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POSITION PAPER

Key Challenges in Fostering **the Environmental Performance of AI**

SOMMET POUR L'ACTION SUR L'IA

February 2025

Preamble

Artificial intelligence (AI) development is rapid and heterogeneous, in terms of both methodology and applications. The number of areas unaffected by AI is most likely far outnumbered by the number of fields that are currently being reshaped by this new technology.

In this document, AI is considered a theoretical and practical field whose aim is to understand the mechanisms of cognition and reflection, and to imitate them using hardware and software. According to the EU AI Act (Art. 3), an artificial intelligence system is a machine-based system designed to operate with varying levels of autonomy. It can exhibit adaptiveness after deployment and, for explicit or implicit objectives, infers from its input on how to generate outputs such as predictions, content, recommendations, or decisions that influence physical or virtual environments. Thus, AI is primarily viewed from the perspective of hardware infrastructure and algorithms, which after a learning phase possibly requiring a very large amount of data, enable various tasks to be carried out, in particular:

- **Perceiving the environment and predicting its evolution;**
- **Processing information**, including analysis, indexing and knowledge extraction;
- **Making decisions, selecting actions** and carrying out tasks to achieve specific goals.

As part of the AI Action Summit, a wide range of issues related to AI development will be addressed. The aim is for everyone to identify this technology's associated risks, as well as its opportunities and benefits. This enables us to outline a path for the evolution and development of AI that aligns with the public interest and the diversity of views. This document focuses on the environmental impacts[1] of AI, and more specifically on the hardware and software components on which AI tools are based, including the design of these tools. More specifically, the goal of this paper is to present five key challenges in fostering the environmental performance of AI. This document does not provide an exhaustive list of challenges, but it is designed to evolve over time to incorporate advancements and emerging challenges through similar consultation processes.

Building on recent developments in AI technology, several challenges have been put forth by a wide range of scientists, industry leaders, international organizations, administrative authorities and other stakeholders. We aim at building a coalition of stakeholders ready to address these challenges in order to maximize the positive impacts of AI, particularly in environmental terms, while minimizing the environmental footprint of deploying AI-based solutions.

To meet each challenge, the contributors sought to establish ambitious, collective objectives based on recent findings and developments. However, this effort was complicated by the lack of precise data on AI's environmental footprint. To address this issue, some of the challenges outlined in this document aim to bridge the gap in available data.

1 According to the EU regulation establishing a framework for the setting of ecodesign requirements for sustainable products, environmental impact means any change to the environment, whether adverse or beneficial, wholly or partially resulting from a product during its life cycle.

Introduction and Findings

Although sometimes relying on algorithmic methods used for years, **the development of AI is now proceeding at a very rapid pace,** sparking numerous controversies that encompass both opportunities and concerns. AI's contribution to environmental protection and climate change is one such controversy.
On the one hand, **AI is a powerful technology that can help us improve our understanding** of geophysical phenomena, improve climate change forecasting, and support the decarbonization of various sectors such as agriculture, industry, mobility and energy, to name just a few examples. On the other hand, the development and operation of AI systems, especially at large scale, have a significant negative impact on the environment, including **high consumption of water, electricity and resources, as well as low recycling rates of components.**

Although digital technologies currently account for only around 3% of global greenhouse gas emissions[2], this figure is rising sharply. At the same time, **digital technologies already account for up to 12% of the world's electricity consumption,** and a major increase in their energy footprint in the coming years could jeopardize electricity production targets related to the ecological transition. At present, the rate of development of AI is far outstripping that of electricity production capacity from renewable energy sources such as photovoltaic panels or wind turbines[3]. In major economies such as the United States, China and the European Union, data centers account for only around 2–4% of total electricity consumption today. However, due to their greater spatial concentration, compared to other similarly energy-intensive infrastructure, their local impact can be significant. For instance, the sector has already exceeded 10% of electricity consumption in at least five US states. In Ireland, it now accounts for over 20% of all electricity consumption[4].

