renewable energy systems

Across the literature, AI enhances four core functions; forecasting, predictive maintenance, storage optimisation, and microgrid management and overall improves accuracy and stability, though these gains vary widely with data quality, model complexity, and deployment context. A consistent finding is that deep-learning models outperform classical methods only when trained on large, high-quality datasets; thus, in data-scarce settings common in LMICs, improvements are often modest. Moreover, many reported "efficiency gains" stem from simulations rather than field deployments, raising concerns about real-world applicability. Three contradictions recur across technical domains: **(1)** accuracy vs. interpretability, as high-performing models like LSTM and hybrid CNN–LSTM remain opaque; **(2)** optimisation vs. generalisability, since models tuned for specific sites often fail under different climatic or grid conditions; and **(3)** automation vs. reliability, as AI controllers can underperform during extreme weather or communication disruptions. Collectively, these issues show that AI's technical benefits are highly context-dependent, shaped by local data systems, operator capabilities, and model design choices.

Environmental implications

The literature generally agrees that AI supports environmental goals by improving forecasting, reducing curtailment, and enhancing resource utilisation; however, a deeper synthesis shows a dual environmental impact. On the positive side, AI can indirectly lower emissions through reduced grid imbalance, optimised storage cycles, and smarter dispatch. On the negative side, training large models particularly transformer-based time-series architectures—demands significant computational energy, generating a carbon footprint that is rarely quantified in energy-sector studies. This creates a central contradiction: while AI is widely promoted as a tool for decarbonisation, the training of advanced models may itself produce substantial emissions, especially when run in fossil-fuel-powered data centres. Notably, few studies include lifecycle assessments of AI models, leaving a major gap in understanding their full environmental impact.

Socio-economic transformations

AI-driven renewable systems shape socio-economic outcomes through employment shifts, skills requirements, energy-access improvements, and distributional equity. Across the literature, AI-driven automation displaces routine middle-skill roles but simultaneously generates new opportunities in digital infrastructure, AI development, and renewable system management (Kanagarla, 2024; Hanna et al., [41]; Brahmaji [18],. The transition from fossil fuels to renewables produces net job gains in installation, grid modernisation, and efficiency services, though regional mismatches create localized strains where job losses and new opportunities do not geographically align [41]. A persistent barrier is the widening AI-skills gap, as many workers lack the competencies needed in data-centric energy systems [33, 41]. Scholars therefore emphasise reskilling, targeted transition programs, and ethical AI deployment as essential components of a just transition (Kanagarla, 2024; Fan [33, 82, 106].

Educational gaps reinforce these labour challenges. Energy systems increasingly require hybrid expertise in engineering, data science, and AI, but such capacity remains limited. Studies highlight urgent shortages in energy data-analytics talent and call for industry–academia collaboration to support new curricula [42]. Proposed models include hybrid multiphysics–machine learning frameworks (Radaideh & Kozłowski, [87]) and the integration of AI into geoscience and physical data-science training [62]. AI adoption in smart buildings further demonstrates new skills demands, as real-time AI control improves HVAC and lighting performance and supports demand-response integration [34]. Together, these dynamics reveal a workforce transition that is technologically promising but socially uneven, especially in LMICs.

Equity and inclusion outcomes show similar contradictions. AI-enabled microgrids can enhance energy reliability and inclusion in underserved regions through improved forecasting, load prediction, and adaptive control [43, 64]. AI also strengthens the performance of decentralized solar systems by supporting predictive maintenance, resource allocation, and real-time demand management [3]; Dawodu et al., [79]). Decentralised infrastructure contributes to reduced emissions, lower costs, and improved quality of life [46, 52]. However, deployment remains limited by cost barriers, institutional weaknesses, and entrenched inequalities that shape energy distribution [46]. Without inclusive governance, AI systems trained on high-income datasets can underperform in rural or tropical contexts, reinforcing digital exclusion.

To achieve genuine energy justice, scholars stress the integration of AI into national energy-policy frameworks, with emphasis on ethical deployment, vulnerable populations, and alignment with SDGs [31, 41]. Effective implementation requires participatory planning, community ownership models, subsidies, and localized training. Despite AI's potential to expand energy access, empirical socio-economic assessments remain scarce, and most "success stories" arise from simulations rather than field deployments.

