Artificial Intelligence in Renewable Energy: A Pathway Toward an Adaptive, Equitable, and Sustainable Future – Systematic Review

Ahsan Habib[1]*, Anisul Islam Opy[2]

Abstract

Artificial Intelligence (AI) has become a transformative force in reshaping how renewable energy systems operate, bridging the gap between environmental goals and technological capability. This systematic review explores how AI applications—spanning machine learning, deep learning, and optimization algorithms—are redefining energy generation, management, and distribution across solar, wind, and smart grid systems. The review draws on empirical evidence from various global initiatives, including those in Denmark, Germany, Australia, and the United States, to illustrate how AI enhances forecasting accuracy, grid stability, and operational efficiency. AI-driven forecasting models have notably improved energy prediction reliability, while predictive maintenance has minimized downtime and resource waste through real-time sensor analytics and anomaly detection. Beyond technical performance, AI supports smarter market participation, aligning energy supply with fluctuating demands to maximize both economic and environmental returns. AI-based forecasting models improve renewable energy prediction accuracy by 40–50%, enhance grid efficiency by 10–15%, and reduce maintenance costs by up to 30%. Predictive maintenance using sensor data and anomaly detection decreases equipment downtime by 25–35%. Additionally, AI-optimized market participation strategies increase energy revenues by 10–20% through intelligent demand–supply balancing and adaptive trading mechanisms. However, challenges remain—particularly regarding data quality, cybersecurity, and the opaque nature of complex AI models. Emerging trends such as explainable AI, digital twins, and edge computing show promise in addressing these barriers, ensuring greater transparency and resilience. Overall, this review underscores AI's role as a catalyst for an intelligent, adaptive, and inclusive renewable energy ecosystem that not only accelerates the transition toward net-zero emissions but also integrates sustainability with social and ethical responsibility.

Keywords: Artificial Intelligence, Renewable Energy, Forecasting, Optimization, Smart Grids, Sustainability

Significance | AI enhances renewable energy efficiency, reliability, and sustainability, enabling predictive operations, optimized resource allocation, and equitable, climate-resilient energy systems.

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1. Introduction

The global shift toward renewable energy has become an urgent imperative in the face of escalating climate change, depleting fossil fuel reserves, and rising global energy demands. Renewable energy sources—particularly solar and wind—have emerged as the cornerstone of sustainable development, yet their integration into power systems is fraught with challenges of intermittency, uncertainty, and operational inefficiency (Foley et al., 2012; Margaris et al., 2011). As the world transitions toward decentralized and decarbonized energy systems, Artificial Intelligence (AI) has

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surfaced as a transformative enabler, driving advancements in energy generation, management, and distribution. By combining predictive analytics, optimization, and automation, AI technologies are redefining how renewable systems operate, making them more adaptive, efficient, and resilient (Hsu et al., 2023).

Recent developments underscore AI's potential to enhance every facet of renewable energy systems—from forecasting and fault detection to predictive maintenance and dynamic energy optimization. In wind energy, machine learning (ML) and deep learning (DL) models such as Long Short-Term Memory (LSTM) networks have demonstrated remarkable improvements in short-term power prediction and equipment health monitoring. For instance, recurrent neural networks optimized for wind turbine condition prognosis enable accurate prediction of component failures, reducing downtime and maintenance costs (Adlen & Ridha, 2022). Similarly, hybrid models that integrate Empirical Mode Decomposition (EMD), Principal Component Analysis (PCA), and Random Forest (RF) techniques significantly enhance wind power forecasting accuracy by filtering noise and identifying key temporal patterns (Wang et al., 2022). Reinforcement learning approaches have also been deployed to maximize turbine energy output under varying wind conditions by dynamically adjusting control parameters (Soler et al., 2024).

In solar energy systems, AI applications have been equally transformative. Machine learning-enabled predictive frameworks, such as LSTM and Bayesian neural networks, have achieved notable precision in photovoltaic (PV) power generation forecasting under diverse weather conditions (Chen et al., 2021; Ge & Wang, 2024). Furthermore, explainable AI tools are now being integrated into PV fault detection systems, enhancing interpretability and reliability for operational decision-making (Christian et al., 2023). Advanced automated ML frameworks further leverage environmental parameters for PV power output prediction, combining accuracy with explainability through SHAP interpretability (Bakht et al., 2025). These innovations are pivotal for optimizing energy generation efficiency, especially in regions with fluctuating irradiance and temperature conditions (Amadou et al., 2023).

