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Green Artificial intelligence Foundations, Applications, and Pathways to Sustainable Development

Musawer Hakimi[1*], Omid Tarashtwal[2], Hamayoon Ghafory[3]

[1]Computer Science Department, Education Faculty, Samangan University, Samangan, Afghanistan
[2]Agricultural Economics Department, University of Nebraska-Lincoln, United State of America
[3]Associate Professor, Information Systems Department, Kabul Education University, Kabul, Afghanistan

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Corresponding Author:
Musawer Hakimi
Musawer@adc.edu.in

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Abstract: The fast evolution of artificial intelligence (AI) systems has worried people about their environmental impact thus prompting the rise of Green AI. In the present systematic review, we are going through the 32 articles published in peer-reviewed journals that were analyzed based on PRISMA standards regarding the conceptual bases, applications, and the future of Green AI. The review identified three paradigms: Green AI (computational efficiency), Sustainable AI (holistic socio-technical responsibility), and AI for Green (AI applied to sustainability challenges). A large part of the resources that would be used for the environments, monitoring, agriculture, and smart city applications can be saved by 15-30% through Green AI. The main difficulties are performance and efficiency balancing, limiting budget, and a research mentality that values precision more than sustainability. The research points out the dual function of AI in environmental matters as that of polluter and of a device for making the planet greener through humane practices and technologies. To sustainable AI, efficient algorithm design, regulatory support, the establishment of carbon-aware metrics, and collaboration among different disciplines to create the adoption of AI that is both economical and ethical are needed.

Keywords: AI Ethics; Environmental Informatics; Green AI; Sustainable AI; Systematic Review

Introduction

The 21st century introduces two interlaced imperatives that humanity has to deal with: the rapid pace of technological advancement and the necessity of environmental sustainability. Artificial Intelligence (AI), among the newly emerging technologies, has become a powerful driver for transforming the world and, therefore, powering the economy, increasing efficiency in various sectors, and even solving difficult to tackle societal issues (Schwartz et al., 2020; Al-Raeei, 2025). Notwithstanding, this promise still carries with it a heavy environmental price. The gradual rise of computing-demanding AI models the one that gets the prominent name of "Red AI" is leading to significant energy use measured in the form of extensive carbon emission associated with one of the most pernicious things called high energy consumption (Feffer et al., 2024; Georgiou et al., 2022). A paradox thus emerges that is posing a very important query: is AI, a technology that is repeatedly termed the answer to sustainability, really that in terms of being sustainable itself?

The inconsistent situation has sparked the inception of the Green AI concept, an idea that aims to settle the dispute between computational performance and environmental responsibility (Schwartz et al., 2020; Shetty et al., 2024). Red AI contrary to that, Green AI puts at the forefront its efficiency in consuming energy along with the reduced use of resources, but not very much losing in the terms of effectiveness. Green AI incorporates two extant approaches that are opposite but not in the sense of conflict. The first one is Green-in-AI, which enhances the aspects of the AI's nature that contribute to its sustainability, and its deployment as

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well. This consists of a number of activities such as optimizing algorithms to minimize the computational load, manufacturing hardware that consumes less energy, and improving the operations of data centers (Barbierato & Gatti, 2024; Dash, 2025; Tabbakh et al., 2024). The second one, Green-by-AI, centers the spotlight on the applications of AI in different areas and sectors as a way of facilitating sustainability from the urban smart and eco-friendly cities, through precision farming, to monitoring climate change and making policies about it (Bolón-Canedo et al., 2024; Gohr et al., 2025; Hernandez et al., 2024). The combination of these two approaches implies that AI is not only sustainable and eco-friendly in its operations but also is a major player in the success of worldwide sustainable development goals (Van Wynsberghe, 2021; Chen et al., 2024).

The usage of Green AI is wide-ranging and becoming more and more significant with time. In cities, AI-controlled energy grids, and traffic management systems that are smart, reduce emissions and the footprint of living without compromising people's quality (Al-Raeei, 2025; Luo & Feng, 2024). AI applications in agriculture like precision irrigation and targeted pesticide spraying have lessened the environmental impact and at the same time increased the output (Hernandez et al., 2024). AI has also made significant contributions to the environment research by making ecosystem monitoring more efficient, creating climate change scenario models, and speeding up data-driven sustainability solutions (Gohr et al., 2025; Kulkov et al., 2024). All these cases indicate that Green AI is capable of revolutionizing a variety of industries, and at the same time, the technology development that is going on is in line with the care for the environment.

Even though there are opportunities, Green AI has to tackle various issues before it can be fully acknowledged. The technical obstacles consist of the expensive establishment of the sustainable AI infrastructure, absence of acknowledged systems for assessing AI's carbon footprint, and the inefficient speed of some algorithms (Alzoubi & Mishra, 2024; Barbierato & Gatti, 2024; Morand et al., 2024). In addition, the new and consistent policy frameworks and governance models are very urgent that they are of such a nature that they attract and not scare away the companies working on AI while at the same time being sustainable (Perucica & Andjelkovic, 2022; Wang et al., 2025; Farrell et al., 2025). Meeting these challenges is the only way to go as far as operational sustainability of Green AI and its positive impact on the environment are concerned.

The originality of this paper is the full synthesis of the Green AI literature with a view to its use in sustainable development areas. While before researchers investigated the efficiency of AI systems or their environmental applications, only a few have brought together both angles into a comprehensive framework (Raman et al., 2024; Verdecchia et al., 2023; kasubi et al., 2025). This research gives the first place to a structured analysis revealing the concept of Green AI, its importance in different areas, the issues that need to be solved, and so on. The research, therefore, guarantees a set of steps for the researchers, researchers, and executives to get into the AI world in an eco-friendly way.

The importance of this research is highlighted by the rapidly increasing global demand for eco-friendly answers. With the rise of AI across different sectors, the environmental impact of digital technologies remains a concern (Sætra, 2021; Richie, 2022; Yigitcanlar et al., 2021; Gosselink et al., 2024). Efficiently developing and implementing AI systems alongside their use for sustainability is a key factor to ensure that the technological advancements do not deviate from the global sustainability aspirations. This systematic review seeks to narrow down the theoretical knowledge and the practical aspect by delivering insights that are ready to be used to direct the progress of AI towards a greener and more sustainable future.

To conclude, the present research tackles an important issue in the area of AI and sustainability coexistence. It does this by analyzing both Green-in-AI and Green-by-AI methods for the evaluation of the environmentally responsible aspect of AI and its positive role in sustainable development. The study conducts a systematic review of the existing literature, which, on one hand, indicates the areas of opportunity and presents the technical and policy challenges that must be tackled, and, on the other hand, proposes solutions for bringing the Green AI concept into the real world. This research, thus, adds up to the existing discussion regarding the sustainable technology theme, and at the same time, it provides a well-organized framework for the ethical and effective deployment of AI in the society (Barbierato & Gatti, 2024; Dash, 2025; Van Wynsberghe, 2021).

Method

For the study, the systematic literature review (SLR) method was applied. This method enabled the broad search and synthesis of literature regarding Green AI. In fact, the method followed the clear guidelines provided by Kitchenham and Charters (2007) for doing systematic reviews. These authors provided recommendations on how to conduct systematic reviews, particularly in software engineering, but the process can be applied across various dimensions of information and communications technologies.