The increase in the use of AI is leading to an increase in the associated computing requirements, which has been noticeable for more than five years, with model training demands increasing fifteenfold every two years. This trend further accelerated over the last two years, driven by the high-speed development of generative AI, with energy demands for training increasing by a factor of 750 during this period, and particularly high environmental costs associated with training large models (see Figures 1-a and 1-b). However, it is worth noting that **a recent decoupling has emerged between the growth in FLOPs[5] and the size of models or training dataset[6].**

2 UNCTAD Digital economy report 2024
3 Goldman Sachs AI, data centers and the coming US power demand surge 2024
4 IEA What the data center and AI boom could mean for the energy sector, 2024
5 Floating point operations (FLOPs)
6 J. Hoffmann et al. Training Compute-Optimal Large Language Models 2023

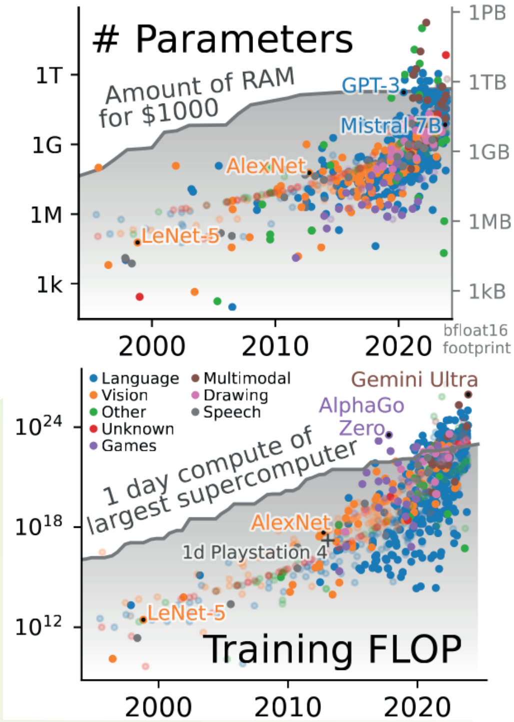

Figure 1-a: *An explosion in model size. Top: The increase[7] in model size means it is more and more expensive to run them in terms of RAM[8]. Bottom: Resource needs are increasing faster than their availability[9].*

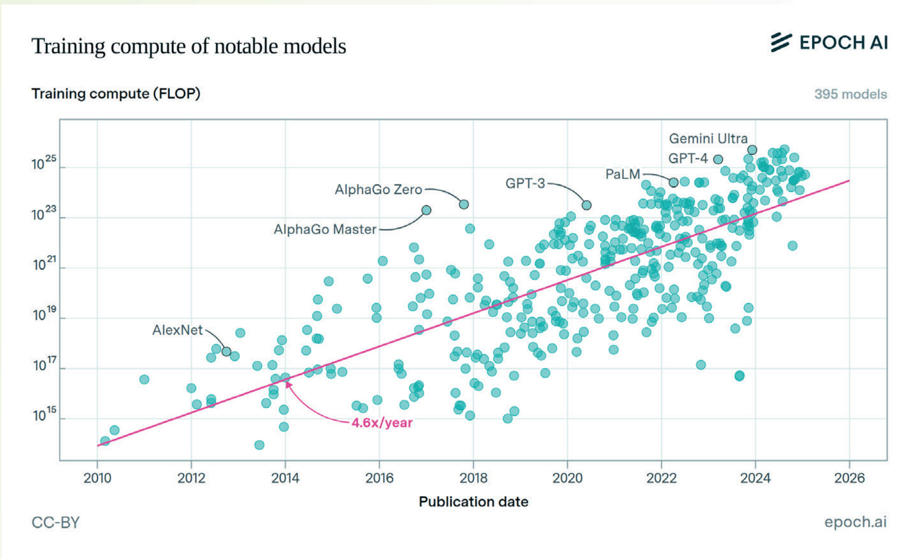

Figure 1-b: *AI models are increasingly demanding in terms of computing capacity—you can see here the total number of operations required to train each AI model, as a function of time[10].*

7 G. Varoquaux, A. S. Luccioni, and M. Whittaker. Hype, Sustainability, and the Price of the Bigger-is-Better Paradigm in AI 2024

8 Random-access memory (RAM)

9 Epoch, *Parameter, compute and data trends in machine learning*, 2023

10 J. Sevilla and E. Roldán, Training Compute of Frontier AI Models Grows by 4-5x per Year, Epoch AI - 2024

While the largest computing machines currently available[11] support exaflops-type computing loads (10^{18} operations per second), the demands of the latest AI models require cumulative power to the order of 10^{25} operations.

