

# Generative AI for Sustainable Business Strategy: Can AI-Powered Decision-Making Improve Corporate Resource Efficiency and Environmental Performance?

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Sustainable Business Strategy,  
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AI-Powered Decision-Making,  
Green Innovation**Abstract**

Generative Artificial Intelligence (GenAI) is increasingly being incorporated into business planning, knowledge work, operational analytics, and decision support. Its sustainability value, however, cannot be inferred from productivity gains alone because AI systems also require electricity, computing infrastructure, water, hardware, and other resources. This study develops an evidence-based framework for examining whether GenAI-enabled decision-making can improve corporate resource efficiency and environmental performance. It distinguishes direct AI resource impacts from indirect efficiency benefits and evaluates five decision pathways: energy optimization, material and waste reduction, supply-chain resource allocation, water management, and sustainability reporting. Empirical evidence indicates that AI adoption can improve enterprise environmental performance through productivity improvement, pollution-control investment, and factor-input optimization. Evidence from building-energy research estimates potential reductions of approximately 8–19% in energy consumption and carbon emissions by 2050 under specified AI adoption scenarios. At the same time, the International Energy Agency reports that data centres consumed approximately 415 TWh of electricity in 2024, around 1.5% of global electricity consumption, demonstrating the resource burden associated with digital infrastructure. The findings therefore support a conditional rather than automatic sustainability effect: GenAI can contribute to resource efficiency when its decision benefits exceed the environmental burden of computation and when organizations implement data governance, measurement, human oversight, and sustainability controls. The paper proposes a Resource-Efficiency Decision Index, equations for avoided resource use and net environmental benefit, an evidence matrix, scenario analysis, and a managerial governance framework for integrating GenAI into sustainable business strategy.

## 1. Introduction

Corporate sustainability is increasingly becoming a strategic decision-making challenge involving energy, materials, water, logistics, investment, and operational risk. Firms must reduce environmental impacts while maintaining productivity, financial resilience, and competitiveness. This raises an important question: can Generative Artificial Intelligence (GenAI) improve corporate decision-making in ways that produce measurable resource-efficiency gains and better environmental performance?

GenAI offers opportunities to support sustainable business decisions by processing structured and unstructured information, summarizing operational records, generating alternative scenarios, and assisting managers in identifying potential improvements. These capabilities can support decisions across procurement, production, maintenance, logistics, and sustainability management. However, the value of GenAI depends on how effectively its outputs are integrated into organizational processes and whether the resulting decisions produce measurable environmental benefits.

Existing research provides evidence that artificial intelligence can influence corporate environmental performance. Cheng et al. (2024) examine the relationship between AI adoption and enterprise environmental performance in China, highlighting the potential role of productivity improvements, pollution-reduction investment, and factor-input optimization. Wang et al. (2024) further examine the relationship between AI, ecological footprints, carbon emissions, and energy transitions. Vinuesa et al. (2020) discuss the broader role of AI in achieving the Sustainable Development Goals, while Dwivedi et al. (2023) examine the opportunities and challenges associated with generative conversational AI. Together, these studies provide a basis for investigating AI-enabled sustainability, although evidence about AI in general should not automatically be interpreted as proof of GenAI-specific environmental benefits.

AI adoption also creates environmental costs. The International Energy Agency (2025) identifies data centres and AI as important considerations in future electricity demand. The environmental implications of AI therefore involve both potential resource savings and the

energy and infrastructure required to develop and operate AI systems. Its overall sustainability contribution depends on factors such as the application, computing requirements, infrastructure efficiency, and electricity sources. Consequently, organizations should assess the net environmental effects of AI rather than assume that adoption is inherently sustainable.

Corporate resource efficiency provides a practical basis for evaluating these effects. It concerns the relationship between business output and the resources required to produce it, including energy, materials, water, and infrastructure. Improvements may result from reducing production waste, avoiding unnecessary transportation, improving asset utilization, lowering energy consumption, and preventing operational disruptions. AI-supported analysis may help organizations identify inefficiencies, compare alternatives, and incorporate environmental considerations into routine decisions. Research on AI adoption in supply-chain management and intelligent digital twins also provides relevant context for examining how digital intelligence can support supply-chain planning, resilience, and operational decision-making.

However, operational improvements do not necessarily guarantee better overall environmental performance. A system may reduce resource consumption in one process while increasing electricity demand or other resource requirements elsewhere. Sustainable business evaluation should therefore consider both operational savings and the environmental burden associated with AI deployment. Relevant indicators include energy intensity, carbon emissions, water consumption, material use, waste generation, and the resources consumed by AI infrastructure. These measures can help organizations distinguish between gross operational savings and net environmental benefits.

This study develops an evidence-based framework for evaluating GenAI as a component of sustainable business strategy. It investigates whether AI-powered decision-making can improve corporate resource efficiency and environmental performance, and identifies the conditions under which such improvements may occur. Rather than assuming a universal causal effect of GenAI, the study synthesizes relevant literature and proposes an operational approach for assessing resource savings, AI-related environmental costs, and net sustainability outcomes.

The study makes three contributions. First, it distinguishes potential resource savings from the environmental costs of deploying AI. Second, it identifies decision-making pathways through which GenAI may support energy, material, water, logistics, and waste management. Third, it proposes a measurement framework incorporating resource-efficiency indicators, environmental performance measures, and organizational governance considerations. The framework emphasizes data quality, model validation, human oversight, and ongoing sustainability measurement as important conditions for responsible adoption.

The remainder of the paper reviews the relevant literature, explains the methodology, presents the analytical framework and illustrative calculations, discusses managerial implications, and outlines the study's limitations and directions for future research.

## 2. Literature Review

### 2.1 Artificial Intelligence and Enterprise Environmental Performance

Recent research examines the relationship between artificial intelligence (AI) adoption and corporate environmental performance. Cheng et al. (2024) investigate this relationship among Chinese enterprises, highlighting productivity improvement, pollution-reduction investment, and factor-input optimization as potential mechanisms. These findings suggest that AI may support environmental improvement through more efficient production and resource-allocation decisions.

Wang et al. (2024) examine the relationship between AI, ecological footprints, carbon emissions, and energy transitions, providing a broader basis for evaluating environmental outcomes. Vinuesa et al. (2020) discuss the potential contribution of AI to the Sustainable Development Goals. However, these studies address AI broadly and should not be interpreted as direct estimates of the environmental effects of GenAI.

### 2.2 Generative AI as a Decision-Support Technology

Generative AI (GenAI) can generate text, summaries, scenarios, code, and recommendations from available information. In corporate settings, these capabilities may help sustainability teams interpret environmental reports, review supplier disclosures, compare resource-use patterns, and prepare operational decisions.

Nevertheless, generated outputs may contain errors, omissions, or unsupported claims. GenAI should therefore be treated as a decision-support tool rather than an autonomous sustainability authority. Decision quality depends on data reliability, model capabilities, workflow design, validation procedures, and human oversight. Dwivedi et al. (2023) discuss the opportunities and challenges associated with generative conversational AI, providing relevant context for these organizational and governance considerations.

### 2.3 AI, Energy Efficiency, and Resource Optimization

Energy management is an important potential application of AI-enabled decision-making. AI can support demand forecasting, predictive maintenance, equipment scheduling, anomaly detection, and renewable-energy integration. These applications may help organizations identify inefficiencies and improve the use of existing infrastructure.

The International Energy Agency (IEA, 2025) highlights the two-sided relationship between AI and energy. AI may improve energy-system operations and efficiency, while the expansion of digital infrastructure increases electricity demand. The environmental value of an AI application therefore depends on whether its operational benefits outweigh the resources required to implement and operate it.

### 2.4 AI, Materials, Waste, and Circularity

Resource efficiency also involves material use, waste, inventory, and asset utilization. AI-supported forecasting and analysis may help firms reduce overproduction, improve inventory allocation, identify abnormal material consumption, and anticipate equipment failures. These applications may reduce avoidable waste and improve the utilization of existing resources.

In circular-economy and supply-chain settings, digital systems can also support traceability, resource planning, and the identification of opportunities for reuse or recovery. These benefits should be evaluated

using operational indicators, such as material intensity, waste per unit of output, inventory losses, and recovery rates, rather than assumed from AI adoption alone.

### 2.5 AI, Water Efficiency, and Environmental Monitoring

Water efficiency is another dimension of sustainable business strategy. AI-enabled monitoring and forecasting may help organizations identify abnormal water consumption, detect leakage, and improve cooling or water-allocation decisions. These applications may be particularly relevant to water-intensive production and digital infrastructure.

Environmental assessments should also consider water consumed directly by computing facilities and indirectly through electricity generation. Organizations should define an appropriate system boundary and measure water consumption alongside energy use and other relevant indicators. The net contribution of AI to water efficiency depends on the application, infrastructure, and measured operational outcomes.

### 2.6 AI and Sustainable Supply-Chain Decisions

Supply chains provide an important setting for AI-enabled resource optimization because environmental outcomes depend on interconnected decisions involving procurement, production, inventory, transportation, and risk management. Baryannis et al. (2019) examine AI in supply-chain risk management, while Kassa et al. (2023) review AI techniques for supply-chain resilience. Ivanov (2023) investigates intelligent digital twins for supply-chain stress-testing, resilience, and viability. Shahzadi et al. (2024) review AI adoption in supply-chain management.

These studies provide a basis for understanding how AI can support operational planning, risk assessment, and resilience. GenAI may complement analytical and optimization systems by summarizing supplier information, interpreting disruption reports, comparing scenarios, and communicating recommendations. Reliable implementation requires generated outputs to be grounded in validated enterprise data and checked against operational constraints.