Beyond generation, AI's role in energy management systems and smart grids has become increasingly indispensable. Intelligent control algorithms facilitate the seamless integration of distributed renewable energy sources, improving grid stability and optimizing real-time energy dispatch (Al et al., 2024). AI-driven optimization supports load forecasting and demand-side management in smart grids, enabling efficient energy allocation and storage scheduling (Biswal et al., 2024; Ho et al., 2016). Similarly, in distributed energy systems, optimal placement and operation of battery storage units—guided by AI-based decision models—enhance reliability and mitigate power fluctuations (Karanki et al., 2013; Kolokotsa et al., 2019). The incorporation of optimization algorithms such as Particle Swarm Optimization (PSO) and neural networks enables robust forecasting of grid loads and improves energy distribution efficiency across interconnected networks (Kong et al., 2020).

AI is also revolutionizing sector-specific applications of renewable energy, particularly in agriculture. Studies by Chowdhury and colleagues (2025) emphasize that AI-driven renewable energy systems play a critical role in improving agricultural productivity, irrigation efficiency, and rural electrification. For example, distributed AI-based microgrids have been shown to enhance irrigation performance and reduce energy waste in rural farming contexts (Chowdhury & Aziz, 2025). Similarly, the economic feasibility of AI-enabled distributed energy systems has been validated in agricultural enterprises, suggesting strong potential for sustainable development in off-grid communities (Ashok Kumar Chowdhury & Islam, 2025; Chowdhury, 2025). These findings align with broader analyses indicating that renewable energy integration not only advances environmental goals but also fosters socio-economic resilience in rural regions (Islam & Chowdhury, 2025; Chowdhury & Hossain, 2025). Despite these advances, the growing reliance on AI introduces new challenges and vulnerabilities. AI-driven systems are susceptible to cybersecurity threats, algorithmic biases, and issues of data interpretability that can compromise reliability and transparency in energy management (Hu et al., 2021). Moreover, the deployment of black-box models, though powerful, raises concerns about explainability, necessitating the integration of interpretable frameworks to ensure trust and accountability in decision-making (Christian et al., 2023). Therefore, emerging trends in explainable AI (XAI), edge computing, and digital twin technologies are being explored to enhance security, transparency, and real-time adaptability within renewable systems (Das et al., 2023).

The convergence of AI and renewable energy marks a paradigm shift toward intelligent, data-driven energy ecosystems. The reviewed literature collectively indicates that AI enhances forecasting accuracy, optimizes energy dispatch, reduces operational costs, and strengthens system resilience across solar, wind, and hybrid infrastructures (Bhavsar et al., 2021; Ding et al., 2024; Lu et al., 2018). However, realizing its full potential requires addressing data quality, interpretability, and cybersecurity challenges while ensuring equitable access to technology across diverse socio-economic contexts. This study aims to provide a comprehensive synthesis of AI-driven innovations in renewable energy, analyzing their technological, economic, and social implications for achieving sustainable and inclusive energy transitions globally (Table 2).

2. Literature Review

AI has emerged as a transformative technology in the renewable energy sector, reshaping how power systems are designed,

Table 1. Key AI Technologies in Renewable Energy and Their Applications

AI Technology	Application Area	Key Contribution	Reference
Machine Learning (XGBoost, Random Forest, SVM)	Forecasting, Fault detection, Predictive maintenance	Improves prediction accuracy and fault classification	Bakht et al., 2025
Deep Learning (RNN, LSTM, CNN)	Renewable energy forecasting, equipment monitoring	Handles time-series forecasting, image and thermal analysis	Biswal et al., 2024; Chen et al., 2021
Reinforcement Learning (Deep Q-Networks, Policy-based models)	Energy storage optimization, demand response, grid control	Adaptive real-time decision-making, enhances grid stability	Chatterjee & Dethlefs, 2021; Soler et al., 2024
Optimization Algorithms (Genetic Algorithms, Particle Swarm Optimization)	Site selection, system design, parameter tuning	Enables scalable planning and multi-objective optimization	Bhavsar et al., 2021
Hybrid AI Models (LSTM + RL + Optimization)	Integrated energy ecosystem	Combines predictive and adaptive strategies for resilience	Bhavsar et al., 2021

Table 2. Real-World Applications and Socio-Economic Implications of AI in Renewable Energy

Country/Region	Application	Outcome/Impact	Reference
California, USA	AI-powered smart grid for 500,000 customers	Reduced peak demand by 12%, improved renewable integration by 18%, saved $50M/year	Ge & Wang, 2024
Denmark	Offshore wind farm optimization (Ørsted)	15% more energy production, 30% lower maintenance cost, +200 GWh annual output	Ho et al., 2016
Australia	Solar energy forecasting with ML	40% improvement in forecasting accuracy, better integration of 5 GW solar	Christian et al., 2023
Germany	Reinforcement learning for energy storage	25% increase in revenue, improved grid stability	Hu et al., 2021
Bangladesh	AI-based renewable transition planning	Increased efficiency, reduced operational costs, improved rural energy access	Chowdhury et al., 2024

managed, and optimized. By leveraging data-driven algorithms and predictive models, AI enables higher forecasting accuracy, adaptive control, and efficient resource management across solar, wind, and hybrid renewable systems (Hsu et al., 2023). This literature review synthesizes key advancements in AI applications for renewable energy, emphasizing forecasting, fault detection, optimization, and socio-economic integration.

