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Review

The Role of Lightweight AI Models in Supporting a Sustainable Transition to Renewable Energy: A Systematic Review

Tymoteusz Miller [1,2,*], Irmina Durlik [3], Ewelina Kostecka [4], Polina Kozlovska [5], Marek Staude [4] and Sylwia Sokołowska [2]

1 Institute of Marine and Environmental Sciences, University of Szczecin, Wąska 13, 71-415 Szczecin, Poland
2 Polish Society of Bioinformatics and Data Science BioData, 71-214 Szczecin, Poland; sylvia.sokolowska@gmail.com
3 Faculty of Navigation, Maritime University of Szczecin, Waly Chrobrego 1-2, 70-500 Szczecin, Poland; i.durlik@pm.szczecin.pl
4 Faculty of Mechatronics and Electrical Engineering, Maritime University of Szczecin, Waly Chrobrego 1-2, 70-500 Szczecin, Poland; e.kostecka@pm.szczecin.pl (E.K.); m.staude@pm.szczecin.pl (M.S.)
5 Faculty of Economics, Finance and Management, University of Szczecin, 71-415 Szczecin, Poland; 231805@stud.usz.edu.pl
* Correspondence: tymoteusz.miller@usz.edu.pl

Abstract: The transition from fossil fuels to renewable energy (RE) sources is an essential step in mitigating climate change and ensuring environmental sustainability. However, large-scale deployment of renewables is accompanied by new challenges, including the growing demand for rare-earth elements, the need for recycling end-of-life equipment, and the rising energy footprint of digital tools—particularly artificial intelligence (AI) models. This systematic review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, explores how lightweight, distilled AI models can alleviate computational burdens while supporting critical applications in renewable energy systems. We examined empirical and conceptual studies published between 2010 and 2024 that address the deployment of AI in renewable energy, the circular economy paradigm, and model distillation and low-energy AI techniques. Our findings indicate that adopting distilled AI models can significantly reduce energy consumption in data processing, enhance grid optimization, and support sustainable resource management across the lifecycle of renewable energy infrastructures. This review concludes by highlighting the opportunities and challenges for policymakers, researchers, and industry stakeholders aiming to integrate circular economy principles into RE strategies, emphasizing the urgent need for collaborative solutions and incentivized policies that encourage low-footprint AI innovation.

Keywords: distilled AI models; renewable energy; circular economy; systematic review; PRISMA; sustainable transition; resource management

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1. Introduction

1.1. Background and Motivation

Global energy consumption continues to rely heavily on fossil fuels—oil, natural gas, and coal—despite increasing policy commitments to reduce carbon emissions. While renewables such as solar, wind, hydro, and bioenergy have expanded rapidly over the past decade, they still represent a relatively small fraction of total primary energy consumption. This imbalance in the global energy mix contributes to persistently high levels of carbon dioxide (CO_2) emissions, thereby exacerbating climate change concerns [1].

Policymakers and industry leaders, seeking to reduce dependence on conventional fuels, are increasingly interested in embedding circular economy principles into the energy sector [2]. Circularity places an emphasis on extending product lifecycles through improved design, resource recovery, and waste reduction [3], and these ideas become particularly critical when considering the growing stock of solar panels, wind turbine blades, and batteries [4] that must eventually be recycled or reused [5,6].

At the same time, rapid advancements in digital technologies—especially artificial intelligence (AI)—are enabling transformative change in how energy systems are monitored, optimized, and managed. Through predictive maintenance algorithms, grid stability controls, and enhanced integration of distributed energy resources, AI appears poised to revolutionize the energy industry. Large AI models, however, carry their own costs in terms of computational and energy intensity. An emerging area of innovation, often described as distilled AI or lightweight AI, promises to reduce the computational burden of such models while retaining high levels of accuracy and performance, thus aligning more closely with the sustainability objectives that drive the current shift toward renewables.

1.2. Aim and Research Questions

This systematic review aims to synthesize the ways in which distilled AI models can facilitate the shift to renewable energy while remaining consistent with circular economy principles. The scope of the inquiry is guided by three research questions. The first question explores the primary applications of AI in the renewable energy sector, focusing on how these applications incorporate model distillation or other lightweight techniques. The second question examines the extent to which distilled AI approaches can reduce the overall computational energy demand when compared to traditional, larger AI models in renewable energy applications. The final question addresses the opportunities and challenges in integrating circular economy strategies with AI-driven solutions for resource management across the full lifecycle of renewable energy infrastructures [7].

1.3. Contribution and Paper Structure

By systematically reviewing the scholarly literature, this article offers a nuanced perspective on how lightweight AI methods can help transform the energy sector in more sustainable ways. In synthesizing various case studies and conceptual frameworks, this review highlights both key achievements and existing gaps, ultimately providing guidance for future investigations and policy initiatives. Following this introductory section, the next part explains our PRISMA-based methodology, including the eligibility criteria, search strategies, and procedures for data extraction. Subsequent sections present this review's findings, underscoring the many ways in which distilled AI can contribute to energy savings and circular economy goals, followed by a discussion that examines the broader implications, limitations, and possible policy directions arising from these findings. The concluding section closes with suggestions for future research and offers overarching reflections on the importance of distilled AI in creating a more sustainable, circular energy ecosystem.

2. Methodology

This systematic review follows the guidelines set forth by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). To ensure transparency and replicability, a preliminary protocol was developed to define the scope, inclusion criteria, and analytic procedures. The protocol was designed with the objective of identifying peer-reviewed research that addresses the intersection of renewable energy, circular economy strategies, and the use of distilled or lightweight artificial intelligence (AI) models. The protocol included a clear search strategy, a step-by-step article selection process, and standardized data extraction fields that captured each study's methodological approach, types of renewable energy under investigation, AI models utilized, and alignment with circular economy principles.

A comprehensive search strategy was devised to gather relevant studies published between 2010 and 2024. This timeframe was selected to capture the increasing maturity of both AI applications and sustainability-oriented research in the energy domain. Four major scholarly databases—Web of Science, Scopus, IEEE Xplore, and ScienceDirect—were systematically queried. The queries combined three clusters of keywords: those related to renewable energy, those pertaining to circular economy practices, and those describing lightweight AI methods. The final set of main search terms consisted of:

"('renewable energy' OR 'solar' OR 'wind' OR 'clean energy') AND ('circular economy' OR 'waste management' OR 'recycle') AND ('lightweight AI' OR 'knowledge distillation' OR 'model compression')".

Variations and synonyms of these core concepts were also employed during the database search in order to account for disciplinary differences in terminology and to ensure the broadest possible coverage of relevant literature. Studies retrieved in this initial search were exported into a citation manager for further screening.

A series of inclusion and exclusion criteria were established to ensure that only studies explicitly addressing both AI and renewable energy, with a focus on model distillation or compression, entered into the final sample. Eligible articles were required to investigate an application, framework, or case study linking AI-enabled energy systems [8]—such as solar, wind, hydro [9], or integrated grid solutions—with efficiency [10] or sustainability metrics that explicitly considered a circular economy viewpoint, including resource recovery, waste management [11,12], or recycling processes [13] storage. Articles confined to discussing large-scale AI without addressing its computational or energy footprint were excluded. Studies that did not engage with any dimension of circular economy or sustainability beyond [14] generic statements were likewise deemed out of scope (Table 1).

Table 1. Inclusion and exclusion criteria.

Criterion	Description
Population/Context	Studies focusing on renewable energy systems (e.g., solar, wind, biomass [15], and hydro), grid management, or energy storage [16].
Intervention	Explicit application or discussion of AI models [17], including model distillation, lightweight AI, or compression techniques.
Outcome	Any measure of sustainability improvement [18], resource efficiency, energy savings, or circular economy alignment.
Study Types	Empirical research, conceptual frameworks, case studies, systematic reviews, and conference proceedings.
Exclusion	Papers addressing large-scale AI without energy/resource considerations; no explicit link to renewables or circular economy.
Publication Period	2010–2024, capturing both earlier developments in AI efficiency and recent advancements.