### 2.7 AI Infrastructure as an Environmental Trade-Off

The environmental burden of AI infrastructure must be considered when assessing its sustainability contribution. According to the IEA (2025), data centres consumed approximately 415 terawatt-hours (TWh) of electricity in 2024, equivalent to around 1.5% of global electricity consumption. Under the IEA's Base Case, data-centre electricity consumption is projected to reach approximately 945 TWh by 2030. These estimates cover data centres as a whole rather than GenAI specifically.

The electricity supply mix also influences the environmental consequences of computing. The IEA (2025) reports that renewables supplied approximately 27% of data-centre electricity in 2024, while coal supplied around 30%, natural gas 26%, and nuclear power 15%. These figures demonstrate why electricity demand, energy sources, and associated emissions should be considered when evaluating AI deployments.

A sustainability assessment should therefore account for both the potential resource savings generated by AI-supported decisions and the environmental burden of the infrastructure required to deliver them. Improvements in operational efficiency do not necessarily produce a net environmental benefit if additional computing and infrastructure requirements offset those gains.

### 2.8 Research Gap

Existing research provides a basis for examining the relationships between AI, environmental performance, resource optimization, and supply-chain resilience. However, several issues remain relevant to GenAI-enabled sustainable business strategy.

First, much of the available evidence concerns AI broadly rather than GenAI-supported corporate decision-making specifically. Second, operational benefits and the environmental burden of AI infrastructure are not always evaluated together. Third, resource efficiency should be considered a strategic business outcome as well as a technical optimization objective. Finally, organizations need a consistent approach to comparing resource savings with the energy, emissions, water, and infrastructure requirements attributable to AI use.

This study addresses these issues by proposing a framework for evaluating GenAI-enabled resource savings alongside the environmental burden associated with AI deployment. Rather than assuming that AI adoption automatically improves environmental performance, the framework emphasizes measurable outcomes and explicit system boundaries.

### 2.9 Evidence from Sustainability-Oriented Studies

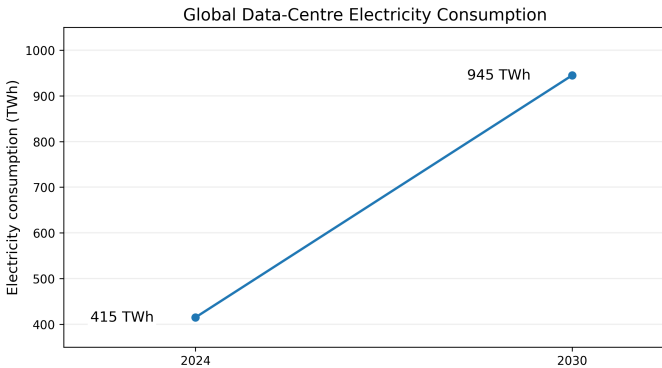
The reviewed literature identifies business decision areas in which AI may support sustainability objectives. Research on enterprise environmental performance examines the relationship between AI adoption and environmental outcomes (Cheng et al., 2024), while research on ecological footprints, carbon emissions, and energy transitions broadens the assessment beyond a single environmental indicator (Wang et al., 2024). Studies of supply-chain risk management, resilience, and intelligent digital twins identify operational settings in which information processing and scenario analysis may support business decisions (Baryannis et al., 2019; Ivanov, 2023; Kassa et al., 2023).

These sources provide contextual evidence rather than direct causal estimates of GenAI’s environmental effects. Their relevance lies in the decision processes they examine and the potential for GenAI to complement existing analytical systems. The present study therefore distinguishes findings reported in the literature from proposed GenAI applications that require further empirical evaluation.

Table 1 summarizes selected studies and illustrates potential connections between established AI applications and GenAI-supported decision-making. The applications in the final column represent proposed opportunities for this study; they are not findings directly established by the cited papers.

### 2.10 Visual Evidence on the Energy Burden of AI Infrastructure

Data-centre electricity consumption provides an important boundary condition for assessing the sustainability of AI. The IEA (2025) estimates that data centres consumed approximately 415 TWh of electricity in 2024 and projects consumption of approximately 945 TWh by 2030 under its Base Case. Figure 1 presents these two values. The projection covers data centres as a whole rather than GenAI alone.



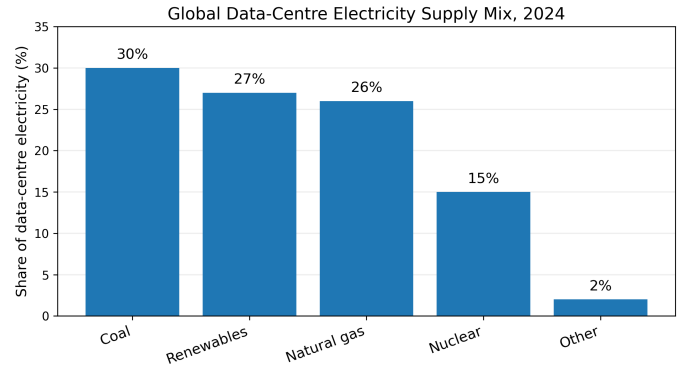
**Figure 1. Global data-centre electricity consumption in 2024 and the IEA 2030 Base Case. Source: IEA (2025).**

The electricity supply mix is also relevant because the environmental consequences of computing depend partly on the sources used to generate the electricity consumed. Figure 2 presents the reported global data-centre electricity supply mix for 2024, as described by the IEA (2025).

These figures illustrate the importance of assessing the environmental costs of AI alongside its potential operational benefits. They do not independently establish the net environmental effect of GenAI in a particular organization. Such an assessment requires application-specific information about resource savings, computing requirements, electricity sources, and other relevant environmental impacts.

### 2.11 Integrated Decision Architecture

The reviewed literature supports a framework in which GenAI acts as a decision-support layer between enterprise information and managerial action. Figure 3 presents the proposed decision cycle. Enterprise data and operational indicators inform the analysis; GenAI helps synthesize



**Figure 2. Global electricity supply mix for data centres in 2024. Source: IEA (2025).**

information and generate recommendations; human review and validation precede implementation; and subsequent measurement determines whether the decisions improve resource efficiency and environmental performance.

The framework emphasizes that generating a recommendation is not equivalent to achieving a sustainability outcome. Organizations must evaluate implemented decisions against defined baselines and indicators while accounting for the environmental burden attributable to AI use. This provides the conceptual basis for the net-effect framework developed in the following sections.

### 2.12 Illustrative Data-Centre Electricity Growth Path

To illustrate the scale of projected change, Figure 4 presents a constant-growth interpolation between the IEA’s reported 2024 estimate and its 2030 Base Case projection. The intermediate annual values are calculated estimates, not individual IEA forecasts. The implied compound annual growth rate is approximately 14.7%, based on the increase from 415 TWh to 945 TWh over six years.

This interpolation is intended only to illustrate the magnitude of the projected change. It should not be interpreted as an official year-by-year forecast or as a projection of GenAI-specific electricity consumption. Together, the evidence and proposed decision architecture establish the central premise of this study: sustainable GenAI adoption requires organizations to evaluate potential operational resource savings and AI-related environmental costs within a consistent measurement framework.

## 3. Methodology

### 3.1 Research Design

### 3.2 Evidence Synthesis and Analytical Logic

The evidence was synthesized using a mechanism-oriented approach. Rather than combining heterogeneous estimates into a single pooled effect, the study identifies how AI-enabled decision-making can influence resource use and environmental performance. The analytical unit is therefore the decision pathway rather than AI adoption in the abstract.

Four evidence classes are distinguished: (1) peer-reviewed empirical studies linking AI with environmental or ESG outcomes; (2) sectoral studies estimating AI-enabled efficiency potential; (3) institutional and corporate disclosures describing infrastructure and operational effects; and (4) sustainability studies that define the business decisions to which AI-enabled decision support may be applied. This structure reduces the risk of presenting a contextual example as a universal causal estimate.

The evidence boundary is January 1, 2026. Sources published during 2026 are excluded from the manuscript’s evidence base, even where later web pages are used for background verification. This boundary is important because the GenAI sustainability literature is changing rapidly and a fixed cutoff improves reproducibility.

