NTT DaTa

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Sustainable AI for a greener tomorrow

How to build AI sustainability metrics into standardized best practices for measurable impact

Contents

Executive summary

As AI adoption accelerates, so does the urgency to ensure its sustainability — not as an afterthought, but as a core principle guiding its development and deployment.

AI is rapidly transforming industries, supporting innovation and redefining business strategies. However, its exponential growth brings significant environmental challenges, particularly in terms of its carbon footprint, energy consumption and water usage.

This guide examines the critical need for sustainable AI and outlines practical, measurable strategies to align AI innovation with ecological responsibility.

Key insights include:

- **Making the shift to Green AI:** Going beyond conventional AI priorities to balance performance with sustainability, with efficiency as a central metric

- **Understanding AI's environmental impact:** Addressing energy consumption, emissions and water footprint through streamlined algorithms, energy-efficient architectures and responsible cooling strategies

- **Mapping the ecosystem of actors:** Identifying the key actors — including hardware manufacturers, data center operators, policymakers and AI developers — shaping AI's environmental footprint and enabling systemic change

- **Standardizing measurement:** Establishing clear, actionable measurement frameworks that organizations can use to assess and refine AI's environmental performance

- **Establishing best practices for end-to-end AI sustainability:** Embedding sustainability into AI workflows through responsible data usage, efficient models, ethical resource allocation and lifecycle-aware deployment

- **Encouraging industry-wide collaboration:** Aligning organizations, policymakers and research communities to drive the adoption of sustainable AI practices through shared knowledge and regulatory engagement

In addition, we explore real-world applications and lessons learned, showcasing how sustainable AI principles are applied in practice through case studies, industry insights and data-driven findings that highlight best practices and potential challenges.

By embedding sustainability into the foundations of AI, we can unlock the full potential of the technology while minimizing its environmental impact.

> " Sustainability in AI is more than an obligation. It is also an opportunity to create long-term value, innovate responsibly and future-proof the role of AI in a resource-conscious world."

The case for sustainable AI: Beyond the checking of a box

As organizations and communities race to unlock the full potential of AI, there is a pressing need to assess and address the impact of this technology on long-term climate and energy projections.

The use of AI in the "green transition" has gained significant attention. From enabling the precise monitoring of environmental impacts to optimizing energy and resource consumption through predictive maintenance systems, AI has demonstrated its capacity to accelerate and improve environmental research through groundbreaking applications.

However, just as AI can serve as a powerful tool to achieve the goals of a green transition, it can also amplify harmful dynamics and create new environmental risks.

With its soaring computational demands and resource-intensive infrastructure, AI is reshaping digital landscapes and our environmental footprint. This has ignited a critical discourse among researchers, policymakers and industry leaders — one that demands the urgent definition, measurement and implementation of sustainable AI practices that ensure innovation is both responsible and regenerative.

Sustainability is now a defining business principle that affects organizations' resilience, their ability to innovate and their long-term success.

Once organizations examine AI initiatives through the lens of sustainability and responsible use, they can mitigate risk and deliver tangible value at the same time. Those that embrace these practices report improved growth and profitability, lower costs and stronger stakeholder trust, all while contributing to a healthier planet.

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Sustainability in AI goes far beyond reducing energy consumption or minimizing carbon footprints."

1 Green Software Foundation, Software Carbon Intensity Specification
2 Everest Group Sustainable IT Services PEAK Matrix® Assessment 2025

Sustainability in AI is a multidimensional issue

At the intersection of environmental, social and economic factors, sustainability in AI requires a fundamental shift in how AI systems are designed and governed.

As organizations increasingly rely on AI to optimize their operations and create new opportunities, one question looms large: **Can AI itself be truly sustainable? The answer lies in rethinking its development and deployment**, both as a tool for progress and as a force aligned with environmental and ethical responsibilities.

Yet, sustainability cannot advance in isolation. **The pace of AI innovation demands a shared foundation built on collaboration and the free exchange of knowledge.** In fast-evolving fields like AI, progress hinges on collective expertise and engagement with regulatory frameworks. Siloed efforts create bottlenecks that stall meaningful progress.

The gap can be closed with robust cooperation among industry peers and policymakers, fostering an environment where insights and best practices can be freely exchanged and avoiding the emergence of unsustainable practices that undermine long-term environmental health and societal wellbeing.

The global Green AI agenda — a shared framework that promotes the industry-wide adoption of sustainable practices — offers a pathway to balance performance with efficiency while reinforcing transparency, fairness and value creation.[1]

NTT DATA has embraced this collaborative ethos by championing sustainable initiatives to becoming a recognized leader in sustainable IT services.[2] Our partnership with the Green Software Foundation has resulted in the development of the Software Carbon Intensity Specification, a critical step toward advancing Green AI.

A framework for reducing AI's sustainability footprint

Behind every model trained, every query processed and every insight generated lies an often overlooked reality: AI's immense resource consumption. To realize AI's full potential, we must first grasp its impact.

As the adoption of AI accelerates, so does its need for computing power, giving rise to shifts in electricity demand and the depletion of natural resources. Its resource-intensive reliance on extensive data storage and its energy needs cast a shadow over this promise. AI-driven sustainability efforts must therefore be anchored in global frameworks that define the pathway toward environmental and societal responsibility.

Environmental, social and governance (ESG) standards serve as a structured lens, setting measurable metrics for combating the climate crisis, transitioning to clean energy and achieving social equity. Each standard can be divided into four broader objectives (see diagram below).

> " The paradox is clear: to be harnessed for sustainability, AI itself must be sustainable."

Sustainability is a multidimensional pursuit

Integrating AI-driven sustainability into AI governance strategies aligns our approach with global objectives while accounting for intricate real-world dynamics. We see sustainability not as a single objective but as a multidimensional pursuit that considers the realities and interconnectedness of the three dimensions of the ESG framework.

What we mean by green

If AI is to be a true enabler of environmental sustainability, it must not become an environmental burden. This is where Green AI emerges — not merely as an idea, but as an imperative.

For over a decade, the pursuit of bigger and better results has driven AI research toward models of ever-increasing scale, complexity and computational intensity. Accuracy has been the undisputed metric of progress, with efficiency relegated to the background.

The result? A system where financial and environmental costs double every few months, placing an unprecedented strain on computing infrastructure, energy grids and water reserves.[3]

The environmental consequences of AI are no longer theoretical

The carbon footprint of AI training alone has skyrocketed, with some models consuming over 300,000 times more computational power than their predecessors. These rising costs, combined with a singular focus on performance, have made AI development an increasingly exclusive domain — accessible only to those with the resources to sustain its insatiable energy demand.

