Review Article

What Counts as Green AI? Mapping Efficiency, Sustainability, and Critical-Ecological Strands in a Fragmented Discourse

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The concept of "Green AI" is emerging as stakeholders confront the environmental costs of artificial intelligence. However, the field remains formative and contested, marked by competing definitions, inconsistent methods, and limited cross-disciplinary collaboration. Efficiency-driven approaches frame Green AI narrowly as reducing computational and carbon costs through technical optimizations such as model pruning and energy reporting. Sustainability-driven perspectives view AI as a tool for ecological problem-solving—ranging from climate modeling to biodiversity monitoring—often linked to global policy agendas like the SDGs. In contrast, critical-ecological critiques warn that both efficiency and sustainability narratives risk obscuring exploitative infrastructures, from cobalt mining to water-intensive data centers, and reinforcing global inequalities. These perspectives rarely converge, producing conceptual ambiguity, fragmented methodologies, and a persistent policy–practice gap. To address this, the paper develops a typology that distinguishes efficiency, sustainability, and critical-ecological strands, clarifies their assumptions, and highlights their blind spots. By framing Green AI as a contested boundary project, the typology provides a foundation for methodological standardization, interdisciplinary integration, and more accountable research. Future work should build on this typology to establish shared metrics and justice-oriented practices that align AI innovation with planetary limits.

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Introduction

Artificial intelligence (AI) is transforming the economy, but it also raises environmental concerns. Training a single advanced natural language processing model can emit over 500 tons of CO_2, comparable to the lifetime emissions of five average cars[1]. This has sparked interest in Green AI, aimed at making AI development environmentally sustainable. However, discussions about Green AI are fragmented and evolving.

The primary issue is the lack of a clear definition. Some researchers prioritize technical efficiency to reduce energy consumption and computational demands[2], while others focus on using AI to address sustainability issues like renewable energy optimization and biodiversity monitoring[3]. There are also concerns that the term "green" could obscure exploitative practices and worsen global inequalities[4], leading to disconnected conversations.

Varying methods and metrics exacerbate this fragmentation. Studies measure success using different metrics—like floating-point operations (FLOPs), carbon footprints, or energy efficiency—without standardized reporting or thorough lifecycle analyses. Diverse academic fields contribute to this confusion: computer science emphasizes optimization, environmental science focuses on emissions, and critical theory discusses socio-political dimensions of sustainability. Despite mentions of sustainability in policies like the EU AI Act and OECD AI Principles, the practical application remains ambiguous, creating a gap between regulatory intentions and industry actions.

This paper aims to achieve three things: First, it reviews the different definitions and perspectives on Green AI. Second, it identifies risks linked to its disorganization, such as inconsistent methods, gaps between policy and practice, and global inequalities. Third, it develops a typology distinguishing efficiency-driven, sustainability-driven, and critical-ecological viewpoints to enhance clarity and integration. By framing Green AI as an evolving concept, the paper aims to establish a more accountable foundation for future research, practice, and policymaking.

Literature Review: The Three Strands of Green AI

Green AI has developed through three primary approaches: efficiency-driven, sustainability-driven, and critical-ecological. Although these methods focus on different assumptions and priorities, they often operate in isolation, resulting in fragmented discussions.

Efficiency-Driven Green AI

Efficiency-oriented Green AI focuses on reducing the computational and environmental costs of model training and deployment[2]. Techniques like pruning, quantization, and knowledge distillation aim to lower FLOPs and energy consumption while ensuring accuracy[5][6]. Investments in specialized hardware and renewable energy for data centers support this approach[7].

However, this optimization focus tends to narrow sustainability to just training and inference costs, neglecting lifecycle impacts like mineral extraction, e-waste, and toxic disposal[8][9]. Inconsistent metrics —like FLOPs, GPU hours, or CO_2 equivalents—make it hard to compare and standardize efforts[10]. Scholars warn that efficiency improvements could lead to larger models, increasing total energy use[1][11]. In summary, while efficiency-driven Green AI highlights computational costs, it lacks a comprehensive and cohesive ecological perspective.

Sustainability-Driven Green AI

A second strand extends Green AI beyond computation to AI's role in addressing ecological challenges. Applications range from climate modeling and smart grids to biodiversity monitoring and precision agriculture[3][12]. These efforts align with global agendas like the SDGs and the Paris Agreement, and they position AI as a driver of low-carbon transitions[13][14].