### 3.3 Measurement Boundary

The proposed measurement boundary includes both the optimized corporate activity and the AI system used to support the decision. For

**Table 1. Selected Literature Relevant to GenAI-Enabled Sustainable Decision-Making**

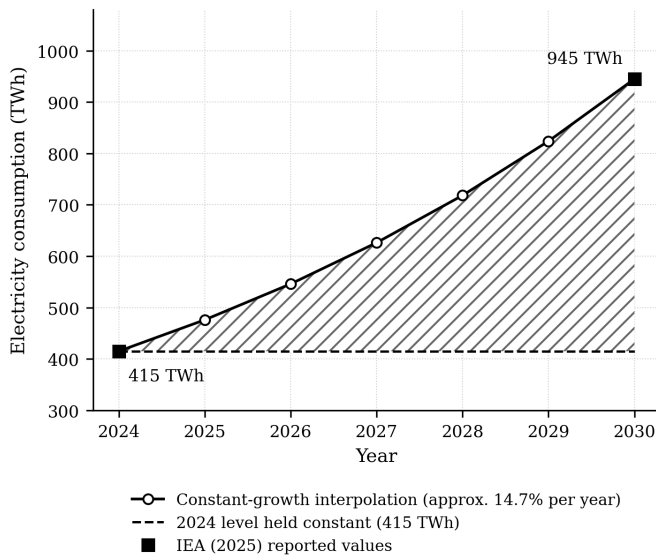
| Study                   | Research Focus                                                      | Decision Relevance                             | Potential GenAI Application                              |
|-------------------------|---------------------------------------------------------------------|------------------------------------------------|----------------------------------------------------------|
| Baryannis et al. (2019) | AI and supply-chain risk management                                 | Risk identification and supply-chain decisions | Risk-information synthesis and scenario support          |
| Cheng et al. (2024)     | AI and enterprise environmental performance                         | Environmental outcomes and resource allocation | Environmental-data interpretation and performance review |
| Ivanov (2023)           | Intelligent digital twins and supply-chain resilience               | Stress-testing and disruption analysis         | Scenario generation and resilience planning              |
| Kassa et al. (2023)     | AI techniques for supply-chain resilience                           | Resilience assessment and operational planning | Disruption-information synthesis and decision support    |
| Shahzadi et al. (2024)  | AI adoption in supply-chain management                              | Supply-chain planning and management           | Natural-language access to operational information       |
| Wang et al. (2024)      | AI, ecological footprints, carbon emissions, and energy transitions | Assessment of environmental outcomes           | Environmental-indicator synthesis and decision support   |

### GenAI-Supported Sustainable Decision Cycle



Measure environmental outcome → update baseline → repeat

**Figure 3. Proposed GenAI-supported sustainable decision cycle.**



**Figure 4. Data-centre electricity consumption path, 2024–2030.**

a given intervention, the baseline should represent the pre-AI or conventional decision process, while the post-intervention measure should represent the same process after implementation. Where possible, the analysis should control for production volume, weather, energy prices, product mix, and other factors that could change resource consumption independently of AI.

The framework also recommends reporting both intensity and absolute measures. For example, energy consumption per unit of output can fall while total energy consumption rises if production expands substantially. The same principle applies to water, material, transport, and waste indicators. This distinction is necessary to identify rebound effects.

### 3.4 Decision-Level Environmental Accounting

A sustainability claim should be linked to a specific intervention. The proposed workflow is: establish a baseline, identify the resource-intensive decision, implement the GenAI-supported intervention, measure the post-intervention outcome, estimate AI-attributable burden, and calculate the net effect. This process is intended to make sustainability claims auditable rather than purely narrative.

The framework also recommends recording uncertainty. If an environmental burden is estimated rather than directly measured, the uncertainty range should be retained. Future empirical implementations can therefore replace the illustrative parameters in this paper with measured electricity, water, emissions, and material-flow data.

The study adopts a structured secondary evidence-synthesis methodology. It combines peer-reviewed research, institutional reports, and corporate sustainability disclosures available before January 1, 2026. The methodology does not claim to generate a new primary firm-level dataset. Quantitative values taken from external studies are retained as reported evidence, while illustrative calculations are explicitly identified as methodological examples.

The analytical structure has five components: (1) GenAI decision pathways, (2) resource-efficiency measurement, (3) environmental-impact measurement, (4) AI infrastructure burden, and (5) governance and decision quality.

Table 2 defines the study architecture. The central methodological principle is that GenAI should be evaluated as part of a complete production and decision system. Resource savings generated by AI are therefore not treated as net benefits until the resources consumed by the AI system itself are considered.

### 3.5 Evidence Selection

Evidence was selected when it directly addressed at least one of the following themes: AI and environmental performance; AI and energy efficiency; AI and resource optimization; AI and sustainable supply chains; AI infrastructure energy or water use; circularity and digital technologies; or corporate environmental performance. Priority was given to peer-reviewed studies and authoritative institutional sources.

**Table 2. Research Design and Analytical Components**

| Component               | Evidence/Method                              | Purpose                                                               | Output                               |
|-------------------------|----------------------------------------------|-----------------------------------------------------------------------|--------------------------------------|
| Research design         | Secondary evidence synthesis                 | Integrate AI, sustainability, energy, resource, and business evidence | Evidence-based framework             |
| AI dimension            | GenAI and broader AI research                | Identify decision-support capabilities                                | GenAI decision pathways              |
| Resource dimension      | Energy, water, materials, waste, logistics   | Measure input efficiency                                              | Resource-efficiency indicators       |
| Environmental dimension | Emissions and pollution indicators           | Assess environmental outcomes                                         | Environmental performance indicators |
| AI burden               | Electricity, water, hardware, infrastructure | Account for AI-related environmental costs                            | AI burden estimate                   |
| Governance dimension    | Data quality, validation, human oversight    | Control decision risk                                                 | Responsible AI framework             |

**Table 3. Evidence Selection Framework**

| Criterion          | Included                                                        | Excluded                                 | Reason                                   |
|--------------------|-----------------------------------------------------------------|------------------------------------------|------------------------------------------|
| Date               | Evidence published before January 1, 2026                       | 2026 publications used as evidence       | Maintains a consistent evidence boundary |
| Quality            | Peer-reviewed studies and authoritative reports                 | Unsupported commentary                   | Improves evidence reliability            |
| Topic              | AI, GenAI, resources, sustainability, environmental performance | Unrelated AI applications                | Maintains research alignment             |
| Outcome            | Energy, water, materials, waste, emissions, productivity        | Outcomes without environmental relevance | Connects AI to sustainability            |
| Business relevance | Enterprise, operations, supply chain, infrastructure            | Purely non-organizational applications   | Supports sustainable business strategy   |

Table 3 shows the inclusion logic. Because the specific GenAI sustainability literature is still developing, relevant evidence on broader AI applications is used to establish mechanisms, while the paper avoids presenting broader AI evidence as direct causal evidence for GenAI.

### 3.6 GenAI Decision Pathways

Five principal decision pathways are analyzed: energy, materials and waste, water, supply chains and logistics, and sustainability information. A sixth pathway, environmental governance, links the other five to corporate strategy.

Table 4 demonstrates that GenAI is most useful when connected to operational data and a clearly defined resource-efficiency objective. A chatbot operating without access to relevant enterprise data may improve communication but cannot by itself establish a measurable resource-saving effect.

### 3.7 Resource-Efficiency Measurement

For resource  $r$ , the gross resource saving generated by a GenAI-supported intervention is:

$$GRS_r = R_{baseline,r} - R_{AI,r} \quad (1)$$

where  $R_{baseline,r}$  is resource consumption under the relevant baseline decision process and  $R_{AI,r}$  is consumption after implementation of the AI-supported decision process.

A percentage efficiency improvement is:

$$REI_r = \frac{R_{baseline,r} - R_{AI,r}}{R_{baseline,r}} \times 100 \quad (2)$$

where  $REI_r$  represents the resource-efficiency improvement for resource  $r$ .

The equations are measurement constructs rather than empirical findings. They require comparable baseline and post-intervention data.

### 3.8 Environmental Impact Measurement

For emissions, the basic avoided-emissions measure is:

$$AE = \sum_{r=1}^m GRS_r \times EF_r \quad (3)$$

where  $EF_r$  is the relevant environmental emission factor for resource  $r$ .

For example, electricity savings can be translated into avoided emissions using the applicable grid emission factor. Fuel, materials, transport, and other inputs require their own appropriate factors.

### 3.9 AI Environmental Burden

The environmental burden attributable to the AI intervention is represented as:

$$AIB = E_{AI}EF_e + W_{AI}EF_w + M_{AI}EF_m + I_{AI} \quad (4)$$

where  $E_{AI}$  is AI-related electricity consumption,  $EF_e$  is the electricity emissions factor,  $W_{AI}$  is AI-related water use,  $EF_w$  is the relevant water-impact factor,  $M_{AI}$  is material or hardware burden,  $EF_m$  is its environmental factor, and  $I_{AI}$  represents other attributable environmental impacts where measurable.

The net environmental benefit can then be represented as:

$$NEB = AE - AIB \quad (5)$$

A positive  $NEB$  indicates that measured avoided environmental impact exceeds the measured AI-related burden under the selected boundary. A negative value indicates that the AI intervention does not produce a net environmental benefit under that boundary.

### 3.10 Resource-Efficiency Decision Index

To support multi-resource decisions, this study proposes a Resource-Efficiency Decision Index (REDI):

$$REDI = w_E E + w_M M + w_W W + w_L L + w_G G \quad (6)$$

where  $E$ ,  $M$ ,  $W$ ,  $L$ , and  $G$  represent normalized performance for energy, materials, water, logistics, and governance, respectively, and the weights sum to one.

$$\sum_{j=1}^5 w_j = 1 \quad (7)$$

The index is a methodological construct. It should be calibrated using organizational priorities rather than treated as a universal sustainability standard.