> **❝** By 2028, more than half of the electricity going to data centers will be used for AI. At that point, AI alone could consume as much electricity annually as 22% of all US households.**"**[4]

This unsustainable trajectory directly contradicts AI's potential as a force for environmental stewardship that helps to manage energy grids, advance climate modeling, improve water conservation, monitor biodiversity, fight wildfires and even identify and recover recyclables.

AI can also accelerate environmental degradation when it is used to optimize fossil-fuel extraction or intensify the consumption of industrial resources.

Another crucial consideration is the vulnerability of AI itself to environmental changes. As the supply chains supporting the underlying hardware, infrastructure and energy supplies become increasingly complex, ensuring their resilience in the face of climate-related disruptions is paramount.

3 Bolón-Canedo et al, A review of green artificial intelligence: Towards a more sustainable future
4 US Department of Energy, DOE releases new report evaluating increase in electricity demand from data centers

Green AI is a responsibility, not a choice

We define Green AI as the development and deployment of AI systems designed to minimize their environmental impact across the entire AI lifecycle. This includes conscious decision-making at every stage — from data processing and model training to operation and hardware use — to reduce energy consumption, greenhouse gas emissions, water usage and the depletion of nonrenewable resources.

Green AI is about integrating sustainability into AI-driven innovations to make them both efficient and ecologically responsible. It is not a choice but a responsibility. Only by embedding sustainability into the design, development and deployment of AI can we ensure that the technology serves as a tool for environmental progress rather than a driver of ecological decline.
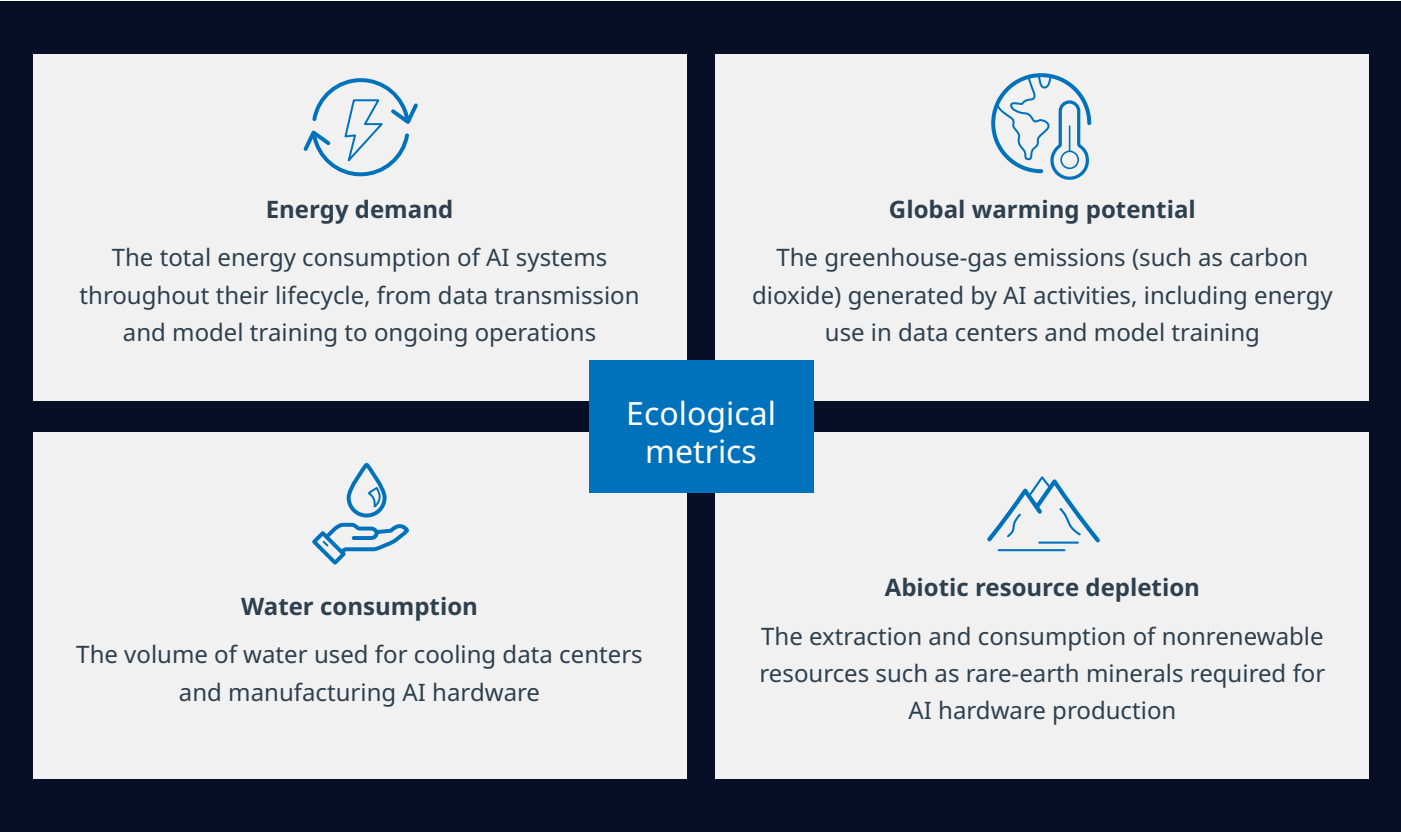
Understanding the complete ecological footprint of AI

Green AI redefines AI evaluation metrics by challenging the notion that progress is measured solely by marginal gains in precision, emphasizing instead the balance between high performance and minimal resource consumption.

In contrast to Red AI, which pursues ever-increasing accuracy regardless of computational cost, Green AI prioritizes efficiency, sustainability and responsible development. It recognizes that energy consumption, carbon emissions and accessibility are fundamental criteria in AI design and assessment.

Achieving this requires a fundamental understanding of AI's ecological footprint, which can be measured through four key metrics: energy demand, global warming potential, water consumption and abiotic resource depletion.

> " The environmental impact of AI systems goes beyond operational energy use and greenhouse gas emissions."

Energy demand

The total energy consumption of AI systems throughout their lifecycle, from data transmission and model training to ongoing operations

Global warming potential

The greenhouse-gas emissions (such as carbon dioxide) generated by AI activities, including energy use in data centers and model training

Ecological metrics

Water consumption

The volume of water used for cooling data centers and manufacturing AI hardware

Abiotic resource depletion

The extraction and consumption of nonrenewable resources such as rare-earth minerals required for AI hardware production

1. Energy demand

Energy demand is a crucial metric for evaluating AI sustainability, as the operational, information and communications technology hardware needed to program, train and deploy AI systems accounts for a significant share of global electricity consumption.

With electricity consumption rising at a sustained rate of 12% per year, data centers already account for about 1.5% of global demand. Forecasts suggest that between 2024 and 2030, this figure will grow even faster — at about 15% per year, a growth rate more than four times those of other sectors.[5] If trends continue, data centers could consume nearly 1,050 TWh by 2026.[6] This escalating consumption risks overshadowing gains in efficiency and threatens to disrupt other critical services.[7]

While advances in energy efficiency like the adoption of hyperscale data centers have mitigated some of this impact, the growing demand for AI-driven applications continues to strain global energy systems.

