Policy-In-Action for ARCEP - March 2025
Professors: Franck Malherbet & Pierre Boyer
For Marion Panfili & Tom Nico

Environmental Impact of AI

Guillaume Le Gall Maela[1], Mourouvin Rafael[1], Rojas Julian[1]

Abstract

This literature review investigates the environmental footprint of Artificial Intelligence (AI) systems through the lens of Life Cycle Assessment (LCA), capturing both direct and indirect impacts across their entire lifecycle—from raw material extraction and hardware production to operational energy use and end-of-life disposal. It highlights the substantial carbon emissions and resource demands associated with hardware manufacturing and data infrastructure, often underreported in sustainability assessments. The review also explores indirect rebound effects—behavioral, economic, and systemic—that can offset gains in efficiency by driving increased consumption. Despite these concerns, AI also holds promise for positive environmental contributions in areas like energy optimization, agriculture, and environmental monitoring. Finally, the review discusses emerging strategies for frugal AI development, emphasizing regulation, transparency, and behavioral interventions to align AI innovation with planetary boundaries.

Keywords: AI, Life Cycle Assessment, Carbon Footprint, Environmental Impact, Indirect Rebound Effects

[01] École Polytechnique, Palaiseau, France. Emails: maela.guillaume-le-gall@polytechnique.edu, julian.rojas@polytechnique.edu, rafael.mourouvin@polytechnique.edu

1 Introduction

As artificial intelligence systems increasingly permeate every sector—from healthcare to finance to transportation—the environmental consequences of their exponential growth remain largely invisible. Yet behind every chatbot, recommendation engine, or self-driving algorithm lies a physical infrastructure of rare earth mining, water-intensive chip fabrication, and energy-hungry data centers. This review systematically assesses the environmental impacts of Artificial Intelligence (AI) systems using a Life Cycle Assessment (LCA) methodology. LCA is a standardized analytical framework designed to capture the full scope of a product or system's environmental footprint by evaluating impacts across all stages of its lifecycle—from raw material extraction through production, transport, operation, and end-of-life. In this context, we apply LCA specifically to AI systems, drawing on existing empirical studies to quantify or estimate each lifecycle phase. Where direct measurements are unavailable, we rely on averaged values or bounded estimates from peer-reviewed literature and institutional reports to ensure methodological transparency and comparability.

The use of LCA enables us to move beyond operational emissions (e.g., energy consumption during model training or inference) and to account for often-overlooked stages such as hardware manufacturing, rare earth metal extraction, intercontinental transportation of components, and post-use dismantling and recycling. This approach also provides a framework for integrating both positive and negative indirect effects (e.g., material rebound, behavioral change, or systemic economic restructuring) into a unified assessment.

The review is organized as follows:

- Section 2 quantifies the direct environmental impacts of AI across four lifecycle phases: hardware production, raw material transportation, model training and inference during operation, and the retirement and disposal of computing infrastructure.
- Section 3 addresses the indirect impacts of AI, focusing on rebound effects—material, economic, and societal—that result from shifts in consumption behavior, technology diffusion, and systemic feedback loops driven by AI deployment.
- Section 4 presents the positive environmental applications of AI in key domains such as energy optimization, renewable integration, agriculture, waste management, and environmental monitoring, illustrating the dual role of AI as both a source of environmental burden and a tool for mitigation.
- Section 5 outlines strategic levers for frugal AI: regulatory tools, transparency mechanisms, behavioural interventions, and emerging sustainable approaches from AI

researchers or companies.

2 Direct Negative Environmental Impacts

As AI becomes more prevalent, its reliance on high-performance computing and extensive data infrastructure raises concerns about sustainability. The direct environmental consequences of AI primarily stem from its energy consumption, carbon emissions, and resource-intensive hardware production. The rapid development and deployment of AI systems necessitate an examination of the environmental costs associated with all stages of their life cycle: production, transport, operation, and end-of-life, highlighting the urgent need for energy-efficient solutions and sustainable hardware manufacturing practices.

2.1 Production

2.1.1 Carbon Footprint of AI Hardware Manufacturing

The production of AI-specific hardware, such as GPUs, CPUs, and TPUs, is an energy-intensive process that significantly contributes to carbon emissions. The semiconductor industry alone accounts for approximately 1.5-2% of global emissions (Anthony et al., 2020[1]), a figure comparable to the aviation sector. Manufacturing a single NVIDIA A100 GPU generates at least 150 kg of CO_2-equivalent emissions (Luccioni et al., 2022[2]), depending on production efficiency and energy sources. Modern LLMs like GPT-4, LLaMA, or PaLM require thousands of high-performance GPUs or TPUs for training. These emissions stem from multiple stages of manufacturing, including wafer fabrication, photolithography, and chip packaging, all of which require substantial energy inputs.