**Table 4. GenAI Decision Pathways for Corporate Resource Efficiency**

| Pathway        | GenAI-Supported Activity                              | Resource-Efficiency Mechanism                                 | Environmental Indicator                  |
|----------------|-------------------------------------------------------|---------------------------------------------------------------|------------------------------------------|
| Energy         | Interpret meter data and generate operating scenarios | Reduce unnecessary consumption and improve scheduling         | kWh/unit; energy cost; Scope 2 emissions |
| Materials      | Analyze bills of materials and procurement records    | Reduce over-ordering, scrap, and inefficient input allocation | Material intensity; scrap rate           |
| Waste          | Analyze waste records and process deviations          | Identify avoidable waste and reuse opportunities              | Waste/unit; diversion rate               |
| Water          | Interpret sensor and maintenance records              | Detect leakage and abnormal consumption                       | m <sup>3</sup> /unit; leakage volume     |
| Supply chain   | Compare supplier, route, and inventory scenarios      | Reduce distance, inventory duplication, and disruption losses | tonne-km; inventory intensity; emissions |
| ESG governance | Extract and validate sustainability information       | Improve data consistency and decision transparency            | Reporting completeness; assurance rate   |

### 3.11 Economic Evaluation

Resource savings can create direct economic value. The annual net economic benefit can be estimated as:

$$ANB = C_{resource} + C_{waste} + C_{logistics} + C_{downtime} - C_{AI} \quad (8)$$

where the  $C$  terms represent annual avoided costs and  $C_{AI}$  represents annual AI-related operating costs attributable to the intervention. Payback is calculated as:

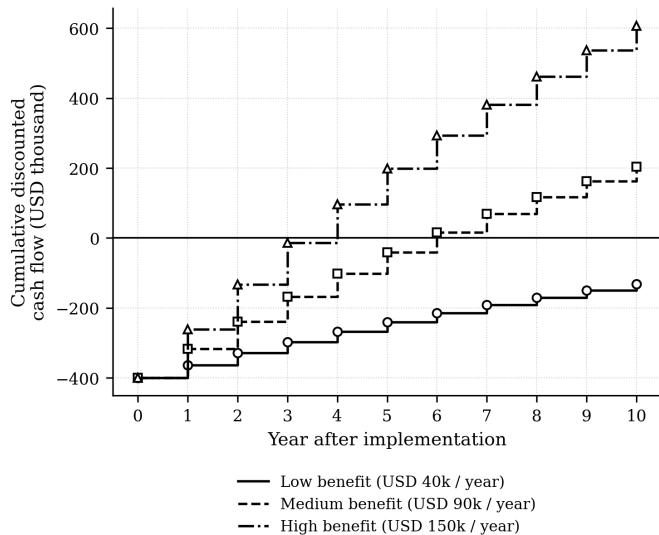
$$Payback = \frac{\text{Initial AI Investment}}{\text{Annual Net Benefit}} \quad (9)$$

Net present value can be estimated as:

$$NPV = -I_0 + \sum_{t=1}^T \frac{CF_t}{(1+r)^t} \quad (10)$$

where  $I_0$  is initial investment,  $CF_t$  is annual net cash flow,  $r$  is the discount rate, and  $T$  is the evaluation period.

Figure 5 illustrates Equation 10 for a hypothetical intervention with an initial investment of USD 400 thousand, an 8% discount rate, a ten-year evaluation period, and constant annual net benefits of USD 40, 90, or 150 thousand. Under these illustrative assumptions, the low-benefit case has not recovered its investment after ten years (NPV of about USD -132 thousand), the medium-benefit case reaches discounted payback in year six (NPV of about USD 204 thousand), and the high-benefit case reaches it in year four (NPV of about USD 607 thousand). The parameters are hypothetical and are intended only to show how discounted payback depends on the size of the annual net benefit.



**Figure 5. GenAI sustainability intervention under three annual net-benefit cases.**

### 3.12 Generative AI and the Economics of Sustainable Decisions

The strategic relevance of GenAI is strongest when information costs are a material constraint on environmental decision-making. Corporate sustainability decisions often require managers to combine operational records, supplier information, energy data, financial constraints, regulatory requirements, engineering assumptions, and environmental targets. These inputs are frequently distributed across different systems and expressed in different formats. GenAI can reduce the time required to synthesize such information and can make analytical outputs more accessible to non-specialist decision makers. The environmental value, however, arises only when improved information leads to a changed decision and the changed decision affects physical resource use.

This distinction can be represented as a decision chain:

$$\begin{aligned} &\text{Data Quality} \rightarrow \text{Information Quality} \rightarrow \text{Decision Quality} \\ &\rightarrow \text{Resource Outcome} \rightarrow \text{Environmental Outcome.} \end{aligned} \quad (11)$$

The chain implies that GenAI should not be evaluated only by output fluency, response speed, or user satisfaction. A sustainability-oriented evaluation must ask whether the system improves the information available to decision makers, whether the resulting recommendation is correct and implementable, and whether implementation changes resource consumption. This is particularly important because a highly persuasive generated answer can be operationally harmful if it is based on incomplete or incorrect data.

The economic logic can also be expressed through marginal benefit. Let  $B_G$  represent the monetary value of the operational improvement attributable to GenAI and let  $C_G$  represent the total incremental cost of the GenAI intervention. Then:

$$NB_G = B_G - C_G, \quad (12)$$

where  $NB_G$  is the net business benefit. For sustainability decisions, the cost term should include not only licensing and labor costs but, where material, electricity, infrastructure, data preparation, governance, and implementation costs. A project can therefore be financially attractive while still requiring environmental scrutiny, or environmentally beneficial while requiring a longer financial payback period.

### 3.13 GenAI Across Corporate Functions

The potential contribution of GenAI varies by business function. In procurement, GenAI can compare supplier information and identify missing sustainability evidence. In operations, it can assist with maintenance interpretation, production scheduling, and anomaly investigation. In logistics, it can support route and fleet scenario analysis. In finance, it can connect investment decisions with environmental assumptions and carbon-related costs. In sustainability reporting, it can organize evidence and identify inconsistencies, although reported figures should remain subject to formal verification.

Table 5 indicates that the strongest environmental applications are those in which a generated recommendation can be connected to a measurable physical or financial decision. The table also illustrates why a common sustainability KPI framework is needed across functions. Without common measurement boundaries, different departments may report isolated efficiency improvements that cannot be aggregated into a corporate environmental account.

**Table 5. Corporate Functions and Potential GenAI Resource-Efficiency Applications**

| Function       | Decision Problem                  | Potential GenAI Contribution                                      | Environmental KPI                                 |
|----------------|-----------------------------------|-------------------------------------------------------------------|---------------------------------------------------|
| Procurement    | Supplier selection and purchasing | Supplier-data synthesis, specification comparison, risk screening | Material intensity; supplier emissions            |
| Operations     | Production and maintenance        | Work-order analysis, anomaly interpretation, scenario generation  | Energy/unit; downtime; scrap rate                 |
| Logistics      | Routing and fleet planning        | Scenario comparison, route explanation, charging-plan support     | tCO <sub>2</sub> e/tonne-km; fuel/electricity use |
| Energy         | Demand and load management        | Forecast interpretation, scheduling support, exception analysis   | kWh/unit; peak demand                             |
| Water          | Leakage and demand management     | Sensor-data interpretation and anomaly reporting                  | m <sup>3</sup> /unit; leakage volume              |
| Finance        | Sustainable investment decisions  | Assumption synthesis and sensitivity narratives                   | NPV; carbon cost; payback                         |
| Sustainability | ESG and environmental reporting   | Evidence organization and consistency checks                      | Verified-data rate; reporting errors              |
| Product Design | Materials and lifecycle decisions | Alternative-material comparison and design scenario generation    | Material footprint; recyclability                 |

### 3.14 Carbon, Trade, and Competitiveness

Carbon regulation represents an important strategic consideration for sustainable business decisions. Carbon-related trade policies can affect firms' production costs, emissions reporting requirements, market access, and international competitiveness. GenAI may help organizations summarize regulatory requirements, organize emissions-related information, and communicate alternative policy scenarios. However, its outputs should be checked against authoritative regulations, verified carbon-accounting data, and appropriate economic models.

These considerations highlight the importance of evaluating environmental and financial outcomes together. Emissions reductions may provide environmental benefits while also affecting operating costs and export competitiveness. Accordingly, a sustainable GenAI decision-support framework should consider environmental indicators alongside relevant economic measures rather than optimizing a single performance metric.

### 3.15 Urban Freight and Low-Carbon Logistics

Transport is a resource-intensive business activity in which operational decisions can affect energy consumption, emissions, costs, and service performance. Fleet electrification introduces interconnected planning considerations, including vehicle utilization, route distances, charging availability, electricity costs, and delivery requirements. These factors make transport planning a relevant application area for AI-supported sustainable business strategy.

GenAI can complement quantitative logistics and optimization models by summarizing fleet scenarios, explaining trade-offs, identifying assumptions that require review, and helping managers explore alternative decisions. However, feasibility calculations and emissions estimates should rely on validated fleet, network, energy, and cost data. A hybrid decision-support approach can therefore combine quantitative models for calculating alternatives with GenAI for interpretation, managerial communication, and scenario exploration.

### 3.16 Renewable Energy, Microgrids, and Manufacturing

Manufacturing firms face complex decisions when evaluating renewable energy and microgrid adoption. These decisions involve balancing environmental performance, technical feasibility, investment costs, energy reliability, and operating requirements. For small and medium-sized enterprises (SMEs), assessing these factors together is essential when determining the feasibility and potential benefits of an energy transition.

GenAI may support energy-strategy planning by synthesizing demand forecasts, production schedules, electricity tariffs, renewable-generation scenarios, and investment assumptions. It can help managers compare alternatives, identify uncertainties, and communicate potential trade-offs. However, engineering assessments, financial projections, and feasibility calculations must rely on validated data and established analytical methods. Sustainability outcomes should be evaluated using indicators such as energy intensity, electricity sources, emis-

sions, system reliability, and lifecycle costs.

### 3.17 Industrial Carbon Dynamics in Developing Asia

The broader macroeconomic context is also important when evaluating industrial emissions and sustainability strategies. Carbon emissions are influenced not only by firm-level technologies but also by economic development, industrial structure, energy sources, and production patterns. These factors highlight the limitations of assessing corporate environmental performance without considering the wider economic and energy context.