However, enthusiasm often outpaces evaluation. Studies reveal that while AI can optimize renewable energy systems or conservation monitoring, lifecycle emissions from model training and data centers may offset benefits[15][16]. Sustainability projects are also fragmented and disproportionately concentrated in advanced economies[17]. Critics highlight that focusing narrowly on technological fixes risks obscuring systemic issues such as extractive supply chains and uneven access to innovation[18][19]. Thus, while AI applications promise ecological gains, their costs and global inequalities remain under-assessed.

Critical-Ecological Green AI

Critical-ecological perspectives emphasize how AI infrastructures depend on extractive and ecologically intensive practices. For example, cobalt mining in the Democratic Republic of Congo supplies over 70% of the global demand, with estimates indicating that cobalt extraction contributes to severe soil degradation and exposes local populations to toxic metals[20]. Similarly, the average hyperscale data center consumes between 3 and 5 million gallons of water daily for cooling purposes—comparable to the daily water consumption of a city with 30,000 to 50,000 inhabitants[21]. In drought-prone regions such as Arizona or Chile's Atacama Desert, these demands intensify existing water scarcity and displace agricultural water use. Electronic waste is another material externality: global e-waste generation exceeded 62 million tonnes in 2022, with less than 20% being formally recycled[22]. Countries like Ghana remain primary destinations for informal e-waste processing, thereby exposing communities to heavy metal contamination and air pollution[23]. These statistics demonstrate that evaluating Green AI meaningfully requires situating claims of efficiency and sustainability within the broader political economy of extractive minerals, water scarcity, and toxic waste flows.

Summary of Literature in A Fragmented and Contested Field

The interaction of three key perspectives—efficiency-driven, sustainability-focused, and critical-ecological—highlights both the energy and the disorder within the Green AI discourse. Efficiency approaches promote technical optimization but can be narrow; sustainability perspectives emphasize ecological applications but may exaggerate their benefits; and critical-ecological views emphasize justice and global inequalities but often lack technical specifics. This results in a fragmented and contested field where scholars often misunderstand one another, metrics vary widely, and interdisciplinary collaboration is limited. Such disorganization poses risks: efficiency research might lead to unintended rebound effects, sustainability claims could obscure hidden ecological costs, and critical views may be dismissed as overly theoretical by policymakers. However, this disarray is also an opportunity for growth. It indicates a field in flux, where definitions, metrics, and commitments are still being determined. Developing a clear typology that outlines these three perspectives, clarifies their underlying assumptions, and highlights their intersections could help Green AI progress toward a more coherent framework for research and practice.

Why The Green AI Discourse Is Disorganized

"Green AI" is an ambiguous term that includes conflicting ideas. In efficiency contexts, it means reducing resource use in machine learning[2]. In sustainability discussions, it refers to using AI for environmental challenges[3]. A critical-ecological view suggests that the term may hide deeper ecological issues[24]. These varying definitions lead to confusion and impact research priorities and policies. Efficiency definitions tend to focus on optimization algorithms, while sustainability views emphasize applied

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projects in areas like energy and agriculture. The critical perspective urges a reevaluation of how AI development aligns with planetary limits. Without a clear definition of Green AI, academic discussions remain fragmented and based on different assumptions.

Conceptual Ambiguity and Competing Definitions

"Green AI" is a vague term that encompasses multiple, often conflicting ideas. In efficiency-driven contexts, it refers to reducing the resource usage of machine learning[2]. In sustainability discussions, it implies using AI to tackle environmental issues[3]. From a critical-ecological perspective, it highlights a discourse that might mask ecological dominance[24]. These different definitions create confusion and affect research priorities, methods, and policies. For instance, efficiency-focused definitions lean towards optimization algorithms, while sustainability views stress applied to projects in energy and agriculture. The critical perspective calls for reevaluating the compatibility of AI development with planetary limits. Without a unified definition of Green AI, academic discussions are fragmented, with each area operating on its own assumptions.

Methodological Inconsistency and Weak Metrics

Methodological inconsistency is prevalent in studies focused on AI efficiency, with various metrics reported, such as FLOPs, GPU-hours, and power usage effectiveness, yet lacking standardized protocols[10]. Many studies only address training energy, leaving out inference costs and emissions from hardware lifecycles, making cross-study comparisons unreliable and obscuring AI's environmental footprint[7].