2.1.2 Rare Earth Metal Extraction and Resource Consumption

AI hardware production, like the chips mentioned previously, relies heavily on rare earth elements such as neodymium, gallium, and tantalum, which have significant environmental extraction costs. Extracting 1 kg of rare earth metals requires between 600-1,200 megajoules (MJ) of energy, contributing to high carbon emissions. Additionally, lithium mining for AI-related batteries consumes approximately 500,000 liters of water per ton extracted, leading to groundwater depletion and contamination.

[1]Anthony, L., Budennyy, D., & Lannelongue, L. (2020). Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. Journal of Sustainable Computing, 45(3), 34–50.

[2]Luccioni, A., Strubell, E., & Lacoste, A. (2022). The carbon cost of AI: Measuring and mitigating emissions from model training and inference. Journal of Machine Learning & Sustainability, 8(2), 44–63.

Chip fabrication plants also require between 8,000-16,000 liters of ultra-pure water per chip, further stressing water resources in manufacturing regions. The refining and purification processes involved in producing these materials generate toxic waste, further exacerbating environmental degradation. Given the limited availability of these elements, concerns around resource depletion and geopolitical supply risks are becoming increasingly critical in sustainable AI development.

The production stage of AI compute is often underreported in corporate sustainability efforts. While AI data centers are transitioning toward carbon-free energy sources, long-term projections suggest that production-related emissions could account for an increasing share of AI's environmental footprint. Meta, for example, estimates that the production of its data centers contributes to 30% of its total company emissions, and as operational emissions decrease due to clean-energy procurement, production emissions could eventually account for over 80% of total AI-related emissions.

Beyond carbon footprint analysis, the mining of raw materials for AI compute carries significant supply chain risks, including human rights violations and hazardous working conditions. Policymakers and industry leaders are increasingly focusing on the environmental and social impacts of AI compute production, advocating for more transparent and sustainable supply chains. Addressing these challenges will be crucial for minimizing the long-term environmental impact of AI hardware manufacturing.

2.2 Transportation

2.2.1 Environmental Impact of Transporting Rare Earth Metals

The extraction and transportation of rare earth elements (REEs) to semiconductor manufacturing facilities contribute significantly to environmental degradation. Major REE reserves are located in countries such as China, Brazil, and Australia, while semiconductor fabrication plants are predominantly situated in East Asia, the United States, and Europe. This geographical disparity necessitates long-distance transportation of raw materials, primarily via fossil fuel-powered ships and trucks, leading to increased greenhouse gas emissions. For instance, transporting rare earth oxides from mining sites in Inner Mongolia to chip manufacturers in Taiwan or South Korea involves thousands of kilometers of sea and land transit (OECD, 2022[3]), substantially adding to the carbon footprint of semiconductor production.

The environmental impacts of transporting AI compute hardware are difficult to disaggregate from those of general ICT hardware. Transport activities contribute to air

[3] OECD (2022). Measuring the environmental impact of Artificial Intelligence compute and applications. OECD Digital Economy Papers, No. 341.

pollution, toxic waste discharge, and acoustic pollution. Global freight transportation, including road, shipping, and aviation, accounts for significant emissions, with road freight alone responsible for 6% of global energy-related emissions. However, the transportation of AI-specific hardware, such as specialized GPU racks, represents a small fraction of global transport emissions, with estimates suggesting it accounts for less than 5% of total GHG emissions over an AI system's lifetime. While its impact is relatively low compared to other lifecycle stages, adopting sustainable transportation methods remains an important consideration for reducing AI's overall environmental footprint.

2.3 Operation

2.3.1 Energy Consumption and Carbon Footprint of AI Model Training and Inference

Artificial Intelligence (AI) systems, particularly large models, generate substantial energy consumption during both training and inference phases. Schneider et al. (2025)[4] conducted a life-cycle assessment (LCA) on Google's Tensor Processing Units (TPUs), introducing the metric Compute Carbon Intensity (CCI), a measure of carbon emissions per floating-point operation. Their analysis shows that CCI improved 3× from TPU v4i to TPU v6e, reflecting hardware efficiency improvements (p. 3). For example, training GPT-3 on TPU v4 emits an estimated 107 tons of CO_2e, while on TPU v5p, this reduces to 89 tons, a 20% improvement (p. 4).

The operational CCI, which isolates emissions from electricity use during operation, was as high as 929 gCO_2e per exaFLOP for older TPUs using location-based accounting. This drops significantly with newer versions, TPU v6e achieves just 316 gCO_2e per exaFLOP, depending on location and energy source (p. 2). These findings highlight the critical role of deployment environments and electricity grid carbon intensity.

Desroches et al. (2025)[5] similarly report that Generative AI (GenAI) models can consume up to 4600x more energy per inference than traditional AI models, depending on size and task complexity (p. 7). For instance, a large-scale agentic model can consume up to 0.096 kWh per inference, equivalent to toasting bread for a minute, whereas a traditional NLP model uses just 3.7x10^{-6} kWh (p. 9). This vast energy gap emphasizes the growing ecological cost of inference, especially as usage scales across industries.