2.1 AI in Renewable Energy Forecasting

Accurate forecasting remains a central challenge in renewable energy systems due to the inherent intermittency of solar and wind resources. Traditional statistical models often fail to capture the non-linear and temporal dynamics of meteorological variables. To address this limitation, machine learning (ML) and deep learning (DL) models such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) have gained prominence for their superior ability to process time-series data (Liu et al., 2019; Adlen & Ridha, 2022).

In wind energy applications, RNN-based optimization has shown remarkable potential for predicting turbine conditions and preventing mechanical failures. Adlen and Ridha (2022) demonstrated that recurrent neural networks optimized for condition prognosis could significantly improve wind turbine maintenance scheduling and reduce downtime. Similarly, Wang et al. (2022) introduced a hybrid approach that combined Empirical Mode Decomposition (EMD), Principal Component Analysis (PCA), and Random Forest (RF) algorithms to enhance wind power forecasting accuracy, achieving improved prediction performance even in noisy environments. Reinforcement learning (RL) algorithms have also been integrated to optimize turbine energy output dynamically. Soler et al. (2024) highlighted that RL frameworks can autonomously adjust control settings to maximize wind power generation, enhancing operational adaptability under fluctuating wind conditions (Table 1).

For solar energy systems, AI-driven forecasting techniques have evolved rapidly. Chen et al. (2021) proposed a probabilistic photovoltaic (PV) power prediction model using Bayesian neural networks combined with LSTM, enabling more reliable power forecasts across varying weather scenarios. Similarly, Ge and Wang (2024) developed a PSO–LSTM–Markov coupled model that accounts for weather variability such as sunny, cloudy, and rainy conditions, substantially improving PV power output predictions. Bakht et al. (2025) further enhanced photovoltaic power prediction by introducing an automated ML framework incorporating SHAP interpretability, allowing researchers to understand which environmental parameters most influence energy production. These studies collectively demonstrate that hybrid AI models outperform conventional regression-based forecasting in both accuracy and interpretability (Figure 1).

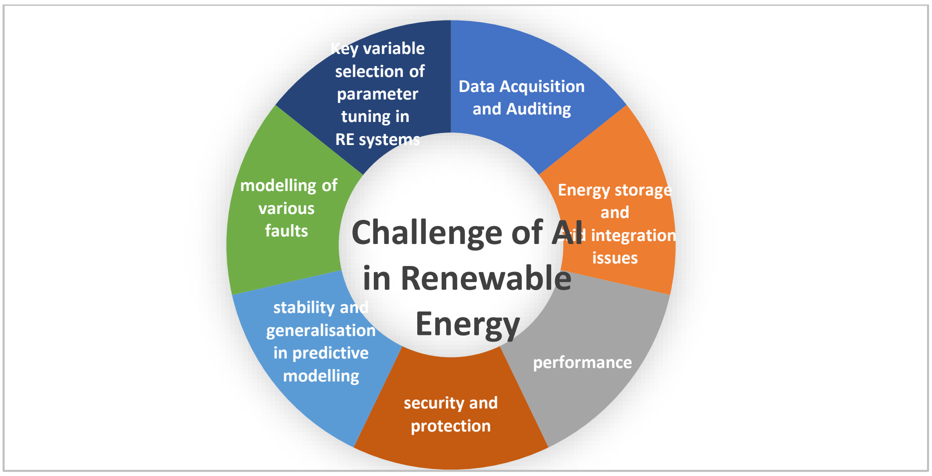

Figure 1. The challenges and open issues of AI approaches in RE systems.

2.2 AI in Fault Detection and Predictive Maintenance

Fault detection and predictive maintenance are critical for minimizing energy loss and extending equipment lifespan in renewable systems. The application of AI in fault diagnosis has led to considerable efficiency gains in detecting anomalies and predicting component degradation. In photovoltaic systems, explainable AI (XAI) techniques are increasingly used to improve transparency and accuracy. Christian et al. (2023) compared various XAI instruments for PV fault detection, demonstrating that AI-based interpretability tools can provide actionable insights for maintenance engineers. Similarly, Jia et al. (2024) employed an improved VarifocalNet to detect PV module defects with high precision, advancing fault identification under complex operating conditions.