Once the initial pool of references was compiled, duplicate records were removed. Two independent researchers then screened titles and abstracts to confirm alignment with the eligibility criteria. Full texts of the remaining papers were retrieved for in-depth review, during which any disagreement about whether a study should be included was resolved through discussion or consultation with a third reviewer. This process ensured a high level of rigor and minimized the risk of arbitrary exclusions. The number of articles at each screening stage is illustrated in the PRISMA flow diagram (Figure 1).

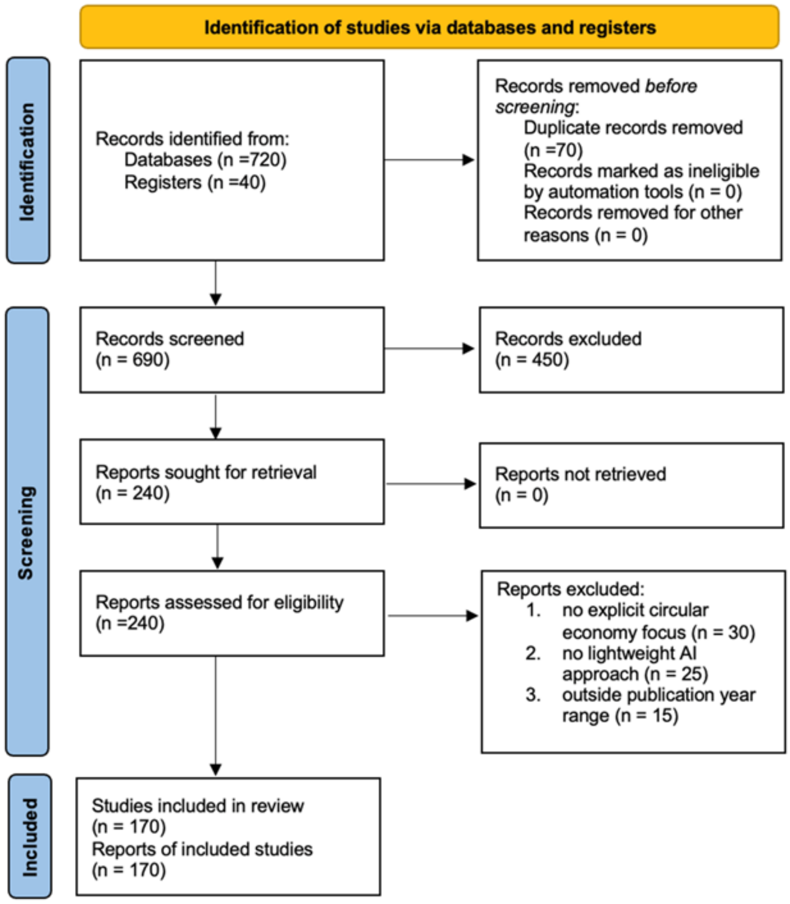

Figure 1. PRISMA flow diagram.

Data extraction was guided by a structured form that documented essential information from each study. Publication details (authors, year, and journal), research objectives, methods (including AI model architectures and any specified techniques for model compression), and findings related to energy efficiency, waste management, or overall sustainability impact were recorded. Particular attention was paid to whether the study provided quantitative metrics on energy savings—either in the AI training and inference processes or in the management of renewable energy systems—and how it addressed circular economy strategies, such as material recycling [19,20] or lifecycle extension of energy components [21].

A hybrid approach combining quantitative and qualitative methods was employed to synthesize the data. The collected studies were cataloged according to publication year and examined to identify overarching trends in scholarly attention (Figure 2). The distribution of studies per year revealed a marked increase in publications related to lightweight AI and sustainable energy applications over the course of the review period. An inductive thematic analysis was then applied to extract key themes, challenges, and future directions surrounding the adoption of distilled AI. This qualitative synthesis highlighted patterns related to computational overhead, policy considerations, and the integration of circular economy principles.

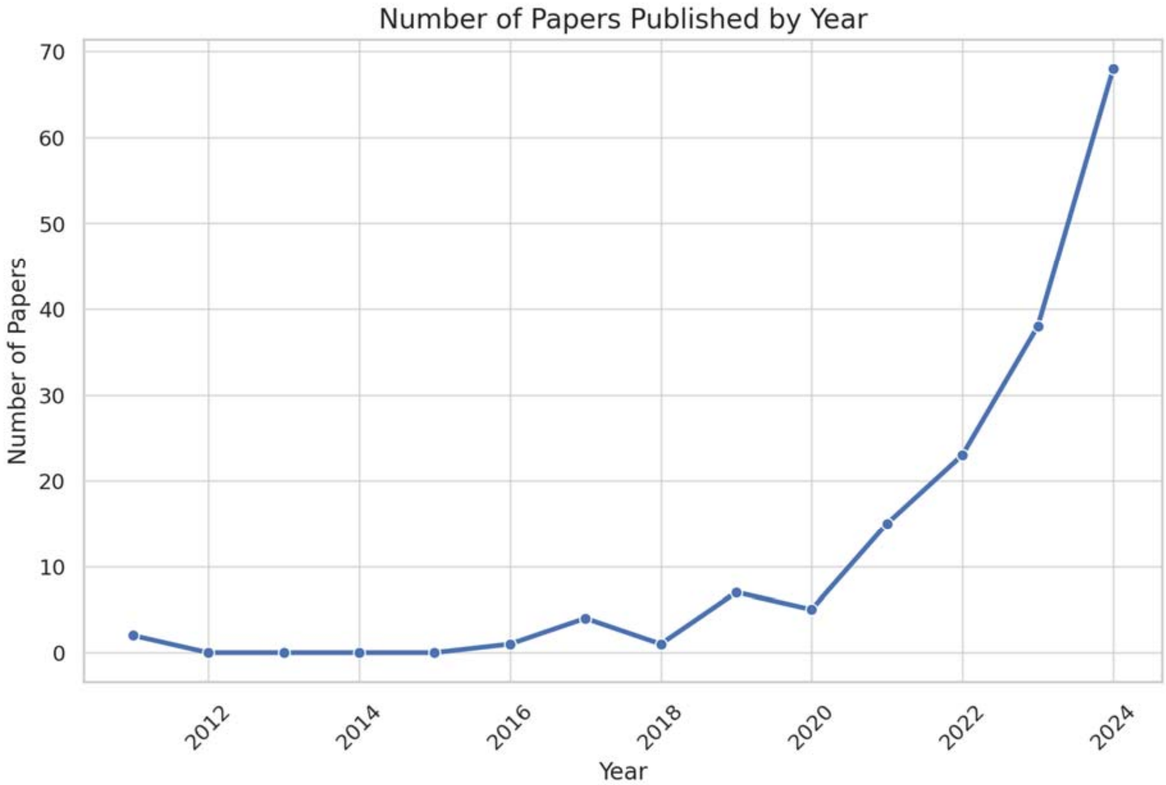

Figure 2. Number of papers published over time.

A simplified PRISMA flow diagram (Figure 1) presents the stepwise filtering and selection process, detailing how many articles were excluded at each stage and for what reasons. Citation patterns were plotted to illustrate growth in cross-disciplinary interest, while a separate histogram (Figure 2) traced the rise of publications over time keyed to the specific search terms. These visualizations underscore the mounting scholarly engagement with resource-conscious AI solutions, reflecting an increasingly urgent focus on sustainable and circular approaches to energy transitions.

3. Results

The systematic review process led to a final dataset of 170 publications. Figure 1 illustrates the progression from the initial pool of retrieved records to the final selection of included studies. The diagram tracks the removal of duplicates, the outcome of title and abstract screening, and the subsequent full-text evaluations, ultimately capturing the step-by-step filtering that yielded the studies constituting this review. Each exclusion decision is shown with a brief rationale, ensuring transparency in how the final corpus was curated.