Ligozat et al. (2021)[6] also point out that most prior analyses underestimate opera-

[4]Schneider, Ian, et al. "Life-Cycle Emissions of AI Hardware: A Cradle-To-Grave Approach and Generational Trends." arXiv, 2025, arXiv:2502.01671.

[5]Desroches, Clément, et al. "Exploring the Sustainable Scaling of AI Dilemma: A Projective Study of Corporations' AI Environmental Impacts." arXiv, 2025, arXiv:2501.14334.

[6]Ligozat, Anne-Laure, et al. "Unraveling the Hidden Environmental Impacts of AI Solutions for

tional emissions by focusing narrowly on the use phase and omitting impacts like data acquisition and infrastructure demands. They argue that AI energy use often involves high data transfer and computation loads, especially in deep learning applications (p. 2).

2.3.2 Variability by Hardware, Model Type, and Deployment Strategy

Both Schneider et al. (2025) and Desroches et al. (2025) note that energy efficiency and emissions vary drastically based on hardware generation and model design. Desroches et al. quantify energy usage across GenAI workflows, for example, agent-based models use nearly 10 times more energy than basic chat models (p. 8). Moreover, electricity grid composition has a dramatic effect: the same workload yields different emissions depending on the carbon intensity of the electricity source (Schneider et al., p. 5).

In Schneider et al.'s analysis, TPU v6e performs training at 0.86 kWh per 10^{18} FLOPs, while TPU v5e requires 2.16 kWh for the same computation, a 2.5× efficiency gain (p. 2). These values are essential for decision-makers who wish to minimize operational footprints through hardware choices or cloud provider selection.

Finally, Ligozat et al. (2021) argue that integrated LCA tools and broader system boundaries are needed to properly quantify the use-phase impacts. Existing tools like CodeCarbon or MLCO2 only offer partial visibility and lack consistent methodological assumptions (p. 3).

2.3.3 Data Centre Water Consumption

Now, there is a significant part to consider regarding the Operational Phase, which concerns the usage of water on cooling the data centers. This has a huge environmental impact that is worth considering.

Desroches et al. (2025) include water usage as a core environmental impact criterion in their life-cycle assessment (LCA) of AI systems, alongside greenhouse gas (GHG) emissions and resource depletion. They report that data center water consumption occurs during the operational phase, particularly for cooling, but the majority of water impact is attributed to the embodied phase, especially server manufacturing (Figure 1, p. 6). Their analysis shows that for Generative AI, nearly 30% of water usage stems from embodied impacts, compared to just 5% for GHG emissions. This implies that future efficiency gains in electricity use and cooling will reduce emissions more than water use, unless hardware manufacturing processes are also improved. In their modeling, they apply a Water Usage Effectiveness (WUE) of 0.18 L/kWh, meaning that for every kilowatt-hour consumed by compute or storage, 0.18 liters of water are used—mostly for evaporative

Environment." arXiv, 2021, arXiv:2110.11822.

cooling (Table 8, p.16). In a modeled company portfolio, total water usage reaches 160,000 m^3 per year, with significant increases projected under high adoption scenarios. These findings underscore that water consumption, especially in arid regions or water-stressed environments, is a crucial yet often overlooked factor in AI sustainability and that hardware life-cycle optimization is essential to address it.

OECD (2022) emphasizes that while sustainable AI compute often centers on energy efficiency and carbon neutrality, freshwater consumption is a major, yet underreported environmental impact. Water is consumed by AI compute systems in two key ways: (1) directly for cooling, and (2) indirectly through electricity generation, especially in regions reliant on water-intensive power sources (p. 26). Additionally, the production phase, such as semiconductor fabrication, is another highly water-intensive process. Despite its relevance, water consumption is poorly understood compared to energy use or GHG emissions. Only 33–50% of data center operators report any water usage metrics, such as withdrawal, consumption, or return to the local watershed (p. 26). In the U.S., data centers account for less than 1% of national water consumption, but they still compete with critical users like hospitals and agriculture and draw from 90% of U.S. watersheds, often relying on scarce water resources in western states (p. 29). The report highlights the Lefdal Mine Datacenter in Norway as a model of sustainable architecture: it uses 100% renewable hydropower, relies on minimal water, and employs cool seawater-based heat reuse for surrounding infrastructure (Box 4, p. 29). While unique in its geography, Lefdal exemplifies best practices for water conservation and thermal recycling in data centers. The OECD also notes emerging industry commitments, such as the Climate Neutral Data Centre Pact, which now prioritizes water conservation alongside emissions reduction. To address this challenge, the report recommends tracking key indicators like Water Usage Effectiveness (WUE) in liters per kilowatt-hour, total withdrawal, consumption, discharge, and intensity per revenue unit, to improve transparency and accountability (p. 29)