2. Global warming potential

The operational carbon footprint of AI computing relates directly to its energy consumption, often from nonrenewable energy sources.

The carbon footprint of data centers is expected to more than double by 2030, reaching about 860 million tons of carbon-dioxide equivalent, which is about 1% of global emissions today.[8]

Without aggressive decarbonization strategies, AI's expanding carbon footprint risks undermining global climate goals, turning innovation into a cause of environmental strain rather than a force for progress.[9]

3. Water consumption

AI's water consumption is a critical yet often overlooked sustainability metric, as large-scale models rely on high-density servers that generate extreme heat and require intensive cooling. Data centers withdraw vast amounts of fresh water for temperature regulation and electricity generation.

Despite advances in cooling technologies, training a single AI model can consume millions of liters of fresh water. Even running as few as 10 to 50 queries can use up to 500 milliliters — the equivalent of a standard water bottle.

As AI models continue to scale, their water footprint will grow, placing a high demand on already limited freshwater resources. Without proactive measurement and mitigation, AI's growing reliance on water risks exacerbating global water stress, which is why both water withdrawal and consumption are key indicators for sustainable AI development.[10]

4 Abiotic resource depletion

Resource consumption and hardware use are critical metrics for AI sustainability, as a growing reliance on digital infrastructure accelerates mineral depletion.

The production of AI hardware, from semiconductors to data center components, demands vast amounts of critical raw materials — many of which are mined in limited quantities. Digital user devices alone drive 9.4% of global cobalt production and 8.9% of palladium output, fueled by short life cycles and relentless replacement rates.[11]

Meanwhile, data centers, the backbone of AI operations, consume vast quantities of copper, aluminum and rare-earth elements, with servers replaced every few years to meet performance demands.

As AI adoption expands, so does the strain on finite mineral reserves. This is a threat to long-term resource availability, and it intensifies geopolitical dependencies on critical supply chains.

5 International Energy Agency, 2025, Energy and AI: World Energy Outlook Special Report

6 MIT Technology Review, 2025, We did the math on AI's energy footprint. Here's the story you haven't heard

7 Desislavov et al, 2023, Trends in AI inference energy consumption: Beyond the performance-vs-parameter laws of deep learning

8 Goldman Sachs, 2024, AI is poised to drive 160% increase in data center power demand

9 International Energy Agency, 2025, Energy and AI: World Energy Outlook Special Report

10 Pengfei et al, 2023, Making AI less "thirsty": Uncovering and addressing the secret water footprint of AI models

11 European Parliament, 2021, The role of artificial intelligence in the European Green Deal
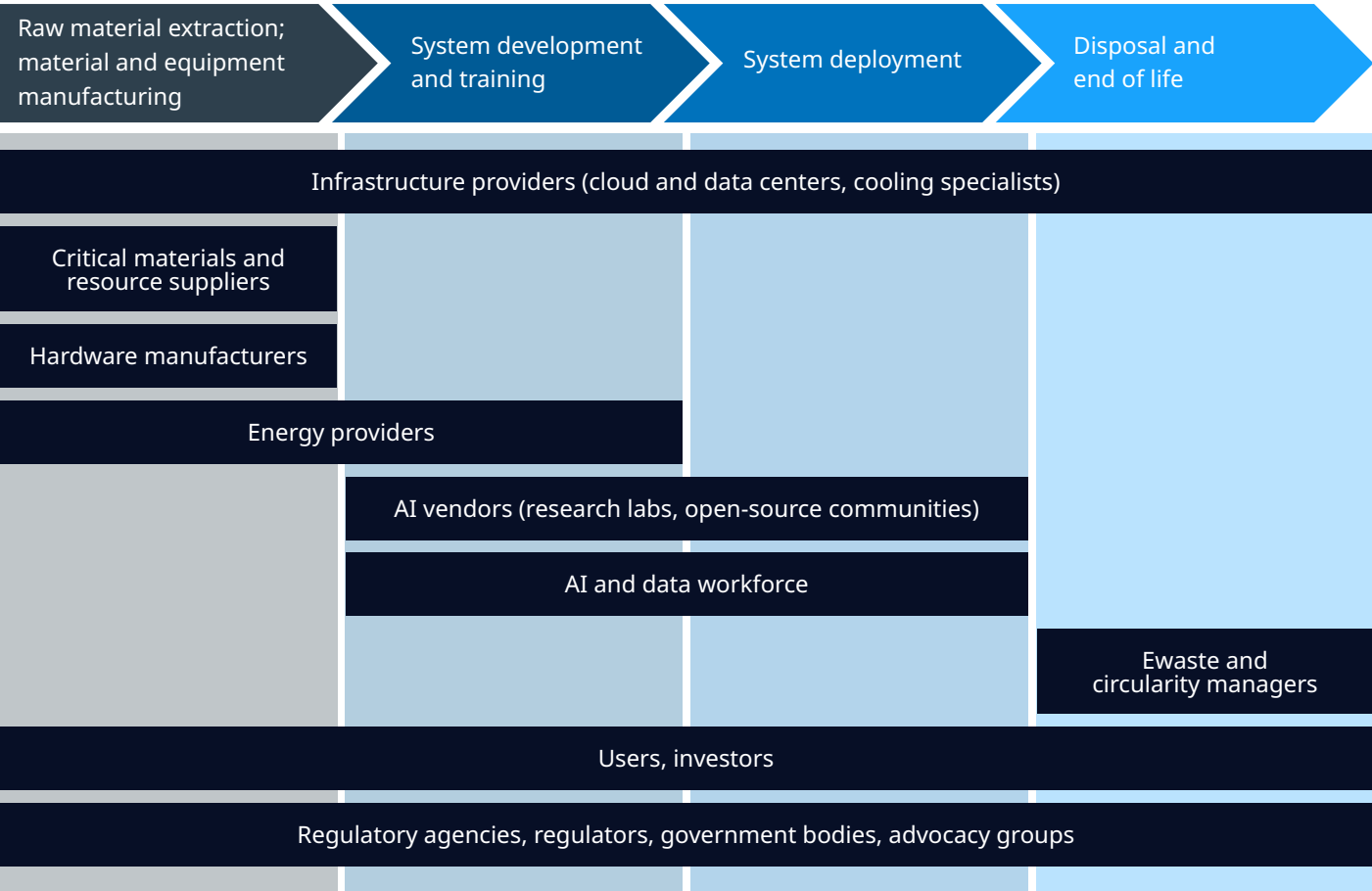
The forces behind sustainable AI

Who's shaping its impact?

Several key players have to collaborate to facilitate sustainable AI development. These actors influence how AI systems consume energy, use resources and affect the environment.

