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The Role of Artificial Intelligence in Advancing Green Management through Digital Transformation

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Abstract
As global environmental sustainability gains momentum as an imperative, Artificial Intelligence (AI) has become a robust driver of green digital transformation. This article recognizes the necessity of AI-driven solutions in solving the world's most severe environmental issues, including increasing carbon emissions, energy inefficiencies, and resource over extraction. With a combination of actual case studies, data, and forecasting models, the article outlines the manner in which AI improves the energy consumption efficiency, lowers emissions, and enables smart resource management. It goes on to define empirical case studies, industrial adoption patterns, and new regulatory discourse. It suggests a Green AI Value Framework for combining the technical, operational, and ethical factors in AI into green management. It not only fills gaps in current quantitative impact analysis but also defines crucial means of scaling sustainable innovation with the help of AI in both developed and developing worlds. There is an Emerging Issues chapter that includes Emerging Technologies. Environmental cost challenge of AI and failures in governance are also mentioned. A green AI deployment approach is suggested as a means to assist policymakers, business, and academia in aligning environmental goals with digital innovation. This paper takes into consideration the role of AI towards environmental sustainability through digital transformation.
Keywords: *Artificial Intelligence, Green Management, Digital Transformation, Sustainability, Smart Grids, Predictive Maintenance, Green AI*

INTRODUCTION

Sustainability of the environment has become an international call in the 21st century, characterized by mounting concerns over global warming, unstable climatic patterns, natural resource depletion, and uniform loss of bio-diversity. These are no longer projections but harsh realities that call for timely and prudent actions from governments, industries, and societies globally. With mounting pressure to shift toward greener, more sustainable systems, technology ceases to be just an issue of convenience, but becomes a strategic impetus to drive system change. Concomitant with this environmental imperative is the uncontrolled runaway of the fourth industrial revolution spurred by the advent of Artificial Intelligence and ML, advanced robotics, and real-time analytics [1]. This technological transformation is redefining all dimensions of economic and social life, from manufacturing and supply chains to transportation and urban development. Most importantly, it offers a new paradigm through which sustainability objectives can be reimagined and responded to. Where these two behemoths cross environmental sustainability and digital transformation a vast possibility for synergistic innovation is generated [2]. This intersection, frequently described as "twin transformation," symbolizes the concurrent realization of digital capability and sustainable growth. Instead of trying to segment technology and sustainability as isolated initiatives, this journey sees these two concepts existing in symbiotic relation to each other where technological innovation fuels ecological development directly. Artificial Intelligence is most clearly at the forefront of this intersection. Its capacity for handling big data, learning from intricate patterns, and producing forecasting findings allows organizations to shift from reactive to proactive approaches in environmental management [3]. AI applications can predict energy demand, detect inefficiencies in industrial processes, manage resource allocation, and even predict equipment breakdowns in advance to ensure minimum wastage, emissions, and unscheduled downtime. Artificial Intelligence is at the center of this intersection. It enables companies to predict, optimize, and streamline operations to minimize resource usage and carbon footprints [4]. According to the PwC (2020) report [5], AI-powered applications would decrease greenhouse gas emissions worldwide by as much as 4% by 2030 and augment global GDP by 4.4% simultaneously. Moreover, AI-facilitating software can aid decision-makers in crafting policies and strategies that reconcile environmental objectives with corporate performance. The application of this, in the pursuit of sustainability, cuts across all sectors. In power grids, it facilitates seamless integration of renewable energy into the grid through real-time monitoring of the supply-demand equilibrium. In manufacturing, AI-enabled predictive maintenance minimizes wastage of resources and maximizes equipment longevity. In farming, AI facilitates precision farming practices that maximize water use, fertilizers, and pesticides [6]. Urban planners are applying it to plan smart cities with cleaner air, enhanced traffic flow, and optimal energy use. Environmental monitoring systems are leveraging AI currently to identify pollution hotspots and respond immediately to environmental crises. As promising as it appears, the application of AI in sustainability interventions is not devoid of a list of challenges. Concerns are raised about the energy usage of it models themselves, the danger of algorithmic decision-making biases, and the responsible use of AI in sensitive environmental contexts [7]. Concerns of unequal access to such high-tech technologies, especially in developing countries, are also raised that can widen the global sustainability gap. Therefore, while AI has transformative potential, its use must be bounded by norms of responsibility, inclusivity, and transparency. This essay explores the multifaceted role of artificial intelligence in enhancing environmental sustainability. It scrutinizes key areas where AI is having an influence, including energy efficiency, preventive maintenance, smart grid management, waste reduction, and pollution alleviation. It accomplishes this while noting the tangible benefits and recently arising limitations of AI-assisted sustainability initiatives [8]. The paper concludes by proposing a framework for the responsible deployment of it in environmental contexts one that balances technological ambition with ecological integrity and social equity. This study examines the various facets of AI application towards environmental sustainability. We address specific areas including energy efficiency, predictive maintenance, smart grids, and pollution control. This article also reconciles the systemic advantages, shortcomings, and trade-offs of AI implementations and concludes with a green AI deployment framework.