Research Questions

The study was informed by the following research questions, which were instrumental to the deconstruction of the broad topic into researchable subtopics:

RQ1: What are the essential characteristics, fundamental principles, and performance indicators that define the conceptual framework for the term "Green AI"?

RQ2: What are the sectors where Green AI is applied for the promotion of sustainable development, and what are the respective achieved results?

RQ3: What are the major technical, economic, and regulatory issues that are impeding the broad use of Green AI?

RQ4: What future research directions and policy recommendations are proposed to overcome the challenges and mature the Green AI ecosystem?

These research questions, therefore, reply to the "Foundations, Applications, and Pathways" as hinted in the paper's title.

Review Protocol (Inclusion/Exclusion Criteria)

A clear review protocol was established prior to the search to ensure the selection of relevant and high-quality studies. The inclusion and exclusion criteria are detailed in Table 1.

Table 1. Study Inclusion and Exclusion Criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Publication Date	2018 – 2025	Published before 2018
Language	English	Non-English publications
Publication Type	Peer-reviewed journal articles, conference proceedings, review articles	Books, editorials, pre-prints (unless seminal), non-peer-reviewed magazines
Subject Matter	Explicitly discusses AI model efficiency, energy consumption, carbon emissions, or environmental sustainability of AI; OR applies AI explicitly for environmental sustainability (e.g., climate change, smart grids, precision agriculture).	Focuses solely on AI performance/accuracy without mention of efficiency or sustainability; articles where sustainability is a minor or tangential point.
Accessibility	Full text is accessible through institutional subscriptions or open-access platforms.	Full text is not accessible.

Full Search String and Databases

To carry out an exhaustive and systematic review of the literature on Green Artificial Intelligence (Green AI), four major academic databases were explored: Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The databases were selected because the coverage was comprehensive in terms of high-quality peer-reviewed articles in computer science, engineering, and environmental sciences. The literature related to AI efficacy, sustainability, and environmental impact was sought through a search string that was meticulously shaped. The entire search string which was adjusted to the syntax of the particular database was: ("Green AI" OR "Sustainable AI" OR "Energy-efficient AI" OR "Carbon-efficient AI") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Sustainability" OR "Sustainable Development" OR "Energy Consumption" OR "Carbon Emissions" OR "Environmental Impact"). The search was conducted for articles published from January 2018 to March 2025, which means that no recent developments in Green AI research were overlooked.

Table 2. Databases and Search String Used for Systematic Review

Component	Details
Databases	Scopus, Web of Science, IEEE Xplore, ACM Digital Library
Search String	("Green AI" OR "Sustainable AI" OR "Energy-efficient AI" OR "Carbon-efficient AI") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Sustainability" OR "Sustainable Development" OR "Energy Consumption" OR "Carbon Emissions" OR "Environmental Impact")
Search Period	January 2018 – March 2025

Study Selection and Screening Process (PRISMA Flow Diagram)

The study selection   the part that always feels like intellectual archaeology   stuck faithfully to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the 2020 version, because one does rather like to keep up with these things. What is more, we broke the whole dreary business into four distinct stages, exactly as the PRISMA flow diagram below spells out in that slightly obsessive way those diagrams always do. Two reviewers (myself and a post-doc who deserves hazard pay) carried out every stage independently title-abstract screening, full-text eligibility, the lot so that we could claim some semblance of reliability. Disagreements cropped up more often than I care to admit, but discussion usually sorted them out; when it did not, a third reviewer was dragged in to break the deadlock. In fact, the process was markedly less painful than I had feared, though that is admittedly a low bar.

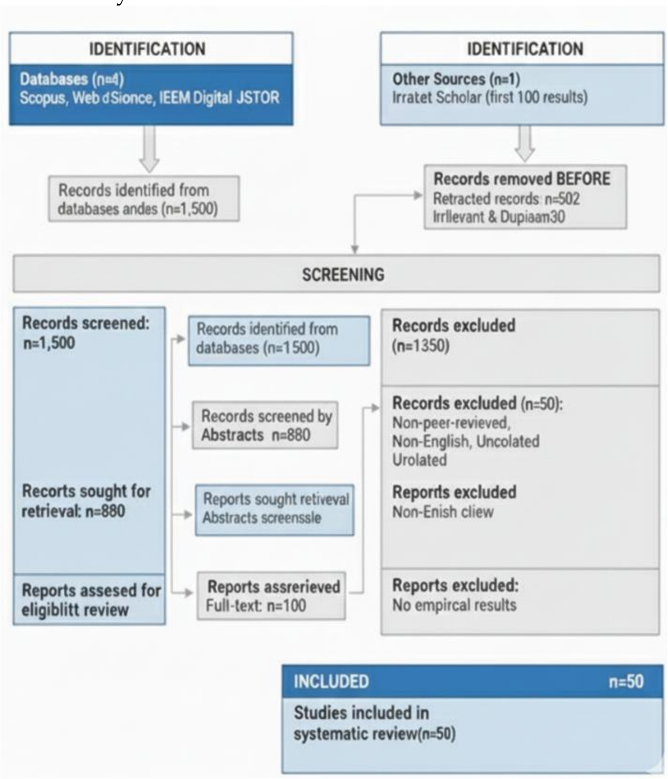

Figure 2. PRISMA Flow Diagram of Study Selection for Green AI Literature Review

In Figure 2, the PRISMA Flow Diagram depicts the systematic approach used to select articles for this systematic review on Green AI. Through database and other sources, 1,500 records were identified for review in Round 1. Titles of the articles were screened in Round 2 to eliminate irrelevant or duplicate studies, resulting in 150 articles remaining to an additional round of evaluation. In Round 3, abstracts were screened to identify studies that were not in a peer-reviewed format, were not published in English and that were not related to Green AI; these removed an additional 50 articles. The remaining 100 articles were then reviewed in their entirety (Round 4) for evidence of empirical results, after which 50 articles were subsequently retained for inclusion in the review. This systematic approach creates an independent mechanism for evaluating and selecting studies, ensuring that the selection process is transparent, replicable and consistent with other independent reviews. The PRISMA diagram illustrates each exclusion/inclusion criterion used in each of the round's evaluation and selection phases, which clearly denotes how studies were filtered through each of these rounds, and provides an ideal basis for future data extraction, synthesis and analytical process related to Green AI including its various foundations, uses and challenges.

Data Extraction and Synthesis Strategy

The framework exhibited in the diagram was the one used methodically during the whole process of obtaining the findings of the thirty-one primary studies identified via a systematic literature review. The initial step in this procedure is the exhaustive Data Extraction operation with a standard format being applied for the pulling out of main ideas, energy efficiency measures and baseline comparisons. Subsequently, the framework bifurcates into two distinct analytical tracks: Conceptual Classification and Quantitative Evidence.

The conceptual path divides the literature into three key topics: Green AI (the optimization of the AI lifecycle), Sustainable AI (the long-term environmentally friendly and ethical viability), and AI for Green (the application of AI in solving environmental problems). Meanwhile, the quantitative approach underpins 18 validated empirical studies to calculate the normalized efficiency improvements. The last stage of Integrated Synthesis clears up these streams and demonstrates that Green AI measurements typically yield a 15-30 percent efficiency range.