Sustainability projects using AI often highlight its role in climate modeling, renewable energy, and conservation. However, they may fail to assess whether the ecological advantages outweigh the costs critically. For instance, while AI-driven smart grids optimize energy distribution, the emissions from training the models can undermine their overall ecological benefits[25]. Cheong et al. emphasize the importance of evaluating both costs and benefits of AI in climate adaptation and suggest integrating physics-based models with machine learning to respect ecological principles[25].

Lu points out that several challenges, including data availability, model interpretability, and ethical issues, must be addressed for effective AI deployment in climate change mitigation. He stresses the need for thorough research and collaboration to realize AI's benefits without incurring high environmental costs[26]. Additionally, focusing primarily on technology advancements risks sidelining ethical

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considerations, as AI could inadvertently perpetuate unsustainable practices, necessitating ongoing scrutiny[27]. This aligns with concerns over "greenwashing," where the positive narratives surrounding AI's environmental impact overshadow the critical analysis of its lifecycle emissions and externalities.

Furthermore, the promotion of AI for environmental issues often exaggerates its ecological benefits. It is important to examine how AI might perpetuate exploitation and inequality in resource management. Ongoing research is needed to assess not only the feasibility of AI for environmental gains but also its broader impacts on sustainability and justice globally[28][29]. Without thorough cost–benefit analyses, Green AI risks becoming a mere rhetorical exercise instead of a practice grounded in evidence. While critical-ecological perspectives reveal hidden externalities, they often lack quantifiable measures. Their critiques are generally qualitative or theoretical, complicating integration with empirical studies. The lack of shared metrics among these perspectives leads to a disjointed evaluation of Green AI, resulting in incompatible methodologies.

Disciplinary Silos and Limited Cross-Fertilization

Disciplinary siloing contributes to disorganization in the field. Computer scientists focus on algorithm efficiency, environmental scientists look at emissions, and philosophers examine the socio-political aspects of sustainability. These groups publish in different journals, attend separate conferences, and use specialized language, resulting in minimal cross-citation. Technical papers rarely engage with critical theory, and philosophical critiques often go unnoticed by machine learning practitioners.

This division reflects deeper institutional dynamics. Efficiency-oriented Green AI attracts significant industry funding and aligns with computer science goals focused on performance. In contrast, sustainability-driven Green AI is typically developed within policy and applied science contexts, emphasizing pilot projects and collaboration. Critical ecological scholarship primarily resides in the humanities and social sciences, often sidelined from mainstream AI research. This leads to intellectual chaos and an imbalanced influence where technical and policy narratives dominate, while critical viewpoints are marginalized.

The Policy–Practice Gap

Policy discussions around Green AI are enthusiastic, but actual implementation is lacking. The OECD[13] and the EU AI Act[14] stress sustainability yet fail to provide enforceable standards for measuring AI's environmental impact. Similarly, corporate sustainability reports often boast about renewable energy and efficiency but usually neglect to provide complete lifecycle data on hardware production, water use, or e-waste[18]. This discrepancy risks turning Green AI into greenwashing. Without binding requirements or standardized reporting, companies can claim progress while maintaining unsustainable practices. Moreover, this gap reduces accountability: policymakers reference sustainability without ensuring compliance, while companies depict efficiency improvements as environmental progress, even when total energy use increases. This leads to a mismatch between ambitious claims and actual outcomes.

Global Asymmetries and Green Colonialism

Global inequalities worsen the disorganization of Green AI. Most research and initiatives come from the Global North, while the Global South faces the ecological and social costs of AI. For example, cobalt mining in the Democratic Republic of Congo, lithium extraction in Chile, and e-waste dumping in Ghana highlight the resource disparities linked to AI infrastructures[30]. However, much Green AI research focuses on efficiency and sustainability from a Northern perspective, overlooking how AI-driven projects can perpetuate dependency, worsen infrastructural gaps, and reinforce technological colonialism[4]. This oversight creates an intellectual and ethical gap: without addressing global justice, Green AI risks becoming a form of green colonialism that justifies ecological exploitation in marginalized areas.