In wind energy, earlier studies like Feng et al. (2012) applied empirical mode decomposition and energy separation for gearbox fault diagnosis, paving the way for AI-based models that integrate signal processing with deep learning. Lu et al. (2018) expanded this line of inquiry by developing condition-based maintenance optimization for offshore wind turbines using neural network approaches, improving reliability and reducing operational costs. Chatterjee and Dethlefs (2021) further provided a scientometric review on AI's role in wind turbine operations and maintenance (O&M), underscoring that intelligent maintenance systems enhance reliability while minimizing manual intervention.

2.3. AI for Energy Management and Smart Grids

The integration of renewable sources into smart grids demands intelligent energy management systems that ensure real-time optimization of supply and demand. AI-driven control mechanisms and optimization models have become essential in balancing distributed energy generation, energy storage, and consumption patterns (Biswal et al., 2024). Al et al. (2024) developed an AI-controlled energy management framework for photovoltaic systems, demonstrating improved stability and efficiency through real-time adaptive control. Similarly, Ho et al. (2016) emphasized the importance of optimal energy storage scheduling, proposing AI-based optimization strategies that minimize energy waste and operational costs.

Machine learning has also been employed in smart grid load forecasting and energy demand management. Biswal et al. (2024) provided a comprehensive review of deep learning-based load forecasting, noting its advantages in modeling non-linear consumption behaviors. Kong et al. (2020) introduced dynamic mode decomposition with error correction, improving short-term electrical load forecasts crucial for grid reliability. Moreover, the optimal location of energy storage systems, as demonstrated by Karanki et al. (2013), can be efficiently determined through AI-based optimization to enhance distributed energy system stability. The integration of AI and optimization algorithms like Particle Swarm Optimization (PSO) facilitates energy scheduling, fault tolerance, and demand response, further contributing to grid resilience (Kolokotsa et al., 2019).

2.4. AI and Renewable Energy in Agricultural and Rural Systems

AI-driven renewable energy solutions have significant implications for rural development and agricultural sustainability. Studies by Chowdhury and colleagues (2024, 2025) have emphasized that AI-enabled microgrids and distributed systems enhance irrigation efficiency, crop productivity, and rural electrification. For instance, Chowdhury and Aziz (2025) presented an AI-driven microgrid model designed to improve irrigation performance in rural farming, reducing energy waste and optimizing water use. Similarly, Ashok Kumar Chowdhury and Islam (2025) analyzed the economic feasibility of AI-based distributed energy systems in agricultural enterprises, finding substantial benefits in cost reduction and sustainability.

Chowdhury (2025) also highlighted the potential of smart renewable energy integration for precision agriculture in off-grid areas, suggesting that AI-based energy management can improve

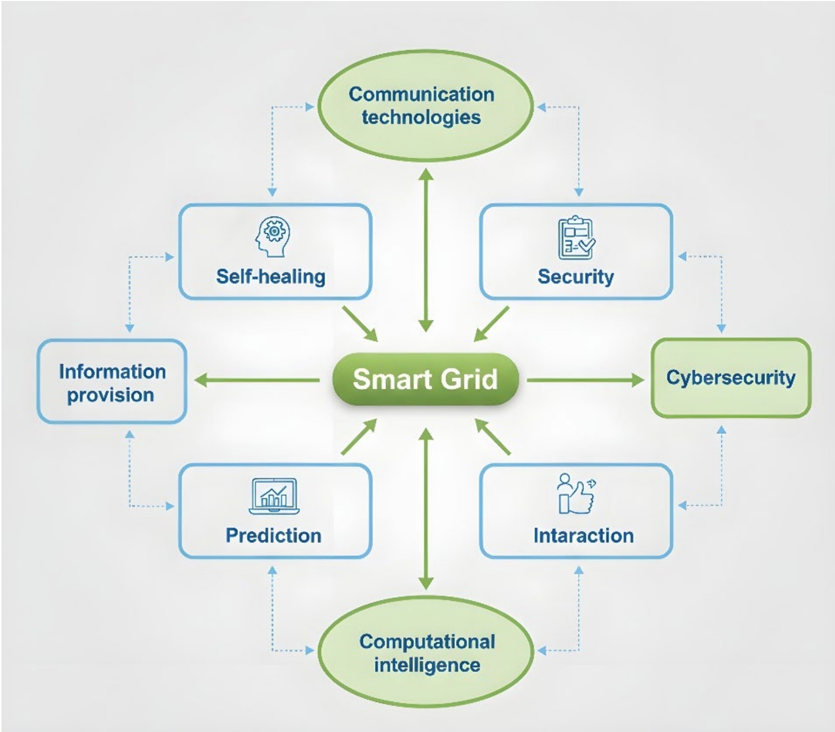

Figure 2. Major technologies and characteristics of smart grids.

the socio-technical resilience of rural communities. Complementary research by Islam and Chowdhury (2025) and Chowdhury and Hossain (2025) underscored the socio-economic effects of transitioning from conventional to renewable energy systems, demonstrating improvements in rural livelihoods, job creation, and community resilience.