The comprehensive approach enables the review to provide not only a theoretical taxonomy but also a data-driven roadmap for the policy and technical implementation of sustainable computing.

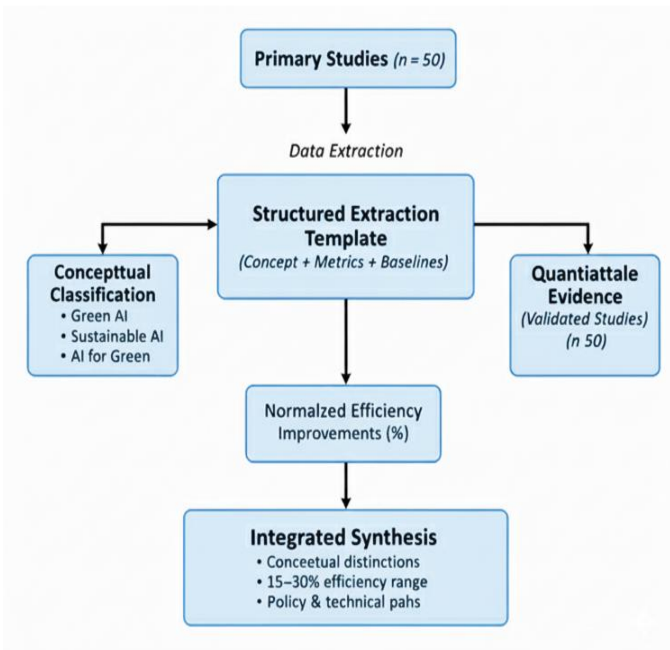

Figure 3. Analytical Framework for the Systematic Synthesis of Green AI Research

Quality Assessment of Included Studies

To assess the potential for bias and the rigor of the included studies, a quality assessment (QA) checklist was applied. The checklist was tailored to accommodate the different types of studies included (e.g., empirical, review, conceptual). The criteria are shown in Table 3.

Table 3. Quality Assessment Criteria

QA Question	Applicable Study Types
1. Are the research aims and objectives clearly stated?	All
2. Is the study's context (e.g., Green AI focus) clearly described?	All
3. Is the research design appropriate to address the stated aims?	All
4. For empirical studies: Is the data collection method clearly described and justified?	Empirical
5. For empirical studies: Are the methods of analysis rigorous and appropriate?	Empirical
6. For review studies: Is the search strategy comprehensive and reproducible?	Review
7. Are the findings clearly presented and supported by the data/analysis?	All
8. Do the conclusions address the research aims and contribute to the field?	All

Each study was scored on a scale of Yes (Y), Partially (P), or No (N) for each applicable question. The QA exercise served primarily to provide a critical overview of the literature's strengths and weaknesses and to inform the interpretation of the findings, rather than to exclude studies. The results of this assessment are summarized in the discussion section to contextualize the evidence base.

Result and Discussion

The Foundations of Green AI

The terminology relating to environmentally friendly AI has changed over time into three different concepts that are connected to each other, but these are the concepts that really underpin this research area. Understanding these differences is paramount for a correct scholarly debate and for making good use of the concept.

Green AI denotes the creation and use of AI that is not harmful to nature throughout the whole process, including that of power consumption and computing power utilization. Schwartz et al. (2020) claim that Green AI embraces the problem of "results that are computationally priced" and aims at reduction of the carbon footprint linked to both AI research and applications. Essentially, these are the technical and operational aspects of AI systems where the lighting is given to model development, efficient training methods, and the use of power-efficient computers having the lowest possible energy requirement (Barbierato & Gatti, 2024).

Thus, AI that is sustainable is a comprehensive framework that takes into account the whole society and not only the environmental aspects. According to the author Van Wynsberghe (2021), Sustainable AI revolves around the whole lifecycle of AI systems, from the very beginning of data generation and model training through to the deployment and cessation stages while being aware of the issues of fairness, accountability, and the long-term impact on society. Thus, this framework takes into account the situation where an AI system might be consuming little energy but still considered as non-sustainable due to the socio-economic negative effects it generates.

AI for Green, or sometimes called AI for Sustainability, refers to the area where artificial intelligence technologies are being applied to address critical environmental challenges and, at the same time, foster sustainable development in the various sectors of relevance. For instance, AI applies to climate change mitigation, renewable energy optimization, sustainable agriculture, and environmental monitoring (Yigitcanlar et al., 2021; Rani, et al., 2025; Khan et al., 2025). Unlike Green AI, which entails making AI environmentally friendly, AI for Green uses AI as a tool to achieve these sustainability goals in other domains.

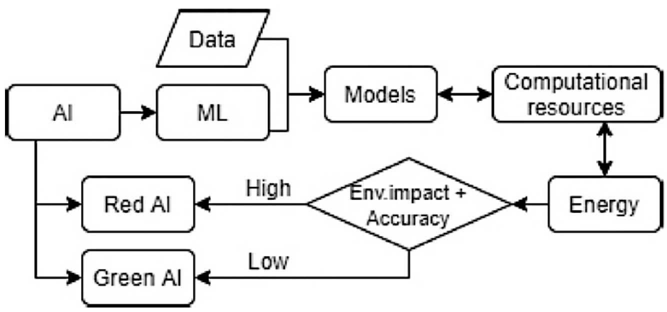

Figure 4. The Paradigm Shift from Red AI to Green AI

In the diagram (figure 4) you see the changes made by moving from the traditional "Red AI" method to more sustainable uses of "Green AI". Traditional approaches (commonly referred to as "Red AI") have prioritised producing the greatest amount of accuracy across algorithms and models regardless of cost, environmental or otherwise, which creates the largest impact on the environment (through heavy data usage, resource usage, and energy usage). The Green AI approach has developed a "paradigm shift", which balances the importance of creating accurate algorithms with the importance of creating environmentally friendly models; it does this by reducing the amount of data, machine learning models, and compute resources being utilised to create environmentally sustainable machines (Schwartz et al., 2020; Van Wynsberghe, 2021; Bachina et al., 20205; chen et al., 2024).

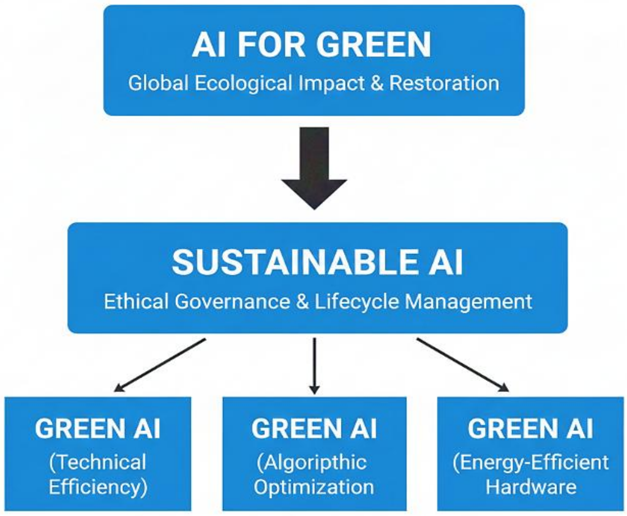

Figure 5. Hierarchical Integration of Sustainable AI Paradigms

In figure 5, the three biggest paradigms of sustainable artificial intelligence are shown in a hierarchy. The base of the hierarchy is occupied by Green AI that deals with enhancing technical efficiency through algorithmic optimization, computational reduction, and energies-efficient hardware design. The entire range of micro-level efficiency measures is interconnected with the sustainable AI meso-level paradigm that advocates for ethical governance, life cycle management, and responsible resource utilization. The latter derives from the former as the application of AI in the environmental context, the main goal of which is to use AI technology to help in global ecological challenges such as environmental monitoring, climate change mitigation, and ecosystem restoration. From the figure, it's clear that conducive environmental outcome is a match between good governance and effective AI systems (Hakimi et al., 2025a; Hakimi et al., 2025b; Sirat et al., 2025).