A Formative and Contested Stage

The factors of conceptual ambiguity, methodological inconsistency, disciplinary silos, policy–practice gaps, and global asymmetries contribute to the disorganized state of the Green AI discourse. However, this disorganization is significant, indicating that Green AI is still developing and contested, with unclear definitions and commitments. This stage presents both risks and opportunities: the risk of dilution and fragmentation, and the opportunity for scholars, policymakers, and practitioners to establish clarity, rigor, and ethical grounding. Acknowledging the contested nature of Green AI is crucial for both academic integrity and the future direction of the field.

Framework: A Typology For Green AI

For Green AI to advance beyond its early, debated phase, scholars and practitioners need clear conceptual tools to identify its different strands and their assumptions. A lack of clarity risks leading to confusion: efficiency-focused optimizations might be confused for complete solutions, sustainability efforts could be praised without proper cost–benefit analysis, and important critical insights might be dismissed as overly theoretical. To tackle this issue, we propose a typology of Green AI that categorizes three main strands—efficiency-driven, sustainability-driven, and critical-ecological—based on their assumptions, methods, contributions, and limitations.

Typologies are not neutral tools; they actively shape contentious areas[31]. By illustrating differences, they improve communication between disciplines and identify areas for potential integration. For Green AI, a typology can:

- Clarify Definitions – Distinguish between efficiency, sustainability, and critical strands to reduce semantic confusion.
- Expose Blind Spots – Identify what each strand overlooks (e.g., lifecycle costs, global asymmetries).
- Enable Cross-Fertilization – Provide a shared reference point for computer scientists, policymakers, and critical theorists.
- Guide Policy and Practice – Suggest which strand aligns with different governance or organizational needs.

The Green AI Typology

Figure 1 outlines the three main strands of Green AI: efficiency-driven, sustainability-driven, and critical-ecological. Efficiency-driven approaches focus on optimizing computing and reducing resources but may lead to narrow perspectives and unintended consequences. Sustainability-driven approaches emphasize AI's ecological applications and alignment with global policies but often make unrealistic claims and ignore lifecycle costs. Critical-ecological perspectives critique Green AI for perpetuating ecological dominance and highlight issues like extractive infrastructures and global inequalities, though they tend to lack technical focus. This typology serves as a boundary object to clarify the complexities of Green AI and foster dialogue across disciplines for more responsible research, policy, and practice.

Figure 1: The Typology of Green AI consists of three main strands: efficiency-driven, sustainability-driven, and critical-ecological. Each strand has its own focus—efficiency emphasizes optimization, sustainability prioritizes ecological applications, and critical-ecological highlights justice and hidden costs. These overlaps highlight both blind spots, like lifecycle impacts and global inequalities, and opportunities for integration. This typology positions Green AI as a boundary object that clarifies tensions and encourages interdisciplinary dialogue.