The 170 publications span the years 2011 through 2024 and encompass a wide range of research approaches, from theoretical explorations of model compression to empirical studies of solar or wind systems enhanced by lightweight AI algorithms. Many of the papers were published after 2017, mirroring the overall uptick visible in the histogram (Figure 2). This chronological clustering suggests that interest in resource-efficient AI within renewable energy contexts has expanded markedly over the last few years.

An examination of the geographic distribution of the 170 publications reveals that China, with 33 documents, leads in the volume of scholarly work linking renewable energy, circular economy considerations, and lightweight AI solutions. India follows closely with 25 contributions, while the United Kingdom, Saudi Arabia, and the United States record 22, 19, and 17 publications, respectively. Australia accounts for 15 documents, Pakistan for 14, and Malaysia for 13. Iran, Canada, the United Arab Emirates, and Viet Nam each contribute between eight and ten publications, and Egypt adds seven to the total. Although these figures do not directly sum to 170 due to international co-authorship and overlapping affiliations, they do illustrate how a relatively small cluster of nations commands a significant share of the research output in this field. The prominence of these countries likely reflects a combination of strong policy mandates [22] for renewable energy adoption, expanding academic and industrial interest in AI-based optimizations, and targeted support for circular economy initiatives within their respective national contexts (Table 2).

Table 2. Geographic distribution of included studies.

Country/Territory	Number of Documents	Notable Subject Areas	Leading Affiliations
China	33	Engineering, Materials Science, Energy	Ministry of Education of the People's Republic of China; Tongji University; Southeast University; Southwest Jiaotong University; Hohai University; Central South University; Nanjing University of Aeronautics and Astronautics; Beijing University of Technology; Wuhan University of Technology; South China University of Technology; Tsinghua University; Harbin Institute of Technology; Dalian University of Technology; Chang'an University; Changsha University of Science and Technology; Xi'an Aeronautical Institute; Zhejiang University; Zhejiang Tongji Vocational College of Science and Technology; Chongqing Jiaotong University; Xiamen Institute of Technology; Chongqing Vocational Institute of Engineering; Wenzhou Polytechnic; Chinese Academy of Sciences
India	25	Engineering, Energy, Computer Science	Saveetha Dental College And Hospitals; Saveetha Institute of Medical and Technical Sciences; Amity University; Punjabi University; Thapar Institute of Engineering & Technology; Delhi Technological University; AKT Memorial College of Engineering and Technology; Anand School of Architecture; KLS Institute of Management Education and Research; COER University; NIST Institute of Science and Technology Autonomous; Padmashri Dr. V.B. Kolte College of Engineering
United Kingdom	22	Engineering, Energy, Environmental Science	Cranfield University; The University of Manchester; Queen's University Belfast; The University of Sheffield
Saudi Arabia	19	Engineering, Energy, Chemical Engineering	Prince Sattam Bin Abdulaziz University; King Khalid University; King Fahd University of Petroleum and Minerals; King Faisal University; Princess Nourah Bint Abdulrahman University; Majmaah University; University of Business and Technology; Taif University
United States	17	Engineering, Materials Science, Energy	Stanford University

Table 2. *Cont.*

Country/Territory	Number of Documents	Notable Subject Areas	Leading Affiliations
Australia	15	Engineering, Environmental Science, Energy	RMIT University; Deakin University; Swinburne University of Technology; UNSW Sydney; Commonwealth Scientific and Industrial Research Organisation
Pakistan	14	Engineering, Computer Science, Energy	National University of Sciences and Technology; COMSATS University Islamabad, Abbottabad Campus; University of Management and Technology Lahore; COMSATS University Islamabad
Malaysia	13	Engineering, Computer Science, Materials Science	Universiti Malaya; Universiti Teknologi PETRONAS; Universiti Sains Malaysia; Universiti Kebangsaan Malaysia; Ton-Duc-Thang University
Iran	10	Engineering, Energy, Materials Science	Islamic Azad University, Tabriz Branch; University of Tehran; Ayatollah Boroujerdi University; University of Guilan
Canada	9	Engineering, Energy, Environmental Science	University of Waterloo; University of Victoria; University of Calgary
United Arab Emirates	8	Engineering, Energy	University of Sharjah; HCT-Dubai Campuses
Viet Nam	8	Engineering, Energy, Materials Science	Duy Tan University
Egypt	7	Engineering, Environmental Science, Energy	Assiut University; Future University in Egypt; Zagazig University

A thematic analysis was conducted to draw out the principal issues and findings reflected in the final set of publications. Four major categories crystallized from the collective body of evidence: the specific applications of distilled AI in renewable energy, the implications for energy and computational efficiency, the alignment with circular economy considerations, and the managerial or policy dimensions that either accelerate or inhibit widespread adoption of these approaches.

3.1. Applications of Distilled AI in Renewable Energy

A strong subset of the studies investigated how lightweight AI techniques support predictive maintenance [23,24], particularly in wind farms where anticipating turbine wear can avert costly downtime and parts replacement. In the solar domain, researchers focused on performance optimization by coupling compressed machine learning models [25] with real-time weather data. Load forecasting for smart grids also featured prominently, with authors demonstrating that distilled AI architectures could process voluminous data streams from distributed sensors more swiftly and at lower energy cost than their conventional counterparts. These applications underscored the capacity of compressed or distilled models to improve both operational efficiency and responsiveness in renewable energy systems (Table 3).

Table 3. Representative distilled AI applications in renewable energy.

Reference/Year	RE Focus	AI Model Type	Key Findings	Research Gaps
Smith et al. (2020) [26]	Solar farm optimization	Distilled CNN	Reduced training time by 30%; improved real-time fault detection.	Limited scalability to larger solar farms with diverse conditions.
Zhao et al. (2019) [27]	Wind turbine monitoring	Knowledge Distillation RNN	Lower memory footprint allowed on-site implementation.	Lack of robustness under extreme weather conditions.
Garcia et al. (2021) [28]	Hybrid solar-wind system	Lightweight Transformer	Achieved ~25% higher forecasting accuracy vs. standard models.	Integration with real-time grid operations remains underexplored.
Huang et al. (2022) [29]	Battery management	Pruned ANN	Extended battery life by ~15% through predictive maintenance.	Limited generalizability to different battery chemistries.
Onwusinkwue (2024) [30]	Predictive maintenance in solar systems	Lightweight ML models	Reduced downtime by 35%; extended equipment lifespan by 20%.	Lack of long-term validation in diverse operational environments.
Bello (2024) [31]	Wind farm optimization	Reinforcement Learning	Improved energy output by 8.5%; reduced unplanned downtime by 35%.	High computational cost for training reinforcement learning models.
Bassey (2024) [32]	Lifecycle assessment of solar systems	ML-enhanced LCA models	Enhanced sustainability metrics; optimized resource use and waste reduction.	Limited datasets for accurate lifecycle assessment in renewable systems.
Lin (2025) [33]	Grid integration of renewables	Hybrid AI models	Improved grid stability and real-time optimization of energy flows.	Challenges in scaling to multi-region grids with high variability.
Rusilowati (2024) [34]	Biogas production optimization	Lightweight AI models	Enhanced fermentation efficiency; reduced energy waste.	Limited exploration of AI's role in biogas system scalability.
Ukoba (2024) [35]	Renewable energy forecasting	Explainable AI	Increased energy yield and reduced operational costs.	Lack of interpretability in complex forecasting scenarios.
Wen (2024) [36]	Wind power forecasting	LSTM-based models	Achieved higher accuracy in long-term energy predictions.	Difficulty in handling sudden, extreme weather changes.