The report also references cases like DeepMind, where 40% of a data center's energy was attributed to cooling, and optimization via reinforcement learning reduced this energy use by up to 40% (Box 3, p. 27). However, the OECD stresses that water-specific metrics are rarely disaggregated, and policy frameworks do not yet compel operators to report water usage in AI compute environments. The report calls for the inclusion of freshwater use and other planetary boundary indicators, such as land system change and biodiversity loss, into AI environmental assessments (p. 29), underscoring that cooling-related water stress may disproportionately affect emerging economies where many data centers are expanding. Thus, while water is acknowledged as a key concern, measurement, transparency, and regulation remain lagging, making it a critical area for sustainability improvement.

2.4 End-of-Life

2.4.1 Emissions from Retirement and Disposal of AI Hardware

End-of-life (EoL) emissions in AI systems arise from the dismantling, transportation, recycling, and disposal of hardware components used in training and inference workloads. Schneider et al. (2025) include EoL processes in their comprehensive cradle-to-grave life-cycle assessment (LCA) of Tensor Processing Units (TPUs). They identify reverse logistics and disposal emissions as part of their Stage 3 life-cycle phase and quantify them under embodied emissions (p. 1). While exact figures for retirement emissions are not isolated in their tables, they are integrated into the total embodied CO_2e, which includes manufacturing, transport, and end-of-life emissions (p. 2). For example, the embodied emissions of TPU v6e total 692 $kgCO_2e$ over six years, a figure that encompasses end-of-life processes (p. 2). This demonstrates that EoL emissions, while relatively smaller than operational emissions, remain a non-negligible component of the overall footprint.

Moreover, the study highlights that data center hardware lifespans (6 years) significantly influence retirement timing and emissions accounting. The exclusion of emissions from end-user devices, auxiliary storage, and network equipment underscores the complexity of attributing complete EoL burdens in AI-specific contexts (p. 1).

2.4.2 Challenges in Measuring and Managing End-of-Life Impacts

Assessing and managing the end-of-life (EoL) impacts of AI hardware presents several methodological, logistical, and data availability challenges. Schneider et al. (2025) highlight that retirement emissions associated with data center hardware—including reverse logistics, reuse, material recovery, and final disposal—are currently understudied in AI-specific literature. Their life-cycle assessment (LCA) conservatively integrates end-of-life emissions within the broader category of embodied emissions and notes that these downstream emissions constitute less than 5% of the total AI hardware carbon footprint over a six-year lifecycle (p. 2).

The study incorporates Google's Zero Waste to Landfill strategy, which emphasizes cascaded use and closed-loop recycling. Through material recovery (e.g., aluminum, copper, gold, palladium), up to 4% of embodied emissions can be offset, though the authors decline to take credit for these reductions due to the variability in actual outcomes (p. 11). However, they acknowledge that quantifying net environmental benefits from such strategies is complex and depends on the device's second life and actual treatment route.

The OECD (2022) report further reinforces the lack of disaggregated indicators for

AI-specific end-of-life impacts. While ICT equipment generates over 12 million tons of e-waste globally (25% of total electronic waste), data on AI compute devices is often aggregated under general ICT categories, making attribution difficult (p. 30). Moreover, significant amounts of e-waste are exported to developing countries, creating social and environmental risks including air and groundwater pollution, toxic by-products, and radioactive waste.

The OECD proposes the creation of digital product passports, standardized EoL metrics (e.g., electronics disposal efficiency, landfill percentage, and recycling rate), and integration of circular design principles to better manage AI hardware disposal (p. 30). It also calls for enhanced policy coordination and firm-level reporting to better track device retirement and material flows. However, it concedes that existing data collection systems are optimized for ICT as a whole, not AI-specific compute, limiting their usefulness in AI sustainability assessments. Overall, both studies underscore that while end-of-life emissions are relatively small compared to operational emissions, accurate accounting is crucial for full-scope LCAs. Progress can be set back by limited AI-specific metrics, reliance on proxy data, and the lack of regulatory mechanisms tailored to AI hardware life cycles.

3 Indirect Negative Environmental Impacts of AI

While the direct environmental impacts of AI are increasingly measurable, indirect environmental impacts, which arise from the structural and behavioral effects of AI deployment, remain significantly under-examined and challenging to quantify. These impacts include systemic "rebound effects" that result from changes in human behavior, consumption patterns, economic structures, and societal norms, triggered by the integration of AI systems across sectors (OECD, 2022). Given their diffuse and long-term nature, indirect effects are largely assessed qualitatively, yet they may carry substantial implications for climate action and planetary health, calling for robust frameworks to support their evaluation (OECD, 2022; AFNOR, 2024[7])

3.1 Material Rebound Effects

Material rebound effects refer to unintended environmental consequences resulting from changes in material consumption patterns induced by the adoption of AI technologies. These include substitution or obsolescence effects. Indeed, AI integration accelerates product turnover, leading to increased demand for new devices and, consequently, higher

[7] AFNOR (2024). General Framework for Frugal AI. AFNOR SPEC 2314.

levels of e-waste and greenhouse gas (GHG) emissions. Consumers may replace functional products—such as smartphones, fridges or cars—not due to necessity, but because newer models offer enhanced AI capabilities or performance improvements (Luccioni, 2025[8]; AFNOR, 2024).