LITERATURE REVIEW

The convergence of artificial intelligence and sustainability has gained significant momentum in the last few years. In a world grappling with the consequences of climate change, biodiversity loss, and depletion of natural resources, digital technologies have become potent agents of change. Artificial intelligence, more so than any other technology, is increasingly being considered not only as a technology but also a revolutionary greener process tool, smarter infrastructure, and more sustainable business models [9]. The term "digital transformation" has been applied most often to explain the use of data, analytics, and automation across business operations. On the issue of sustainability, it has a different connotation: it is a strategic redesign that applies innovative systems to reduce environmental footprints, conserve waste, and maximize the use of resources. The intersection of AI and sustainability is a starting point for a two-way transformation where innovation and green accountability fuel one another [10]. The following subsections discuss broad areas where such integration is most pronounced.

Energy and Emissions

AI has been shown to have quantifiable effects in some of the most highlighted areas such as emissions reduction and efficiency in energy use. With sophisticated algorithms, AI machines are capable of tracking historical and real-time process data to forecast emission levels with high accuracy [11]. In light of such forecasts, industries are able to pre-emptively modify rates of combustion, ventilation processes, or chemical feedstock to remain within regulatory limits. Reinforcement learning and deep learning algorithms have been widely used to develop dynamic energy optimization systems that can continuously learn and enhance. For industries like manufacturing, construction, and heavy industry, AI-based emission control platforms enable policymakers to model various operational scenarios and select the lowest-carbon option [12]. Aside from that, artificially smart energy management systems in offices and homes have minimized the use of energy greatly by automatically adjusting the heating, cooling, and lighting based on real-time occupancy and ambient weather conditions. Deep learning and reinforcement learning have been used widely in industrial emissions management [13]. Neural networks, for example, can accurately forecast nitrogen oxide emissions up to a level of 95% in an attempt to make real-time adjustments. In addition, intelligent energy management systems using AI are able to conserve 10–25% of energy usage in office buildings. Therefore, AI not only helps make production processes greener but also helps towards developing a culture of anticipatory action instead of reactive compliance, changing the way energy and emissions are treated at scale.

Environmental Monitoring

AI's ability to analyze big and complex data has revolutionized environmental monitoring. Leveraging technologies like computer vision, satellite imagery, and remote sensing, AI algorithms can now identify patterns and anomalies in air, water, and land systems. The smart monitoring systems can identify deforestation, illegal logging, or coastal erosion in real-time and trigger alarms to governments and environment agencies [14]. Artificial intelligence systems have been used in urban areas for tracking levels of air pollution, water quality, and forecasting flood risk. Computer vision coupled with geospatial information has made it possible to monitor deforestation in real-time, illegal fishing, and plastic waste in oceans. Artificial intelligence-driven early-warning systems have assisted city governments in restricting the impacts of water pollution and air pollution [15]. By interlinking different streams of data, for instance, meteorological data, traffic of vehicles, and industrial pollution, AI is able to provide forecasts and early warnings that prevent environmental disasters or reduce their impact. The true potential of AI in this example is the speed and scalability. What previously would have taken weeks of human monitoring is now merchandisable, with AI systems correlating terabytes of information in minutes [16]. This not only contributes to better validation of environmental choices but also enables quicker policy reactions and more effective implementation of regulation.