Even if the figures presented in this document explicitly focus on model development, assessing the performance of AI systems -particularly in terms of the environmental impact- often remains very difficult. Indeed, the necessary information such as the size of the system, the learning corpus, the frequency of updates or the volume of inference is not always publicly available and has to be estimated using proxy variables.

The considerable increase in model size can be attributed to three factors:

- The drive to develop generalist AI models.
- The significant improvement in Large language model (LLM) performance beyond a certain critical size, as shown in **Figure 2.**
- The common approach of improving LLM performance by increasing the volume of data used for training.

The consequences of this race to gigantism go beyond the environmental impact. The cost of developing and maintaining large AI systems is increasing so rapidly that owners are encouraged to favor applications that generate substantial revenue at the expense of those supporting the common good.

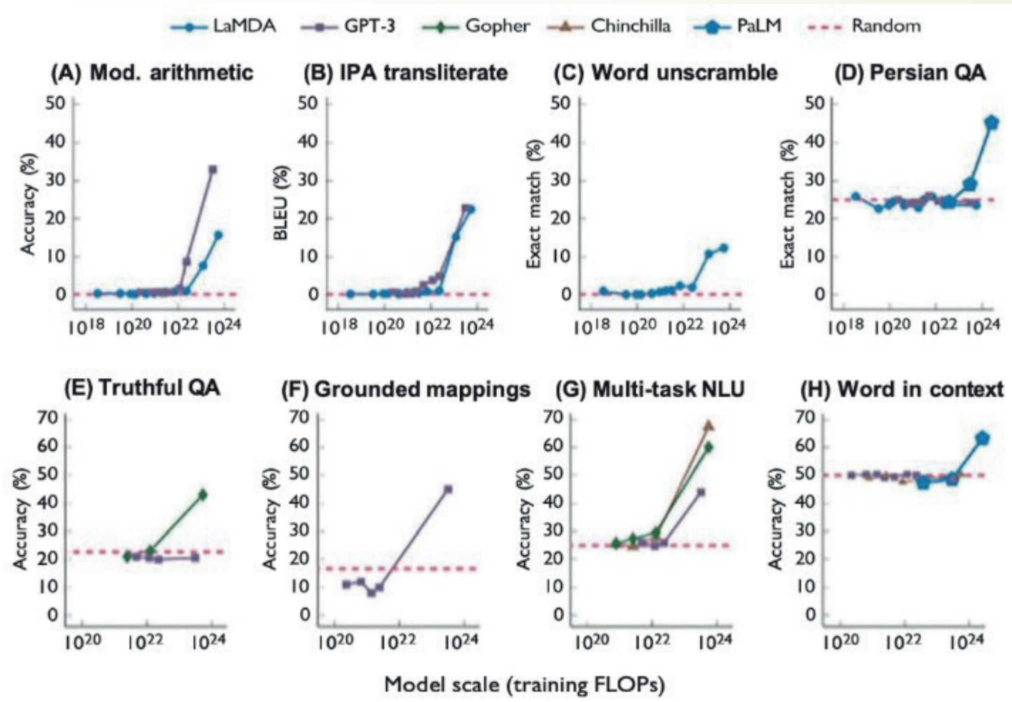

Figure 2: *Jumps in capabilities on eight reasoning benchmarks for five different generative language models as a function of the number of floating-point operations (FLOPs) invested for optimizing model parameters during training. The jumps have been referred to as the emergence of specific capabilities at particular thresholds of model size*[12].

11 See https://top500.org/

12 J. Wei et al, *Emergent Abilities of Large Language Models*, 2022.

However, for many tasks, the performance of AI systems tends to decrease as the size of the system (particularly the memory footprint) increases, as shown in Figure 3 and the reference[13].

These trends support the development of AI systems that focus on the quality of data used for learning rather than the quantity and leverage a priori information - such as symmetry, invariance and expert knowledge - to improve performance while reducing the cost of the learning phase.

SLMs (Small Language Models) with just a few billion parameters have recently been proposed, offering high performance while remaining resource-efficient and suggesting a certain decoupling between performance and size.