For GenAI-supported business strategy, this means that proposed interventions should be evaluated in relation to the systems in which firms operate. A model may identify a process improvement that reduces resource consumption within a facility, but its overall environmental impact may depend on the electricity mix, production scale, transport networks, and surrounding industrial conditions. Accordingly, AI-supported sustainability assessments should account for relevant contextual variables and avoid assuming that efficiency gains observed in one country, sector, or operating environment will apply equally elsewhere.

### 3.18 Green Innovation and Organizational Capability

AI-enabled sustainability also depends on organizational capability. Environmental improvement requires more than a technically capable model; firms need data ownership, process knowledge, environmental accounting, managerial accountability, and implementation capacity. The enterprise evidence discussed earlier suggests that AI can operate through productivity improvement, factor-input optimization, green innovation, and pollution-reduction investment. These mechanisms imply that organizational capability mediates the relationship between digital intelligence and environmental performance.

A useful conceptual representation is:

$$\begin{aligned}
 &\text{AI Capability} + \text{Sustainability Capability} \\
 &\quad \rightarrow \text{Decision Quality} \\
 &\quad \rightarrow \text{Operational Change} \\
 &\quad \rightarrow \text{Environmental Performance}
 \end{aligned} \tag{13}$$

This proposition has an important managerial implication. Firms should not measure AI maturity and sustainability maturity separately. The strategic objective is to develop an integrated capability in which AI systems can access reliable environmental information, operate under defined constraints, and produce auditable recommendations.

### 3.19 Data Quality, Hallucination, and Environmental Decision Risk

The reliability of GenAI-enabled sustainability decisions is constrained by data quality. Environmental information may be incomplete because supplier inventories are missing, measurement systems are inconsistent, boundaries differ across facilities, or emission factors are outdated. GenAI can organize these data but cannot automatically resolve an underlying measurement problem.

For this reason, every sustainability-oriented GenAI workflow should maintain a source hierarchy. Primary measurements and audited records should be prioritized over estimates; documented assumptions should be separated from measured values; and generated text should not be treated as evidence unless it can be traced to a validated source. The risk of hallucination is particularly serious where generated statements are incorporated into environmental disclosures or investment decisions.

A useful reliability ratio is:

$$VR = \frac{N_v}{N_g} \times 100, \quad (14)$$

where  $N_v$  is the number of material generated claims verified against authoritative evidence and  $N_g$  is the total number of material generated claims reviewed. A high verification rate does not prove environmental performance, but it provides a governance indicator for the reliability of AI-assisted sustainability communication.

### 3.20 Rebound Effects and Absolute Environmental Performance

Efficiency improvements can create rebound effects. If GenAI reduces the resource intensity of production but simultaneously encourages higher production volume, total resource use may remain unchanged or increase. Therefore, environmental monitoring should include both intensity and absolute indicators.

Let  $R_I$  denote resource intensity and  $Q$  denote output. Total resource use is:

$$R_T = R_I \times Q. \quad (15)$$

If resource intensity decreases by 10% while output increases by more than 11.1%, total resource use can increase despite the efficiency improvement. This simple relationship demonstrates why corporate sustainability dashboards should report both resource-per-unit measures and total resource consumption.

Figure 6 plots Equation 15 for intensity reductions of 5%, 10%, 15%, and 20%. Each line crosses the baseline at the output growth rate at which the efficiency gain is fully offset, given by  $1/(1-\delta) - 1$  for an intensity reduction  $\delta$ : 5.3%, 11.1%, 17.6%, and 25.0%, respectively. Above these thresholds, absolute resource use exceeds its pre-intervention level even though intensity has improved.

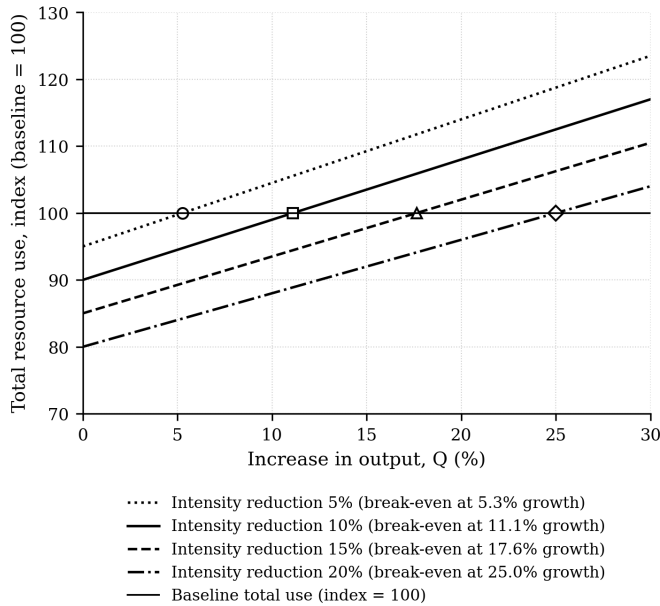


Figure 6. Total resource use as a function of output growth for four intensity-reduction levels.

### 3.21 Portfolio-Level GenAI Sustainability

Organizations rarely deploy one AI application in isolation. A portfolio may include customer-service models, coding assistants, document summarization, energy optimization, procurement intelligence,

and sustainability reporting tools. The aggregate environmental effect depends on the composition of this portfolio.

Let  $NEB_i$  denote the net environmental benefit of application  $i$ . A simplified portfolio measure is:

$$NEB_{portfolio} = \sum_{i=1}^n NEB_i, \quad (16)$$

provided that the applications have compatible boundaries and double counting is avoided. This final condition is critical. For example, a logistics application and an energy application may both attribute the same avoided emissions to themselves if their accounting boundaries overlap. Portfolio governance should therefore establish common base-lines and ownership rules.

### 3.22 Sensitivity Analysis

Because the net benefit depends on uncertain parameters, organizations should conduct sensitivity analysis rather than reporting a single deterministic estimate. For the illustrative equation

$$NEB = (R_B - R_P)EF - AI_B, \quad (17)$$

where  $R_B$  is baseline resource use,  $R_P$  is post-intervention resource use,  $EF$  is the relevant environmental conversion factor, and  $AI_B$  is AI-attributable environmental burden, the result can vary substantially if the emission factor or AI burden changes.

A practical sensitivity analysis should vary at least three parameters: the expected operational saving, the environmental conversion factor, and AI infrastructure burden. Decision makers can then identify whether the conclusion is robust or depends on a narrow set of assumptions.

Table 6 provides a template rather than an empirical estimate. In future firm-level studies, each parameter should be populated with observed data and uncertainty intervals. Sensitivity analysis is especially important when the estimated environmental benefit is relatively small compared with the uncertainty surrounding AI-related infrastructure impacts.

Figures 7 and 8 make the sensitivity template quantitative using the worked example of Section 4 (baseline electricity use of 10,000 MWh and an AI-attributable burden of 50 MWh). Figure 7 varies the grid emission factor for operational savings of 5%, 10%, and 15%. Because both avoided emissions and AI-attributable emissions scale with the same factor, the net environmental benefit is linear in the emission factor and its slope is set by the net electricity saving. The vertical reference line marks the illustrative factor of 0.45 tCO<sub>2</sub>e/MWh used in the worked example, where the 10% case yields 427.5 tCO<sub>2</sub>e.

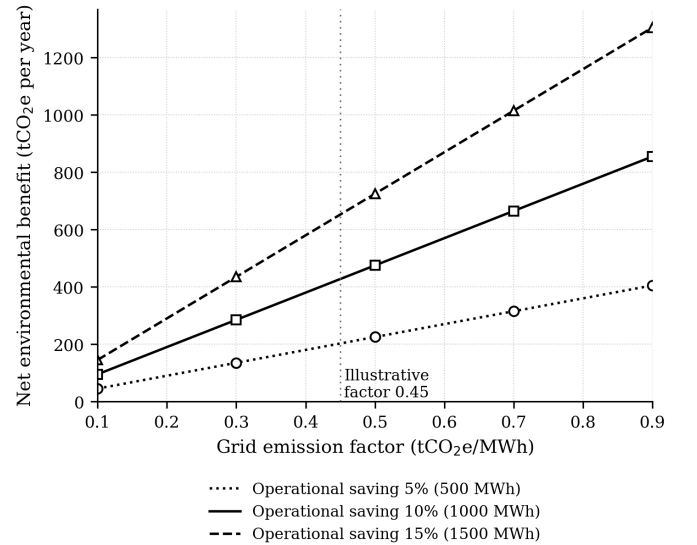


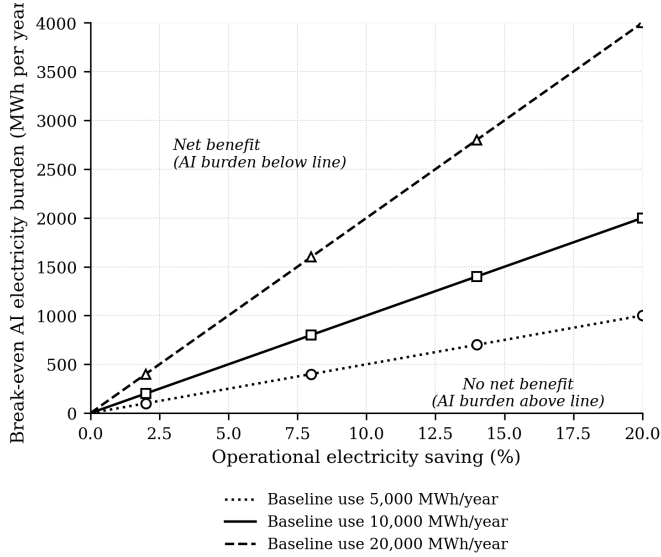
Figure 7. Net environmental benefit as a function of the grid emission factor for three operational-saving levels.