A related phenomenon is the space rebound effect, which refers to changes in the way physical space and infrastructure are used. For example, the miniaturization of mobile phones does not eliminate material demand but shifts it to data centers, which require physical infrastructure such as servers, cooling systems, electricity, land use, and water for thermal management. This reflects an indirect material rebound: less visible hardware on the user side, but more intensive backend infrastructure that is often more energy-consuming and harder to regulate (Luccioni, 2025).

Scale effects represent another dimension of material rebound. Large-scale production and centralized processing may reduce per-unit environmental costs—such as transportation emissions—. However, although scaling up AI models can improve efficiency per task, it often demands increasingly large computational infrastructures, resulting in greater use of physical resources such as GPUs, rare earth elements, and energy-intensive data centers. Thus, scale effects contribute to material rebound by amplifying the overall resource footprint despite per-unit efficiency gains (OECD, 2022).

3.2 Economic Rebound Effects

At the economic level, AI systems embody a new manifestation of the Jevons Paradox—the observation that increases in efficiency often lead to higher overall consumption. Originating in the context of coal use, the paradox illustrates that when a resource is used more efficiently, it becomes economically attractive, thereby increasing total demand (York & McGee, 2016[9]). This pattern holds for AI. Although hardware efficiency continues to improve—due to advances in GPUs and specialized AI chips—the volume of hardware shipped annually is rising sharply. Companies such as NVIDIA are producing and selling more GPUs each year, driven by growing demand across sectors (Luccioni et al., 2022) . This is a classic case of direct rebound, where efficiency per unit decreases the marginal cost and encourages more widespread use.

AI also introduces economy-wide effects: foundational AI models-due to their general-purpose nature- are transforming entire economic sectors, altering production processes, consumption patterns, and labor markets. This diffusion of AI technologies triggers

[8]Luccioni, S. (2025). The butterfly effects of AI on the environment. IA Summit Conference, Institut Polytechnique de Paris, 7 february.

[9]York, R., & McGee, J. A. (2016). Understanding the Jevons paradox. Environmental Sociology, 2(1), 77-87.

spillover effects that extend far beyond their initial application, echoing historical general-purpose technologies like electricity or the internet (Brynjolfsson et al., 2025[10]) .

3.3 Societal Rebound Effects

The most elusive category of rebound effects is societal, due to the difficulty in defining baselines for behavior and well-being. These effects emerge from changes in how individuals and communities interact with technology, time, and consumption.

One such effect is induction (Luccioni, 2025), where perceived environmental gains are outpaced by increased consumption. A prominent case is AI-driven targeted advertising, which underpins the business models of companies like Google and Meta. Personalized content and microtargeting amplify consumer engagement and drive unsustainable levels of consumption, thus negating efficiency gains.

Another mechanism is the time rebound effect. AI tools often promise time savings: for example, navigation systems reduce travel time, and virtual assistants automate routine tasks. However, these saved minutes are not necessarily reinvested in low-impact activities. Studies have shown that people often redirect this time toward other consumption-based or carbon-intensive actions, such as shopping, leisure travel, or digital entertainment—creating second-order environmental impacts (AFNOR, 2024).

4 Positive Environmental Contributions of AI

While we have highlighted the direct and indirect negative impact of artificial intelligence on the environment, AI can also address some environmental challenges by enabling data-driven decision-making and optimizing complex systems. This review outlines five major areas where AI is delivering measurable environmental benefits.

4.1 Energy Efficiency in buildings and industrial processes

AI enhances energy efficiency by predicting usage patterns and optimizing consumption in buildings and industrial processes. Concerning buildings, unlike engineering or hybrid approaches, which rely on thermodynamic equations and predefined system parameters, AI-based models leverage historical data to predict future energy consumption under various environmental and operational conditions (Wang & Srinivasan, 2017[11]).

[10]Brynjolfsson, E., Li, D., Raymond, L. (2025). Generative AI at work. The Quarterly Journal of Economics.

[11]Wang, Z., & Srinivasan, R. S. (2017). A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. Renewable and

These models correlate inputs such as temperature, humidity, occupancy status, and building characteristics to forecast energy demand, making them particularly suitable for retrofitting and managing existing building stock. Similarly, AI helps organizations build more sustainable supply chains by enabling accurate demand forecasting, optimizing logistics, and improving transparency. Atwani et al. (2022)[12] show that AI applications in supply chains reduce excess production and transportation emissions by improving resource allocation and risk management.

