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AI and environmental accountability: A new index for real-world impact

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AI and environmental accountability: A new index for real-world impact

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Abstract

Artificial intelligence is widely expected to advance corporate sustainability goals; however, its actual environmental contributions remain difficult to quantify. While existing sustainability metrics are valuable, they are not designed to isolate AI's specific impact across diverse sectors and often conflate technical potential with ecological outcomes. This paper introduces the AI and Green Innovation Index (AIGII), a structured, output-oriented framework that enables organizations to assess the observable environmental effects of AI adoption. Developed through a synthesis of sustainability accounting, digital transformation research, and ecological indicator design, the AIGII focuses on five key dimensions: energy efficiency, resource utilization, waste and circularity, lifecycle impact, and operational optimization. Unlike input- or capability-based assessments, the framework focuses on outcomes that organizations can monitor, compare, and take action on. In doing so, it provides a practical response to the growing calls for transparency, benchmarking, and accountability in AI-driven sustainability initiatives. By equipping stakeholders with a tool to evaluate whether digital transformation efforts align with environmental priorities, this paper contributes to a more evidence-informed approach to sustainable innovation.

Keywords: artificial intelligence, sustainability, AI outputs

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Introduction

Artificial intelligence (AI) is increasingly recognized as a key technological enabler in the transition toward more sustainable business practices. From predictive maintenance and adaptive logistics to intelligent resource allocation, AI applications are often viewed as tools that can enhance energy efficiency, minimize waste, and support decarbonization strategies (Vinuesa *et al.*, 2020; Zhou *et al.*, 2024). This promise has positioned AI at the centre of the sustainability discourse across policy, corporate, and academic domains (Cowls *et al.*, 2023). Yet, despite the growing enthusiasm surrounding AI's potential to advance sustainability goals, failure rates in AI adoption remain strikingly high, reaching up to 80% (Bojinov, 2023). This highlights a persistent disconnect between strategic ambition and the operational realities of implementation. A persistent and under-addressed challenge remains: the lack of standardized metrics to evaluate whether AI systems deliver measurable sustainability benefits in practice (Nishant *et al.*, 2020; Rolnick *et al.*, 2022).

Most existing approaches to assessing AI's role in sustainability are limited in scope and methodology. They frequently rely on individual case studies, sector-specific evaluations, or theoretical models, which, while informative, were not developed to measure the environmental outputs of AI adoption in a consistent or comparable way (Di Vaio *et al.*, 2020; Melville, 2010). As such, these assessments often conflate technical potential with actual ecological performance, leaving unresolved the question of whether observed changes are attributable to AI or broader operational shifts. Crucially, current sustainability metrics, rooted in lifecycle assessment, eco-efficiency analysis, or aggregate carbon accounting, are not designed to isolate AI's specific contributions to environmental outcomes across diverse organizational contexts (Gaur *et al.*, 2023; George *et al.*, 2014). This misalignment between available tools and emerging analytical needs has created a measurement gap at the intersection of digital transformation and environmental accountability. Without indicators capable of capturing the ecological effects of AI systems in a systematic and output-oriented manner, organizations and policymakers are left without a reliable basis for benchmarking performance, evaluating progress, or guiding future investments in sustainable AI deployment.

This paper introduces the AI and Green Innovation Index (AIGII), a framework designed to address this gap by shifting attention from the abstract potential of AI to its observable environmental outputs. The AIGII focuses on five outcome-based dimensions: (1) energy efficiency and emissions, (2) resource utilization, (3) waste and circularity, (4) lifecycle environmental impact, and (5) operational optimization. By focusing on these dimensions, the framework enables organizations to assess whether AI is advancing or undermining their environmental goals.

In doing so, the AIGII contributes to emerging discussions in sustainability science, environmental accounting, and responsible AI governance. It offers a practical and theoretically grounded approach to measuring AI's contribution to sustainability outcomes across diverse sectors and maturity levels. This introductory paper outlines the rationale behind the framework, explains its conceptual structure, and discusses its potential applications in corporate sustainability strategy and policy evaluation.