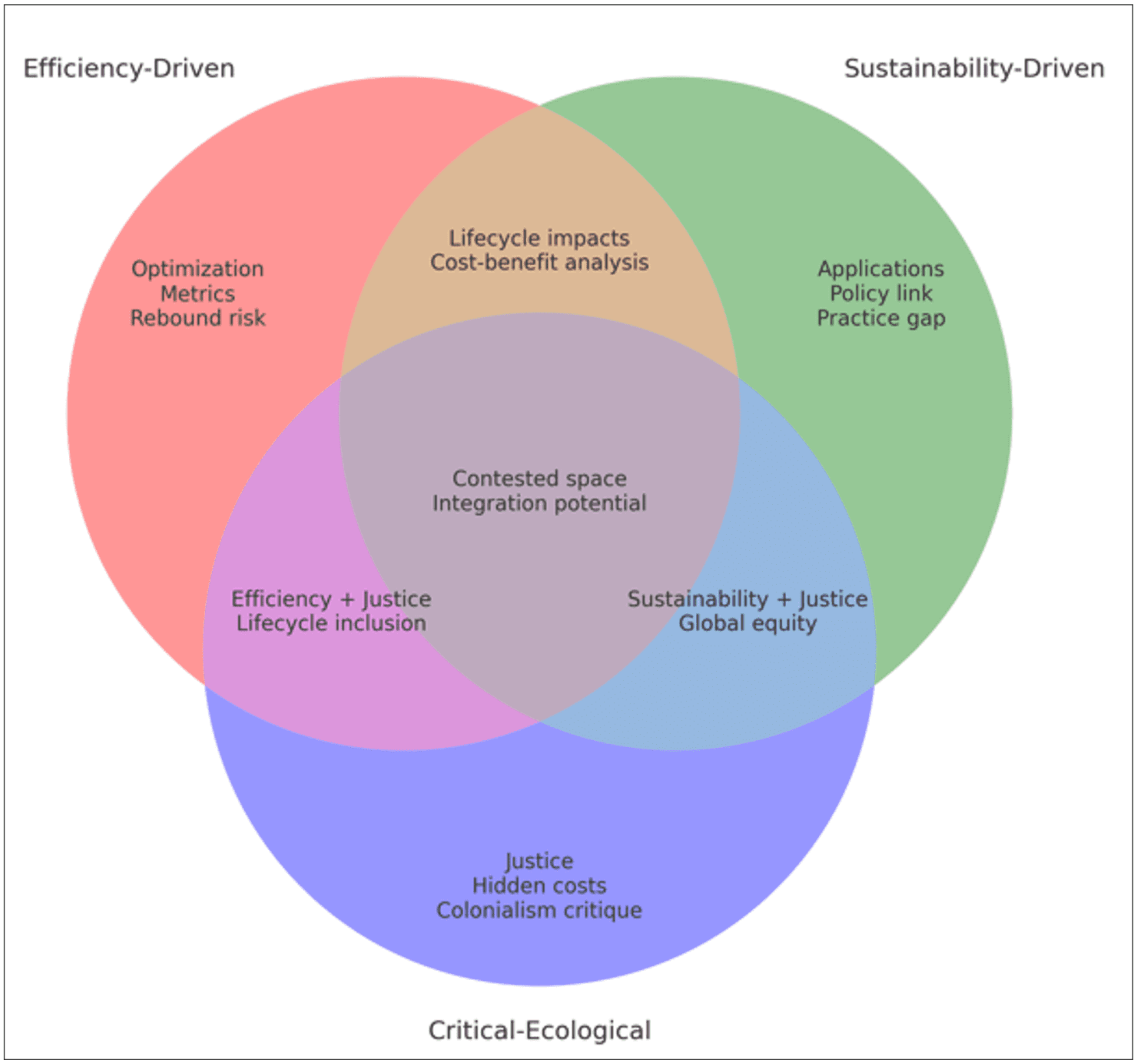

Figure 1. *Typology of Green AI: Efficiency, Sustainability, and Critical-Ecological Strands. Credit: The Author, 2025*

Contested Boundary

The typology shows how three approaches can work together effectively. Efficiency-driven methods can be improved by incorporating lifecycle analysis and justice factors from critical scholars. Sustainability projects can gain from efficiency metrics and addressing global inequalities found in critical research. Similarly, critical-ecological perspectives can enhance their impact by engaging with technical standards and policy discussions. This typology seeks to improve communication among various academic communities while preserving their unique contributions.

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It frames Green AI not as a singular approach, but as a contested boundary project[32]. The disorganization reflects a field in the process of defining its identity, grappling with issues of optimization versus justice, technological solutions versus systemic critiques, and the leadership of the Global North versus the marginalization of the Global South. This typology highlights these tensions and encourages more coherent debate.

Implications

The typology of Green AI developed in this document not only organizes a fragmented discourse but also bears substantial implications for theory, methodology, and practice. By considering Green AI as a foundational and debated field, the framework emphasizes opportunities for conceptual innovation, advocates for methodological standardization, and offers practical guidance for policymakers and organizations.

Theoretical Implications

The typology contributes to theoretical debates on AI and sustainability in three ways:

Clarifying Boundary Work: By differentiating between efficiency-driven, sustainability-driven, and critical-ecological strands, the typology illustrates that "Green AI" is not a singular paradigm but a contested boundary project. This acknowledgment conforms to sociological perspectives on how emerging fields establish authority through definitional conflicts[32]. Clear conceptual distinctions allow future research to position itself explicitly within, across, or against these strands.

Expanding the Normative Scope: The critical-ecological perspective emphasizes that sustainability transcends mere technical considerations, encompassing issues of justice, extraction, and global inequality. Incorporating this perspective into mainstream AI ethics broadens normative discussions beyond fairness and bias to address ecological dominance and digital colonialism[24][4].