Figure 8 shows the break-even AI electricity burden, that is, the level of AI-attributable electricity use at which the net electricity saving falls to zero. It is the product of the baseline consumption and the

**Table 6. Illustrative Sensitivity Analysis for Net Environmental Benefit**

| Parameter                       | Low Case        | High Case        | Interpretation                                                      |
|---------------------------------|-----------------|------------------|---------------------------------------------------------------------|
| Operational resource saving     | 5%              | 15%              | Measures effectiveness of the intervention                          |
| Environmental conversion factor | Lower intensity | Higher intensity | Depends on electricity or fuel system                               |
| AI-attributable burden          | High            | Low              | Depends on model, workload, infrastructure, and accounting boundary |
| Production volume               | Higher          | Lower            | Determines whether rebound effects occur                            |
| Implementation success          | Partial         | Full             | Determines realized rather than theoretical savings                 |

fractional saving, so larger facilities can tolerate a larger absolute AI burden for the same percentage saving. Points below each line indicate a net electricity benefit; points above indicate that the AI intervention consumes more electricity than it saves.



**Figure 8. Break-even AI electricity burden as a function of operational electricity saving for three baseline consumption levels.**

### 3.23 Research Propositions

The evidence synthesis supports a set of testable propositions for future empirical research:

**P<sub>1</sub>:** GenAI decision support is positively associated with resource efficiency when it is deployed in resource-intensive operational processes and supported by validated data. (18)

**P<sub>2</sub>:** Data quality positively moderates the relationship between GenAI use and environmental performance. (19)

**P<sub>3</sub>:** AI environmental burden reduces the net environmental benefit of GenAI interventions. (20)

**P<sub>4</sub>:** Human oversight strengthens the reliability of GenAI sustainability decisions. (21)

**P<sub>5</sub>:** Rebound effects weaken the relationship between resource efficiency improvements and absolute environmental reductions. (22)

These propositions provide a basis for future panel-data. They also clarify that the paper's evidence synthesis should not be interpreted as a universal causal estimate.

### 3.24 Expanded Research Agenda

Future empirical research should move from broad AI-adoption measures toward decision-level treatment definitions. A useful dataset would record the date of GenAI deployment, task type, model characteristics, inference volume, electricity use where measurable, process baseline, environmental KPI, production volume, and financial outcome. Such a dataset would permit researchers to distinguish productivity effects from environmental effects and to estimate whether sustainability gains persist over time.

Research should also compare model classes and workflows. Smaller task-specific models may provide adequate decision quality with substantially lower computational requirements than large general-purpose systems for some applications. The relevant optimization problem is therefore not simply model accuracy but decision quality per unit of environmental burden.

Cross-country studies are another priority. Electricity carbon intensity, water stress, industrial structure, regulatory systems, and supply-chain configuration vary considerably across countries. The emerging-economy studies incorporated in this paper demonstrate why context matters. Future research should therefore avoid transferring a sustainability estimate from one energy or industrial system to another without adjustment.

Finally, future work should examine the interaction between GenAI and established quantitative methods. The most credible sustainability architecture may combine GenAI with optimization, forecasting, life-cycle assessment, technoeconomic analysis, carbon accounting, and digital twins. Such hybrid systems can use GenAI for synthesis and interaction while retaining specialized mathematical models for calculations that require reproducibility and formal validation.

## 4. Analysis and Results

### 4.1 Evidence on AI and Environmental Performance

The evidence synthesis indicates a positive association between AI adoption and enterprise environmental performance in several empirical studies, but the evidence should not be interpreted as proof that GenAI itself produces a uniform environmental improvement. Cheng et al. (2024) report that AI reduces pollution-emission intensity and improves enterprise environmental performance among Chinese firms. Their mechanism analysis identifies productivity improvement, pollution-control investment, and factor-input optimization.

A separate 2024 study in the *Journal of Environmental Management* similarly reports significant improvement in enterprise environmental performance associated with AI and identifies green innovation and financing constraints as relevant mechanisms. Together, these studies suggest that the environmental value of AI can arise from better allocation of production factors and stronger innovation capacity.

Table 7 is central to the study because it places potential benefits and costs in the same evidence structure. The reported 8–19% building result is scenario-specific, while the 415 TWh data-centre figure describes the electricity demand of the broader data-centre sector. Neither number should be interpreted as a universal GenAI effect.

### 4.2 Energy Resource Efficiency

Energy is a major pathway through which AI-supported decisions can create environmental value. AI systems can forecast demand, identify

**Table 7. Empirical Evidence Linking AI to Environmental Performance**

| Evidence                                   | Context                   | Reported Finding                                                                             | Relevance to GenAI Strategy                           |
|--------------------------------------------|---------------------------|----------------------------------------------------------------------------------------------|-------------------------------------------------------|
| Cheng et al. (2024)                        | Chinese enterprises       | AI significantly reduces pollution-emission intensity and improves environmental performance | Supports productivity and input-optimization pathways |
| Journal of Environmental Management (2024) | Chinese enterprises       | AI significantly improves environmental performance; green innovation is a mechanism         | Supports innovation-oriented AI strategy              |
| Wang et al. (2024)                         | 67-country panel          | Examines AI, ecological footprint, carbon emissions, and energy transition                   | Supports multi-indicator environmental assessment     |
| Nature Communications (2024)               | U.S. commercial buildings | AI scenarios estimate 8–19% reductions in energy use and carbon emissions by 2050            | Illustrates sector-specific efficiency potential      |
| IEA (2025)                                 | Global data centres       | 415 TWh electricity use in 2024; about 1.5% of global electricity                            | Establishes AI infrastructure burden                  |

abnormal consumption, schedule equipment, and support optimization of energy-intensive operations. The building-energy evidence provides a quantitative indication of the potential scale: the 2024 *Nature Communications* study estimates approximately 8–19% reductions in energy consumption and carbon emissions by 2050 under the scenarios considered.

**Table 8. Evidence-Based Energy Indicators**

| Indicator                                | Reported Value | Interpretation                                 |
|------------------------------------------|----------------|------------------------------------------------|
| Global data-centre electricity use, 2024 | 415 TWh        | Approx. 1.5% of global electricity consumption |
| AI-enabled building energy reduction     | 8–19%          | Scenario-based estimate to 2050                |
| AI-enabled building carbon reduction     | 8–19%          | Scenario-based estimate to 2050                |

Table 8 shows why a net-effect perspective is required. If GenAI improves an organization’s energy efficiency by reducing operational electricity use, the organization should still account for the electricity consumed by the GenAI workflow and its supporting infrastructure.

For an organization that consumes 10,000 MWh annually, an illustrative 10% reduction would represent 1,000 MWh of gross operational savings. If the GenAI intervention itself were responsible for 50 MWh of attributable electricity use, the net electricity saving would be 950 MWh. This example is methodological and not an observed company result.

#### 4.3 Materials and Waste Efficiency

GenAI can support materials management by interpreting procurement records, production reports, quality-control notes, and inventory information. The expected mechanism is not direct material transformation but improved decision quality. Better demand estimates can reduce overproduction; improved anomaly identification can reduce scrap; and better documentation can improve reuse and recycling decisions.

Microsoft’s 2024 sustainability report provides a corporate example of circularity in digital infrastructure: the company reported an 89.4% reuse and recycling rate for servers and components across its cloud hardware in 2023. This figure describes Microsoft’s hardware-management performance and should not be interpreted as an average GenAI recycling rate.

Table 9 indicates that GenAI is most valuable when it converts dispersed operational information into a decision that can be measured against material-use outcomes.

#### 4.4 Water Resource Efficiency

Water efficiency is increasingly important in both industrial production and digital infrastructure. GenAI can support leakage detection, demand forecasting, maintenance prioritization, and interpretation of water-quality or facility records. Microsoft reports AI-enabled acoustic analysis for leakage reduction and describes new data-centre designs intended to use zero water for cooling.

$$\text{Water Efficiency} = \frac{\text{Water}_{\text{baseline}} - \text{Water}_{\text{AI}}}{\text{Water}_{\text{baseline}}} \times 100 \quad (23)$$

The equation provides a straightforward operational metric, but organizations should use consistent boundaries and measurement periods. A water-saving intervention should also account for indirect water use where material to the decision.

#### 4.5 Supply-Chain Resource Efficiency

Supply chains combine energy, fuel, inventory, materials, and transportation resources. GenAI can support supply-chain managers by synthesizing supplier data, identifying concentration risks, generating route alternatives, explaining inventory scenarios, and translating external environmental information into operational implications.

Table 10 shows that the sustainability value of GenAI can be indirect. A generated recommendation may reduce emissions only because it changes a transport, inventory, supplier, or scheduling decision.

#### 4.6 Environmental Reporting and Data Quality

Sustainability decisions require reliable data. GenAI can reduce the administrative burden of reviewing environmental documents, but generated summaries must be traceable to source information. This is particularly important because errors in emissions, energy, water, or supplier data can propagate into strategic decisions.

The reliability relationship is:

$$\begin{aligned} \text{Data Quality} &\rightarrow \text{Model Reliability} \\ &\rightarrow \text{Decision Quality} \\ &\rightarrow \text{Environmental Outcome} \end{aligned} \quad (24)$$

The equation emphasizes that AI capability does not compensate for systematically poor source data. Organizations should therefore retain source-level evidence, record model outputs, validate material claims, and establish clear responsibility for final decisions.