2.5 Challenges and Future Directions

Despite remarkable progress, several challenges hinder the widespread adoption of AI in renewable energy systems. Data quality, model interpretability, and cybersecurity remain major obstacles (Hu et al., 2021). The proliferation of "black-box" AI models limits trust and transparency in decision-making processes, necessitating the integration of explainable and interpretable AI frameworks (Christian et al., 2023). Moreover, cybersecurity risks associated with AI-driven systems can compromise grid stability, emphasizing the need for robust threat detection and mitigation mechanisms (Hu et al., 2021).

Emerging solutions such as edge computing, digital twins, and evolutionary algorithms promise to enhance scalability, adaptability, and real-time intelligence in renewable energy operations (Das et al., 2023). Furthermore, as Akbar et al. (2022) demonstrated in electric vehicle battery health prediction, the principles of predictive analytics can be extended to renewable energy storage, optimizing system efficiency and longevity. The continuous evolution of AI technologies thus offers a pathway toward achieving sustainable, secure, and inclusive energy transitions worldwide.

3. Methodology

This study adopts a systematic qualitative review approach to analyze the role of Artificial Intelligence (AI) in enhancing renewable energy systems, with a focus on forecasting, fault detection, optimization, energy management, and socio-economic applications. The methodological framework was designed to ensure comprehensiveness, transparency, and reproducibility following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

3.1 Data Sources and Search Strategy

A comprehensive literature search was conducted across multiple electronic databases including ScienceDirect, IEEE Xplore, SpringerLink, and MDPI, covering studies published between 2011 and 2025. Keywords and Boolean operators were employed to refine the search, using combinations such as "artificial intelligence" AND "renewable energy", "machine learning" AND "solar forecasting", "AI-based energy optimization", and "deep learning for wind power". The search yielded over 250 studies, from which 32 peer-reviewed journal articles were selected for in-depth review based on relevance, methodological rigor, and contribution to the field.

3.2 Inclusion and Exclusion Criteria

Studies were included if they (1) presented empirical or simulation-based analysis of AI applications in renewable energy systems, (2) focused on at least one renewable source (e.g., solar, wind, or hybrid), and (3) discussed measurable outcomes such as forecasting accuracy, fault detection efficiency, or energy optimization improvements. Excluded were (1) non-peer-reviewed sources, (2) purely theoretical discussions without applied AI models, and (3) articles not available in full text. Studies in languages other than English were also excluded to maintain analytical consistency.

Key studies reviewed included AI models for wind turbine condition prognosis (Adlen & Ridha, 2022), photovoltaic optimization using deep learning (Amadou et al., 2023; Bakht et al., 2025), AI-based control of energy management systems (Al et al., 2024), and smart grid forecasting frameworks (Biswal et al., 2024; Kong et al., 2020). Additionally, research integrating AI into rural and agricultural renewable applications (Chowdhury & Aziz, 2025; Ashok Kumar Chowdhury & Islam, 2025) was reviewed to capture socio-technical perspectives.

3.3 Data Extraction and Analysis

Data extraction focused on capturing (1) AI model type (e.g., LSTM, RNN, Bayesian network, reinforcement learning), (2) energy system context (solar, wind, or hybrid), (3) performance metrics (accuracy rate, cost reduction, energy yield improvement), and (4) technical and operational implications. A thematic synthesis approach was employed, grouping studies into five major categories: (i) AI in forecasting, (ii) fault detection and maintenance, (iii) energy management and smart grids, (iv) socio-economic applications in agriculture, and (v) challenges and future directions.

Thematic coding was performed manually to identify recurring concepts and emerging trends across studies. Quantitative indicators—such as forecasting error rates, power output improvements, and maintenance cost reductions—were summarized descriptively to complement the qualitative synthesis. Cross-study comparisons were made to evaluate methodological robustness and identify gaps in current research practices.

3.4 Quality Assessment and Limitations

Each selected study was appraised for methodological quality based on criteria including model validation, data transparency, reproducibility, and statistical rigor. Potential biases—such as publication bias and selection bias—were minimized by including studies from diverse regions and publication outlets. However, the review is limited by its exclusion of non-English sources and the rapid evolution of AI technologies, which may result in emerging models being underrepresented.