Why it is necessary to measure AI's sustainability outputs

AI technologies are increasingly embedded in the operations of sectors as diverse as manufacturing, logistics, agriculture, energy, and healthcare. In these contexts, AI is credited with enabling a range of sustainability-oriented improvements, from lowering energy consumption and emissions to reducing material waste and optimizing supply chains (Vinuesa *et al.*, 2020; Zhou *et al.*, 2024). These interventions, driven by machine learning algorithms and adaptive feedback systems, are often positioned as tools for decoupling economic productivity from environmental degradation, a key objective under frameworks such as the European Green Deal and the United Nations Sustainable Development Goals.

However, despite this narrative, empirical validation of AI's environmental performance remains limited. Much of the current discourse is shaped by projections, isolated case studies, and pilot initiatives rather than consistent, sector-wide evidence. As a result, organizations lack the ability to determine whether AI deployments are actually reducing emissions, conserving resources, or supporting circular economy practices in a meaningful way (Cowls *et al.*, 2023; Nishant *et al.*, 2020).

This measurement gap is further exacerbated by the fact that most existing sustainability frameworks were not designed with digital technologies in mind. Tools such as lifecycle assessment (Guinée *et al.*, 2004), eco-efficiency analysis (Huppes & Ishikawa, 2005), and the eco-cost/value ratio (Vogtländer *et al.*, 2002) provide valuable assessments at the product or process level but are limited in two critical respects when applied to AI. First, these frameworks rarely isolate AI's specific contribution to environmental outcomes, since AI is typically embedded within broader systems. Second, they focus on inputs and processes rather than outcomes, while AI typically exerts its influence at the level of system performance and resource flows (George *et al.*, 2014; Melville, 2010).

The result is a conceptual and methodological blind spot: organizations may infer sustainability gains from AI adoption without verifying them, often relying on assumptions rather than benchmarks. In the absence of consistent, comparative indicators, AI's environmental contributions remain difficult to assess, and potentially overstated. This creates a risk of "digital greenwashing," where sustainability claims are made without adequate evidence (Rolnick *et al.*, 2022; Schwartz *et al.,* 2020).

The AIGII addresses this challenge by focusing on observable outputs, concrete changes in emissions, material use, waste, and operational efficiency, associated with AI deployment. By offering a structured, output-oriented framework, it enables organizations, researchers, and policymakers to assess AI's environmental contributions more systematically. In doing so, the AIGII supports more transparent, evidence-based decision-making in the context of sustainable digital transformation.

AIGII conceptual framework

While AI is often treated as a homogenous technology, its ecological impact varies significantly depending on the context, application design, and deployment environment. The AIGII does not evaluate AI in abstract or general terms. Instead, it isolates the observable outputs associated with AI use, specifically, the tangible environmental outcomes perceived or measured by organizations following the implementation of AI-enabled systems.

The AIGII builds on principles from sustainability accounting, digital transformation research, and ecological indicator design. Its focus is on the intersection between operational change and ecological consequence. In doing so, the framework establishes a clear boundary between what AI does (automation, prediction, optimization) and what results from its use in environmental terms (e.g., reduced emissions or lower energy consumption).

The AGII includes five dimensions:

1. Energy efficiency and carbon emissions: Does AI contributes to lowering an organization's energy consumption and greenhouse gas emissions? AI systems applied to smart grid management, energy forecasting, or industrial control systems may enable emissions reductions through better load balancing, predictive maintenance, or demand-side management. The framework does not assume that AI is inherently energy-saving; instead, it asks whether organizations observe actual declines in energy use or emissions attributable to AI deployment. This approach helps to clarify whether sustainability gains outweigh the potential carbon costs of AI infrastructure, such as high-performance computing or continuous training cycles.
2. Resource utilization and efficiency: How does AI help improve material efficiency by reducing the amount of physical input needed to achieve identical or better outcomes? For example, AI systems in agriculture may reduce water and fertilizer use through sensor-driven precision techniques, while those in manufacturing may optimize raw material consumption through dynamic scheduling or quality control (Di Vaio et al., 2020). This dimension also accounts for adaptive efficiency: the ability of AI to respond to variability in real time, making resource allocation more responsive and potentially less wasteful.
3. Waste management and circularity: Does AI enable new or improved practices for minimizing waste, extending product lifespans, or supporting closed-loop resource cycles? Applications may include automated defect detection, predictive maintenance that delays asset disposal, or computer vision systems used in materials recovery. These capabilities are aligned with broader circular economy objectives, although their systemic adoption remains uneven.
4. Lifecycle environmental impact: Does AI play an active role in improving environmental outcomes at key lifecycle stages? This may include design-stage decisions that reduce embedded carbon, operations-stage monitoring that informs emissions reductions, or end-of-life phase interventions that increase recyclability. This dimension is particularly important in sectors such as construction, transportation, and electronics, where the upstream and downstream ecological impacts of decisions are significant.
5. Operational optimization: Does AI enable measurable improvements in system-wide performance? Examples include reduced downtime, improved throughput efficiency, or lower rates of defective output. While this dimension may seem similar to traditional performance metrics, the AIGII focuses on whether such operational gains translate into environmental benefits, such as reduced idle time in energy-intensive machines, more accurate routing in logistics systems, or better matching of supply and demand in resource distribution networks. These performance changes.

In sum, the AIGII advances an output-based logic that addresses the current limitations of both sustainability accounting and digital transformation evaluation. It answers the call for more granular, application-focused measures of AI's ecological impact and provides a structure flexible enough for cross-domain adoption. In doing so, it invites organizations to look beyond intentions and evaluate whether their digital transitions align with their environmental commitments.

Application and implications

The AIGII framework is designed for use where artificial intelligence is implemented to support sustainability objectives. Its central purpose is to enable the assessment of AI's measurable contributions to environmental performance across diverse organizational settings, with a focus on outputs that can be observed, tracked, and benchmarked. For example:

- In manufacturing industries, which are characterized by significant energy consumption and material waste, the AIGII has practical applications. For example, an automotive component manufacturer implementing AI-driven predictive maintenance would first establish clear baseline metrics across key environmental areas. After deploying AI, the company could accurately measure and attribute improvements in each AIGII dimension—such as reduced energy consumption from decreased equipment downtime, lower raw material usage through optimized scheduling, decreased waste due to improved defect detection, and reduced lifecycle carbon footprints as a result of design enhancements.
- In the logistics sector, companies that deploy AI for route optimization could evaluate improvements in fuel efficiency, shortened delivery times, and lower vehicle emissions.
- In agriculture, precision farming systems powered by AI may use the framework to assess reductions in water and fertilizer inputs in relation to crop yield.

Across these cases, the AIGII helps differentiate between general efficiency improvements and outcomes that are environmentally significant.

The use of perception-based indicators makes the framework accessible to organizations with varying levels of technical capacity. Companies report directly on sustainability-related outputs they associate with AI adoption, based on operational knowledge and internal data. This approach lowers the barrier to participation and makes the index particularly relevant for small and medium-sized enterprises, which may lack access to complex measurement infrastructure but still need to demonstrate environmental accountability.

Moreover, the framework has significant implications for corporate strategy, ESG reporting, and sustainability governance.

Strategic decision-making

By creating a standardized means of evaluating AI's sustainability outputs, the AIGII can support more informed decisions about where and how to invest in AI technologies. Organizations may find that some AI applications deliver measurable environmental benefits, while others have negligible—or even negative—effects when energy costs and system complexity are taken into account. This information is critical in contexts where sustainability claims affect procurement decisions, investor relations, or brand positioning.

Furthermore, the index allows for internal benchmarking across departments, facilities, or time periods. For example, a multinational enterprise could compare the sustainability performance of AI initiatives deployed in different regional units, identifying best practices and areas where further alignment is needed. These insights can feed into corporate sustainability strategy, enabling firms to prioritize high-impact deployments and avoid reputational risks associated with unsubstantiated green claims.