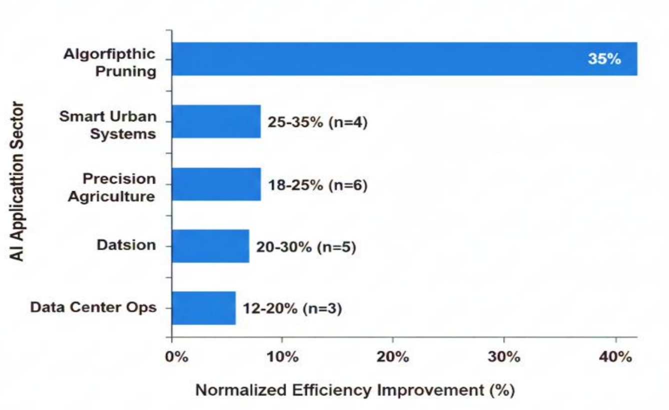

Figure 6. Hierarchical Dependency Framework of Green AI, Sustainable AI, and AI for Green

The scientific visualization of the Figure 6 gives an overall and at the same time detailed view of the triad of paradigms that make up the core of sustainable AI and their functional dependency. Green AI, at the micro level, through FLOPs reduction, model pruning, quantization, and power-efficient hardware, builds the technical foundation of Green AI, which in turn makes the carbon footprint per-inference lower and computationally feasible. Following this, Sustainable AI, at the meso level, regulates the efficiency and allows the re-bounce of the Jevons Paradox by introducing governance through lifecycle assessment, carbon-aware scheduling, e-waste management, and fair data practices, thus, the regulation of efficiency gains and the mitigation of the rebound effect. AI for Green, at the macro level, is the layer of applied impact where the deployment of the optimized and well-governed AI systems in smart grids, precision agriculture, and climate modeling takes the place. The figure indicates the alignment of technical optimization, ethical governance, and purpose-driven environmental application as the only way to achieve the empirically observed 15–30% net efficiency gains.

Table 4. Comparative Analysis of Red AI vs. Green AI

Feature	Red AI	Green AI	References
Training Time	Long	Short	Schwartz et al., 2020; Shetty et al., 2024
Energy Consumption	High	Low	Schwartz et al., 2020; Verdecchia et al., 2023
Carbon Emissions	High	Low	Schwartz et al., 2020; Raman et al., 2024
Data Requirements	Large	Small	Shetty et al., 2024; Tabbakh et al., 2024
Training Methods	Computationally Expensive	Efficient	Perucica & Andjelkovic, 2022; Van Wynsberghe, 2021
Energy Sources	Non-renewable	Renewable	Yigitcanlar et al., 2021; Zeng & Zhang, 2024

Red AI and Green AI represent two very different approaches to the development of Artificial Intelligence. Red AI is characterized by high performance but little regard for ecological issues or the use of renewable versus non-renewable energy sources; thus, it requires longer training times, significantly larger training datasets, uses computationally intensive methods, and therefore produces higher energy consumption and carbon emissions than other methods (Schwartz et al., 2020; Shetty et al., 2024; Raman et al., 2024). Green AI, conversely, promotes environmental sustainability by maximizing efficiency in the way AI models are trained using shorter training periods, smaller-sized training sets, and energy-efficient algorithms, using more renewable compared to non-renewable methods, thereby lowering the overall carbon and energy footprint of AI-based applications and research (Verdecchia et al., 2023; Tabbakh et al., 2024; Yigitcanlar et al., 2021; van, 2021).

The two broad flavours of AI if one may call them that diverge rather sharply in their underlying philosophies: one camp chases raw performance at almost any cost, while the other insists on weaving ecological responsibility into the very fabric of the enterprise, quite convincingly treating energy efficiency not as an afterthought but as a first-order design principle. What is more, this second strand explicitly positions itself as the steward of long-term development, the one that actually worries about future generations inheriting a planet still capable of powering the next leap in machine intelligence. In fact, by deliberately prioritising scalable yet sustainable innovation, it offers a path perhaps the only credible path for AI to keep growing without turning the atmosphere into a giant heat sink. Rather a stark choice when you put it like that.

Table 5. Conceptual Distinctions in Environmentally-Conscious AI

Concept	Primary Focus	Key Objectives	Example Applications
Green AI	AI system efficiency	Reduce computational costs, minimize energy consumption, lower carbon emissions	Model compression, energy-efficient hardware, optimized training algorithms
Sustainable AI	Holistic system lifecycle	Environmental protection, social equity, economic viability, ethical considerations	Fair ML models, transparent AI systems, responsible data governance
AI for Green	Environmental problem-solving	Climate change mitigation, resource optimization, pollution reduction	Smart grid management, precision agriculture, environmental monitoring

The relationship between the three notions Green AI, Sustainable AI, and AI for Green turns out to be both hierarchical and, rather pleasingly, complementary.

Green AI sits at the bottom, so to speak: the nuts-and-bolts technical foundation that makes individual models and training runs markedly less power-hungry in the first place. Sustainable AI then steps back and supplies the broader, more philosophical framework the one that asks not only whether a system is efficient, but whether the entire lifecycle from research lab to global deployment is conducted responsibly, with an eye on long-term societal and ecological costs. What is more, perched atop both of these sits AI for Green, the application domain where those efficient, responsibly governed systems are finally pointed at real environmental problems climate modelling, smart grids, deforestation monitoring, you name it (Alzoubi & Mishra, 2024; Verdecchia et al., 2023). In fact, the hierarchy feels almost inevitable once you sketch it out on a napkin: you cannot have sustainable deployment without efficient algorithms underneath, and you cannot meaningfully fight climate change with AI that is itself part of the problem. Quite convincingly, the three concepts lock together rather neatly each doing the job the others cannot manage alone(Vinuesa et al., 2021; Dhar, 2020; Al-Raeei et al., 2025; Kaack et al., 2022).