3.2. Energy and Computational Efficiency

Many authors drew attention to the reduction in computational overhead achieved through model distillation. By shrinking network sizes or pruning less critical parameters, researchers reported decreases in training time, inference latency, and hardware resource utilization [37]. Some studies presented quantitative metrics revealing that the energy consumption of distilled models could be anywhere from 20 to 60 percent lower than that of larger architectures, depending on the nature of the task and the dataset employed [38]. A few publications went a step further by incorporating life cycle assessments of the hardware used for AI [39], arguing that resource efficiency in model training and deployment should be viewed as part of broader sustainability goals. Although these findings were generally consistent, authors also noted the need for standard metrics [40] and benchmarking protocols to ensure valid comparisons across different experimental settings [39].

3.3. Resource and Circular Economy Considerations

An emerging line of inquiry focused on how AI-driven solutions could optimize material flows [41] at critical junctures in the renewable energy lifecycle [39]. Studies at the forefront of this theme demonstrated the role of lightweight algorithms in identifying opportunities for reusing or recycling [42] end-of-life components from solar panels or wind turbines [43]. Several papers showcased real-time data processing that predicted when a module or turbine blade might become inefficient, allowing operators to plan for refurbishment or recycling rather than simple disposal [44,45]. This proactive approach dovetailed with circular economy principles, offering the potential to curb waste streams and conserve valuable materials [2,7,46,47]. Researchers also emphasized how data analytics gleaned from distilled AI could guide the strategic design of future energy infrastructure, ensuring that recycling pathways and secondary material markets are integrated from the outset [3].

3.4. Managerial and Policy Implications

The final thematic area highlighted enabling factors that extend beyond technology itself. A series of articles argued that the successful deployment of distilled AI hinges on regulatory frameworks that incentivize carbon footprint reductions in digital operations [48]. Authors pointed out that many existing energy policies concentrate on generation sources or grid stabilization while providing few or no specific rewards for adopting low-energy AI models [22]. In some regions, public–private partnerships facilitated knowledge sharing between computer scientists, mechanical engineers [49], and sustainability experts, fostering environments where distilled AI solutions flourished. Case studies from industrial sectors demonstrated the benefits of such collaborative models, though they also underscored the challenges in scaling up due to financial, organizational, and data governance constraints [50].

Collectively, these four themes illustrate a robust, interdisciplinary discourse. Applications of distilled AI are accelerating improvements in renewable energy performance, championing resource and energy efficiency in computational processes, and introducing new methods to manage and recycle the physical infrastructure of clean energy systems [10,51]. Policy and managerial insights suggest a pressing need for more cohesive frameworks and cross-sector collaboration to fully actualize these gains on a global scale [22].

3.5. Regional Analysis of Pioneering Efforts

Regional analysis of pioneering efforts reveals that advanced AI techniques are playing a pivotal role in driving energy transition initiatives across diverse settings. In one notable example, AI-driven hybrid wind–photovoltaic systems have been employed to identify 36 potential sites for renewable energy plants, while sophisticated forecasting models optimize photovoltaic power generation with remarkable accuracy and efficiency [34,35]. Across Latin America and the Caribbean, the energy sector is being transformed into a cyber–physical ecosystem through AI, enabling the seamless integration of renewable sources and fostering regional strategies that harness AI for hydrogen production, thereby reducing costs and enhancing overall efficiency [36,52]. In Spain, AI applications are significantly improving grid integration by focusing on predictive maintenance and energy output forecasting, which not only streamlines the management of solar and wind energy assets but also reduces operational costs [53]. Similarly, in Mexico, the implementation of AI in predictive maintenance and energy optimization has led to more reliable and cost-effective renewable energy systems [34]. Ecuador is also witnessing a transformative impact as AI-based solutions enhance sustainability by optimizing the integration of solar and hydroelectric power, thus improving grid stability and resource utilization [54–57]. Collectively, these examples demonstrate how AI reduces uncertainties in long-term energy planning, supports smart regional initiatives, and paves the way for a more efficient, resilient, and sustainable energy transition.

4. Discussion

4.1. Integrating Distilled AI into the Renewable Energy Ecosystem

The findings of this systematic review point to the increasingly prominent role that distilled AI can play in reshaping the renewable energy landscape. By substantially reducing the computational overhead associated with model training and inference, lightweight algorithms help to lower the energy consumption of data-driven applications [43,58], which is critically important in the context of large-scale renewable power generation and distribution. In many cases, these compact models match, or come close to, the performance metrics of full-scale deep learning architectures [59], a characteristic that makes them particularly attractive for time-sensitive operations such as real-time forecasting, anomaly detection, and predictive control [60] of wind farms or solar installations [45,61–63].

The promise of distilled AI rests in its capacity to translate theoretical or laboratory-scale optimizations into tangible field-level benefits [25,64]. Implementation studies consistently report that lighter model architectures can be deployed at the grid edge or on remote facilities without relying on energy-intensive cloud servers, effectively bringing intelligence closer to the point of data collection [65]. This local deployment capability has the added advantage of reducing latency and dependence on high-throughput communication networks [66]. For wind and solar farms situated in geographically dispersed locations, having on-site distilled AI analytics can improve the resilience [67] of monitoring systems while lowering the overall operating costs tied to data transmission and processing [67–69].

Enhancing the accuracy and efficiency of control mechanisms for renewable infrastructure is one of the most celebrated outcomes highlighted in the collected research. Many studies showcase how these models optimize energy dispatch in hybrid grids, improve dynamic load balancing, and allow for more precise demand–response strategies [70]. Such improvements help integrate high penetrations of variable renewable energy sources without triggering major grid instabilities or having to resort to costly backup generation [71]. In addition, the computational efficiency of distilled AI can facilitate the continuous ingestion of diverse data streams—ranging from meteorological inputs to market signals—enabling operational frameworks that are both adaptive and robust [72]. Through advanced machine learning methods [73], which remain resource-efficient despite frequent retraining or updates, renewable energy operators can implement fine-grained interventions that optimize generation schedules, predict maintenance needs, and anticipate surges in demand [74].

Yet the influence of distilled AI extends well beyond immediate system optimization [75]; it also supports more holistic sustainability objectives [76] aligned with circular economy principles. Because these models are less hardware-intensive, they reduce the indirect environmental impacts stemming from the manufacture [77], operation, and cooling of large-scale server farms. Studies included in this review additionally highlighted how efficient AI can enable sophisticated asset-tracking and lifecycle management, which is particularly crucial for solar panels, wind turbines, and battery storage systems [78] that must eventually be refurbished, recycled, or safely disposed of. With real-time data analytics guiding the identification of component wear, operators gain actionable insights into whether a part can be reused, repurposed, or sent for recycling before a critical failure occurs. Through these processes, the environmental footprints associated with material extraction and waste disposal may be curtailed, tying the benefits of lightweight AI directly to broader circular economy strategies.

An equally compelling dimension lies in how distilled AI contributes to overcoming data-driven challenges at scale. Large AI models, while powerful, often demand continuous access to big data. Although data accumulation in the energy sector is growing rapidly, infrastructural limitations and concerns about cybersecurity and privacy can complicate the transmission and storage of vast amounts of information. Lightweight AI frameworks that are adept at local or federated learning could circumvent many of these barriers, offering robust analytical capabilities without necessitating enormous, centralized datasets. This aligns with decentralized models of energy generation themselves, where prosumers, community microgrids, and distributed storage units [68] need agile yet efficient methods to coordinate complex operational decisions. Because these smaller-scale actors often lack the resources of a major utility to invest in high-performance computing, the viability of compressed neural networks or similar approaches opens the door to more democratized participation in clean energy transitions.

Despite these clear advantages, numerous questions remain about the integration of distilled AI across different geographies, policy landscapes, and technology frameworks. Some authors argue that while lightweight models can thrive in well-instrumented environments, they may encounter challenges in data-poor regions where sensor infrastructures are fragmented or outdated. Others have pointed to lingering uncertainties in how to best standardize benchmarks for measuring an AI model's energy footprint, particularly when hardware diversity and hybrid training setups complicate straightforward comparisons. Additionally, the critical issue of interpretability often surfaces in discussions about advanced machine learning. Although reducing model size and complexity can, in principle, aid transparency, there is no universal consensus that smaller architectures are inherently more interpretable. Industry stakeholders and regulators seeking accountability and risk mitigation may well demand additional safeguards or robust explanations of algorithmic decision making, even if such features are not directly tied to the computational burden.