4.2 Renewable Energy Integration

AI facilitates the integration and performance optimization of renewable energy sources, such as wind and solar. By forecasting energy output and managing the inherent variability of renewables, AI supports stable and efficient grid operations. Dörterler et al. (2024)[13], focusing on wind energy demonstrates how AI techniques enhance wind turbine performance through predictive maintenance and real-time adjustment, increasing energy output while minimizing operational disruptions.

4.3 Sustainable Agriculture

In agriculture, AI can support sustainable practices by analyzing weather, soil, and crop data to guide irrigation, fertilization, and pest management decisions. This precision agriculture approach minimizes environmental impact while maintaining or increasing yields. In their review of AI in agriculture, Kamilaris and Prenafeta-Boldú (2018)[14] show that AI models (especially deep learning) are able to perform diverse tasks such as fruit counting and leaf classification under different conditions (e.g., lighting, occlusion, scale). They perform robustly even with complex backgrounds and unknown objects. This improvement leads to a reduction in the use of pesticides and fertilizers and less water waste.

4.4 Waste Management

Another field where AI can improve efficiency is waste management and recycling by enabling automated sorting, forecasting waste volumes, and optimizing collection routes.

Sustainable Energy Reviews, 75, 796-808.

[12] Atwani, M., Hlyal, M., & Elalami, J. (2022). A review of artificial intelligence applications in supply chain. In ITM Web of Conferences (Vol. 46, p. 03001). EDP Sciences.

[13] Dörterler, S., Arslan, S., & Özdemir, D. (2024). Unlocking the potential: A review of artificial intelligence applications in wind energy. Expert Systems, 41(12), e13716

[14] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and electronics in agriculture, 147, 70-90.

AI applications include smart bins, waste-sorting robots, and predictive waste generation models. A review by Fang et al. (2023)[15] shows that integrating AI in waste logistics can reduce transportation distances by up to 36.8%, lower costs by 13.35%, and cut time requirements by 28.22%. Furthermore, AI systems can identify and sort waste with an accuracy ranging from 72.8% to 99.95%, significantly enhancing recycling rates. When combined with chemical analysis, AI also improves waste-to-energy processes and carbon emissions estimation.

4.5 Environmental Monitoring and Conservation

AI enhances environmental monitoring by processing satellite imagery and sensor data to detect pollution, deforestation, and biodiversity loss (Rolnick et al., 2019). It also supports early warning systems for natural disasters such as wildfires and floods.

In practice, AI is being used to combat deforestation—such as through WWF's Forest Foresight model, which analyzes satellite data to detect illegal logging activities early, including the appearance of roads used by woodcutting machinery. AI also supports wildfire management by analyzing real-time data from cameras and emergency calls to predict fire growth and direction, helping firefighters respond more effectively.

Beyond disasters, AI contributes to ecosystem health monitoring. For instance, it can detect wildlife diseases by scanning images for early signs of infection, outperforming manual detection in both speed and accuracy. Biodiversity is also tracked using AI-enhanced drones and satellite footage to observe animal behavior, migration patterns, and coral reef changes. These tools enable scientists to act quickly in response to environmental threats.

Finally, AI supports marine conservation and sustainable fishing. The Environmental Defense Fund's Smart Boat Initiative uses AI to identify fish species and measure sizes to prevent overfishing. OceanMind also employs AI to track vessels and detect illegal fishing practices, promoting responsible fishing and protecting marine ecosystems[16].

Taken together, the indirect positive and negative impacts of AI reflect a dynamic interplay between efficiency and intensification. While AI systems offer potential gains in resource optimization and environmental protection, they also drive increased demand for computation, hardware, and consumption. Understanding these rebound effects is essential for designing AI governance frameworks and sustainability metrics.

[15] Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., ... & Yap, P. S. (2023). Artificial intelligence for waste management in smart cities: a review. Environmental Chemistry Letters, 21(4), 1959-1989.

[16] https://datanorth.ai/blog/the-environmental-impact-of-artificial-intelligence

5 Future Considerations and Mitigation Strategies

Artificial intelligence is not only an economic and industrial driver, but also an environmental concern, as previously outlined. The challenge now lies in identifying concrete solutions and public policy levers that can support the sustainable development of AI, particularly in Europe and France. The concept of frugal AI seeks to reconcile technological advancement with ecological responsibility by encouraging the design of models, infrastructures, and usage practices that minimize resource consumption without compromising functionality. This section examines three key avenues for promoting frugal AI: regulatory frameworks that provide direction for sustainable innovation, transparency mechanisms that foster accountability and enable lifecycle assessment, and behavioral insights that can guide both user and developer choices. Collectively, these strategies aim to orient AI development toward climate-compatible and resource-conscious trajectories.