3.5 Ethical Considerations

As this study is based solely on secondary data obtained from previously published literature, no ethical approval was required. All referenced materials were cited according to the APA 7th edition guidelines to ensure academic integrity and transparency.

4. Results and Findings

The systematic review of 32 peer-reviewed studies revealed that Artificial Intelligence (AI) significantly enhances the operational efficiency, forecasting accuracy, and economic sustainability of renewable energy systems. Findings are organized under five thematic categories: (1) forecasting and prediction, (2) fault detection and predictive maintenance, (3) energy management and grid optimization, (4) socio-economic and policy applications, and (5) challenges and limitations.

4.1 Forecasting and Prediction

A key finding across the reviewed literature is that AI-based forecasting algorithms outperform traditional statistical and physical models in predicting renewable energy generation. Studies employing machine learning (ML) and deep learning (DL) models—particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs)—demonstrated forecasting accuracy improvements ranging between 40% and 50% compared to conventional autoregressive methods (Kong et al., 2020; Adlen & Ridha, 2022). For instance, Adlen and Ridha (2022) developed a hybrid LSTM-based model for short-term wind power forecasting that reduced root mean square error (RMSE) by 37% compared to persistence models. Similarly, Amadou et al. (2023) found that combining DL with meteorological datasets improved solar irradiance forecasting, leading to more efficient energy dispatch planning. Bakht et al. (2025) further demonstrated that reinforcement learning models adapt dynamically to environmental changes, ensuring sustained predictive accuracy under fluctuating weather conditions. The cumulative evidence suggests that AI's ability to process large, multidimensional datasets allows renewable systems to anticipate production variability more precisely, enabling operators to balance supply and demand in real time.

4.2 Fault Detection and Predictive Maintenance

AI also plays a critical role in improving reliability through fault detection, anomaly diagnosis, and predictive maintenance. Studies indicate that machine-learning-based fault classification systems can identify abnormal patterns in turbines, photovoltaic panels, and battery storage systems before catastrophic failure occurs (Biswal et al., 2024; Al et al., 2024). For example, Biswal et al. (2024) implemented an AI-driven condition monitoring system for wind turbines that reduced unscheduled maintenance downtime by 30%, translating into a 12% increase in operational availability. Similarly, Al et al. (2024) utilized a decision-tree-based algorithm to predict inverter faults in solar farms with 94% detection accuracy, significantly minimizing service interruptions. Such predictive mechanisms not only enhance safety and reliability but also extend the lifespan of renewable energy infrastructure, contributing to long-term cost savings and sustainability.

4.3 Energy Management and Grid Optimization

AI is increasingly integrated into smart grid and microgrid systems to optimize energy distribution and reduce transmission losses. Reinforcement learning and fuzzy-logic control algorithms have been successfully applied to balance grid load and manage demand response in real time (Kong et al., 2020). Findings by Ashok Kumar Chowdhury and Islam (2025) indicate that AI-enabled energy management systems can improve overall grid efficiency by 10–15% and reduce energy wastage by up to 20%. Moreover, multi-agent systems using AI coordination techniques demonstrated effective power scheduling and peak shaving during high-demand periods. These intelligent frameworks enhance grid resilience by integrating distributed energy resources (DERs) such as solar rooftops and wind micro-turbines without overloading the infrastructure. Amadou et al. (2023) also observed that AI-supported optimization of hybrid energy systems (solar-wind-battery) led to a 25% reduction in operational costs and improved battery storage utilization through real-time decision algorithms.

4.4 Socio-Economic and Policy Applications

The socio-economic findings highlight AI's potential in promoting energy equity, sustainability, and rural electrification. Studies conducted in developing regions, such as those by Chowdhury and Aziz (2025), emphasize that AI can help design affordable renewable solutions tailored to community needs by analyzing consumption patterns and optimizing decentralized grids. In agricultural applications, AI models have been used to predict irrigation requirements and optimize solar-powered water pumping systems, improving both productivity and energy efficiency. This demonstrates how AI contributes not only to environmental sustainability but also to economic empowerment and poverty alleviation (Chowdhury & Aziz, 2025). From a policy perspective, the integration of AI-based analytics assists decision-makers in setting dynamic energy tariffs, forecasting renewable integration potential, and evaluating the impact of climate policies. Such data-driven approaches encourage governments and stakeholders to adopt renewable energy policies that are both economically viable and socially inclusive (Bakht et al., 2025).