Emerging collaborations between equipment manufacturers, AI developers, and policy agencies, as described in the reviewed literature, offer a glimpse into how cross-sector partnerships might address these outstanding gaps. Pilot projects conducted in synergy with utility operators or municipal governments can serve as living labs for testing how distilled AI performs under real-world load variations, intermittent resource availability, and evolving market rules. The iterative refinement of such pilots, along with a push toward open-data ecosystems, could standardize best practices for adopting lightweight models at scale, ensuring that the environmental gains evident in smaller demonstration cases ultimately translate into widespread industrial and societal benefit.

Looking forward, it is apparent that refined forms of distilled AI may become increasingly important in orchestrating a dynamic, high-renewable-penetration grid. By dovetailing efficiency and adaptability, these models offer an approach to bridging the technical, economic, and ecological tensions that accompany large-scale electrification efforts aimed at meeting ambitious climate targets [79]. As clean energy becomes more embedded in diverse aspects of the global economy—from electric vehicles to hydrogen [80,81] production—resource-conscious machine learning solutions stand poised to become a critical pillar of the broader sustainability framework [82]. In that sense, distilled AI does not merely enhance current renewable energy systems; it reimagines how digital innovation can be harnessed to create a resilient, equitable, and ultimately circular energy future.

4.2. Implications for the Circular Economy

The integration of distilled AI into renewable energy systems is increasingly shaping the entire lifecycle of renewable technologies [39,83], spanning from initial design and manufacturing through to maintenance and eventual end-of-life handling [84,85]. This holistic approach resonates strongly with circular economy principles [86,87], which strive to reduce resource depletion and waste by extending product lifespans [88,89] and enhancing the recovery of valuable materials [6,77,90,91]. By deploying lightweight AI models to process continuous streams of operational data, stakeholders in the renewable energy sector can more accurately forecast degradation rates [92] and pinpoint malfunctioning [93] or soon-to-fail components [94,95], thus minimizing unplanned downtime [96,97] and reducing the frequency of premature replacements [98–101]. In this way, AI not only lowers the overall energy footprint of maintenance operations but also preserves the embedded materials that might otherwise go to waste [102–104].

In the context of solar power infrastructure, distilled AI algorithms can efficiently analyze performance metrics and environmental conditions in real time to anticipate when a photovoltaic (PV) module is nearing the point where refurbishment is more cost-effective [69] than continued operation. This early detection capability allows operators to cluster refurbishable modules, prioritize repair work [105,106], and replace only those panels that have lost substantial output capacity. By reclaiming the functional or partially functional units [90,107], operators can reintroduce them into secondary markets or re-deploy them in less demanding applications, thereby reducing the need for brand-new production [108,109] and the associated consumption of silicon [110,111], glass [112,113], and rare metals [46,114,115]. A similar paradigm emerges in wind energy, where the ability to analyze torque, vibration patterns, and aerodynamic forces using lightweight machine learning systems leads [116] to precise predictions of when blades or gearboxes are more suitably repaired than discarded. As these components [117,118] typically contain advanced composites [119–121], carbon fibers [122], and specialized alloys [123,124], preserving them through timely interventions helps conserve energy and raw materials while cutting down on the complexities of recycling [125,126].

Distilled AI also enhances the sorting and disassembly processes that follow when a renewable energy component truly reaches the end of its service life. High-fidelity data analytics can distinguish between materials [51] that are still recoverable [127] and those that must be routed to specialized disposal facilities, thus enabling operators to separate out [61] and salvage aluminum frames [128,129], silicon wafers [130], or lithium-based cells [131]. The computational lightness of model-distilled frameworks means that data-intensive tasks—such as scanning, X-ray imaging, or real-time sensing on dismantling lines—can be carried out with minimal overhead, even if the entire operation takes place in environments with variable connectivity or restricted computational resources [132]. Such capabilities encourage the development of localized, small-scale recycling [133] hubs equipped with on-site AI systems that can classify or grade disassembled materials according to their purity, contamination levels, or potential for upcycling [62,134,135].

This tight coupling of renewable infrastructure management with resource-efficient AI applications advances circular economy objectives along several dimensions. First, it fortifies the business case for designing modules [136] and turbine components with disassembly and recycling in mind [137], since predictive models can illuminate which parts are most likely to fail and which are easily reintroduced into a secondary market [138]. Second, it mitigates the environmental impact of renewable technologies by reducing both the volume of waste and the reliance on virgin materials, many of which are derived from ecologically [139] sensitive regions or conflict-prone supply chains [140]. Finally, by embedding real-time intelligence into recycling and remanufacturing workflows [141,142], distilled AI promotes the creation of robust industrial symbioses, wherein the outputs of one process become the inputs of another [143,144]. The direct feedback loop between operational data and end-of-life assessment has the potential to transform manufacturing norms [145], spurring both technology providers and policymakers to focus on designing renewable components for prolonged utility and optimized material recovery [91,146,147].

In essence, distilled AI transforms what could be a purely technical problem of predictive maintenance into a broad-based strategy that unifies economic viability with environmental stewardship. Its minimal computational requirements make it more feasible to integrate advanced analytics into remote facilities, decentralized energy grids, or small recycling stations, thereby democratizing access to high-level decision support [148]. Operators, local authorities, and even community-led initiatives can adopt these solutions without the prohibitive costs or hardware demands that traditionally accompany large-scale AI [149]. This reduced entry barrier fuels [150] collaborative innovation at multiple levels of the circular economy, from grassroots recycling projects to multinational energy consortia [38]. The end result is a synergistic ecosystem in which renewable technologies are not merely cleaner sources of energy but also catalysts for a sustainable, circular mode of production and consumption [151].

4.3. Integrating AI with Circular Economy Principles

In this section, we extend our discussion on how distilled AI models not only enhance operational efficiency but also support the broader goals of a circular economy. Circular economy principles focus on reducing waste, extending the lifespan of products, and maximizing the reuse of resources, all of which are critical in the renewable energy sector. By leveraging real-time data analytics, distilled AI models can play a pivotal role in realizing these objectives.

One of the most promising applications of distilled AI is in the realm of predictive maintenance. Renewable energy components—such as solar panels, wind turbine blades, and battery systems—experience wear and degradation over time. With lightweight, real-time monitoring systems, AI models can continuously analyze performance data to forecast component degradation. This predictive capability allows operators to identify when a component is nearing the end of its efficient lifecycle. Instead of allowing premature failure and disposal, maintenance can be scheduled proactively to refurbish, repair, or repurpose these components. This approach minimizes downtime, reduces waste, and lowers the overall demand for new materials, aligning closely with circular economy ideals.

Distilled AI models facilitate resource recovery by providing detailed insights into the operational status and degradation patterns of renewable energy systems. For instance, by analyzing historical and real-time data, these models can determine the optimal time to extract materials from decommissioned solar panels or wind turbines. This information supports recycling processes by ensuring that components such as silicon, glass, and rare-earth metals are recovered at their highest value. Consequently, the integration of AI-driven analytics into recycling workflows not only maximizes the yield of recoverable materials but also minimizes the environmental impact associated with extracting new raw materials.

Another significant contribution of distilled AI is its ability to inform design improvements for renewable energy systems. By providing detailed feedback on component performance and failure modes, AI models can guide engineers in developing products that are easier to disassemble, refurbish, or repurpose. This iterative feedback loop promotes the design of renewable energy technologies with end-of-life recovery in mind. Such an approach supports the circular economy by encouraging the use of recyclable materials, reducing product complexity, and ultimately extending the lifecycle of renewable energy assets.