Guaranteeing sustainable AI therefore requires both improved technology and well-coordinated governance with clearly defined responsibilities for stakeholders.

By mapping the relationships between these stakeholders, each representing key elements of the sustainable AI ecosystem, we can see what they contribute to the different phases of the AI lifecycle.

And, by categorizing actors according to their roles, we can better illustrate their interdependencies and responsibilities.

Raw material extraction; material and equipment manufacturing	System development and training	System deployment	Disposal and end of life

Infrastructure providers (cloud and data centers, cooling specialists)

Critical materials and resource suppliers

Hardware manufacturers

Energy providers

AI vendors (research labs, open-source communities)

AI and data workforce

Ewaste and circularity managers

Users, investors

Regulatory agencies, regulators, government bodies, advocacy groups

Given the complexity of the sustainable AI ecosystem, it is essential to recognize that responsibility is distributed across all actors rather than falling on a single entity.

The increasing demand for AI applications escalates the need for computing, storage and data center capacity, particularly GPUs — and, in turn, a surge in energy demand.

This interconnectedness means that improvements in one area, such as system development, training or deployment, can inadvertently amplify demand elsewhere, creating a disproportionate knock-on effect.

By comprehensively mapping the relationships between these actors, we can identify and optimize the positive impacts of our efforts. This holistic understanding is essential for fostering a truly sustainable AI ecosystem.

Actors in the ecosystem of sustainable AI

To better understand the distribution of responsibilities throughout the AI lifecycle, we examine each key actor in detail, highlighting where interventions can be most effective and assessing their impact, associated risks and contributions to sustainability goals.

By recognizing the individual actions that contribute to resource management and outcome generation, as well as their responsibilities and interactions, we can evaluate their true influence on sustainable practices.

1. Energy providers

Energy providers — including utility companies, renewable energy firms and smart grid operators — supply the electricity that powers AI infrastructure, including data centers and computational clusters. They play a crucial role in migrating AI systems to renewable energy sources while maintaining reliability and efficiency.

2. Hardware manufacturers

Hardware manufacturers design and produce semiconductors, processors and AI-specific hardware that dictate energy efficiency and computational power. Meanwhile, cloud and data center operators manage the storage and computational power for AI workloads. These entities determine AI's hardware footprint and cooling requirements, affecting sustainability.

3. Users

Individual users engage with AI-powered applications daily, providing feedback that drives improvements in AI systems. Their usage patterns and concerns help to shape ethical and practical AI considerations. Corporate users integrate AI into finance, healthcare, retail and manufacturing, among others, shaping demand for AI products and services. These entities often invest in sustainable AI practices to make their implementations environmentally friendly, socially responsible and economically viable.

4. AI ethics and advocacy groups

Beyond formal governance, AI's environmental impact is scrutinized by academic institutions, nonprofit organizations and watchdog organizations advocating for transparency and accountability.

5. Mining supply chains

Many AI components rely on critical minerals such as lithium, cobalt and silicon, which are often sourced through environmentally harmful extraction processes. Mining and rare-earth supply chain practices dictate the ecological and ethical footprint of AI hardware.

6. Technology investors and venture capital

Large-scale AI sustainability initiatives rely on Big Tech venture-capital funding. These investors determine whether AI innovation prioritizes energy efficiency or resource-intensive computation. While companies drive innovation, consumer awareness and regulatory frameworks are needed to enforce environmental responsibility.

7. Policymakers and regulatory agencies

Governments and regulatory bodies shape sustainable AI by implementing policies related to energy consumption, data ethics and carbon-footprint reporting. Examples include the European Commission's AI Act, the United Nations' AI for Good and national AI oversight bodies such as the National Institute of Standards and Technology in the US. These entities set industry standards and enforce compliance.

8. Ewaste management providers

Obsolete AI hardware contributes to ewaste, with limited systems in place for recycling and repurposing. Key players in AI sustainability include Umicore, Sims Recycling Solutions and government-backed ewaste programs focused on circular-economy principles.

9. AI vendors

AI vendors and developers create and refine AI algorithms, machine-learning architectures and model-optimization techniques. They decide how models are trained, how much computational power they need and how efficiently they perform in real-world applications. Organizations and initiatives such as OpenAI, DeepMind, Meta AI, Hugging Face and IBM Watson lead in developing energy-efficient AI through innovations like model pruning, quantization and federated learning.

Measuring sustainable change

Sustainability isn't just compliance. How we measure it defines how we succeed.

In the accelerating race toward sustainability, measurement is power. Quantifying, analyzing and acting on ecological performance has become paramount. Organizations now recognize that sustainability is more than a compliance exercise; it drives risk mitigation, brand resilience and long-term value creation.

But with this recognition comes a challenge: How do we measure sustainability effectively so that our progress is not just rhetorical?

Accurately measuring sustainable AI is fraught with complexity, and the absence of standardized sustainability reporting frameworks presents a significant hurdle. Unlike traditional industries, which benefit from established frameworks like the Greenhouse Gas Protocol, AI lacks cohesive guidelines on consistently evaluating energy consumption, carbon emissions, water usage and ewaste generation collectively.[12] This situation is further complicated by the need to consolidate diverse data points across the AI lifecycle, leaving stakeholders to navigate a fragmented landscape of inconsistencies and incomplete assessments.

Much of the essential data needed to assess AI's sustainability can already be logged automatically. Some hardware manufacturers report emission levels for specific products, while operational data such as calculation frequency, runtime and hardware use provide the foundation for efficiency metrics that inform sustainability performance.

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The real challenge lies in developing solutions that are both user-friendly and capable of capturing the full spectrum of data needed for meaningful sustainability assessments."

However, these tools often face a trade-off between ease of use and accuracy. Obtaining precise results requires significant input information, which can be burdensome for users and hinder widespread adoption. While automated logging systems reduce some of this complexity, they fall short of fully bridging the gap between accessibility and a comprehensive analysis.

Using existing methods to measure end-to-end sustainability

AI's distributed global infrastructure presents unique challenges in accurately measuring its environmental impact.

For instance, a significant factor such as the carbon intensity of data centers varies significantly across regions due to differences in energy grids and the timing of their use. This variability makes carbon-emission calculations highly contextual, requiring the integration of dynamic factors such as the grid's energy mix as well as hardware efficiency and operational practices.

12 SustAIn magazine, 2023, How sustainable is my AI?

Existing tools rely on a series of assumptions and estimates based on available information, offering basic estimate modeling and reporting that is often not publicly available to users.

As AI adoption accelerates, organizations must refine their approach to measuring sustainability metrics collectively.

Some organizations have implemented automated reporting mechanisms, but their effectiveness remains limited by a lack of standardized, integrated frameworks for tracking environmental factors collectively.