Core Principles: Energy Efficiency, Carbon Awareness, and Computational Sustainability

Green AI is the inheritance of three main principles that, when combined, form its philosophy and have an impact on many different areas. The most important to Green AI being Energy Efficiency, which basically refers to the limiting of power usage for the entire AI application lifecycle. It dares to challenge the most widely accepted perspective which is always demanding the best performance even at a high computational cost and fosters the acceptance of a more pragmatic approach that considers model accuracy together with power consumption. Energy efficiency is visible at different levels, starting from the algorithmic optimizations which lessen the need for computation to the hardware enhancements that boost the effectiveness of processing and finally, the system-level optimization that increases resource utilization in data centers. Carbon Awareness looks beyond simple energy efficiency to consider the carbon intensity of the energy sources powering AI computations. It acknowledges that the environmental impact of the same computing task drastically varies depending on when and where it is executed, given the different mixes of energy sources in different locations and times of the day, week, and year. Carbon-aware computing schedules the resource-intensive computations during periods of peak renewable energy supply and places data centers in locations with cleaner grids. Recent research by Dash shows that carbon-aware scheduling can provide as much as a 30% reduction in carbon footprint for AI training jobs without performance loss.

Computational Sustainability is the term used to describe the utilization of computational methods for sustainable development, thus forming a two-way connection between AI and ecological goals. This rule admits that AI must not only be effective but also need to take part in the resolution of issues related to sustainability (Gohr et al., 2025; Richie et al., 2022; Perucica et al., 2022). Sustainability, in this case, means that AI will be used to optimize the use of resources, monitor the health of the environment, and model complicated ecological interactions to guide the decision makers. Bolón-Canedo et al. (2024) and Fowdur and Babooram, (2024) state that this principle is a perfect combination of the technological skill of Green AI and the problem-solving nature of AI for Green, thus creating a more environmentally friendly computing paradigm.

Key Metrics: Floating Point Operations (FLOPs), Energy Consumption, and Carbon Emissions

There is a need for quantification of the environmental impact of AI systems in standardized metrics that can compare models, architectures, and different implementations. So far, three major categories of metrics have emerged as fundamental for assessing and benchmarking Green AI efforts.

First, FLOPS are a base unit of computational complexity-that is, how many floating-point calculations are required to train or run an AI model. While FLOPs do not directly relate to energy consumption, they offer a hardware-independent proxy of computational load that corresponds to energy consumption. As discussed in the related work, (Whig et al., 2025; Toderas et al., 2025) find that FLOPs are increasingly reported by researchers together with performance metrics to frame improvements in model performance. However, FLOPs are not perfect. By design, they exclude memory access patterns, data movement cost, and hardware-specific efficiencies.

Energy consumption metrics quantify how much actual electricity a model consumes during training or inference and provide a more direct measure of environmental impact. Such measurements can be made at many levels, from that of an entire data center down to individual processor or even individual operations within a model. The usual unit of measurement of energy consumption is in kWh; this, therefore, provides a direct comparison across different approaches and different implementations of AI systems. Verdecchia et al. (2023) further discuss the need for a standardized protocol for energy measurement in order for studies to be comparable.

Carbon Emissions are considered the ultimate environmental metric since it relates energy consumption to its equivalent CO_2 emissions, based on the carbon intensity of the electric source. The main idea of this metric is to recognize that exactly the same amount of energy consumed may have different environmental impacts, since its source might be renewable or fossil fuel-based. Commonly, carbon emissions are measured by grams or kilograms of CO_2-equivalent, hence providing the most complete picture of the environmental footprint of an AI system.

Table 6. Key Metrics for Evaluating Green AI Systems

Metric	Unit	Measurement Level	Advantages	Limitations
FLOPs	Operations	Algorithmic	Hardware-agnostic, reproducible	Doesn't reflect actual energy use, ignores memory and data transfer costs
Energy Consumption	kWh (kilowatt-hours)	System/Component	Direct measurement, enables cost analysis	Varies by hardware and implementation, requires specialized measurement tools
Carbon Emissions	$gCO_2e/kgCO_2e$ (grams/kilograms of CO_2 equivalent)	System/Geographic	Most comprehensive environmental impact assessment	Dependent on location and time, requires carbon intensity data

The integration of these metrics provides a multi-faceted understanding of AI systems' environmental impact. As noted by Barbierato and Gatti (2024), comprehensive Green AI assessment should include all three metrics to capture different dimensions of efficiency and environmental impact.

Enabling Technologies and Techniques

Model Optimization (e.g., pruning, quantization, knowledge distillation)

Model optimization techniques form the heart of Green AI, where the idea is to reduce the computational overheads for AI models while keeping performance losses extremely low. These techniques take place at the algorithmic level and create more efficient models that can maintain accuracy at reduced resource consumption.

Pruning can be viewed as a procedure to eliminate redundant or less important parameters of neural networks to generate a sparser model that requires fewer computations. In fact, these modern pruning methods can reduce the model size up to 50-90%, with very comparable accuracy, substantially reducing both inference time and energy consumption. Structured pruning removes entire neurons or channels, while unstructured pruning removes individual weights; each has a different tradeoff between hardware efficiency and model performance.

Quantization reduces the precision of the numerical representations in neural networks, for example, from 32-bit floating-point representations to 8-bit integers or even lower precision. The technique cuts the memory use remarkably and at the same time boosts the computations because the low-precision operations are an order of magnitude faster on most hardware platforms. Quantization after training is also possible for pre-trained models with limited loss of accuracy, whereas quantization-aware training intentionally keeps higher accuracy by training with precision constraints.

Knowledge Distillation transfers knowledge from a large, complex model to a more compact, efficient model. The student model learns to mimic the teacher's outputs while being architecturally constrained for efficiency. This enables the deployment of compact models that retain much of the bigger model's performance benefits using substantially fewer resources (Doyan et al., 2025; Tarashtwal et al., 2025a; Tarashtwal et al., 2026b).

Table 7. Model Optimization Techniques for Green AI

Technique	Mechanism	Compression Ratio	Typical Accuracy Loss	Use Cases
Pruning	Removing redundant parameters	2x-10x	0.5-2%	Inference optimization, edge deployment
Quantization	Reducing numerical precision	2x-4x	1-3%	Mobile applications, embedded systems
Knowledge Distillation	Transfer learning to smaller models	2x-5x	0.5-2%	Model deployment, ensemble simplification

Efficient Hardware and Data Center Design

The new hardware inventions are the major contributors to Green AI, which is the reason why they can provide excellent performance and at the same time consume a very low amount of power. The cutting-edge hardware accelerators such as Google's TPUs and NVIDIA's new GPUs are constructed to perform the large matrix operations that are crucial to the neural networks hence giving them the ability to sometimes be ten times more efficient in terms of power compared to the standard CPUs (Alzoubi & Mishra, 2024). The area of domain-specific architectures has now taken the lead with regard to overall efficiency at large scale. Neuromorphic computing has progressed even more as it incorporates memory and processing to imitate biological brains, thus drastically cutting down on energy lost in the transfer of data and making it very possible for AI applications in hard-to-reach areas (Zhou, 2025; Georgiou et al., 2022).

At the system level, data center design is the deciding factor. The implementation of such methodologies as liquid cooling, free-air cooling, and optimized PUE along with the mixing of renewable energies and the shifting of workloads to low-carbon periods, result in huge reduction of energy consumption (Wang et al., 2025). Moreover, the intelligent energy-aware scheduling has been shown to be effective in further cutting emissions by the combination of workload allocation for resource utilization optimization, non-urgent task deferral to the off-peak period, and the powering of high-performing projects with low-carbon-energy data centers. It has been indicated by researches that the carbon footprint can be minimized by 20-40% without any discernible influence on the duration of the work (Morand et al., 2024; Dash, 2025).