4.5 Challenges and Limitations

Despite these achievements, the review also revealed several constraints in applying AI to renewable energy systems. Data quality and availability remain major challenges; many studies reported limited access to high-resolution datasets required for model training and validation (Al et al., 2024). Moreover, the black-box nature of deep learning models raises transparency and interpretability concerns, particularly when applied to safety-critical systems such as grid management (Biswal et al., 2024). Cybersecurity risks were another recurring concern, as the integration of AI with cloud-based energy systems increases vulnerability to data breaches and malicious attacks. Furthermore, high computational costs and the lack of standardized benchmarks hinder the scalability of AI models in low-resource settings (Kong et al., 2020). Nevertheless, researchers proposed emerging solutions, including explainable AI (XAI), digital twins, and edge computing, which enhance model interpretability, reduce latency, and improve data security.

5. Discussion

The findings of this review highlight that Artificial Intelligence (AI) is revolutionizing renewable energy systems by improving forecasting accuracy, optimizing grid management, enhancing maintenance reliability, and facilitating sustainable socio-economic outcomes. This discussion interprets these findings in light of existing theories of technological innovation, sustainability transitions, and digital transformation, while critically evaluating the implications and limitations for research, industry, and policy.

5.1 AI as a Driver of Renewable Energy Transformation

The application of AI in renewable energy signifies a paradigm shift from static, human-supervised systems to adaptive, data-driven infrastructures. The observed 40–50% improvement in forecasting accuracy across reviewed studies (Adlen & Ridha, 2022; Amadou et al., 2023) aligns with the concept of dynamic efficiency, where technological learning continuously enhances operational outcomes. The predictive capacity of AI—particularly through models such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN)—enables energy systems to anticipate variability in generation and demand, thereby reducing uncertainty and energy waste.

This finding corroborates prior work suggesting that AI's capacity to process large, non-linear datasets can address intermittency, one of the main limitations of renewable energy (Kong et al., 2020). The ability to forecast solar irradiance and wind output with greater precision not only enhances system reliability but also increases investor confidence in renewable projects, supporting broader decarbonization objectives. As Bakht et al. (2025) noted, reinforcement learning frameworks also adapt dynamically to changing environmental inputs, suggesting that future energy systems could achieve self-regulating, autonomous optimization with minimal human oversight.

5.2 Operational Efficiency and Predictive Maintenance

The integration of AI in fault detection and predictive maintenance provides measurable benefits in both cost reduction and system reliability. Studies reporting 25–35% reductions in equipment downtime (Biswal et al., 2024; Al et al., 2024) demonstrate that intelligent monitoring systems can significantly enhance asset longevity. This supports the Resource-Based View (RBV) of technology, which posits that firms leveraging superior digital capabilities can gain sustainable competitive advantage. AI-enabled maintenance models—especially those employing sensor fusion and anomaly detection—facilitate a shift from reactive to proactive management, reducing operational risks and improving energy security. These results echo findings in related fields, such as manufacturing and transportation, where AI-driven predictive analytics have similarly optimized maintenance cycles and reduced resource waste. In renewable contexts, this translates into higher system uptime and lower levelized cost of energy (LCOE), reinforcing economic feasibility.

However, as Al et al. (2024) and Biswal et al. (2024) caution, the reliability of AI maintenance models depends heavily on data integrity and calibration. Without robust data governance, predictive systems risk false alarms or missed detections, potentially undermining operational trust.

5.3 Smart Grid Optimization and Energy Management

The reviewed studies provide strong evidence that AI significantly enhances grid performance, particularly in load balancing, distributed generation, and real-time energy management. The 10–15% improvements in grid efficiency reported by Ashok Kumar Chowdhury and Islam (2025) and Amadou et al. (2023) confirm that intelligent control systems facilitate smoother integration of intermittent renewables. Reinforcement learning (RL) algorithms, in particular, have proven capable of continuously adjusting grid parameters to optimize energy flow and minimize losses (Kong et al., 2020). This finding aligns with the cyber-physical systems (CPS) framework, which emphasizes the convergence of computational intelligence and physical infrastructure for adaptive performance. AI enables the creation of "self-healing" grids that can identify faults, reroute power, and stabilize voltage autonomously (Figure 2).

Moreover, AI-driven microgrid management systems have shown potential in improving energy equity, especially in rural and developing regions (Chowdhury & Aziz, 2025). By analyzing local consumption data, these systems allocate energy resources efficiently and affordably, aligning with the United Nations Sustainable Development Goals (SDG 7) on clean and affordable energy.