Although established techniques exist for tracking individual metrics, their full potential lies in harmonized, real-time sustainability assessments that provide a comprehensive, cross-metric view of AI's environmental impact. Without these assessments, sustainability efforts risk overlooking critical trade-offs and making misguided optimizations that shift environmental burdens rather than reduce them.

A bird's-eye view of sustainable progress

Most current measurement methods quantify individual environmental metrics rather than providing an integrated, end-to-end view of the effects of sustainable AI practices.

This narrow focus can lead to an incomplete understanding of the overall environmental impact. For instance, optimizing energy consumption in one part of the AI lifecycle might inadvertently increase water usage or ewaste generation in another.

Through a combination of multiple measurement tools and a holistic perspective, organizations can implement sustainability measures that reduce environmental impact in one area while exacerbating it in another.[13]

To advance sustainability in AI, organizations need a complete view of their efforts in mitigating environmental impact. Lifecycle assessments provide this clarity by simultaneously evaluating AI systems at every stage, from hardware production to decommissioning.

These frameworks shine a light on the most resource-intensive stages, enabling organizations to identify critical areas for intervention. Paired with scenario-modeling tools, lifecycle assessments allow organizations to anticipate trade-offs, project the impact of sustainability strategies and implement targeted interventions such as shifting to renewable energy or optimizing hardware usage.

Identifying high-impact phases

Not all stages of AI development and deployment carry the same environmental burden.

Some phases, such as hardware manufacturing and large-scale model training, consume energy, raw materials and water disproportionately. The following table serves as a guide to identifying metrics that require urgent attention and facilitating transparent reporting by breaking down each lifecycle phase and the corresponding metrics.[14]

🟢 Environmentally significant
🔴 High-impact area that requires urgent attention

	Raw-material extraction	Material manufacturing	Equipment manufacturing	System development and training	System deployment	Disposal and end of life
Energy			🟢	🟢	🔴	
Emissions (carbon dioxide and other greenhouse gases)	🟢	🟢	🟢	🟢	🔴	
Water	🟢	🟢	🟢	🟢	🟢	
Minerals	🔴	🔴				🟢
Ewaste						🟢

13 Longpre et al, 2024, The Responsible Foundation Model Development Cheatsheet: A Review of Tools & Resources
14 SustAIn magazine, 2023, Just measure it: The environmental impact of AI

Energy-tracking tools to quantify power demands

Standardized energy benchmarking frameworks offer a structured method to select models based on end-to-end computational efficiency, guaranteeing cross-model insights.

These frameworks evaluate both open source and proprietary models in secure testing environments to provide transparent insights into energy performance across AI applications. For users and developers, they provide actionable insights that go beyond raw energy-consumption data to offer clear, interpretable metrics that help AI practitioners understand trade-offs between model performance and efficiency. This enables them to choose models that align with sustainability priorities without sacrificing capabilities.

Beyond individual model comparisons, energy scores and ratings provide a crucial foundation for end-to-end lifecycle assessments, extending sustainability evaluations beyond training efficiency to encompass the total use of resources.

To support widespread adoption, energy-efficiency ratings can be incorporated into technical documentation, model cards and AI product disclosures, fostering a culture of accountability.

Benchmarking labels ensure standardized, verifiable energy reporting, which reinforces the importance of energy transparency throughout the AI ecosystem. Additionally, regular leaderboard updates allow for continuous reassessment, keeping model rankings relevant as new standards emerge and technology evolves.

A leading example is the AI Energy Score, which introduces a relative efficiency rating across AI applications.[15] By embedding energy tracking into AI governance, procurement and regulatory policies, these tools support industry-wide sustainability standards as energy-efficient AI systems become the norm rather than the exception.

The role of hardware in end-to-end sustainability

Beyond computational efficiency, AI's physical infrastructure remains a major determinant of sustainability. The energy consumption of AI models is inextricably linked to the hardware that powers them, from semiconductors and accelerators to data center servers.

Compute carbon intensity (CCI) is a new metric that addresses this challenge. It is a standardized measure of hardware efficiency, allowing developers, organizations and policymakers to assess the carbon footprint of AI accelerators across workloads.[16]

CCI offers a complete view of hardware sustainability by incorporating emissions from raw-material extraction, chip fabrication and operational energy consumption. It allows for transparent benchmarking and supports data-driven decision-making in AI infrastructure development.

By integrating embodied emission calculations into AI sustainability strategies, organizations can optimize hardware procurement so that AI workloads run on the most carbon-efficient accelerators available.

Developers can use CCI to evaluate hardware selection, balancing computational power with sustainability, and organizations can use these insights to align procurement with corporate ESG goals. Lastly, policymakers can incorporate CCI into regulatory frameworks to ensure that the expansion of AI does not come at an unsustainable environmental cost.

As AI sustainability efforts move beyond energy efficiency alone, CCI complements existing benchmarks by enabling end-to-end carbon tracking of AI infrastructure. By embedding hardware lifecycle assessments into AI governance, organizations can establish industry-wide standards for carbon efficiency, making sustainability a core principle in AI's continued advancement.

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15 Hugging Face, 2025, AI Energy Score

16 Google Cloud, 2025, Designing sustainable AI: A deep dive into TPU efficiency and lifecycle emissions

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Currently, about half of Fortune 500 companies have established net zero goals, which is a remarkable rise compared to 2020, when only 8% had made such commitments" [17]

Theory to action: Best practices for maximum impact

This section presents a framework of practical strategies for embedding sustainability into AI workflows without hindering technological progress.

Understanding AI's environmental footprint is only the beginning. Measuring emissions, energy use and resource consumption provides a critical foundation, but measurement alone does not drive change. Organizations must move beyond data-collection and embed sustainability into the full AI lifecycle by implementing strategies that educe its footprint without compromising performance or innovation.

True sustainability demands action.

Sustainable best practices must be designed for real-world applications. Ambitious environmental goals are essential, but they must be paired with structured, actionable methodologies that address sustainability at every stage of AI implementation.

Sustainability in AI is an end-to-end challenge that requires intervention at multiple levels, and the best practices outlined here are structured accordingly. Some focus on the design and development phase, ensuring that AI systems are built with efficiency in mind rather than treated as an afterthought.

Others address the infrastructure that powers AI, recognizing that the energy demands of large-scale computing must be managed strategically. A final set of practices tackles the broader resource lifecycle, acknowledging that sustainability is not only about energy but also about responsible data usage, hardware longevity and waste reduction.

Making sustainability a reality demands coordinated action across these levels. By embedding these best practices into the AI lifecycle, organizations can align innovation with environmental responsibility.

17 Nov 2024, Anthesis Group Insights, which also cites Climate Impact Partners, Research on Fortune 500 Companies' Net Zero Trends, 2023.