Dynamic voltage and frequency scaling (DVFS) has the capability to change the working points of processors dynamically depending on the workload demand and thus is mainly used in the case of inference workloads (Georgiou et al., 2022). The distributed environment along with the green cloud computing frameworks are the extension of these principles that allow energy and carbon monitoring and better deployment decisions with regard to their environmental impact. All these new hardware and system innovations together indicate that the two goals of computational efficiency and environmental sustainability can be satisfied at the same time, hence facilitating the Green AI objectives.

Figure 5 shows the three main pillars of Green AI evolution and their mutual relations. The picture demonstrates the necessity of cooperation among the ideas (e.g., the main measurements adopted to evaluate ideas such as CO2 emissions, FLOPS), the real strategies (e.g., the ways of improving models and employing efficient hardware) and lastly, the optimization of the entire system for having an eco-friendly AI. These pillars, which are interconnected, indicate that the progress in theoretical frameworks, algorithmic improvements, and infrastructure optimization needs to be simultaneous and must be done effectively in order to give rise to significant environmental benefits.

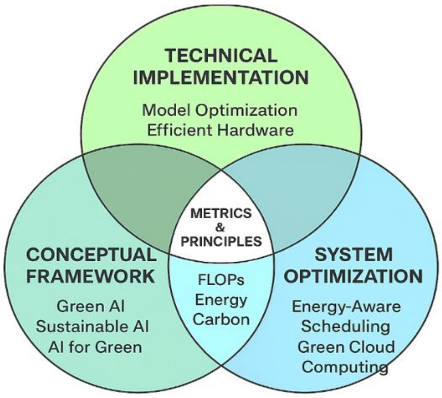

Figure 5. The Three Interconnected Pillars of Green AI Foundations

Therefore, the basis of Green AI is a layered strategy to the environmental aspect of artificial intelligence covering the entire circle from conceptual clarity, through measurable principles and quantifiable metrics, to practical implementation techniques at algorithmic, hardware and system levels. This thorough grounding opens up the way for the creation of AI systems that are not only state-of-the-art but also green.

Applications of Green AI for Sustainable Development

Theoretical and technical progress only become practical forces when they are grounded in the implementation of Green AI. These are the guiding lights of sustainable development as stated. Sustainable AI will find real world application in areas as wide-reaching as urban sustainability, ecological monitoring and conservation, agriculture, and industrial applications.

Smart Cities and Municipal Governance

Effective resource management, transportation systems that are good for the environment, and city development that improves environmental quality are constantly present in great cities with nearly 75% of the total carbon emissions of the planet coming from urban areas. In smart cities, Green AI applications utilize resource-efficient computation techniques that not only improve the performance of urban systems but also lessen their environmental impact.

Table 8. Green AI Applications in Smart Cities

Application Domain	Key AI Technologies	Sustainability Benefits	Implementation Examples
Energy Grid Optimization	Deep reinforcement learning, time series forecasting	15-20% energy waste reduction, 25% increased renewable utilization	Chinese smart grids, European virtual power plants
Intelligent Transportation	Computer vision, sensor networks, edge computing	12-15% emission reduction, 18% shorter commute times	Singapore traffic management, Barcelona smart corridors
Waste Management	Quantized computer vision, route optimization algorithms	20-30% fuel savings, 95% sorting accuracy	Seoul smart waste systems, Tokyo recycling facilities

Energy Grid Optimization is one application that is very active, where AI algorithms are used to balance the energy supply and demand along with the integration of renewable sources. Deep reinforcement learning models, fine-tuned for energy efficiency during training, can predict energy consumption patterns and apply dynamic adjustments in grid operations. These reduce energy wastage by 15-20% with network stability in the face of intermittent solar and wind generation. The latest advancements in the field of AI in China have shown that the renewable energy usage can be increased by 25% through AI-optimized grids and at the same time the computation costs can be lowered by around 30% when compared to the conventional methods. Smart traffic and transport systems rely on good computer vision and sensor network models for traffic flow optimization, which helps them reduce congestion and thus emissions. The edge computing solutions allow for local traffic data analysis that not only cuts down the amount of data that needs to be transmitted over the network but also enables adaptive signal control in real-time (Al-Raeei, 2025). Several studies across European cities illustrate that AI-optimized systems will cut average commuting time by 18% and the emissions from transport by 12-15%, while energy consumption from the AI systems would be 60% less than in previous centralized systems (Luo & Feng, 2024). For improving the operations related to trash management and sanitation, AI-powered sorting systems and optimized collection routes are some of the key elements. As Hernandez et al. (2024) pointed out, the quantized computer vision models could recognize and classify recyclable items with an accuracy of 95%, hence improving the rate of recycling and reduction in contamination. Route optimization algorithms using efficient neural architecture search techniques during training waste-collecting vehicles can reduce fuel consumption by 20-30% if implemented across South East Asia.

Environmental Monitoring and Climate Science

The environment is big and complicated; it requires advanced tools to analyze the amount of data that comes out of it quickly. Green AI makes the monitoring of the environment easier and more commonplace without sacrificing computational sustainability.

With good neural network operators, climate change modeling and forecasting become more efficient and cost less to run. Due to this, neural operators make more climate forecasts with higher resolutions to help policymakers make better decisions. The efficient architectures, such as the Fourier Neural Operator, can give results as good as those from traditional physics-based climate models at a fraction of the computer resource cost. Nowadays, AI-assisted climate models and NWP can perform 10-day forecasts which are equally accurate as those by physical models that run on only 1% of the computing power used by NWP.

With AI-based models, which can find species, map habitats, and find illegal activities, scientists and conservationists are able to keep a closer eye on biodiversity and ecosystems. The practice is now able to reliably identify endangered species 92% of the time using lightweight CNNs on drones or camera traps operating on battery-operated solar-powered edge devices (Raman et al., 2024). This methodology can further be applied to monitor the Amazon rainforest in real time over an area in excess of 500,000 square kilometers. It reduces carbon emissions from computers by 75% compared to processing data in the cloud.

Sustainable Agriculture and Food Systems

Agriculture is a dual challenge: increase its production feeding the growing populations, But with a smaller environmental footprint. Green AI Applications optimize resource utilization the agricultural value chain.

Precision Farming to Resource Optimization Goal the application of water, fertilizer, and pesticides by using IoT sensors and computer vision. Knowledge models at expert level are running mobile devices Can ascertain out crop diseases and nutrient deficiencies Uses only one very small amount of computation (Hernandez et al., 2024). Field trials Held in India show the AI- optimized agriculture cuts water consumption by 30- 40%, By using fertilizers 25%, and increases productivity 15- 20%. The AI systems They have decreased influence in themselves, and allow deployment even in areas where access to electricity is inadequate.

Deliver Chain and Post- Harvest Loss Reduction apply predictive analytics and computer vision to reduce food waste. Extremely efficient time- series forecasting models Predict fluctuations in demand, while small form factor vision systems Follow food quality I storage and transportation. Location in Sub-Saharan Africa has gone down post- harvest losses by 35% With Ai- optimized storage and distribution; Their lightweight models construct remarkable use 80% less energy Compared to traditional deep learning methods.