Governance, standards, and institutional readiness

Governance is a central but underdeveloped area in AI-enabled energy systems. The literature highlights weak regulatory structures for algorithmic transparency, limited data-governance policies, and the absence of standards for reporting accuracy, uncertainty, and energy consumption. Explainable AI (XAI) is widely recognized as a solution to enhance trust, interpretability, and social legitimacy, especially in public energy systems [14, 25, 63]. XAI is increasingly embedded in ethical AI frameworks to mitigate opacity, discrimination, and algorithmic misuse [26].

Regulatory frameworks such as the EU AI Act and guidelines from international bodies aim to ensure fairness, rights protection, and accountability in AI systems [59, 102, 103]. Complementary academic models propose fairness, inclusiveness, accountability, dataset diversity, and cross-disciplinary collaboration as anchors for responsible energy-sector AI [5, 57, 65]. Despite these initiatives, major challenges remain: persistent algorithmic bias, uneven performance across demographic groups, and difficulty auditing black-box models exacerbate governance gaps, especially in regions with low AI literacy and weak digital infrastructure.

Data ownership and privacy represent a further unresolved issue. Energy-sector AI depends on large volumes of user and operational data, raising questions about consent, control, and equitable data-sharing mechanisms. Without strong governance, these gaps risk amplifying socio-economic inequalities and undermining trust in AI-enabled renewable systems.

Table 4 summarizes the interrelated dimensions of employment impacts, equity considerations, and governance issues in AI-enabled renewable energy systems. It also includes concrete examples of ethical lapses and explainability failures that underscore the urgent need for context-sensitive and inclusive deployment frameworks.

Cross-cutting contradictions and evidence gaps

Across technical, socio-economic, environmental, and governance domains, several contradictions remain evident. First, a persistent gap exists between simulation and real-world performance, as most reported gains in forecasting accuracy, microgrid stability, or energy-access improvements still originate from laboratory or simulation studies rather than field deployments [3, 41]; Dawodu et al., [26, 31, 42, 64, 79].

Table 4 Summary of Socio-Economic and ethical dimensions of AI in renewable energy systems

Dimension	Considerations	Examples/Challenges
Employment	AI may displace low-skilled jobs while creating demand for data scientists, energy analysts, and automation engineers. Skills gaps risk deepening labor inequality.	In South Africa, AI-based smart grid systems reduced technician roles without reskilling support [39, 40, 105].
Equity and Inclusion	Gender, geographic, and digital divides may limit participation in AI-driven energy transitions, especially in LMICs and rural areas.	In Kenya, solar-AI platforms failed to account for low female digital literacy, excluding women from energy access programs [53, 58].
Governance and Ethics	Lack of transparency, algorithmic bias, and data colonialism can undermine trust. Most energy-AI models are "black boxes" and not explainable to local users.	AI in energy systems faces key challenges, including lack of transparency, algorithmic bias, and weak data governance. Black-box models reduce trust, while biased data can lead to unfair outcomes [8, 69, 77].
Explainability & Accountability	Many AI tools lack explainable outputs, making it hard for regulators, users, and communities to audit or contest decisions.	Explainability in AI is essential for accountability, yet it poses challenges by sometimes shifting responsibility away from developers. Current policies often focus on risk but overlook how explanations serve different users [54, 70, 96].