1. Sustainable by design

Green Software Patterns

Applying Green Software Patterns — available as an online, open source database[18] — is essential in optimizing AI systems for efficiency, longevity and minimal environmental impact from the outset.

Sustainable AI development can then prioritize energy-efficient code structures, lightweight architectures and algorithmic optimizations that reduce computational overhead. Alignment with these standardized patterns provides a structured approach to integrating sustainability into AI model development so that efficiency becomes a measurable, actionable component of AI system design.

Sustainable model alternatives

Sustainable AI development demands model architectures that minimize computational overhead without compromising performance. Lightweight model architectures, adaptive reuse strategies and precision-driven optimization techniques offer viable pathways to reducing environmental impact while maintaining high functionality.

Avoiding unnecessary computation by using smaller, purpose-driven models, recycling pretrained architectures and fine-tuning for specific tasks keeps AI systems efficient without redundant processing. By embedding efficiency into model design, stakeholders can curb energy use while still being efficient.

Standardized sustainability reporting for accountability

Standardized sustainability reporting is critical in ensuring transparency, accountability and comparability across AI models. Without a unified reporting mechanism, sustainability assessments remain fragmented, making it difficult to measure real progress.

Aligning with globally recognized carbon accounting frameworks such as the Greenhouse Gas Protocol reinforces the credibility of sustainability assessments. By embedding standardized impact reporting into AI workflows, organizations can make their sustainability efforts rigorous, measurable and actionable rather than vague commitments.

2. Optimizing at an infrastructure level

Synchronized AI workloads

AI's environmental footprint depends not only on energy consumption but also on when and where computing occurs. Spatiotemporal optimization ensures that AI workloads are executed in regions with the cleanest energy mix and during timeframes that minimize resource strain.

Cloud and data center operators can prioritize training in renewable-heavy grids to lower carbon emissions, while AI developers and organizations can schedule workloads during off-peak hours or in cooler climates to minimize reliance on water-intensive cooling systems. Embedding real-time environmental data into scheduling decisions further curtails emissions and reduces grid strain.

Data center efficiency and cooling systems

Even the most sustainable AI models depend on energy-intensive data centers, making infrastructure-level improvements critical.

Data centers must meet the same sustainability standards applied to AI models. This includes certification-backed environmental management, in line with the ISO 14001:2015 standard, and optimizing power and water usage effectiveness to make AI computing less resource-intensive. Intelligent workload distribution, low-impact semiconductor fabrication and liquid cooling solutions that minimize water withdrawals further mitigate environmental strain.

Energy-proportional computing

Most AI infrastructure remains inefficient at lower usage rates, consuming significant energy even when idle. With energy-proportional computing, power consumption scales dynamically with computational demand, reducing waste in underused systems.

Cloud providers and data center operators must implement workload consolidation to dynamically distribute tasks across fewer servers to maintain higher efficiency. Additionally, AI-powered energy management systems can optimize power distribution by turning off redundant infrastructure without compromising reliability. When every watt of power contributes to meaningful computation, energy-proportional computing minimizes waste and makes AI more sustainable.

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18 Green Software Foundation, Green Software Patterns

3. Closing the loop

Using data responsibly

Avoiding redundant data storage is a critical yet overlooked strategy for AI sustainability. Storing, processing and transferring duplicate datasets increases energy consumption, storage demands and carbon emissions, straining computing infrastructure.

Implementing robust data-management strategies such as deduplication protocols, efficient data-compression techniques and centralized repositories prevents redundancy while supporting accessibility. Federated learning and edge computing reduce data transfers, optimizing AI performance while cutting storage costs and energy use.

Disaggregated environmental metrics for precision

AI's environmental footprint consists of interdependent factors that must be reported separately to avoid misleading comparisons.

Embedding disaggregated environmental metrics within a broader resource-cycle framework allows tracking not just of emissions but also of material extraction, water consumption and ewaste.

Without clear differentiation, sustainability efforts risk shifting burdens rather than reducing overall impact. Reporting frameworks must ensure transparency across energy, carbon, water and material consumption while accounting for these interdependencies.

Extended hardware lifecycles through circular practices

The rapid evolution of AI accelerates hardware obsolescence, increasing ewaste and resource depletion from outdated GPUs, CPUs and specialized accelerators. A sustainable AI ecosystem requires circular-economy principles that extend hardware lifespans through refurbishment, reuse and responsible recycling.

Stakeholders across the AI lifecycle must prioritize modular, upgradable components over frequent replacements. Firmware upgrades and second-life applications for aging accelerators reduce turnover, while collaboration with manufacturers keeps AI systems compatible with energy-efficient, long-lasting hardware. By embedding circular IT strategies, stakeholders can lower hardware-related emissions, limit material waste and build a more sustainable AI infrastructure.
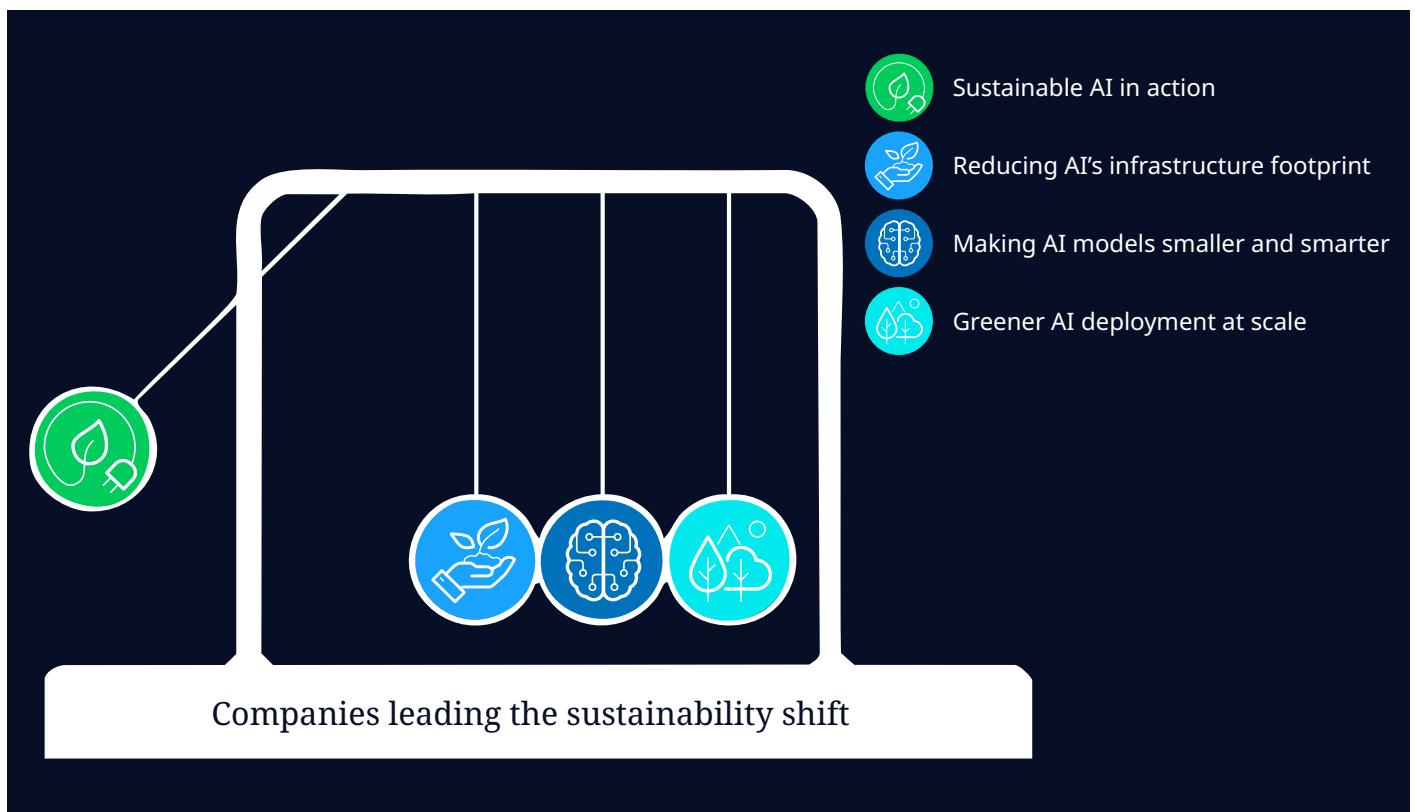
Vision to impact: Sustainable AI in motion