Smart Grids and Renewable Energy

The shift towards renewable energy sources such as solar and wind poses a new challenge and their generation cycles are intermittent and variable. AI has a solution in the form of making energy grids smarter, responsive, and adaptive. Based on machine learning models, algorithms can accurately predict electricity supply and demand from renewable energy, keeping the grid stable and efficient [17]. In intelligent grid infrastructure, networks based on artificial intelligence enable demand-side management through peak consumption identification and load diversion. Predictive models minimize the use of backup systems based on fossil fuel by optimizing energy storage. AI's predictive nature proves to be priceless in delivering balance in decentralized smart grids between supply and demand [18]. Various research studies have concluded that AI-integrated demand forecasting optimizes grid efficiency by 12–15%. It also allows for greater integration of solar and wind energy that have hitherto been constrained by their intermittency. Solar energy harvested during the day can be stored and used at peak times in the evening according to AI predictions [19]. Such smart systems also make the grid resilient by sensing faults, forecasting equipment failure, and real-time redirection of energy flows. In off-grid or remote locations, AI can assist in powering microgrids, making decentralized energy solutions cleaner and more efficient. In an integrated manner, combining renewable sources of power into the grid, AI is driving the transition to low-carbon energy systems globally.

Challenges of Green AI

Ironically, environmental advantages of AI come at environmental costs. Huge models such as GPT-3 may emit over 550 tons of CO2 and consume millions of liters of water in training. Such findings raise challenging questions for responsible AI innovation, lifecycle assessment, and carbon labeling. Even though AI is so capable of promoting sustainability, its own environmental impact cannot be overlooked [20]. Heavy training of AI models is computationally intensive, typically performed on energy-hungry data centers and high-computational configurations. This makes them responsible for releasing greenhouse gases and putting pressure on water resources in cooling and maintenance. In addition, AI hardware production and end-of-life disposal like sensors, chips, and servers are issues in electronic waste and resource depletion. There is also the likelihood of badly designed AI systems creating new forms of environmental inefficiency through encouraging over-automation or over-consumption [21]. These raise issues that one should use the life cycle perspective when designing AI that captures energy use, material extraction, emissions, and waste at all points in the life cycle of the technology. Concept of "Green AI" is thus being developed as a philosophy, contending that infrastructures and algorithms need not only to be functionally efficient but environmentally sound as well [23]. The interlink between AI and environmental sustainability has increasingly been researched in the last decade. Hence, from literature, it is evident that AI is a critical enabler of environmental sustainability across a wide array of applications from reducing energy usage and minimization of ecosystem monitoring to supporting smart infrastructure and allowing the exploitation of renewable energy. Nevertheless, to maximize its potential, environmental AI technology expenses must be dealt with. There must be an equilibrium approach founded on green stewardship, ethical design, and innovation in order to unlock the full potential of digital transformation in the sustainable world.

METHODOLOGY

This research utilizes a mixed-method methodology to analyze the role played by artificial intelligence towards promoting environmental sustainability. It combines three key elements: a 98 peer-reviewed article meta-analysis from 2020-2024 examining varied AI applications across sustainability scenarios; an aggregation of 18 company and state pilot project case studies presenting real-world implementations; and secondary analysis of data through quantitative examination of reputable sources like PwC, IEA, OpenAI, and MDPI. The gathered data were categorized into four main application categories energy and emissions control, predictive maintenance, smart grids, and pollution monitoring. In every category, the analysis concentrated on key performance indicators of energy savings, emission reduction, and predictive accuracy to allow an all-inclusive assessment of AI contribution toward green management practices.

Table 1: Energy & Emissions Control

Metric	Baseline (Manual)	AI-enabled Outcome	% Improvement
CO_2 emissions (tons/year)	15,000	12,000	20% reduction
NO_x prediction accuracy	–	> 90%	Significant
Energy consumption (kWh/year)	3,000,000	2,400,000	20% saving

Source: Martin et al. (2023) [24]

Artificial intelligence-based systems for combustion efficiency enhancement and schedule operation have saved approximately 20% of industrial processes' CO_2 emissions and total energy consumption. Real-time sensor data, machine learning software, and adaptive control tactics are employed to enhance fuel consumption, regulate process temperatures, and predict peak demand hours. In addition, the AI models have also been observed to make correct predictions of NO_x emissions at more than 90% a highly toxic group of pollutants that bring on smog and respiratory disease. This degree of precision is highly essential in energy-intensive industries like steel production, cement manufacture, and thermal power generation, where conventional human-managed control and monitoring processes are bound to create inefficiencies and environmental surpluses. In contrast to traditional approaches, based on fixed cutoffs and reactive maintenance, AI technologies provide dynamic predictive control not just to make operations more efficient but also to achieve higher compliance with stricter environmental regulations. This represents a paradigm shift to proactive environmental management that strengthens AI's role as a prime driver of green industrial transformation.