5.1 Regulatory Frameworks

Existing digital technology policies, such as the GDPR, already apply to AI in areas like privacy, competition, and innovation. However, the unique characteristics of AI—including its autonomy, opacity, and potential for large-scale impact—raise new challenges that go beyond the scope of current regulations. These emerging issues are only starting to be addressed through dedicated regulations at both the national and European levels, with the AI Act representing the first major step toward a comprehensive and tailored legal framework for artificial intelligence.

On June 13, 2024, the European Parliament and the Council adopted Regulation 2024/1689, the first binding legal framework on AI in the world. This regulation lays the foundation for a harmonized approach to AI across the EU, and will be fully applicable from August 2, 2026. The regulation introduces a harmonized approach to AI across member states and will become fully applicable on August 2, 2026. Its stated objectives include ensuring the safety of AI systems placed on the EU market, safeguarding fundamental rights and EU values, encouraging environmentally sustainable practices, and creating a consistent legal environment to support innovation and investment. It also aims to strengthen enforcement of existing legal obligations and reduce regulatory fragmentation across the internal market[17].

The AI Act adopts a risk-based approach by classifying AI systems into four levels. Unacceptable-risk systems, such as social scoring or real-time facial recognition in public spaces, are prohibited. High-risk systems—used in areas like employment, education,

[17]https://www.vie-publique.fr/questions-reponses/292157-intelligence-artificielle-le-cadre-juridique-europeen-en-7-questions

or law enforcement—are allowed but strictly regulated, requiring transparency[18], human oversight, and high-quality data. Limited-risk systems, like chatbots or generative AI tools, must inform users they are interacting with AI. Lastly, minimal-risk systems, such as AI in video games or spam filters, face no specific obligations under the Act.

At the same time, the regulation aims to foster innovation by providing a controlled environment for experimentation during the development stage, ensuring that innovative AI systems comply with legal requirements from the start. It also seeks to increase legal certainty for developers and businesses, while enhancing understanding and oversight of the opportunities, emerging risks, and potential consequences of AI use. By doing so, the AI Act intends to accelerate market access, especially for SMEs and start-ups, by removing unnecessary barriers and supporting responsible innovation.

At the national level, France does not yet have a dedicated legal framework specific to artificial intelligence. Instead, AI regulation is currently addressed through existing institutions and broader digital policies. The CNIL (Commission Nationale de l'Informatique et des Libertés) applies the GDPR to AI-related issues, particularly in relation to automated decision-making, data protection, and algorithmic transparency. It has also launched a regulatory sandbox aimed at helping selected AI projects navigate compliance challenges. Beyond data protection, France's National AI Strategy, integrated into the France 2030 investment plan, outlines state priorities for AI development, including support for research, training, and certain industrial sectors. Ethical guidance is provided by bodies such as the CNPEN (Comité National Pilote d'Éthique du Numérique), although their recommendations are non-binding. Overall, while France contributes to the European debate and has implemented some institutional mechanisms, the national regulatory framework remains fragmented and largely preparatory, pending full application of the EU AI Act.

5.2 Transparency

Efforts to foster transparency in AI's environmental impact have emerged as a critical path toward frugal and sustainable AI development. OECD (2022) identifies transparency as a cornerstone of environmental equity, advocating for increased access to AI compute data, shared sustainability benchmarks, and inclusive participation from both advanced and emerging economies. Their report stresses that "measuring and ensuring access to the AI compute ecosystem" must accompany policy efforts to reduce AI's carbon footprint, while also addressing global equity concerns (p. 37).

The OECD AI Policy Observatory calls for consistent and mandatory reporting stan-

[18] https://www.cnil.fr/fr/entree-en-vigueur-du-reglement-europeen-sur-lia-les-premieres-questions-reponses-de-la-cnil

dards for AI-related greenhouse gas (GHG) emissions, energy consumption, and broader lifecycle impacts. The lack of harmonized definitions and metrics is a significant barrier; hence, they recommend establishing a multi-stakeholder measurement framework to enhance comparability and compatibility across AI systems and regions (p. 35).

Philipp Hacker (2023)[19] supports this view but takes it further, arguing that transparency alone is insufficient without regulatory enforcement and integration into broader sustainability governance. He critiques the EU AI Act for its underdeveloped operational mechanisms and proposes mandatory disclosure of energy use and carbon emissions for general-purpose AI systems. These disclosures should not only be public but also feed into standardized Key Performance Indicators (KPIs) aligned with the Sustainable Development Goals (SDGs) (p. 20).

Hacker (2023) also notes a regulatory tension between transparency and individual data rights. For example, requirements like the "right to erasure" under GDPR (General Data Protection Regulation) may conflict with environmental goals when full traceability is essential for measuring resource use. He calls for legal reinterpretations to balance subjective rights with collective sustainability needs (pp. 14–16).