Having explored the principles, best practices and measurement techniques that define sustainable AI, the next step is to examine how these strategies translate into real-world implementation.

The true test of sustainability lies in its execution, where strategies move beyond theoretical frameworks and into structured, results-driven action. Without these demonstrable results, sustainability risks becoming a fragmented effort rather than a systemic transformation.

Case studies provide a bridge between high-level commitments and measurable progress. Real-world applications offer insights into what succeeds, what falls short and how organizations can course-correct to maximize impact. These case studies reveal the complexities of applying sustainability principles in practice, where competing priorities, technological constraints and operational realities must be carefully navigated. They also highlight the importance of context. Solutions that work for one AI system may not be universally applicable, reinforcing the need for adaptability in sustainability strategies.

This chapter examines three pioneering initiatives that translate sustainability commitments into measurable impact.

Each case study represents a distinct approach to optimizing the AI lifecycle, from minimizing infrastructure-related emissions to redefining efficiency standards in large-scale model training. Evaluating their outcomes provides a foundation for organizations to refine their own sustainability roadmaps.

Sustainable AI in action

Reducing AI's infrastructure footprint

Making AI models smaller and smarter

Greener AI deployment at scale

Companies leading the sustainability shift

1. Remote GPU services for large language models

The challenge: The energy cost of large-scale AI deployment

The rapid expansion of AI has pushed computational demands beyond sustainable levels. Large language models (LLMs) require high-performance GPUs, constant data transfers and large-scale cooling, contributing to significant carbon emissions. Many organizations rely on cloud-based data centers, often powered by nonrenewable energy, to support their AI workloads.

However, growing adoption has exposed the inefficiencies and environmental costs of traditional AI infrastructure. **A scalable, energy-conscious alternative is needed.**

The solution: Remote GPU services for energy-efficient AI training

NTT DATA, through the IOWN Global Forum, has introduced remote GPU services for GenAI, using all-photonic network (APN) technology. This solution shifts AI workloads to energy-optimized locations, reducing carbon impact without sacrificing performance.

Processing is no longer confined to centralized data centers. AI models train and operate in environments designed for maximum efficiency. High-bandwidth, low-latency networking eliminates bottlenecks, making AI training both faster and more sustainable.

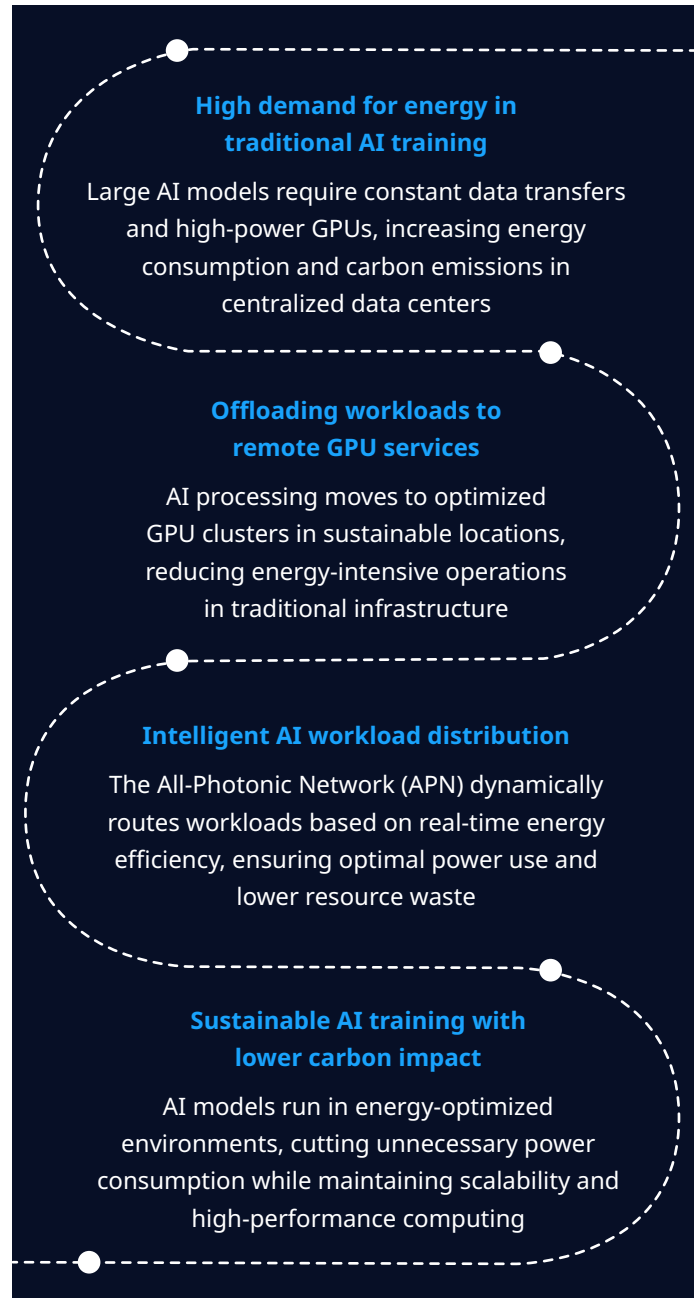### The impact: Rethinking AI deployment

- **Lower carbon emissions:** AI workloads move to optimized facilities, cutting reliance on high-carbon infrastructure.