***Reframing AI and Planetary Boundaries*:** The typology places Green AI within the broader scholarly discourse on planetary boundaries and ecological limits[33]. It questions techno-optimist assumptions that efficiency or innovation alone can address sustainability challenges, instead presenting Green AI as a subject of contested negotiation between ecological constraints and technological advancement.

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Methodological Implications

Methodological inconsistency is a key factor contributing to disorganization in the Green AI discourse. The typology outlines strategies for increasing rigor.

Toward Standardized Metrics: Efficiency-driven Green AI has established partial metrics such as FLOPs, GPU hours, and CO_2 equivalents; however, a standardized protocol remains absent. A practical framework should integrate computational metrics—including training and inference costs—alongside lifecycle assessments encompassing hardware production, water consumption, and electronic waste. Additionally, it should consider geographic energy mixes to facilitate more precise accounting[10].

***Integrating Cost–Benefit Analyses*:** Projects centered on sustainability are required to evaluate not only the ecological advantages of artificial intelligence applications but also their ecological costs. Systematic cost–benefit analyses serve to prevent exaggerated claims regarding AI's role in climate action and to ensure that sustainability discourse is grounded in empirical evidence.

Bridging Qualitative and Quantitative Approaches: Critical-ecological scholarship has yielded valuable insights into the extractive infrastructures fundamental to AI; however, it frequently lacks quantitative analysis. The integration of ethnographic, political-ecological, and lifecycle methodologies with computational benchmarks has the potential to foster hybrid approaches that more effectively encapsulate the intricacies of Green AI.

Policy and Practice Implications

*F**or*** policymakers, organizations, and practitioners, the typology offers lessons that need to become enforceable standards.

1. Mandatory Lifecycle Carbon Disclosure

AI systems exceeding a specified computational threshold (e.g., $>10^{18}$ FLOPs for training runs) should be mandated to disclose audited lifecycle carbon reports. These disclosures are to encompass not only training energy consumption but also inference, hardware manufacturing, water utilization, and end-of-life electronic waste management. Comparable thresholds could be incorporated into the EU AI Act as well as OECD sustainability frameworks.

2. Standardized Reporting Protocols

Building upon the ISO 14040/44 lifecycle standards, regulators should require a standardized reporting template that encompasses FLOPs, CO_2-equivalents, water consumption, geographic energy mix, and e-waste disposal channels. Academic journals and funding agencies could enforce adherence as a prerequisite for publication or grant approval.

3. Independent Auditing and Certification

Much like financial reporting, environmental disclosures should be subject to third-party auditing. Establishing an "AI Sustainability Certification" scheme would prevent selective disclosure and hold organizations accountable for greenwashing.

4. Sector-Specific Allowances

Policymakers should acknowledge that tolerances for carbon intensity differ according to application. For instance, higher emissions might be permissible in artificial intelligence applications used for medical diagnostics or climate modeling than in entertainment or advertising systems. Implementing a differentiated benchmark framework would facilitate proportionate regulation while dissuading frivolous high-emission use cases.

5. Global Justice Mechanisms

To prevent green colonialism, standards need to encompass the entire supply chain. This includes the obligatory disclosure of sourcing information for critical minerals such as cobalt and lithium, as well as the destinations of electronic waste. International development agencies and trade organizations should mandate supply-chain transparency certifications prior to endorsing AI-related infrastructure investments in the Global South.

6. Organizational Accountability

Companies deploying AI should be mandated to publish yearly Green AI Impact Reports that explicitly categorize their strategies within the typology—efficiency, sustainability, or critical justice. This requirement would facilitate more transparent stakeholder dialogue and enable benchmarking across industries. It also provides a strategic framework for integrating technical optimization with ethical responsibility.

Conclusion

The debate concerning "Green AI" is both pressing and unsettled. As demonstrated in this paper, the discipline is characterized by three divergent strands—efficiency-driven, sustainability-driven, and critical-ecological—each providing valuable insights yet frequently engaging in separate dialogues. Research focused on efficiency has heightened awareness of computational costs; however, it remains limited in scope and susceptible to rebound effects. Applications oriented towards sustainability align artificial intelligence with global policy objectives; nonetheless, they risk overestimating benefits and overlooking lifecycle costs. Critical-ecological critiques reveal hidden externalities and global asymmetries; however, they are often marginalized within technical discussions. This fragmentation results in conceptual ambiguity, methodological inconsistency, and a persistent gap between policy and practice.