#### 4.7 AI Burden and the Net Sustainability Test

The evidence indicates that AI infrastructure creates a measurable environmental burden. The IEA’s estimate of 415 TWh of data-centre electricity use in 2024 illustrates the scale of digital infrastructure. Microsoft’s reporting also shows that rapid data-centre expansion can contribute to higher Scope 3 emissions even while the company pursues operational efficiency and renewable-energy measures.

Table 11 demonstrates why the sustainability test should compare benefits and burdens within a common boundary. The appropriate conclusion is not that GenAI is inherently sustainable, but that specific GenAI applications can be sustainable when measurable resource savings exceed attributable environmental burdens.

#### 4.8 Illustrative Net-Effect Calculation

Consider a hypothetical manufacturing facility with annual electricity consumption of 10,000 MWh. Suppose a GenAI-supported energy-management workflow produces a 10% reduction in operational electricity use. Gross savings would be:

$$\text{GRS}_E = 10,000 - 9,000 = 1,000 \text{ MWh} \quad (25)$$

If the AI workflow is attributable to 50 MWh of electricity consumption, the net electricity saving becomes:

**Table 9. Material and Waste Decision Framework**

| Decision Area   | GenAI Contribution                    | Expected Resource Mechanism                 | Metric                         |
|-----------------|---------------------------------------|---------------------------------------------|--------------------------------|
| Demand planning | Explain demand scenarios              | Lower overproduction and excess inventory   | Inventory turnover; waste/unit |
| Procurement     | Compare supplier information          | Reduce unnecessary or duplicated purchasing | Material intensity             |
| Quality control | Summarize defect patterns             | Identify recurring causes of scrap          | Scrap rate                     |
| Maintenance     | Interpret maintenance records         | Reduce premature replacement and downtime   | Asset life; material use       |
| Circularity     | Extract reuse/recycling opportunities | Extend material life                        | Reuse rate; diversion rate     |

**Table 10. GenAI-Supported Supply-Chain Resource Decisions**

| Decision              | Input Information                               | Potential Efficiency Mechanism                             | Key Metric                   |
|-----------------------|-------------------------------------------------|------------------------------------------------------------|------------------------------|
| Supplier allocation   | Supplier capacity, location, environmental data | Reduce risk-driven emergency sourcing and excess transport | Supplier distance; emissions |
| Inventory positioning | Demand, lead time, disruption data              | Reduce excess stock while maintaining service levels       | Inventory intensity          |
| Route planning        | Distance, traffic, vehicle and delivery data    | Reduce fuel and transport requirements                     | tonne-km; fuel/unit          |
| Production scheduling | Orders, capacity, energy data                   | Shift production toward efficient periods                  | kWh/unit                     |
| Disruption response   | Weather, supplier, logistics information        | Reduce downtime and emergency resource use                 | Downtime; recovery cost      |

**Table 11. AI Sustainability Trade-Offs**

| Benefit Channel          | Potential Benefit                 | Potential Burden                                      | Measurement                |
|--------------------------|-----------------------------------|-------------------------------------------------------|----------------------------|
| Energy optimization      | Lower operational electricity use | AI compute electricity                                | Net MWh saved              |
| Logistics optimization   | Lower fuel and transport use      | Compute and data infrastructure                       | Net tonne-km/fuel          |
| Material optimization    | Lower material and scrap use      | Hardware and infrastructure materials                 | Net material saved         |
| Water optimization       | Lower process water use           | Data-centre cooling and electricity-related water use | Net m <sup>3</sup> saved   |
| Decision automation      | Lower administrative resource use | Model inference and infrastructure                    | Cost/resource per decision |
| Sustainability reporting | Better data consistency           | Additional digital infrastructure                     | Verified reporting quality |

$$Net\ Saving_E = 1,000 - 50 = 950\ MWh \quad (26)$$

If the applicable electricity emission factor is 0.45 tCO<sub>2</sub>e/MWh, the corresponding gross avoided emissions would be:

$$AE = 1,000 \times 0.45 = 450\ tCO_2e \quad (27)$$

and the AI-attributable emissions would be:

$$AI\ Burden = 50 \times 0.45 = 22.5\ tCO_2e \quad (28)$$

giving an illustrative net environmental benefit of:

$$NEB = 450 - 22.5 = 427.5\ tCO_2e \quad (29)$$

These values are illustrative calculations, not observed results. They demonstrate the measurement procedure required to determine whether a particular AI application creates a net environmental benefit.

**Table 12. Illustrative Net Environmental Benefit Calculation**

| Variable                  | Illustrative Value          | Calculation   |
|---------------------------|-----------------------------|---------------|
| Baseline electricity      | 10,000 MWh                  | Given         |
| Post-AI electricity       | 9,000 MWh                   | 10% reduction |
| Gross saving              | 1,000 MWh                   | Difference    |
| AI electricity burden     | 50 MWh                      | Given         |
| Net saving                | 950 MWh                     | 1,000–50      |
| Emission factor           | 0.45 tCO <sub>2</sub> e/MWh | Illustrative  |
| Gross avoided emissions   | 450 tCO <sub>2</sub> e      | 1,000×0.45    |
| AI-attributable emissions | 22.5 tCO <sub>2</sub> e     | 50×0.45       |
| Net environmental benefit | 427.5 tCO <sub>2</sub> e    | 450–22.5      |

Table 12 demonstrates that a sustainability claim should not be based solely on gross operational savings. The AI burden must be included before the net environmental effect is calculated.

#### 4.9 Scenario Analysis

Three scenarios are used to evaluate the conditions under which GenAI is likely to produce a net resource benefit.

Table 13 indicates that business strategy should prioritize use cases with a clear resource-efficiency mechanism. The objective is not to maximize AI usage but to maximize measurable value per unit of environmental burden.

Figure 9 gives a quantitative illustration of the three scenarios over ten years, using the same 10,000 MWh baseline and 0.45 tCO<sub>2</sub>e/MWh emission factor as the worked example. The efficiency-led case assumes an annual saving of 1,200 MWh against an AI burden of 40 MWh per year; the balanced case assumes 800 MWh against 80 MWh per year; and the compute-intensive case assumes 300 MWh against an AI burden that starts at 150 MWh and grows by 40 MWh each year as usage expands. Cumulative net benefit reaches about 5,220 and 3,240 tCO<sub>2</sub>e in the first two cases, whereas in the compute-intensive case it peaks in the fourth year and turns negative from the ninth year onward, ending at about –135 tCO<sub>2</sub>e. All parameters are hypothetical and serve only to show how growing inference demand can erode an initially positive net benefit.

#### 4.10 Governance and Decision Reliability

The evidence supports a human-in-the-loop model. GenAI can accelerate information processing, but corporate decision makers remain responsible for resource allocation, investment, compliance, and risk acceptance.

Table 14 shows that sustainability governance must extend beyond conventional AI accuracy. A model can be technically accurate while

Table 13. GenAI Sustainability Scenarios

| Scenario                   | Operational Condition                              | AI Resource Condition                          | Expected Sustainability Result                    |
|----------------------------|----------------------------------------------------|------------------------------------------------|---------------------------------------------------|
| Efficiency-led             | Strong process optimization and measurable savings | Efficient models and low unnecessary inference | High potential for net resource benefit           |
| Balanced adoption          | Moderate operational savings                       | Moderate compute and infrastructure burden     | Benefit depends on measurement and governance     |
| Compute-intensive adoption | Limited operational improvement                    | High-frequency or high-compute AI use          | Net environmental benefit may be weak or negative |

Table 14. GenAI Governance Controls for Sustainable Decision-Making

| Risk                  | Potential Problem                               | Control                                    | Indicator                 |
|-----------------------|-------------------------------------------------|--------------------------------------------|---------------------------|
| Data quality          | Incorrect environmental inputs                  | Source validation and data lineage         | Error rate                |
| Hallucination         | Unsupported generated recommendation            | Human verification and retrieval grounding | Verified-output rate      |
| Overuse               | Excessive AI inference                          | Model/task selection and usage limits      | Compute per decision      |
| Bias                  | Unequal supplier or operational recommendations | Bias testing and review                    | Disparate-error measures  |
| Opacity               | Managers cannot explain decisions               | Documentation and explainability           | Audit completeness        |
| Environmental rebound | Efficiency gains increase total usage           | Net-effect accounting                      | Net environmental benefit |

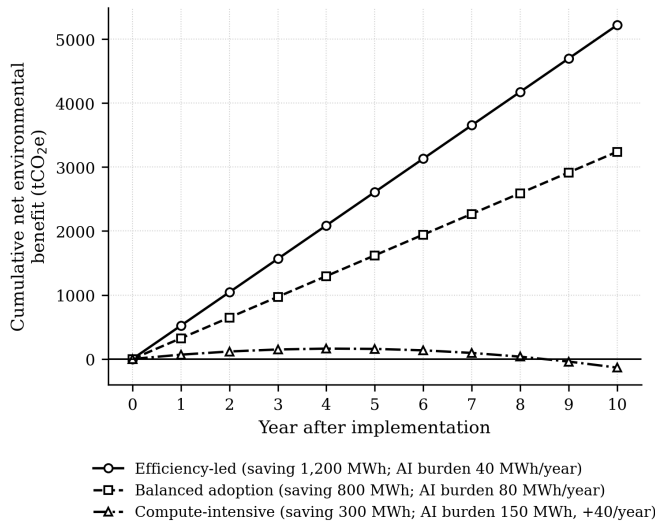


Figure 9. Cumulative net environmental benefit over ten years under the three sustainability scenarios (hypothetical parameters).

still generating poor sustainability decisions if the underlying objective is poorly defined or if rebound effects are ignored.