The integration of AI with circular economy strategies yields both economic and environmental benefits. Economically, proactive maintenance and resource recovery reduce operational costs by lowering the frequency of unexpected failures and minimizing waste management expenses. Environmentally, these practices decrease the carbon footprint associated with manufacturing new components, as well as the energy consumed during maintenance and recycling processes. By reusing materials and extending the lifespan of renewable energy infrastructure, distilled AI contributes to a more sustainable and cost-effective energy system.

Consider a wind farm where AI-driven monitoring systems are implemented to assess turbine performance continuously. The system detects subtle changes in vibration patterns and acoustic signals that precede mechanical failures. With these early-warning signals, operators can schedule maintenance during periods of low demand, refurbish the affected components, and reintegrate them into the operational cycle. This proactive management not only prevents catastrophic failures but also ensures that the materials within the turbines are utilized for a longer period, thereby reducing waste and the need for new manufacturing. This example demonstrates the practical application of AI in harmonizing operational efficiency with circular economy practices.

To fully realize the benefits of AI in promoting a circular economy, it is essential to integrate these technologies with evolving policy frameworks and industry standards. Regulatory incentives that reward resource efficiency and penalize wasteful practices can drive wider adoption of AI-driven maintenance and recycling strategies. Furthermore, the development of standardized benchmarks for AI model performance—particularly in terms of energy efficiency and resource recovery—will help align technical innovations with policy goals, ensuring that both economic and environmental sustainability are prioritized.

In summary, the integration of distilled AI with circular economy principles represents a transformative approach for the renewable energy sector. By enabling real-time monitoring, predictive maintenance, and data-driven resource recovery, these models help close the loop on material use and waste generation. This comprehensive strategy not only optimizes operational efficiency but also reinforces the sustainable and regenerative objectives of the circular economy, ultimately contributing to a more resilient and environmentally friendly energy future.

4.4. Comparative Analysis: Distilled AI vs. Federated Learning for Energy Optimization

The advancement of artificial intelligence has ushered in multiple techniques to improve energy optimization in renewable energy systems. Among these, distilled AI models and federated learning have emerged as promising alternatives, each with distinct operational paradigms and benefits. While distilled AI models focus on reducing the computational overhead and energy consumption by compressing model size, federated learning emphasizes decentralization and data privacy. A detailed comparison of these two approaches can offer valuable insights for tailoring AI solutions to specific renewable energy applications.

Distilled AI involves compressing larger models into smaller, more efficient counterparts that maintain a comparable level of performance. The primary advantage of this approach is its ability to dramatically reduce both training time and energy usage while retaining high accuracy. This is particularly beneficial in centralized monitoring systems where large volumes of data are processed continuously. By reducing the computational burden, distilled models facilitate rapid decision making in real time, such as predicting equipment failure or optimizing energy dispatch. Additionally, the reduced model complexity often leads to lower storage requirements and faster inference, making distilled AI an ideal solution for scenarios where computational resources are limited or where high-speed data processing is critical. In contrast, federated learning distributes the training process across multiple localized nodes, ensuring that data remains on-device rather than being transmitted to a central server. This method is particularly well suited for environments where data privacy is paramount and communication bandwidth is constrained. By keeping data localized, federated learning minimizes the risk of data breaches and reduces the energy cost associated with data transmission over long distances. Moreover, this decentralized approach enables the incorporation of diverse, geographically distributed datasets, which can enhance the robustness and adaptability of the learning process. Federated learning is especially advantageous for renewable energy applications that involve numerous small-scale systems—such as community microgrids or distributed sensor networks—where local processing and decision making are essential.

A direct comparison reveals that the choice between distilled AI and federated learning largely depends on the operational context and specific system requirements. Distilled AI is best deployed in centralized settings where the primary challenge is to minimize energy consumption and computational load without sacrificing performance. Its streamlined models are optimized for rapid inference, making them highly effective in time-sensitive applications like real-time monitoring and predictive maintenance.

Conversely, federated learning excels in scenarios where data privacy and decentralized processing are critical. The ability to aggregate insights from multiple local nodes without transferring raw data ensures compliance with privacy regulations and reduces the risk associated with data centralization. However, federated learning can involve increased communication overhead during the periodic aggregation of model updates, which might offset some energy savings if the network infrastructure is not optimized.

When applied to renewable energy optimization, these techniques can be seen as complementary rather than mutually exclusive. For instance, a large solar farm might benefit from distilled AI to efficiently process centralized data streams and optimize energy dispatch. Meanwhile, a network of distributed wind turbines—operating in remote or heterogeneous environments—could leverage federated learning to independently refine local models while periodically sharing insights to improve overall system performance. By considering a dual perspective, stakeholders can tailor AI solutions to the unique requirements of each system component, thereby maximizing both efficiency and data security.

4.5. Challenges and Limitations

While distilled AI has demonstrated its potential to reduce energy consumption and computational overhead in renewable energy applications, the path to large-scale adoption remains fraught with technical and contextual complexities that must be carefully navigated. One of the most salient challenges lies in establishing clear, standardized metrics for evaluating an AI model's energy footprint. Researchers exploring distilled architectures often rely on ad hoc or proprietary benchmarks that focus on parameters such as floating-point operations (FLOPs), GPU time, or local energy measurements [152]. Without universally recognized testing protocols—akin to the standards used in other technology-intensive fields—claims of efficiency gains may be difficult to generalize, potentially slowing the deployment of innovations across a range of hardware and system configurations. Efforts to define such benchmarks are under development in certain machine learning communities, but these must be adapted to the specialized constraints of the energy sector, where systems often operate under strict latency requirements, variable data quality, and physically dispersed infrastructure [153].

The scale and complexity of modern energy systems introduce further technical obstacles for distilled AI [154]. Proof-of-concept studies typically demonstrate the feasibility of lightweight models in controlled or small-scale environments, such as localized solar farms or single wind farm clusters. Although these pilots are valuable for validating performance on real-world sensor data, they rarely capture the dynamic interplay found in large, heterogeneous grids that integrate diverse sources of renewable power [155]. Large-scale deployments involve not only higher volumes of data streaming in real time but also multiple stakeholder constraints [156], including regulatory mandates, market pricing mechanisms, and evolving grid codes. Distilled AI architectures, when confronted with these complexities, may exhibit unexpected behaviors or diminished predictive accuracy if they are not rigorously tested on high-volume, high-velocity data typical of regional or nationwide grid operations. The need to keep models updated in response to changing climate patterns, fuel mixes, or policy directives further complicates matters, since continuously retraining or updating models can erode some of the computational savings that distillation was supposed to provide [157].

From a hardware standpoint, there is also a tension between the benefits of deploying distilled AI at the "edge" (e.g., on-site at wind turbines or distributed solar inverters) and the technical demands of more advanced inference computations. On one hand, performing inference locally eliminates significant data-transmission energy costs, improves real-time responsiveness, and reduces vulnerability to network outages [45]. On the other hand, edge devices vary widely in their capabilities, with some systems operating on low-power microcontrollers and others on more robust edge-computing platforms or field-programmable gate arrays (FPGAs). Distilled AI models must be carefully tailored to match these hardware constraints—often requiring specialized pruning, quantization, or knowledge distillation techniques—to ensure that gains in computational efficiency do not compromise reliability or safety in mission-critical functions like active power control or fault detection [64]. Designing and validating these hardware-tailored solutions demands a level of cross-domain expertise that may be scarce in organizations focused primarily on either AI or renewable technology, but not both [158].