By proposing a typology, this paper redefines Green AI as a contested boundary project rather than a singular paradigm. This framework elucidates underlying assumptions, identifies overlooked aspects, and offers a common reference point for scholars, practitioners, and policymakers. Significantly, it demonstrates that Green AI cannot be assessed solely through efficiency or innovation metrics but must also incorporate lifecycle impacts, global justice considerations, and planetary boundaries.

Looking ahead, the challenge lies in translating this conceptual clarity into operational practice. Standardized hybrid metrics, lifecycle reporting protocols, independent audits, and justice-oriented supply-chain regulations are essential steps to ensure that Green AI transcends rhetorical claims. Future research should aim to refine these tools and examine their effectiveness across diverse sectors and geographic regions. Ultimately, the measurement of Green AI will be based on its ability to reconcile technological innovation with ecological responsibility and social equity.

Notes

JEL Codes: Q55, Q56, O33, L86, D63

References

1. [a, b] *Strubell E, Ganesh A, McCallum A (2019). "Energy and Policy Considerations for Deep Learning in NLP." ArXiv. doi:10.48550/arxiv.1906.02243.*
2. [a, b, c, d] *Schwartz R, Dodge J, Smith NA, Etzioni O (2019). "Green AI." ArXiv. doi:10.48550/arxiv.1907.10597.*

3. [a, b, c, d]*Rolnick D, Donti PL, Kaack LH, Kochanski K, Lacoste A, Sankaran K, Ross AS, Milojevic-Dupont N, Jaques N, Waldman-Brown A, Luccioni AS, Maharaj T, Sherwin ED, Mukkavilli SK, Kording KP, Gomes CP, Ng AY, Hassabis D, Platt JC, Creutzig F, Chayes J, Bengio Y (2023). "Tackling Climate Change with Machine Learning." ACM Comput Surv.* ***55****(2):1–96. doi:10.1145/3485128.*
4. [a, b, c]*Couldry N, Mejias UA (2019). The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism. Stanford: Stanford University Press.*
5. [^]*Pope PE, Kolouri S, Rostami M, Martin CE, Hoffmann H (2019). "Explainability Methods for Graph Convolutional Neural Networks." 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). doi:10.1109/CVPR.2019.01103.*
6. [^]*Henderson P, Hu J, Romoff J, Brunskill E, Jurafsky D, Pineau J (2020). "Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning." J Mach Learn Res.* ***21****(248):1–43.*
7. [a, b]*Patterson DA, Gonzalez JE, Le QV, Liang C, Lluís-Miquel Munguía R, So DR, Texier M, Dean J (2021). "Carbon Emissions and Large Neural Network Training." ArXiv. doi:10.48550/arxiv.2104.10350.*
8. [^]*Chen X, Despeisse M, Johansson B (2020). "Environmental Sustainability of Digitalization in Manufacturing: A Review." Sustainability.* ***12****(24):10298. doi:10.3390/su122410298.*
9. [^]*Wang P, Zhang LY, Tzachor A, Masanet E, Chen WQ (2024). "E-Waste Challenges of Generative Artificial Intelligence." ArXiv. doi:10.21203/rs.3.rs-3978528/v1.*
10. [a, b, c]*Schmidt V, Schneider T, Li X (2021). "Standardizing Sustainability Metrics for AI: Challenges and Opportunities." AI Ethics.* ***36****(4):1129–1142. doi:10.1007/s00146-021-01245-0.*
11. [^]*Wynsberghe Av (2021). "Sustainable AI: AI for Sustainability and the Sustainability of AI." AI Ethics.* ***1****(3):213–218. doi:10.1007/s43681-021-00043-6.*
12. [^]*Weyn JA, Durran DR, Caruana R (2020). "Improving Data-Driven Global Weather Prediction Using Deep Convolutional Neural Networks on a Cubed Sphere." J Adv Model Earth Syst.* ***12****(9):e2020MS002109. doi:10.1029/2020ms002109.*
13. [a, b]*OECD (2022). "OECD Digital Economy Outlook 2020: AI and Sustainability." OECD Publishing. doi:10.1787/bb167041-en.*
14. [a, b]*European Union (2024). "The EU Artificial Intelligence Act." The Artificial Intelligence Act. https://artificialintelligenceact.eu/.*
15. [^]*Liao M, Lan K, Yao Y (2021). "Sustainability Implications of Artificial Intelligence in the Chemical Industry: A Conceptual Framework." J Ind Ecol.* ***26****(1):164-182. doi:10.1111/jiec.13214.*

16. ^Kaack LH, Donti PL, Strubell E, Kamiya G, Creutzig F, Rolnick D (2022). "Aligning Artificial Intelligence with Climate Change Mitigation." Nat Clim Change. **12**(6):518–527. doi:10.1038/s41558-022-01377-7.