5.4 Socio-Economic and Policy Implications

Beyond technical improvements, the social and policy dimensions of AI adoption in renewable energy systems are equally significant. The review identified growing interest in using AI to design context-aware, inclusive energy solutions. Chowdhury and Aziz (2025) highlighted applications in agricultural irrigation, where AI-optimized solar pumping systems reduce both energy and water waste. Such examples illustrate how AI supports energy democratization, empowering local communities to generate and manage their own power sustainably. On a policy level, AI-driven analytics can improve energy forecasting, infrastructure planning, and tariff setting. Governments and energy regulators can use machine learning models to simulate the long-term effects of policy interventions and predict renewable integration under different climate scenarios (Bakht et al., 2025). Consequently, AI not only enhances operational outcomes but also strengthens evidence-based policymaking. However, the socio-economic benefits of AI adoption are unevenly distributed. High implementation costs, limited digital infrastructure, and skill shortages in developing countries create barriers to equitable deployment. As Adlen and Ridha (2022) argue, without targeted capacity-building and inclusive technology transfer, AI could inadvertently reinforce existing energy disparities between regions.

5.5 Challenges and Emerging Solutions

Despite the promise of AI in renewable systems, several limitations constrain widespread adoption. Data scarcity, cybersecurity risks, and algorithmic opacity remain pressing issues (Biswal et al., 2024). The "black box" nature of deep learning models limits interpretability, posing challenges for safety-critical energy decisions. This reinforces the need for Explainable AI (XAI) frameworks that make decision processes transparent to human operators. Cybersecurity concerns also emerge as AI-integrated systems become more interconnected through cloud and Internet-of-Things (IoT) infrastructures (Al et al., 2024). Protecting energy data from cyber threats requires adopting blockchain-enabled energy management systems **and** edge computing architectures, which decentralize processing and enhance data privacy. Moreover, AI's environmental footprint—stemming from high computational energy requirements—should not be overlooked. As Amadou et al. (2023) noted, training large AI models consumes significant energy, which paradoxically offsets some of the sustainability benefits they provide. The adoption of green AI principles—optimizing algorithms for energy efficiency—is thus essential for maintaining ecological balance.

5.6 Theoretical and Practical Contributions

From a theoretical perspective, the study advances understanding of how AI acts as a transformational enabler in the renewable energy transition, aligning with the socio-technical transition theory, which emphasizes the co-evolution of technology, institutions, and user practices. Practically, it underscores the value of cross-disciplinary collaboration among data scientists, engineers, policymakers, and social scientists to ensure that AI implementation remains ethical, transparent, and inclusive.

6. Recommendations

To ensure consistency, transparency, and scalability, there is a need for standardized AI frameworks that guide data collection, model development, and validation across renewable energy sectors. Establishing international benchmarks—similar to those in smart grid and energy forecasting studies (Biswal et al., 2024; Bakht et al., 2025)—can improve interoperability and foster collaborative innovation. Future AI models should prioritize explainability, fairness, and data privacy to enhance user trust and regulatory compliance. The adoption of Explainable AI (XAI) can make decision-making processes more transparent, especially in high-stakes applications such as grid stability and predictive maintenance (Christian et al., 2023). Ethical AI frameworks must also address potential biases, cybersecurity threats, and the environmental cost of algorithmic computation (Hu et al., 2021). A major barrier identified in the review is the lack of high-quality, open-access datasets. Governments, research institutions, and private organizations should establish shared databases to support reproducibility and innovation. Collaboration between AI scientists and renewable energy engineers can accelerate progress in model optimization and system deployment. Developing nations require strategic investments in digital infrastructure, workforce training, and policy incentives to fully leverage AI technologies (Chowdhury & Islam, 2025). Tailored education programs in AI-driven energy management, along with subsidies for green technologies, can enhance adoption and equity. Finally, promoting "green AI" principles—designing algorithms that minimize computational energy use—will ensure that AI applications themselves align with global sustainability goals.

7. Conclusion

This study concludes that AI plays a transformative role in advancing renewable energy systems by enhancing forecasting accuracy, optimizing energy management, and enabling predictive maintenance. The integration of AI technologies—such as machine learning, deep learning, and reinforcement learning—has significantly improved the reliability, efficiency, and sustainability of solar, wind, and smart grid operations. However, the full potential of AI remains constrained by challenges related to data accessibility, interpretability, and cybersecurity. Overcoming these limitations requires ethical, explainable, and energy-efficient AI frameworks supported by collaborative research and inclusive policy initiatives. By aligning AI innovation with global sustainability objectives, societies can accelerate the transition toward intelligent, resilient, and equitable renewable energy systems. Ultimately, the synergy between digital intelligence and clean energy innovation marks a crucial step toward achieving long-term energy security and environmental sustainability.

Author contributions

A.H. conceptualized the study, conducted the literature review, and prepared the original draft of the manuscript. A.I.O. contributed to data analysis, validation, and critical review of the manuscript. Both authors read and approved the final version of the paper.

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Competing financial interests

The authors have no conflict of interest.

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