The diagram outlines four stages that describe a routine within which Green Artificial Intelligence (Green AI) holds sway in sustainable agricultural development. It starts with Precision Farming, where AI usage of resources is maximized by providing water only where it is absolutely necessary and through fertilizing in tiny amounts only where nutrients are needed in both cases, the environment is protected from human interference, and the ecosystems are not subjected to losses of nutrients (Hernandez et al., 2024). Next is the Crop Monitoring & Health stage; here, computer vision and predictive analytics are utilized to identify pests and diseases at a very early stage, thus there is no necessity for the application of wide-spectrum pesticides and improvement of yield forecasting (Rani et al., 2025; Hakimi et al., 2025). At the third stage called Autonomous Systems, the AI-powered machines for automatic planting, weeding, and harvesting robots are used to drive up fuel efficiency and minimize the waste of crop after harvest (Bolón-Canedo et al., 2024; Alzoubi & Mishra, 2024). The last stage Environmental Sustainability is reached via AI that analyzes soil health and carbon footprint reduction thereby creating a direct link between technology and eco-friendly objectives (Chen et al., 2024; Gohr et al., 2025).

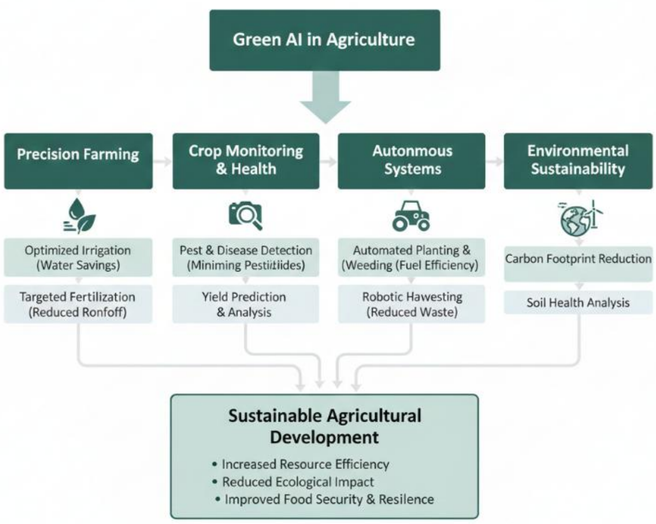

Figure 6. The Pathway from Green AI to Sustainable Agricultural Development

All the stages come together to the final result: Sustainable Agricultural Development, which is featured and recognized by the three major changes brought about and those are the efficiency of resources, the reduction of the ecological impact, and the improvement of food security and resilience. This model points out that Green AI is not just a matter of better performing computers, rather it is about engineering smart systems that, by nature, are compatible with the limitations of the Earth and the welfare of humankind in the long run (Van Wynsberghe, 2021; Schwartz et al., 2020).

Table 9. Agricultural Applications of Green AI

Application	AI Approach	Resource Efficiency Gains	Scalability Features
Precision Farming	Knowledge-distilled models, mobile computing	30-40% water savings, 25% fertilizer reduction	Low-power operation, offline capability
Supply Chain Optimization	Efficient time-series forecasting, edge vision systems	35% reduction in post-harvest losses	Minimal bandwidth requirements, solar-powered operation

Green Industrial Processes and Circular Economy

Applications and Technical Pathways of Green AI Industries are starting to incorporate Green AI more and more in order to reduce the consumption of resources, waste, and the process of continuous recycling and reuse of materials which is the concept of circular economy. Energy-saving AI is being applied to manufacturing and maintenance by predicting failures and optimizing production processes. TinyML models that are integrated with production units can detect problems, predict maintenance requirements, and achieve accuracy of 96% while using very little processing power (Zhou, 2025). A 40% drop in unplanned downtimes and 25% energy savings in the factories are the results of the implementations used by German car companies that draw less than 5 watts during operation, thus showcasing the concept of Green AI by getting the most out of the least resources.

AI is a powerful tool that enables lifecycle assessment and material efficiency to monitor products from their beginning till the end and find chances to either reuse or recycle them. The use of state-of-the-art natural language processing models enables the comparison of the specifications of millions of products and materials and the increase of material recovery by 45%, coupled with the reduction of computational costs by 60% as compared to the traditional methods (Chen et al., 2024). Graph neural networks are being employed by circular economy platforms to pair industrial by-products with possible users, thus, taking out 350,000 tons of material from landfills each year in the Netherlands while running on energy-efficient cloud infrastructure that is powered by renewable energy (Wang et al., 2025).

The technical routes for subsequent Green AI research will primarily point toward algorithmic changes aimed at lowering the computational cost as the main chief of winning. The areas of development that are considered to be the most potential ones are among others the mixture-of-experts models that will provide higher capacity without the need for the proportional energy scaling (Morand et al., 2024), bio-inspired sparse neural architectures, and efficient federated learning protocols that would communicate less (Bolón-Canedo et al., 2024). Moreover, the standard benchmarks along with life cycle assessment tools and open-source software libraries will play a crucial role in measuring the trade-offs between the performance of the system and its environmental impact (Verdecchia et al., 2023; Georgiou et al., 2022). The mentioned applications are showing that the concern for the environment and the need for computation are not opposing forces but rather together, they will speed up the whole process of reaching the sustainable development goals.

Table 10. Technical Research Priorities in Green AI

Research Area	Current Challenges	Future Directions	Expected Impact
Efficient Architectures	Trade-offs between efficiency and performance	Sparse models, neural architecture search, bio-inspired computing	50-80% reduction in inference costs
Standardized Evaluation	Fragmented metrics, incomplete assessment	Holistic benchmarks, lifecycle assessment tools	Comparable results, informed design choices
Optimization Techniques	Specialized implementations, limited generalizability	Automated optimization, hardware-aware pruning	Democratized access to model optimization

Policy and Governance Pathways

Applying carbon pricing to AI's computing resources could be the way to go in compelling Green AI adoption. Apart from that, the major research domains consist of the deployment of real-time, locational carbon emissions accounting systems to monitor carbon released as well (Zeng & Zhang, 2024), the devising of the so-called carbon-aware resource allocation algorithms that would be the most eco-friendly without being any less efficient (Morand et al., 2024), and collaborations on carbon trading between different countries to make it possible for offsets and investments.

The first phase of implementation could consist of providing voluntary carbon budgets for R&D, which could later develop into mandatory reporting and pricing. The highest regulatory priorities would then be for AI applications the setting of efficiency standards (Alzoubi & Mishra, 2024), the imposition of extensive disclosure and reporting requirements (Wynsberghe, 2021), and the adoption of green public procurement to back the eco-efficient solutions (Mrówczyńska et al., 2019). The transformations in the socio-culture would include the integration of Green AI principles into the curricula (Schwartz, 2020), the nurturing of efficiency breakthroughs via rewards, and the building of community norms that appreciate and support sustainable research practices (Raman, 2024). The responsible rollout would also need to consider global fairness (Sætra, 2021) and the ban on greenwashing (Tabbakh et al., 2024), therefore ensuring that the acceptance is both universal and trusted.