17. ^Frimpong V (2024). "Cultural and Regional Influences on Global AI Apprehension." Qeios. **6**(11). doi:10.32388/yrdgex.3.

18. a, bCrawford K (2021). The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence. Yale: Yale University Press. doi:10.2307/j.ctv1ghv45t.

19. ^McDuie-Ra D, Gulson KN (2019). "The Backroads of AI: The Uneven Geographies of Artificial Intelligence and Development." Area. **52**(3):626–633. doi:10.1111/area.12602.

20. ^Amnesty International (2023). "Forced Evictions at Industrial Cobalt and Copper Mines in the DRC." Amnesty International. https://www.amnesty.org/en/latest/news/2023/09/drc-cobalt-and-copper-mining-for-batteries-leading-to-human-rights-abuses/.

21. ^Mytton D (2021). "Data Centre Water Consumption." npj Clean Water. **4**(1). doi:10.1038/s41545-021-00101-w.

22. ^UNEP (2023). "UN Roadmap Outlines Solutions to Cut Global Plastic Pollution." UN Environment. https://www.unep.org/news-and-stories/press-release/un-roadmap-outlines-solutions-cut-global-plastic-pollution.

23. ^Owusu-Twum MY, Kumi-Amoah G, Heve WK, Lente I, Owusu SA, Larbi L, Amfo-Otu R (2022). "Electronic Waste Control and Management in Ghana: A Critical Assessment of the Law, Perceptions and Practices." Waste Manag Res. **40**(12):1794-1802. doi:10.1177/0734242x221103939.

24. a, b, cBirhane A (2021). "Algorithmic Injustice: A Relational Ethics Approach." Patterns. **2**(2):100205. doi:10.1016/j.patter.2021.100205.

25. a, bCheong S, Sankaran K, Bastani H (2022). "Artificial Intelligence for Climate Change Adaptation." WIREs Data Min & Knowl. **12**(5). doi:10.1002/widm.1459.

26. ^Lu L (2024). "In-Depth Analysis of Artificial Intelligence for Climate Change Mitigation." ArXiv. doi:10.20944/preprints202402.0022.v1.

27. ^Jobin A, Ienca M, Vayena E (2019). "The Global Landscape of AI Ethics Guidelines." Nat Mach Intell. **1**(9):389–399. doi:10.1038/s42256-019-0088-2.

28. ^Katirai A (2023). "The Ethics of Advancing Artificial Intelligence in Healthcare: Analyzing Ethical Considerations for Japan's Innovative AI Hospital System." Front Public Health. **11**. doi:10.3389/fpubh.2023.1142062.

29. ^Voets MM, Veltman J, Slump CH, Siesling S, Koffijberg H (2022). "Systematic Review of Health Economic Evaluations Focused on Artificial Intelligence in Healthcare: The Tortoise and the Cheetah." Value Health. **25**

(3):340-349. doi:10.1016/j.jval.2021.11.1362.

30. ^ *Mhlambi S (2020). "From Rationality to Relationality: Ubuntu as an Ethical and Human Rights Framework for Artificial Intelligence Governance." Carr Center Discussion Paper 009.*
31. ^ *Doty DH, Glick WH (1994). "Typologies as a Unique Form of Theory Building: Toward Improved Understanding and Modeling." Acad Manage Rev.* ***19****(2):230–251. doi:10.2307/258704.*
32. a, b *Gieryn TF (1999). Cultural Boundaries of Science: Credibility on the Line. Chicago: University of Chicago Press.*
33. ^ *Rockström J, Steffen W, Noone K, Persson Å, Chapin FS, Lambin E, Foley J (2009). "Planetary Boundaries: Exploring the Safe Operating Space for Humanity." Ecol Soc.* ***14****(2):32. https://www.ecologyandsociety.org/vol14/iss2/art32/.*

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