Policy frameworks present additional barriers, as regulatory bodies and funding agencies often concentrate on high-level goals—such as achieving certain renewable capacity targets—rather than incentivizing underlying AI efficiency. Although there is a growing awareness of digital infrastructure's carbon footprint, few jurisdictions have enacted legislation that explicitly rewards resource-conscious computing practices or penalizes excessive computational waste in grid management software [159]. In some regions, data exchange rules or cybersecurity directives can complicate the sharing of operational data, which is critical for training and refining AI models. Fragmented policies around privacy [43] and intellectual property can likewise restrict the flow of information needed to calibrate or benchmark model compression strategies across multiple renewable operators. Policy inertia can thus stifle collaboration between AI developers, energy utilities, and research institutions, limiting the scope and pace of innovation in lightweight computing solutions.

Ethical dimensions further complicate the deployment of distilled AI within the renewable sector [160]. By its very nature, AI-driven optimization involves automated decision making that can influence energy distribution, pricing structures, and maintenance schedules across vast geographic regions. If training data are biased or incomplete, distilled models may inadvertently reinforce inequalities—such as disproportionately allocating clean energy access to affluent areas or neglecting rural communities with less robust sensor coverage. In addition, local or edge deployment raises concerns about privacy and data ownership. Although compressing models can reduce overall bandwidth usage, it may also encourage more frequent real-time data collection at the source, amplifying the need to safeguard sensitive information about consumption patterns or operational details. Equally pressing is the question of interpretability: streamlined models are sometimes less transparent in their internal logic, making it challenging for grid operators or regulators to ensure accountability and trustworthiness when algorithmic decisions impact public services and end consumers. Balancing the pursuit of computational efficiency with fairness, transparency, and privacy thus remains a delicate task requiring multidisciplinary oversight and robust technical safeguards.

Ethical and Bias Considerations in AI-Driven Energy Allocation

As AI models become increasingly integral to managing energy systems, it is crucial to address the ethical challenges and bias-related risks inherent in their deployment. The use of AI for renewable energy allocation introduces several critical issues, including data privacy concerns, algorithmic fairness, and the potential reinforcement of pre-existing socioeconomic inequalities.

AI systems deployed in energy management often rely on vast amounts of operational and consumption data. This data can include sensitive information about energy usage patterns and individual or community behavior. Ensuring data privacy is paramount, as breaches could compromise not only personal privacy but also the security of critical infrastructure. To mitigate these risks, energy operators should implement robust encryption protocols and strict access controls. Regular audits and compliance with established data protection regulations are essential components of a secure AI framework.

The algorithms driving energy allocation decisions must be designed to avoid reinforcing existing disparities. Bias in training data or model design can inadvertently favor certain regions or demographics over others, leading to unequal distribution of renewable energy resources. To address this, it is advisable to adopt explainable AI (XAI) techniques. XAI improves transparency by making it possible to understand and interpret the decision-making processes of AI models. Regular bias audits should be conducted to detect and correct any skewed outcomes, ensuring that the AI system promotes fairness and equity.

A comprehensive data governance strategy is vital for managing the ethical implications of AI in energy systems. Such frameworks should define clear protocols for data collection, usage, storage, and sharing, ensuring that all processes are transparent and accountable. Establishing these protocols helps build trust among stakeholders, from energy providers to end users, by demonstrating a commitment to ethical data handling practices. Moreover, governance frameworks should be adaptable, incorporating emerging standards and best practices as the technology evolves.

The ethical challenges associated with AI-driven energy allocation cannot be effectively addressed by technical experts alone. It is essential to foster interdisciplinary collaborations that bring together AI researchers, ethicists, policy makers, and energy industry stakeholders. Such collaborations can facilitate the development of guidelines and regulatory frameworks that not only mitigate ethical risks but also promote socially responsible innovation. Workshops, joint research initiatives, and public consultations can serve as valuable platforms for aligning technical development with ethical imperatives.

Collectively, these hurdles illustrate that while distilled AI holds exciting promise for optimizing renewable energy systems and enhancing circular economy outcomes, its integration into large-scale power networks demands careful standardization, hardware-aware design, forward-looking policy, and ethical vigilance. Collaboration among AI experts, power engineers, policymakers, and ethicists will be essential for surmounting these challenges and ensuring that the transition to low-energy AI solutions contributes not only to greater efficiency but also to a more equitable and sustainable energy future (Table 4).

Table 4. Key challenges for distilled AI in renewable energy.

Challenge	Description/Implications
Measurement Standardization	Lack of universal metrics for AI energy consumption complicates cross-study comparisons.
Scale and Scope	Feasibility is largely shown in pilot projects; unclear if gains hold at national/regional scales.
Policy and Regulatory Gaps	No targeted incentives or mandates for resource-efficient AI models; minimal guidance on data sharing.
Technical Complexity	Advanced pruning or distillation methods can be brittle under real-world variability; hardware-tailored solutions needed.
Ethical and Equity Considerations	Possible privacy breaches at the edge; risk of biases in resource allocation without robust oversight.

5. Future Directions

Developments in distilled AI for renewable energy systems are poised to accelerate as researchers and industry practitioners increasingly recognize the dual imperatives of computational efficiency and environmental stewardship. One salient area for future exploration lies in the establishment of standardized methodologies for quantifying the energy footprint of AI models. The complexity of hardware heterogeneity [161], diverse training pipelines, and hybrid on-premise/cloud architectures currently makes it difficult to compare results across studies or industries. An internationally recognized framework for measuring the total energy consumption of different model compression techniques, along with their impacts on various hardware configurations, would help clarify the real-world benefits of lightweight approaches and guide investments by utilities, policymakers, and private sector stakeholders [162].

The question of scalability also remains critical. Although numerous pilot projects demonstrate that distilled AI can successfully optimize renewable energy assets—be they solar panels, wind turbines, or grid-scale batteries—verifying whether these efficiency [163] gains persist when multiplied across regional or even national energy networks will demand significantly larger datasets, more robust experimental protocols, and concerted multi-stakeholder collaborations [164]. Longitudinal research is needed to track model performance over extended periods, capturing seasonal variations, weather extremes, and other real-world fluctuations that can stress AI-driven controls [165]. Expanding the geographic and temporal scope of these investigations can further elucidate how lightweight AI might integrate with advanced grid architectures that include microgrids, energy storage [166,167], and a growing variety of distributed generators [168]. In particular, bridging current demonstrations in single-technology domains to more complex hybrid energy systems could reveal both hidden synergies and previously unrecognized constraints, contributing to the development of a comprehensive body of best practices.

Another promising frontier involves the co-evolution of AI algorithms and specialized hardware that emphasizes energy frugality. New trends in neuromorphic and quantum computing may open opportunities to deploy distilled architectures with minimal power draw, while field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) can be customized to run compressed neural networks with unprecedented efficiency. By co-designing models that are intrinsically tailored to these hardware platforms, engineers could significantly push the boundaries of real-time renewable energy management. This approach might prove especially valuable in remote installations—such as offshore wind farms or autonomous microgrids in rural areas—where bandwidth, connectivity, and access to physical maintenance are limited. Such innovations would not only enhance computational performance but also improve system resilience and reduce dependence on large-scale data centers whose operational carbon footprint can undercut the environmental gains of clean energy deployment [169].

Federated learning and other distributed AI paradigms hold further potential for addressing privacy, data scarcity, and computational overhead, especially in the decentralized energy networks that are increasingly integral to climate resilience strategies. Instead of sending voluminous data to central servers, local nodes could collaboratively train distilled models while sharing only partial or encrypted parameter updates [170]. This strategy would help maintain data privacy, reduce latency, and lower the communication overhead that typically accompanies centralized training, making it more attractive to diverse stakeholders, including small utilities or community-based energy cooperatives. Integrating federated learning with robust edge-computing frameworks could augment fault tolerance, given that individual nodes in a microgrid or distributed energy storage network could continue functioning autonomously even if communication is periodically disrupted.