- **Faster, more efficient AI training:** APN's high-bandwidth, low-latency connectivity eliminates bottlenecks, allowing models to train faster and more efficiently.

- **Dynamic energy management:** AI workloads are intelligently distributed based on real-time energy efficiency so that only the necessary computing power is used.

- **Enhanced digital sovereignty:** Organizations gain greater control over how and where AI is processed, enabling regional energy optimization and compliance with sustainability regulations.

The future: A new model for AI infrastructure

AI sustainability depends on more than energy savings. Infrastructure choices directly shape AI's long-term environmental impact. Offloading workloads to energy-optimized locations eliminates unnecessary resource use while preserving performance.

The shift toward remote GPU services and APN technology represents a fundamental change in AI deployment. Computational efficiency and sustainability evolve together, setting a new benchmark for AI infrastructure.

How remote GPU services reduce AI's energy consumption

High demand for energy in traditional AI training

Large AI models require constant data transfers and high-power GPUs, increasing energy consumption and carbon emissions in centralized data centers

Offloading workloads to remote GPU services

AI processing moves to optimized GPU clusters in sustainable locations, reducing energy-intensive operations in traditional infrastructure

Intelligent AI workload distribution

The All-Photonic Network (APN) dynamically routes workloads based on real-time energy efficiency, ensuring optimal power use and lower resource waste

Sustainable AI training with lower carbon impact

AI models run in energy-optimized environments, cutting unnecessary power consumption while maintaining scalability and high-performance computing

2. "tsuzumi": A low-carbon approach to LLMs

The challenge: The unsustainable growth of LLMs

The rapid expansion of LLMs is pushing energy consumption to unsustainable levels. Training and inference require massive computing power, with models like GPT-3 demanding hundreds of terawatt-hours, intensifying carbon emissions and straining infrastructure.

The industry's reliance on scaling model size to improve performance has compounded the problem, leading to exponential increases in energy costs with diminishing returns. Addressing the unsustainable growth of LLMs is crucial to finding a more efficient approach.

The solution: A model that rethinks efficiency

NTT's tsuzumi challenges the assumption that bigger models equate to better performance.

The tsuzumi-7B model shows that AI's computational demands can be drastically reduced without compromising performance, offering a low-carbon alternative to conventional LLMs.

By leveraging quantization, model pruning and compression, tsuzumi makes energy consumption for training 250 to 300 times lower than traditional models and inference costs 20 to 70 times less, all while maintaining high performance.

This approach redefines the efficiency-performance trade-off, proving that AI innovation need not come at an unsustainable environmental cost.

The impact: A sustainable path for AI development

- **Lower power consumption, greater efficiency:** The lightweight tsuzumi architecture ensures that AI operations require far less energy, reducing strain on data centers and computing infrastructure.

- **Minimized AI hardware waste:** By eliminating the need for continuous model scaling, tsuzumi allows organizations to maximize the usability of existing AI infrastructure, decreasing ewaste and the environmental cost of hardware production.

- **A shift toward energy-conscious AI development:** tsuzumi sets a new benchmark for low-carbon AI, demonstrating that sustainability and performance can coexist without compromise. Its success challenges AI developers to prioritize energy-efficient architectures rather than relying on unrestrained model growth.

The future: Designing AI for performance and sustainability

With tsuzumi, we enter a new era of energy-conscious AI development, proving that efficiency can drive progress without environmental trade-offs.

As AI adoption accelerates, organizations must move beyond size-driven expansion and embrace optimization as the path to sustainable AI innovation.

3. Sustainable on-premises AI: Reducing cloud dependence for lower emissions

The challenge: The growing energy cost of AI training

Training LLMs demands immense computing power, leading to high energy consumption, carbon emissions and infrastructure strain. Traditional AI training methods rely on energy-intensive GPUs, continuous data transfers and large-scale cooling systems, exacerbating their environmental impact.

As models scale, existing infrastructure cannot sustain their growth without escalating energy costs and emissions. A more efficient, scalable and sustainable approach is needed to mitigate these effects.

The solution: Sustainable on-premises AI solutions

To address this challenge, NTT DATA has developed sustainable on-premises AI solutions that allow organizations to host AI workloads within their own infrastructure rather than relying on cloud data centers.

By eliminating the need for constant data transfers and optimizing energy usage locally, this approach reduces AI's carbon footprint while maintaining performance.

Organizations can process data onsite with greater control over energy efficiency, reducing their reliance on high-carbon central facilities without sacrificing AI capabilities.

The impact: Smarter, greener AI training

- **Lower carbon emissions:** AI training offloads to optimized facilities, minimizing unnecessary energy use and cooling demands.

- **Optimized efficiency:** APN's high-speed, low-latency connectivity reduces bottlenecks, enabling faster training with fewer resources.

- **Intelligent energy management:** Workloads are dynamically distributed based on real-time energy efficiency, ensuring AI training occurs only when and where it is most sustainable.

The future: Scaling AI, not its environmental footprint

Sustainable AI requires more than performance improvements. It also demands infrastructure built for energy efficiency. NTT DATA's remote GPU services redefine AI training, proving that scalability and sustainability can coexist. As organizations increasingly adopt AI, intelligent, distributed processing will be key to reducing the technology's long-term environmental impact.

Closing thoughts

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Sustaining progress through collaboration

Sustainable AI is not a fixed goal but an evolving pursuit that demands ongoing innovation and cross-sector collaboration.

No single entity can address AI's environmental impact alone. Policymakers, technology providers and industry leaders must work together to refine sustainability metrics, support technological advances and embed responsible practices at scale. By fostering shared knowledge and collective action, organizations can ensure AI remains both powerful and sustainable.

Embedding sustainability into governance

Clear, enforceable guidelines are essential to ensure that environmental responsibility is prioritized alongside performance and innovation.

Sustainability must be embedded into the very foundation of AI governance, shaping policies, development frameworks and regulatory standards. Standardized reporting, energy-conscious design and lifecycle impact assessments must become integral to AI systems, enabling accountability and aligning technological progress with global sustainability goals.

Committing to long-term change

By prioritizing energy-efficient AI architectures, advocating for industry-wide standards and investing in scalable green solutions, NTT DATA continues to make a meaningful difference.

We're not just adapting to sustainability pressures by shaping the future of responsible AI. As an AI service provider, we have years of experience and the tools to create awareness of the importance of ethical AI, define responsible governance and implement these solutions in a secure and compliant way.

Our commitment extends beyond compliance, demonstrating that sustainable AI is not a constraint but an opportunity to redefine how technology serves both business and the planet. As AI adoption accelerates, so does the urgency to align innovation with sustainability — ensuring that the next generation of AI is both powerful and responsible.

Learn more about NTT DATA's Data and Artificial Intelligence services.

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