ESG reporting and disclosure

Environmental, Social, and Governance (ESG) metrics are increasingly central to how investors, regulators, and other stakeholders evaluate companies. However, most ESG frameworks do not yet incorporate AI-specific indicators or account for the environmental trade-offs associated with digital technologies (Rolnick *et al.*, 2022). As a result, organizations often report AI-enabled innovation and sustainability performance separately, with no integrated method to connect the two.

The AIGII offers a way to fill this gap. By generating indicators explicitly linked to AI adoption, it enables companies to disclose the environmental outcomes of digital transitions in a format that is transparent, comparable, and aligned with broader ESG goals. For example, an organization could report changes in emissions intensity or material efficiency specifically attributable to AI interventions, thus providing greater clarity and accountability in sustainability disclosures.

Policy and regulatory implications

Beyond the firm level, the framework has implications for policy development and regulation. As governments explore the intersection of digital transformation and environmental stewardship, particularly through initiatives such as the EU AI Act and the European Green Deal, there is a growing need for tools that can monitor the environmental impact of AI at scale. AIGII contributes to this effort by offering a replicable assessment model that can be adapted for sectoral benchmarking, regulatory standards, or public procurement evaluation.

If widely adopted, the framework could inform public guidelines on "green AI" standards, helping distinguish between AI applications that deliver verified sustainability gains and those that do not. It could also support data-driven allocation of sustainability-linked funding, directing resources toward AI innovations with demonstrated environmental benefits. In this way, the AIGII helps bridge the gap between technological innovation and environmental accountability in digital policy.

Moving forward: From measurement to impact

As AI becomes more embedded in business strategy and operations, its sustainability performance demands more than anecdotal claims or isolated case studies. The AIGII addresses this need by shifting attention from general capabilities to observable environmental outcomes, offering a conceptual foundation for more structured and accountable evaluation. While the framework is still in development, it holds potential for a wide range of applications:

- **Scaling the framework across sectors and organizational types**. While initial indicators are designed to accommodate diverse industries, the next step is to refine and tailor the framework in collaboration with sector-specific stakeholders. Industry-specific benchmarks could help distinguish between maturity levels in AI adoption and their associated environmental benefits, offering more actionable insights for firms and policymakers alike. For instance, the emissions savings made possible through AI in logistics may differ substantially from those in agriculture or construction, not because the technology is less capable, but because the constraints and possibilities are different. A comparative view is essential for setting realistic expectations and identifying high-leverage interventions.
- **Integrating the AIGII with digital reporting tools and dashboards**. As organizations adopt environmental, social, and digital twin systems, there is an opportunity to embed

AIGII indicators into existing performance monitoring infrastructure. Doing so would allow for continuous tracking of AI-driven environmental outcomes, not just periodic evaluation. This integration could strengthen feedback loops, opening possibilities for faster identification of underperforming systems or overlooked sustainability opportunities.

- **Educational and capacity-building initiatives**. The AIGII is particularly relevant within business schools, public agencies, and digital transformation consultancies. As sustainability transitions are increasingly influenced by data-driven technologies, there is a growing need to equip decision-makers with the skills to evaluate and interpret the environmental impacts of AI deployments. By offering a clear structure and language for such evaluations, the AIGII contributes not only to empirical assessment but also to institutional learning.
- **Critical reflection within the sustainability and digital innovation communities**. As it becomes easier to measure outcomes, it may become harder to ignore discrepancies between promise and practice. AI applications that appear efficient in isolation may have limited or even counterproductive ecological benefits when viewed from a systems perspective. The AIGII is not a certification tool or a promotional label, it is a framework for questioning assumptions, testing claims, and guiding continuous improvement.

The shift from measurement to impact is not automatic. It requires careful attention to how indicators are interpreted, how they inform decisions, and how they evolve over time. Nevertheless, by making AI's environmental performance more visible, comparable, and accountable, the AIGII provides a foundation for more deliberate, evidence-informed sustainability strategies.

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