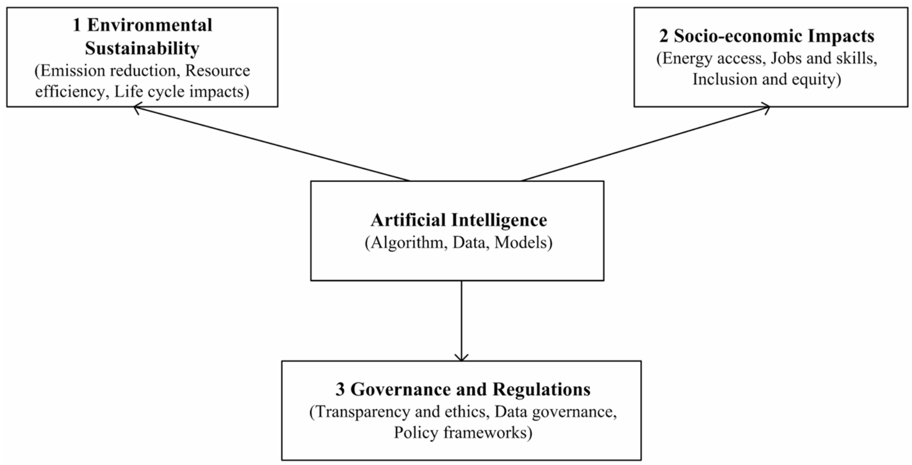

Fig. 3 Integrated Framework of AI Impacts in Renewable Energy Systems

Table 5 Balancing ai's efficiency gains with environmental and social costs

Theme	Findings
Energy Demand vs. Sustainability	Large models demand high energy, raising carbon neutrality concerns [12, 30, 85].
Positive Contributions	AI enables emission reductions and resource efficiency in energy, agriculture, etc [19, 109].
Environmental Trade-offs	High energy use in training and deployment may offset sustainability gains [19, 51].
Mitigation Strategies	Design energy-efficient AI models, use carbon-aware tools, apply Green AI principles [17, 97].
Policy & Governance Needs	Incentivize sustainable AI use, promote renewable infrastructure and ensure tech accountability [47, 67, 85].

The conceptual framework (Fig. 3) illustrates how AI influences renewable energy systems through three interconnected dimensions: environmental sustainability, socio-economic outcomes, and governance. AI acts as the central enabler, shaping efficiency, access, and decision-making, while environmental and social impacts depend on how AI tools are deployed and regulated. Governance structures such as policies, ethics, and data standards guide these interactions, ensuring AI contributes to equitable and sustainable energy transitions.

Balancing efficiency gains with environmental and social externalities

To complement the discussion on AI's dual role in sustainability, Table 5 provides a structured summary of the key trade-offs and opportunities in balancing AI's efficiency gains with its environmental and social externalities. As detailed, while AI technologies enhance energy efficiency and reduce emissions in critical sectors such as energy and agriculture [19, 109], their development particularly of large language models and generative systems demands substantial energy, raising serious concerns about carbon neutrality [12, 30, 85]. The box further outlines strategic mitigation pathways, including the use of energy-aware AI architectures, adoption of Green AI principles, and carbon tracking tools [17, 97]. It also highlights governance considerations, emphasizing the need for regulatory incentives, transparent impact reporting, and coordinated efforts across stakeholders to ensure that the benefits of AI do not come at an unsustainable environmental cost [47, 67, 85]. This synthesis reinforces the importance of adopting a holistic and anticipatory approach in AI development one that aligns innovation with broader sustainability goals.

System-level reforms and global policy coordination are essential to align AI development with environmental sustainability. While AI offers great potential for advancing sustainable development, its environmental costs especially from energy use must be addressed. Integrating energy-efficient design, transparent impact metrics, and strong policy frameworks will ensure AI remains a net-positive force in the global sustainability agenda.

Challenges and knowledge gaps in AI-Driven renewable energy transitions

While AI presents vast opportunities for advancing renewable energy systems, several critical challenges and knowledge gaps particularly in LMICs continue to hinder its effective implementation. These gaps span data accessibility, policy frameworks, technological capacity, and issues of fairness and accountability. Addressing them is essential for ensuring that AI contributes to inclusive and sustainable energy transitions. Table 6 summarizes these key challenges, aligning them with priority actions across four domains: Data, Policy, Technology, and Social Justice.

Future research and policy agenda

To address the challenges identified in integrating AI within renewable energy systems particularly in LMICs there is an urgent need for forward-looking, interdisciplinary research and policy innovation. Table 7 synthesizes priority research themes and corresponding interdisciplinary actions that can guide future work toward inclusive and sustainable AI deployment in energy transitions. These recommendations are grounded

Table 6 Matrix of challenges and knowledge gaps vs. Priority actions across key domains

Challenge/Gap	Data	Policy	Technology	Social justice
Data Access Disparities	Invest in local data infrastructure; standardize open data protocols [1]	Develop national data-sharing frameworks and public-private data access agreements [86]	Promote interoperable AI models that work with low-resource datasets [73]	Ensure community ownership of data; avoid extractive data practices [92]
Lack of Impact Assessment Standards	Develop regional databases for sustainability indicators [92]	Mandate lifecycle AI impact audits in energy policies [73]	Create benchmarking tools for environmental AI assessments [86]	Incorporate social impact metrics into AI deployment models (Durmus Senyapar et al., [95]
Gaps in Socio-political Inclusion and Just Transition Policies	Disaggregate datasets by socio-economic indicators [1]	Co-develop policies with local stakeholders to support inclusive transitions [111]	Embed participatory AI design approaches in tool development (Durmus Senyapar et al., [95]	Ensure AI projects address gender, rural equity, and energy poverty [92]
Explainability and Accountability of AI Systems	Provide traceable model documentation and metadata [73]	Set legal standards for AI transparency and auditability [86]	Advance interpretable models using XAI techniques (e.g., SHAP, LIME) (Ersöz et al., [32])	Build trust through user education and participatory monitoring [92]
Limited Local Capacity in LMICs	Build open-access learning repositories; support South-South data exchange [1]	Allocate policy funding for research and skills training in AI & renewables [86]	Promote low-cost, modular AI toolkits suitable for LMICs [73]	Train marginalized groups in digital skills and energy literacy (Durmus Senyapar et al., [95]