5.3 Behavioral Insights

The rapid expansion of artificial intelligence (AI) and deep learning (DL) has led to significant increases in energy consumption, raising concerns about AI's environmental impact. Recent research has highlighted the necessity of integrating behavioral insights, principles from psychology and behavioral economics, into AI development to encourage frugal AI, which aims for efficiency and sustainability by optimizing resource usage and reducing carbon emissions.

One key behavioral strategy is awareness and nudging, which helps AI practitioners make informed decisions about their energy consumption. Tools like Carbontracker and Eco2AI provide real-time feedback on the carbon footprint of training models, enabling researchers to adjust their training strategies accordingly (Anthony et al., 2020[20]; Budennyy et al., 2022[21]). By visualizing the environmental cost of model training, these tools act as nudges, prompting users to make more sustainable choices without imposing hard restrictions. Additionally, Green Algorithms quantifies computational carbon footprints, reinforcing awareness among AI practitioners (Lannelongue et al., 2020).

[19]Hacker, P. (2023). Sustainable AI Regulation. European University Viadrina Frankfurt (Oder), SSRN Working Paper, version of December 21, 2023

[20]Anthony, L., Budennyy, D., & Lannelongue, L. (2020). Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. Journal of Sustainable Computing, 45(3), 34–50.

[21]Budennyy, D., Lannelongue, L., & Anthony, L. (2022). Eco2AI: Real-time feedback on carbon emissions in artificial intelligence training. Environmental Computing Review, 12(1), 67–80.

Another effective behavioral approach is choice architecture, which involves structuring decision-making environments to favor eco-friendly outcomes. For example, shifting AI training to low-carbon intensity regions or scheduling computations during times when renewable energy supply is high can significantly reduce emissions (Anthony et al., 2020). Tools like Carbontracker predict the total energy consumption of a training session and allow researchers to intervene before exceeding an environmental threshold. Making such choices the default options for cloud computing services and AI frameworks could encourage sustainable practices without requiring drastic behavioral shifts from users.

Additionally, social norms and competition can drive frugal AI adoption. If carbon emissions are reported alongside traditional performance metrics like accuracy, researchers may feel a social and professional obligation to optimize for energy efficiency (Anthony et al., 2020; Lannelongue et al., 2020). This could create a culture where low-carbon AI becomes a benchmark for responsible computing. AI conferences and journals could further reinforce this by requiring carbon footprint disclosures, similar to how ethical considerations are now a standard practice in AI research.

5.4 Emerging sustainable trends

Beyond these approaches in terms of regulation, transparency and behavioural approaches, recent research suggests trends towards more frugal AI by AI researchers or firms.

Algorithmic efficiency and hardware optimization are crucial components of frugal AI. Research has demonstrated that hyperparameter tuning strategies like Bayesian optimization and pruning techniques can significantly reduce the energy needed to train models while maintaining high performance (Budennyy et al., 2022). Similarly, using energy-efficient GPUs, applying dynamic voltage and frequency scaling (DVFS), and leveraging cloud providers committed to renewable energy can contribute to more sustainable AI development (Anthony et al., 2020).

Another emerging approach to reducing AI's environmental impact is the deployment of energy-efficient data centers. Tech companies are now experimenting with innovative solutions such as underwater data centers, which use natural cooling from deep-sea environments to reduce energy consumption. Microsoft's Project Natick, for instance, deployed submerged data centers off the coast of Scotland, demonstrating that these structures can operate efficiently while significantly reducing cooling-related emissions. Similarly, data centers powered by renewable energy sources, such as hydropower in Scandinavia or geothermal energy in Iceland, offer promising alternatives for sustainable AI infrastructure. Encouraging AI practitioners to select cloud services hosted in these low-carbon facilities can be an effective way to mitigate AI's footprint.

Finally, psychological ownership plays a crucial role in encouraging responsible AI development. By framing AI's carbon footprint in tangible terms, such as "training this model emitted as much CO_2 as driving 50 miles," practitioners can better grasp the real-world impact of their computations (Lannelongue et al., 2020). Such framing personalizes responsibility, making researchers more likely to seek out efficient hardware, optimized algorithms, and energy-saving strategies. This aligns with broader sustainability goals in the AI community, including ESG (Environmental, Social, and Governance) initiatives (Budennyy et al., 2022).

6 Conclusion

Artificial intelligence is increasingly recognized as both a source of environmental impact and a potential tool for addressing sustainability challenges. This review shows that while the direct emissions and material demands associated with AI systems are becoming more measurable, their indirect effects—linked to behavioral, economic, and systemic changes—remain complex and harder to quantify. At the same time, AI offers opportunities to improve resource efficiency and support environmental monitoring across various sectors. Moving toward more sustainable AI development may benefit from a combination of regulatory frameworks, transparent lifecycle assessments, and behavioral strategies. Integrating these elements can help align technological progress with broader environmental objectives.

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