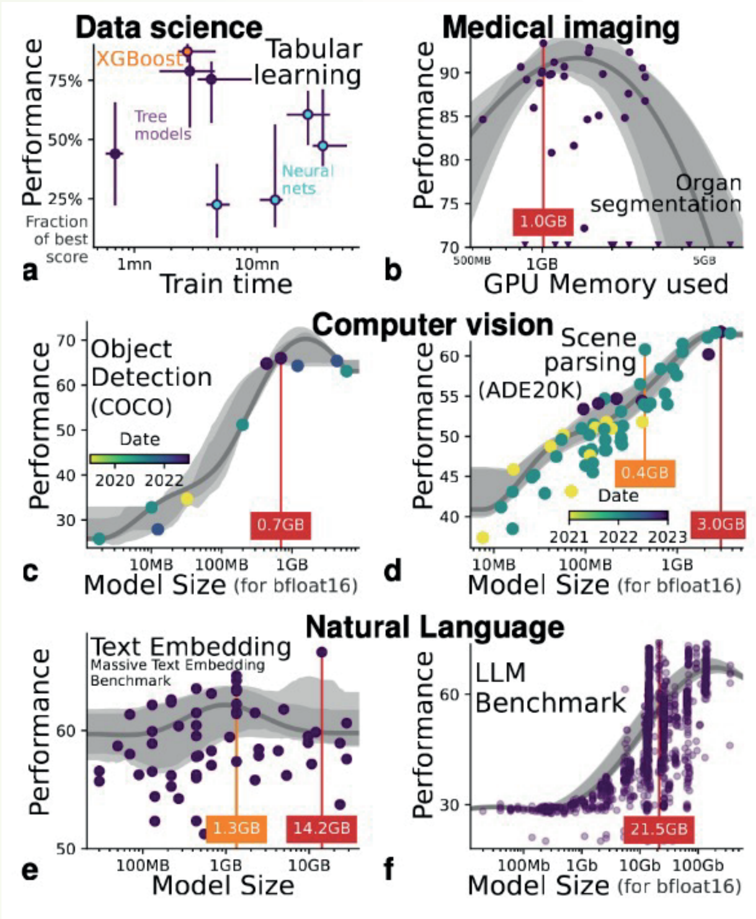

Figure 3: *Plots of performance as a function of scale (time or memory footprint) on benchmark data from a) tabular learning, b) a medical image segmentation challenge, c) computer-vision object detection, d) scenes parsing, e) text embedding and f) text understanding.*

13 E. Horvitz and T. M. Mitchell, Scientific Progress in Artificial Intelligence: History, Status, and Futures 2024 In Realizing the Promise and Minimizing the Perils of AI for Science and the Scientific Community. University of Pennsylvania Press

Information and communication technologies (ICT) have always operated at the nexus between centralized systems (servers, data centers) and decentralized systems (terminals, interfaces). We are now seeing the emergence of AI systems running on mobile phones or even connected devices. This trend is set to intensify, with a number of consequences:

- Less traffic on networks and less computing in data centers;
- An increased use of terminals possibly less optimized than data centers;
- A possible acceleration in the obsolescence of devices that do not support these new systems, leading to a possible early replacement of digital equipment in the years to come.

While drawing up a clear path of future developments in AI remains difficult, we can still draw some conclusions:

- **The potential of AI is extensive and real,** and it would be unrealistic to try to do without this technology entirely;
- We need to find a development path for AI that reconciles **the preservation of our planet** with innovation;
- **The development of AI raises many questions, many of which go beyond the environmental impact.** It is therefore essential to be able to evaluate AI systems, so that these new technologies can factually demonstrate their potential to serve the general interest.

The challenges proposed below have two objectives. The aim is, of course, **to limit the environmental footprint of AI.** At the same time, the development of sustainable AI tools should enable scientific advances and innovations. These advances, which go well beyond the optimization of existing systems, can profoundly transform current practices and facilitate the ecological transition.

Proposals

Challenge 1

Environmentally performant technologies

The environmental impacts of an AI system are wide-ranging, from manufacture, lifespan, use, recycling, to and-use changes, and must be explored from a holistic perspective, that takes into account system hardware, data and algorithms[14]. Energy consumption[15] -which is calculated throughout the lifecycle and weighted by use- serves as a good proxy for these impacts but other types of impacts, such as water consumption, have to be considered.