Table 2: Predictive Maintenance & Resource Efficiency

Metric	Traditional Systems	AI-enabled Systems	% Efficiency Gain
Downtime (hours/month)	25	10	60% reduction
Maintenance costs ($/year)	100,000	70,000	30% saving
Energy use per machine (kWh/month)	400	320	20% saving

Source: Zhou & Lee (2022) [25]

Artificial intelligence-based predictive maintenance solutions result in 60% less unplanned downtime, 30% lower maintenance expense annually, and 20% energy reduction in machines. All this is as a direct result of the fact that sophisticated sensor analytics, machine learning software, and real-time condition monitoring are combined. Artificial intelligence examines vast amounts of equipment data vibration, temperature, load characteristics, and acoustic signals and predicts imminent probable failures much earlier than they happen. This allows companies to transition from time- or reactive maintenance plans to condition- and predictive maintenance, reducing unnecessary downtime and extending equipment lifespan. The end result is not only financial savings but also better continuity of operation and reduced wastage of resources. At another level, optimized use of machines and scheduling mean reduced energy consumption, especially by manufacturing, logistics, and utility industries. By minimizing energy-hungry emergency maintenance and load balancing optimization, predictive AI systems are key drivers of sustainable resource utilization and carbon reduction.

Table 3: Smart Energy Grids & Renewable Integration

Metric	Before AI	After AI	Impact
Grid efficiency (%)	78	90	+12%
Renewable energy usage (%)	22	34	+12%
Emissions per kWh (grams CO_2)	500	430	−14%

Source: Biswas et al. (2025) [26]

The implementation of AI in smart grid management leads to a total 12% increase in grid efficiency, a 12% increase in renewable energy penetration, and a 14% decrease in CO_2 emissions per kilowatt-hour (kWh). The benefits demonstrate the crucial role that AI has in achieving clean energy transition. Artificial intelligence algorithms allow for real-time prediction of electricity demand and supply, load balancing optimization, and real-time response to variability from intermittent renewable sources such as solar and wind. This leads to a more stable and responsive grid and reduced dependence on high-emitting peaking power plants based on fossil fuels. In addition, AI-driven forecasting optimizes decision-making in peak shaving, deployment of storage, and demand response programs. The outcome is not only a more responsive and reliable energy system, but one that actually foresees and drives decarbonization. With increasing numbers of regions enforcing electrification and integrating renewables, AI comes to be the key enabler of sustainable low-carbon power systems.

Table 4: Environmental Monitoring & Pollution Control

Application Area	Baseline	AI System Output	Impact
Urban air quality (AQI)	Manual sensors (~170 avg)	AI + IoT (~140 avg)	17% improvement
Water pollution detection	Periodic lab analysis	Real-time satellite + AI	90% faster detection
Plastic leakage tracing	None	AI + remote sensing	Enabled global mapping

Source: Global Environmental Solutions (2024) [27]

AI-enhanced environmental monitoring yields a 17% improvement in average urban Air Quality Index (AQI), accelerates water pollution detection nearly tenfold, and enables real-time, global-scale tracking of plastic leakage. These outcomes underscore AI's transformative impact on environmental governance and public health. By leveraging AI-integrated IoT sensors, satellite imagery, and machine learning algorithms, authorities can shift from reactive to proactive monitoring systems. The decline in AQI values is caused by improved identification of sources of pollution and timely response, which contributes to urban habitability. In water quality management, conventional laboratory analysis is substituted by AI algorithms that translate remote sensing and biosensor data, enabling real-time identification of chemical pollutants and biological agents. In addition, AI-based satellite analysis enables global organizations to map plastic waste density in oceans and rivers with unheralded accuracy and frequency. These technologies give the granularity of data and spatial-temporal scope required for timely policy response and enforcement so that governments and NGOs may create more precise, evidence-based interventions to deal with air, water, and plastic pollution.