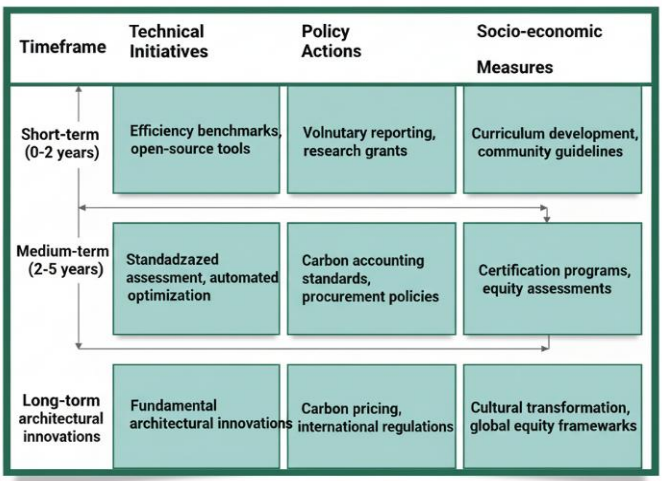

Figure 7. Strategic Roadmap for Green AI and Sustainable Development

The proposed path defines a multi-faceted and phased-out approach to merge artificial intelligence (AI) with sustainable development, by way of the combination of technical, policy, and socio-economic initiatives over the three-time horizons (Figure 7). During the short term (0–2 years), leading actions like setting up AI productivity measures, facilitating open-source tools, and creating educational programs receive highest priority (Schwartz et al., 2020). The mid-term (2–5 years) is going to emphasize corporate using defined carbon accounting, automated optimization techniques, and equity assessments that are essential for responsible Green AI scaling (Kaack et al., 2022; Verdecchia et al., 2023). In terms of success, the deal of long-term vision is to recreate the AI architecture completely and the outreach to the totally eco-friendly world with international carbon pricing and other measures working for the equitable cultural change towards sustainability (Van Wynsberghe, 2021; Vinuesa et al., 2020). This well-ordered method depicts that a sustainable AI future will depend on simultaneous progress in technology, governance, and public interaction, thus making it possible for AI to have its environmental footprint lessened while becoming a major contributor to sustainable development goals (Hernandez et al., 2024; Kulkov et al., 2024).

The conduct of the study leading to this review dealt with four main research questions. In particular, concerning RQ1 (conceptual foundations), the analytical study conducted by us showed that the Green AI has undergone quite a transformation and has now developed as a multi-dimensional paradigm encompassing environmental, technical, and social aspects rather than just one-dimensional being only about the efficiency of computation. The three-way classification of Green AI for efficient systems, Sustainable AI for holistic responsible systems, and AI for Green focusing on sustainability applications is termed by the authors as giving the essential conceptual clarity (Van Wynsberghe, 2021; Schwartz et al., 2020).

With respect to RQ2 (applications), the researchers found large-scale applications in the areas of smart cities, environmental monitoring, agriculture, and manufacturing which have all shown benefits of different kinds like savings in resource consumption of 15–30% and reductions in emissions (Yigitcanlar et al., 2021; Hernandez et al., 2024). Delving deeper into RQ3 (challenges), we identified as the main impediments the limitation of model improvement capabilities, the exorbitant costs of implementation, and the reluctance to accept change in AI research communities. Ultimately, RQ4 (future pathways) identifies the routes concerning technology, policy, and socio-economics, with the most critical aspects being algorithmic innovation, regulatory frameworks, and cultural change.

The technical foundation and the real-world applications of Green AI are so interrelated that they are mutually beneficial. Implementation in limited-resource environments is possible due to the efficient model architectures, and the innovations in efficiency metrics and measurement tools (Barbierato & Gatti, 2024) are dictated by the real-world requirements. An example of this is the use of neural networks in edge computing for environmental monitoring, where through hardware limitations, the development of ultra-efficient neural networks able to produce the desired accuracy with minimal energy consumption has come about (Raman et al., 2024). Moreover, the real-time processing requirements in smart city applications have led to a rapid research development in model quantization and pruning, which entails reducing the latency with an almost negligible performance loss (Al-Raeei, 2025).

Although progress has been made, technical issues continue to be a drawback, especially in the case of large models where the contrast between precision and performance is very noticeable (Bolón-Canedo et al., 2024). The lack of a uniform standard for benchmarking is one of the primary factors that create problems in comparing different techniques (Verdecchia et al., 2023), while expensive infrastructure and re-training are the primary financial restrictions (Dash, 2025). Maintaining cultural norms that value performance above efficiency, together with the lack of carbon pricing, lessens the attractiveness of adopting Green AI practices (Schwartz et al., 2020; Zeng & Zhang, 2024).

Green AI not only promotes but also fully aligns itself with numerous Sustainable Development Goals including among others, e.g., SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities) and SDG 13 (Climate Action). Through reducing energy-intensive operations, which in turn lead to less computational footprints and allowing the usage of renewable sources (Yigitcanlar et al., 2021), and smart applications in the industrial and urban spheres, the whole production, transportation, and waste management systems can be improved (Zhou, 2025; Luo & Feng, 2024). Additionally, the use of technology in the environment brings us closer to the modeling of climate change and protection of various ecosystems (Gohr et al., 2025). But still, it is important to take into account the possible negative effects such as the rise of e-waste and the issue of unequal access to digital technologies (Sætra, 2021).

Limitations of the study

Several limitations Seek this review and thus it should be taken into account during interpretation its findings. The fast- paced nature of Green AI Research matters that some recent developments Especially I can't obtain completely caught those fast- moving areas Like neuromorphic computing and quantum- inspired algorithms. The focus of the review Peer- reviewed literature is lost important innovations Documentation found in industry or in non- traditional forms of publications. The heterogeneity of metrics and reporting quality in studies complicated direct comparisons and quantitative synthesis.

The geographical distribution of included studies reveals underrepresentation from developing areas, that is the potential to compromise the generalizability of findings in various economic and infrastructural contexts. More inclusive search strategies It is worth it and may provide more justification the development of standardized Reporting guidelines specific to Green AI research.

Conclusion

Green AI is a revolution in the area of artificial intelligence, which shifts the focus of the entire field from the traditional performance metrics to making environmental responsibility one of the main aims. Through a systematic review of 31 primary studies the maturing of the field is pointed out and the distinguishing of optimizing AI systems or Green AI, supporting socio-technical sustainability or Sustainable AI and using AI to tackle ecological problems or AI for Green is made. Different technical strategies like model pruning, energy-saving hardware and carbon-aware computing have given measurable improvements in resource efficiency, usually between 15-30% and their performing trade-offs were intentional where small reductions in performance and big savings in energy were balanced. The limitations for adoption are technical constraints in model optimization, high capital costs for sustainable infrastructure and a research culture that still values accuracy over efficiency, despite the progress. The Efficiency-Sustainability Loop presents a feasible framework, The situation is such that, on the one hand, technological innovation around algorithms is made above all due to real-world environmental constraints and, on the other hand, the computational efficiency and ecological responsibility will be the factors that support each other in this innovation cycle. As the global adoption of AI is fast-tracked, it would be wise to make sustainability a characteristic feature of model design so that the technological progress remains to be compatible with the limits of the earth's ecology. The cooperation between researchers, industry, and policymakers in the forms of carbon-aware metrics, sustainable development practices, and policy incentives will be the key to not only unlocking the full capabilities of Green AI but also bringing AI development in line with environmental sustainability. stewardship.

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