Table 7 Recommended research themes and interdisciplinary actions

Research theme	Priority areas	Suggested interdisciplinary actions
Community-Based AI Design	Localized AI models Participatory innovation	Co-design with communities, Collaboration with energy experts, and ICT developers
Environmental AI Standards	Metrics for sustainability, Lifecycle assessment of AI tools	Input from environmental scientists, policy-makers, and data scientists
Equitable Data Access Frameworks	Data sovereignty, Open data protocols	Legal reforms, Involvement of civil society, legal scholars, and digital infrastructure planners
AI Ethics and Governance	Explainability, Fairness and accountability	Joint input from ethicists, engineers, and human rights institutions
Socio-political Inclusion	Just transition policies, Gender and regional equity in AI energy access	Cross-sectoral partnerships between social scientists, gender experts, and energy planners
Capacity Building in LMICs	Local expertise in AI and energy planning	Investment in training programs, North-South and South-South academic networks

in critical gaps highlighted earlier, such as inequitable data access, limited community involvement, and weak governance structures.

Key among the proposed directions is the co-design of community-based AI solutions, ensuring that local knowledge systems and contextual realities inform both algorithm development and implementation. The establishment of national and global environmental AI standards is also imperative, particularly to monitor the life-cycle impacts of AI tools and align their use with climate and sustainability goals. Furthermore, promoting equitable data access frameworks will require legal, infrastructural, and governance reforms to address power asymmetries in data ownership and use.

Complementing these efforts, ethical and explainable AI governance should be embedded across design and deployment stages to strengthen transparency and social trust. Cross-cutting concerns around social inclusion and just transition must also shape research and policy agendas ensuring AI supports marginalized communities and addresses gender and regional disparities in energy access. Finally, sustained investment in capacity building is essential to empower researchers and practitioners in LMICs through collaborative networks and localized expertise development.

Conclusion

This review has shown that the integration of Artificial Intelligence into renewable energy systems is marked by both substantial potential and significant constraints. Across forecasting, predictive maintenance, storage optimisation, and microgrid control, AI offers meaningful improvements, but these gains are highly dependent on data quality, contextual conditions, and institutional capacity. A key finding of this review is the presence of unresolved tensions—between optimisation and equity, accuracy and interpretability, efficiency and environmental burden—that limit the generalisability of many reported successes.

Unlike existing reviews that focus primarily on technical performance, this study contributes an integrated assessment that synthesises technical, environmental, socio-economic, and governance dimensions. It highlights underexplored risks, including the computational energy demands of AI, data and model biases affecting LMICs, and the growing concentration of technological power in corporate entities. These insights demonstrate that AI is not a uniform solution but a socio-technical intervention shaped by infrastructure, governance, and equity considerations.

Building on this synthesis, several evidence-based recommendations emerge. For researchers, there is a need for empirical validation of AI models in real-world conditions, especially outside high-resource settings, and for rigorous reporting of uncertainty, lifecycle impacts, and computational costs. For policymakers, priority areas include developing transparency and accountability frameworks, investing in data and digital infrastructure, strengthening national capacity to manage AI tools, and establishing standards for ethical and environmentally responsible AI deployment. For practitioners, effective implementation will require strengthening local technical skills, ensuring model interpretability, and co-designing AI systems with communities and energy operators to enhance trust and adaptability.

This review also acknowledges several limitations. The analysis relies on published studies, most of which originate from high-income regions, potentially underrepresenting experiences from LMICs. Furthermore, the predominance of simulation-based research limits understanding of long-term field performance. These limitations point to the need for more context-sensitive evidence and longitudinal studies.

In sum, the findings indicate that AI can support renewable energy transitions under the right enabling conditions, but its benefits are neither automatic nor universally accessible. Real progress will depend on grounded, context-specific deployment strategies, strengthened governance, and sustained investment in local capacity. Rather than assuming AI as a catalyst for transformation, future work should focus on building the institutional, social, and environmental foundations that allow AI to contribute responsibly and equitably to sustainable energy futures.

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