Table 5: System-Level & Economic Benefits

Indicator	Without AI	With AI	Impact
Global GDP growth (%)	Baseline	+4.4%	Operational efficiency gains globally
Global CO_2 emissions (Gt)	53	50.6	~2.4 Gt reduction via AI optimization
Corporate GHG growth (%)	+2.5%	+1.2%	Emission growth rates halved

Sources: PwC (2020) and IEA (2023) [5]

The use of AI for green management generates a 4.4% rise in world GDP potential and a reduction of 2.4 gigatonnes in CO_2 emissions based on reasonable macroeconomic and environmental projections. At the enterprise level, the firm growth rates in greenhouse gas (GHG) decline from 2.5% to 1.2%, reflecting that operational efficiencies with AI equally address environmental sustainability and profitability. These dual bottom-line gains are byproducts of the synergistic effect of AI investments—efficiency, waste elimination, and automation of processes save cost while also achieving net-zero goals. Supply chain optimization, intelligent logistics, and emission forecasting AI models minimize overproduction, enhance demand forecasting, and automate energy-intensive processes, generating quantifiable carbon and cost savings. In addition, multinationals have (e.g., Siemens, Bosch) achieved 15–30% cost savings by applying AI to environmental management and energy saving, confirming the economic efficiency of green AI initiatives. This set of economic and environmental returns indicates that AI will be a key driver for sustainable development goal (SDG) realization in ensuring competitive advantage

Table 6: Meta-Analysis Summary (2018–2024)

Domain	Energy ↓ (%)	CO_2 ↓ (%)	Cost ↓ (%)	n
Smart Energy Grids	14.6	11.3	9.1	17
Industrial Automation (AI + IoT)	18.2	15.5	12.7	21
Smart Buildings (HVAC + AI)	16.5	13.2	11.4	12
Predictive Maintenance	9.8	7.6	6.4	14
Environmental Monitoring (Air/Water)	–	6.9	–	18
Waste Management (AI routing)	12.4	10.5	7.9	10

Source: Zhou et al. (2023) [25]

The 92 industry reports and peer-reviewed articles meta-analysis identifies AI integration as a common sustainability practice with measurable metrics. To put it succinctly, the average fall of 14.3% in energy and 10.5% in CO_2 emissions indicates the extensive adoption of AI in minimizing environmental impacts in industries such as smart grids, industrial automation, building control, and predictive maintenance. Additionally, cost savings of 6.4–12.7% do not only include the enhancement of efficiency but also enhanced asset longevity and operation resilience. Of special note in this context is enhanced performance of hybrid AI architectures like CNN-LSTM hybrids and deep neural networks with fuzzy logic compared to traditional machine learning models by 8–12% in green performance. This demonstrates that as AI architectures evolve in complexity, so too does their ability to model nonlinear environmental systems and optimize sustainability parameters. Overall, the findings highlight AI's systemic role as a cross-sectoral enabler of both environmental stewardship and operational cost efficiency.

Table 7: Environmental Cost of AI

AI Application	Carbon Emissions	Water Use
GPT-3 (training)	~552 tons CO_2	~700,000 liters
Single AI search/query	2–5 grams CO_2	0.5–1.2 liters

Source: Strubell, E., Ganesh, A., & McCallum, A. [28]

Training a single massive AI model such as GPT-3 releases approximately 552 tons of CO_2—five cars' lifetime emissions—and uses approximately 700,000 liters of water that is mainly dedicated to cooling data centers. Although an individual AI operation, like an individual search query, has a lesser environmental impact (2–5 g CO_2 and ~1 liter water), because they exist in tremendous numbers worldwide, their collective impact is the problem. This figure highlights the unseen environmental expense of AI and demands the acceptance of green computing practices, including the use of renewable energy and energy-efficient optimization of models, in order to render AI programming greener.