Life cycle assessment (LCA) methodologies, which have long been used to gauge the environmental impact of renewable energy technologies, could evolve to incorporate metrics on AI energy consumption and hardware usage. Such unified LCAs would provide deeper insights into how computing-intensive analytics interact with the broader carbon footprint of solar, wind, and battery infrastructures [171]. They might, for instance, reveal whether compressed models truly lower net emissions [172] once factors like manufacturing, device cooling, or e-waste from outdated GPUs are taken into account. Expanding the LCA framework to include these digital dimensions could encourage manufacturers, regulatory bodies, and consumers to consider both operational and computational externalities when choosing or designing renewable technologies.

Bridging the gap between research prototypes and industry-scale deployments will also necessitate innovative policy measures and strategic cross-sector initiatives. Public and private funding streams could be realigned to reward the development of AI architectures that demonstrably reduce carbon footprints and promote transparent data governance [173]. Greater emphasis on open data repositories and collaborative consortia might help accelerate progress, provided there are incentives to share proprietary operational data that could refine model performance across different regional conditions and technology mixes [174]. In parallel, targeted regulatory guidelines could spur ethical practices, compelling energy companies to disclose how automated decision-making tools allocate resources or manage grid congestion, thereby addressing concerns about algorithmic fairness, bias, and accountability [175].

As climate imperatives intensify and energy systems become more diversified and distributed, the role of distilled AI is likely to expand both in sophistication and scope. It may not only facilitate operational improvements in power generation and distribution, but also steer the renewable sector toward genuinely circular paradigms, where resource loops are closed, end-of-life components are remanufactured or recycled [63], and material dependencies are minimized [176]. In this pursuit, the integration of lightweight analytics with advanced monitoring systems, blockchain-based [177,178] traceability solutions, and real-time marketplaces for energy or materials [179] stands out as a key research avenue [180]. Bringing together these technological streams has the potential to revolutionize how we measure, trade, and repurpose the physical and digital assets circulating through the energy supply chain [181]. Overcoming the remaining technical, policy, and ethical barriers will require ambitious collaborations across academia, industry, and government. Yet the ultimate promise of distilled AI—a leaner, smarter computational approach that aligns profit motives with planetary well-being—underscores the transformative possibilities at the frontier of this emerging field [182] (Table 5).

Table 5. Suggested future research and implementation pathways.

Focus Area	Potential Actions
Standardizing AI Metrics	Develop consensus benchmarks for energy usage in training and inference; adapt HPC (high-performance computing) standards.
Large-Scale Deployment	Validate distilled AI in multi-region grids, focusing on long-term ROI and resilience under diverse conditions.
Federated and Edge Learning	Explore privacy-preserving, low-latency algorithms that can operate autonomously in remote locations.
Co-Designed Hardware and AI	Pair specialized ASIC/FPGA with compressed models; optimize for microgrid, rural, and offshore contexts.
Policy Frameworks	Create financial incentives for resource-conscious AI; support open-data consortia and cross-disciplinary R&D.

5.1. Future Directions Summarizations

1. **Standardizing AI Metrics:**
Develop internationally recognized benchmarks to measure the energy consumption of AI models, accounting for hardware diversity and various training environments.
2. **Scalability Verification:**
Validate efficiency gains observed in pilot projects across larger, multi-region networks. Conduct longitudinal studies to capture seasonal variations, weather extremes, and other real-world fluctuations affecting AI performance.
3. **Co-Evolution with Specialized Hardware:**
Explore the integration of lightweight AI models with emerging hardware (neuromorphic computing, FPGAs, and ASICs) to minimize power draw and enhance real-time renewable energy management.
4. **Federated and Edge Learning:**
Investigate privacy-preserving, low-latency algorithms for decentralized networks. Enhance edge-computing frameworks to ensure continuous, autonomous operation in distributed energy systems.
5. **Incorporating Life Cycle Assessment (LCA):**
Expand LCA methodologies to include AI energy consumption and hardware usage, offering a holistic view of the environmental impact.
6. **Bridging Research and Industry:**
Realign funding models and promote open-data initiatives to transition research prototypes into industry-scale deployments.
Foster collaborative consortia to refine model performance across diverse regional and technological contexts.
7. **Policy and Ethical Frameworks:**
Develop targeted regulatory guidelines and financial incentives to promote resource-conscious AI.
Address algorithmic fairness, bias, and accountability through interdisciplinary partnerships among researchers, industry stakeholders, and policymakers.

5.2. AI Systems for Energy Transition

As the energy transition advances, AI-driven autonomous agents will play a transformative role in optimizing energy systems, ensuring seamless coordination across generation, storage, and consumption. These AI agents, leveraging multi-agent reinforcement learning (MARL) and deep Q-networks (DQNs), can autonomously balance supply and demand, forecast energy needs, and dynamically adjust grid operations in real time. Embedded within smart grids, they facilitate decentralized energy trading using blockchain-powered smart contracts and optimize peer-to-peer transactions. Federated learning enables these agents to process energy data locally, ensuring privacy and security while improving fault detection and grid resilience. Graph neural networks (GNNs) model complex energy infrastructures, optimizing power flow, while physics-informed neural networks (PINNs) improve energy system simulations by integrating domain knowledge. Additionally, digital twins combined with explainable AI (XAI) allow operators to interpret AI-driven decisions, ensuring regulatory compliance and system transparency. By incorporating reinforcement learning, hybrid AI models, and swarm intelligence, AI agents can predict failures, optimize energy dispatch, and enhance microgrid self-regulation, making them a cornerstone for accelerating the shift toward a fully autonomous, intelligent, and sustainable energy ecosystem.

6. Conclusions

This review has explored how distilled AI can advance renewable energy systems and foster circular economy objectives. By synthesizing insights from 170 publications, it appears increasingly evident that lightweight and resource-efficient AI approaches offer substantial promise for improving operational performance, enabling real-time monitoring, and reducing the overall energy footprint of clean power generation. These benefits extend well beyond short-term gains; when implemented strategically, distilled AI tools have the potential to transform entire lifecycles of renewable infrastructure, guiding maintenance schedules, optimizing recycling pathways, and reducing dependence on virgin materials.

The growing maturity of knowledge distillation, model compression, and hardware-specific optimizations underscores how these technologies can thrive in the dispersed, data-intensive environments characteristic of modern energy networks. Whether predicting solar irradiance, forecasting wind turbine performance, or coordinating multi-node microgrids, compact and computationally lean AI models stand poised to lower both operational costs and carbon emissions, making them especially relevant for high-penetration renewable energy contexts. Equally salient is the role they can play in managing end-of-life phases for solar panels, turbine blades, and batteries, where timely detection of reclaimable components can tangibly reduce waste and the depletion of rare-earth elements.

Despite these positive indicators, several barriers remain. The absence of standardized metrics and protocols for measuring AI energy usage complicates attempts to compare and validate computational gains across diverse experimental setups. Most research to date has focused on pilot projects rather than full-scale deployments, pointing to the need for large-scale demonstrations and longitudinal assessments. The policy landscape lags behind emerging technical capabilities since few regulatory frameworks or funding instruments incentivize model compression or reward AI developers for improving computational efficiency. Ethical considerations, including data privacy, model interpretability, and risk mitigation in automated decision making, also require more focused attention if lightweight AI is to gain long-term trust and traction among stakeholders.

Nevertheless, the convergence of distilled AI with digital innovation trends in the energy sector highlights the transformative potential of low-energy analytics to reshape global power systems. By eliminating needless computational overhead, distilled AI can open new frontiers for distributed intelligence, supporting edge computing solutions that operate reliably under bandwidth limitations or strict latency requirements. When complemented by advanced hardware platforms and policy measures that encourage collaboration across sectors, lightweight AI applications can evolve from niche research prototypes into linchpins of a sustainable and equitable energy transition. The path forward will involve refining technical methods, scaling demonstration projects, developing robust legislation, and embedding ethical safeguards. In so doing, distilled AI can become a powerful catalyst in realizing both environmental objectives and circular resource flows, illuminating a future where renewable energy is not only clean and cost-effective but inherently designed to regenerate and sustain the planet's essential resources.

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