#### 4.11 Strategic Decision Framework

The evidence synthesis supports a six-step strategic process:

*Measure → Identify → Generate → Validate → Implement → Monitor* (30)

The first step establishes a resource baseline. The second identifies inefficient processes. The third uses GenAI to generate alternatives. The fourth validates the alternatives against enterprise data and sustainability constraints. The fifth implements the selected decision. The sixth monitors both operational and environmental outcomes and feeds them back into the next decision cycle.

## 5. Discussion

The results provide a conditional answer to the research question. AI-powered decision-making can improve corporate resource efficiency and environmental performance when it is connected to measurable operational processes and when the resource burden of AI is included in the assessment. The evidence does not support treating GenAI adoption itself as an environmental intervention.

The first implication is that sustainability value is decision-specific. GenAI used to summarize documents may produce administrative productivity but little direct resource saving. By contrast, GenAI integrated with energy-management, procurement, logistics, or maintenance sys-

tems can influence physical resource flows. Consequently, the appropriate unit of analysis is not “AI adoption” in the abstract but the AI-enabled decision and its measurable downstream effect.

The second implication concerns measurement boundaries. Organizations frequently measure the resource use of the optimized process but not the resource use of the AI system. This can overstate sustainability benefits. The net-environment equation proposed in this study addresses this issue by subtracting attributable AI burden from avoided environmental impact.

The third implication concerns organizational capability. AI cannot compensate for absent measurement systems. If an organization does not know how much energy a production line consumes, how much material becomes scrap, or how much water is lost through leakage, GenAI cannot reliably demonstrate improvement. Data governance therefore becomes a prerequisite for sustainability-oriented AI.

The fourth implication concerns rebound effects. Efficiency improvements can reduce resource use per unit while total production increases. For example, an AI system might reduce energy intensity by 10% while production volume rises sufficiently for total energy use to increase. Environmental performance should therefore be monitored using both intensity and absolute measures.

The fifth implication concerns strategic integration. GenAI should be embedded within enterprise sustainability strategy rather than deployed as an isolated productivity tool. Resource-efficiency targets, environmental KPIs, capital-allocation rules, and AI governance should be connected. This aligns the technology with corporate sustainability objectives.

The sixth implication concerns infrastructure. The IEA’s 415 TWh estimate for global data-centre electricity use in 2024 demonstrates that digital intelligence has a material energy footprint. Firms should therefore consider model efficiency, workload selection, renewable electricity, data-centre efficiency, and hardware circularity as part of the sustainability strategy for AI itself.

Table 15 converts the findings into management categories. The central recommendation is measurement discipline: every claimed sustainability benefit should be connected to a baseline, an intervention, an outcome indicator, and an accounting boundary.

## 6. Managerial and Policy Recommendations

### 6.1 Managerial Recommendations

First, organizations should establish resource baselines before deploying GenAI for sustainability. Baselines should include energy, water, material, waste, transport, and relevant emissions measures. Without a baseline, organizations cannot distinguish actual improvement from perception.

Second, firms should prioritize use cases where GenAI changes a physical or resource-intensive decision. Examples include energy scheduling, maintenance, procurement, inventory, logistics, water mon-

**Table 15. Strategic Implications of GenAI for Sustainable Business**

| Strategic Area    | GenAI Opportunity                             | Required Control                           | Primary KPI          |
|-------------------|-----------------------------------------------|--------------------------------------------|----------------------|
| Operations        | Resource and process optimization             | Baseline and post-intervention measurement | Resource/unit        |
| Supply chain      | Scenario comparison and supplier intelligence | Validated operational data                 | Emissions/tonne-km   |
| Energy            | Forecasting and scheduling support            | Meter integration and model validation     | kWh/unit             |
| Materials         | Procurement and waste analysis                | Material-flow accounting                   | Material intensity   |
| Water             | Monitoring and anomaly interpretation         | Sensor validation                          | m <sup>3</sup> /unit |
| Governance        | Sustainability-information synthesis          | Audit trail and human review               | Verified-data rate   |
| AI infrastructure | Efficient model and workload selection        | Compute and environmental accounting       | AI impact/decision   |

itoring, and waste reduction. Administrative use cases can still create business value, but they should not automatically be classified as environmental interventions.

Third, organizations should implement a net-effect accounting process. AI-related electricity, infrastructure, water, and hardware impacts should be estimated using the best available data. The boundary should be documented so that environmental claims remain comparable over time.

Fourth, firms should integrate GenAI into existing sustainability and ERM governance. Environmental decision owners should define targets, approve use cases, monitor outcomes, and establish escalation procedures when model recommendations conflict with sustainability constraints.

Fifth, human verification should be mandatory for high-consequence sustainability decisions. Generated recommendations should be traceable to source data, and material environmental claims should be independently checked.

Sixth, organizations should adopt a portfolio approach. Some GenAI applications may primarily reduce energy use, others may reduce material waste, and others may improve reporting quality. The portfolio should be assessed using common environmental and financial criteria.

## 6.2 Policy Recommendations

Policymakers can support sustainable AI adoption by improving access to reliable environmental data and by encouraging standardized disclosure of AI-related energy and water consumption. Interoperable environmental data systems can reduce the information burden faced by firms attempting to calculate resource-efficiency improvements.

Public policy can also support efficient digital infrastructure through incentives for low-carbon electricity, efficient data centres, water-efficient cooling, and circular hardware systems. Such measures can reduce the environmental burden associated with the growth of AI.

Regulators should also distinguish between AI-enabled environmental claims and independently measured environmental outcomes. Firms should be encouraged to disclose both the benefits achieved through AI-supported processes and the material environmental burden associated with AI deployment.

## 7. Limitations and Future Research

Several limitations should be considered. First, the study is a secondary evidence synthesis and does not provide a newly collected firm-level causal dataset. Consequently, the evidence cannot establish a universal causal effect of GenAI on corporate environmental performance.

Second, much of the empirical literature concerns AI broadly rather than GenAI specifically. GenAI differs from conventional AI in model architecture, interaction style, workload, and infrastructure requirements. Future empirical work should isolate GenAI deployments.

Third, environmental impacts are highly context dependent. Electricity mix, data-centre efficiency, model size, utilization, geography, process characteristics, and organizational scale can materially change the net effect.

Fourth, some corporate environmental disclosures are self-reported. Independent assurance and standardized measurement are therefore important.

Future research should develop longitudinal firm-level datasets linking GenAI deployment records with energy, water, material, waste, emissions, productivity, and financial outcomes. Such datasets could

estimate causal effects using difference-in-differences, panel regression, or quasi-experimental designs.

Research should also compare different GenAI models and workflows according to environmental impact per completed decision. This would allow organizations to select models based not only on accuracy and cost but also on resource intensity.

Another important research direction is multi-objective optimization. Future systems could jointly optimize financial cost, service quality, emissions, water use, material use, and resilience. This would move GenAI from descriptive assistance toward constrained sustainable decision optimization.

Finally, future studies should investigate rebound effects and decision quality. A resource-efficient recommendation is valuable only if it is implemented correctly and does not generate compensating increases elsewhere in the system.

## 8. Conclusion

This study examined whether Generative Artificial Intelligence can improve corporate resource efficiency and environmental performance when integrated into sustainable business strategy. The evidence indicates that AI can contribute to environmental improvement through productivity, factor-input optimization, green innovation, pollution-reduction investment, energy management, and other decision pathways. However, these benefits are not automatic and should not be attributed to GenAI without measuring the actual intervention and its downstream outcomes.

The central finding is that GenAI should be evaluated as a net environmental decision technology. Gross resource savings represent only one side of the equation. Electricity, water, hardware, and infrastructure requirements associated with AI must also be considered. The proposed framework therefore measures gross resource savings, avoided environmental impact, AI environmental burden, and net environmental benefit.

The evidence illustrates both sides of this relationship. Empirical enterprise studies report improved environmental performance associated with AI, while the IEA documents substantial electricity demand from data-centre infrastructure. Building-energy research provides scenario-based evidence of potential energy and carbon reductions from AI, while corporate sustainability reporting demonstrates the continuing importance of hardware circularity, water efficiency, renewable electricity, and Scope 3 management.

The answer to the research question is therefore conditional. AI-powered decision-making can improve resource efficiency and environmental performance when it is applied to measurable resource-intensive decisions, supported by reliable data, evaluated against a baseline, governed through human oversight, and assessed after accounting for AI-related environmental burdens.

The strategic objective should consequently not be “more AI” but “better decisions with measurable net environmental value.” Organizations that follow this principle can position GenAI as one component of a broader sustainable business strategy in which digital intelligence, resource efficiency, environmental accountability, and economic performance are evaluated together.

The study also shows that sustainability-oriented GenAI strategy should be evaluated at three levels. At the process level, the question is whether an AI-supported decision reduces resource intensity or improves operational control. At the organizational level, the question

is whether multiple AI applications reinforce a coherent sustainability strategy without creating contradictory targets or double counting. At the infrastructure level, the question is whether the energy, water, hardware, and lifecycle burdens of AI are being managed alongside the benefits generated by its applications.

For corporate strategy, the practical principle is straightforward: environmental value should be demonstrated through measurable changes in resource use rather than inferred from the presence of AI. Firms should establish baselines, identify material decision pathways, quantify AI-related burdens, validate generated recommendations, monitor implementation, and disclose uncertainty. This approach makes it possible to distinguish genuine environmental improvement from administrative productivity, technological novelty, or unverified sustainability claims.

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