3.2. Case Study Evidence: Integrated AI Applications in Environmental Sustainability

To supplement the meta-analytic results, we present three exemplar real-world case studies that demonstrate the transformative effects of AI integration in enhancing energy efficiency, emissions reductions, and economic performance by industry sector. Siemens at its Amberg electronics factory in Germany launched an AI-based energy optimization system using Long Short-Term Memory forecasting and reinforcement learning to assess real-time inputs from more than 1,200 sensors integrated into HVAC, lighting, and equipment systems. This intervention achieved a 17.8% decrease in energy consumption, a 12.5% reduction in CO_2 emissions, and a 23% increase in operating uptime with ROI achieved in 1.9 years (Siemens AG, 2021) [30]. Infosys implemented a smart building management system at its Mysore and Bangalore campuses in the Indian context based on AI developed on the foundation of Python and TensorFlow over a centralized Building Management System (BMS). The AI dynamically regulated occupancy-based climate control and energy loads, leading to 31% energy saving, 21% GHG emissions saving, and 14% water savings. These projects were largely the reason for Infosys's success in becoming carbon neutral in 2020 with a projected return on investment (ROI) of 2.1 years (Infosys Ltd., 2020) [31]. At the same time, Google collaborated with DeepMind [32] to implement deep reinforcement learning and Bayesian optimization on cooling equipment in its data centers in the U.S. The AI system used historical and real-time thermal data to lower cooling set-points, bringing a 40% reduction in cooling energy usage, a 15% overall decrease in energy usage, and an 18% decrease in operational emissions, achieving an instant ROI of 1.4 years (Google DeepMind, 2018). These examples repeatedly illustrate how AI systems—especially those created for real-time feedback, control, and high-frequency data processing—are able to deliver enormous environmental advantages and quick economic payback. Additional comparative studies also demonstrate that energy saving is most pronounced where AI engages most directly with mechanical gear (e.g., HVAC or chillers), and the sophistication of the AI model (e.g., reinforcement learning) is in proportion to performance enhancement. This empirical basis warrants building an AI-Green Value Framework (AIGVF), considering that the sustainability impacts are fueled by the use of AI type, sectoral context, data setting, feedback loops, and the occurrence of constraints like model carbon footprint, data quality, and ethical regulation.

Table 8 Integrated Case Study Summary: AI Applications in Environmental Sustainability

Company	Country	Sector	AI Application	AI Techniques Used	Energy Saved (%)	CO_2 Reduced (%)	Other Benefits	ROI (Years)

Siemens	Germany	Manufacturing	AI-based energy management for HVAC, lighting, and equipment	LSTM forecasting, Reinforcement Learning (RL)	17.8%	12.5%	23% increase in uptime	1.9
Infosys	India	Smart Buildings	Intelligent building automation system (BMS integration)	TensorFlow-based ML, Python-driven control loops	31%	21%	14% water savings; Carbon Neutral in 2020	2.1
Google/DeepMind	USA	Data Centers	AI-optimized cooling and thermal control	Reinforcement Learning + Bayesian Optimization	15%	18%		

Case study synthesis reveals that AI provides a substantial gain in business and environmental performance. Energy savings were between 15% and 31%, while CO_2 emissions reductions were between 12.5% and 21%, with ROIs of between 1.4 and 2.1 years, indicating high economic feasibility. Infosys achieved maximum impact through smart building automation, and Google's sophisticated AI was highly efficient in data center cooling. Siemens achieved energy savings balanced with higher uptime. In all, AI is a robust sustainability and cost-effectiveness enabler across industries.

3.3. Skills Gap and Governance Gaps

72% of the sustainability professionals have moderate-to-severe digital skill gaps, based on Reuters (2024) [29]. Additionally, the companies surveyed had full disclosure of AI model life cycle environmental impacts only 15% of the time.

CONCLUSION

The ecological impact of artificial intelligence is now no longer insignificant. As illustrated, the training of behemoth models such as GPT-3 can release more than 550 tons of CO_2 and use hundreds of thousands of liters of water, while even the most rudimentary AI operations such as single search queries add to a mounting expanding world energy load. These facts demonstrate the twofold character of AI: it is instrumental in ushering in sustainable solutions across sectors like energy, manufacturing, and pollution control, yet it has a heavy environmental cost during development and deployment. Without prudent regulation and eco-friendly design, the rapid expansion of AI may inadvertently exacerbate the same ecological problems that it aims to solve.

RECOMMENDATIONS

In order to align AI innovation with environmental sustainability, a multi-faceted approach must be followed. First, green AI practices like model pruning, federated learning, and training optimization need to become the standard in order to minimize the energy demands. Second, cloud providers and AI labs need to transition to renewable energy sources and implement transparent carbon tracking at points along the AI life cycle. Third, research centers and policymakers need to include environmental KPIs in the evaluation of AI projects and encourage energy-friendly algorithm design standards. Last but not least, developers and users need to be educated about the environmental consequences of AI in order to enable responsible consumption at every point within the digital ecosystem.

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