A large number of research projects are currently underway and many technologies will emerge to improve the performance, particularly the energy efficiency, of AI architecture, such as:

- Highly energy-efficient digital accelerators;
- Specialized microarchitectures, specialized chiplets, 3D integration;
- Integration of in-memory computing enabled analogic and photonic accelerators;
- Vector processing, tensor calculus[16], hyper dimensional computing, quantum computing in AI workflow;
- Edge or embedded AI, remote AI systems on terminals;
- Lower inference costs thanks to smaller, easier-to-run models;
- New cooling techniques (liquid, immersive) and reuse of the extracted energy.

These hardware improvements require algorithms tailored to this new architecture:

- Quantization, multiple, reduced and adapted precision, as well as strategies for network topology optimization;
- New algorithms for optimization and back propagation;
- Algorithms and models for agent-based AI, federated learning, and distributed learning that will contribute to the development of more flexible, privacy-preserving, and scalable AI systems.

14 C. Wu et al., *Sustainable AI: Environmental implications, challenges and opportunities* 2022.
15 *IEA Electricity 2024,* Paris. This report and the section devoted to artificial intelligence shed light on how to build a more optimised energy system and show the relative weight of AI compared with other electricity-consuming sectors.
16 N. P. Jouppi et al. *In-Datacenter Performance Analysis of a Tensor Processing Unit,* 2017.

It should also be noted that responsible data management practices can play a key role in reducing unnecessary data storage, including data wastage, redundant, unused or inefficiently managed data.

Developing efficient technologies requires addressing key challenges, such as creating co-integrated software platforms and application software stacks designed for neural network development (learning and inference) in resource-constrained and context-dependent environments. **We can also think of new approaches based, for example, on nature-inspired technologies**[17] **such as:**

- Neuromorphic architectures for sparse and low-precision computation;
- Spiking-based neural networks for low-power event-based processing;
- Oscillator-based neural networks for solving combinatorial optimization problems and pattern retrieval;
- Associative memories for pattern search and distance estimation;
- Other bio-inspired approaches using memristive devices[18], photonic neural networks for ultra-fast computations and DNA-based computing for massive parallelism.

Challenge 2

Towards specialized, nimble models, trained on trusted datasets

When a new technology emerges, there is a natural tendency to develop generalist tools using that technology. However, dedicated tools often emerge soon after.

This can be seen in the development of generative AI, with the emergence initially of large models that provide general-purpose functions. We need to reinforce the development of more task-specific and therefore smaller AI tools, as these tools, in contrast to large models, are more likely to reconcile environmental protection with innovation.

As Figure 3 shows, growth in the volume of data used for AI training does not necessarily improve the performance of an AI system. In fact, performance can decrease when the data used is redundant. The goal is thus to define a framework that is conducive to the development of small, sufficient and resilient solutions. Sophisticated AI solutions designed to solve specific problems may sometimes be preferable to fine-tuning general-purpose models.

17 D. S. Modha et al., *Neural inference at the frontier of energy, space, and time - Science 382,* pp. 329–335, 2023.

18 Memristive devices are electrical switches that retain a resistance state based on past voltage and current history, enabling them to store and process information. A key type, based on ionic motion, consists of a conductor/insulator/conductor thin-film stack. First proposed in the 1960s, recent advancements have led to fast, low-energy, high-endurance devices that can be scaled below 10 nm and stacked in 3D. However, the mechanisms behind these devices remain unclear, hindering their broader application [Yang, J., Strukov, D. & Stewart, D. *Memristive devices for computing. Nature Nanotech 8,* 13–24 (2013)].

The key issues we face in meeting this challenge are:

- ➔Encouraging the availability and increasing the visibility of precise datasets, domain-specific data to certain fields or for certain applications. These datasets, which should comply with current legislation, can be used by a wide range of players, particularly emerging players, for training, as well as for evaluating the systems developed.
- ➔Encouraging the development of digital commons, such as open-source tools, that will bring together not only datasets, but also software building blocks and architectures.

Challenge 3

New methods and better data to assess the environmental footprint of AI

One way of responding to the concerns raised by AI is to be transparent about its impact, particularly on the environment. The environmental impact of AI is an integral part of its assessment. Limiting these impacts requires a detailed understanding, with their assessment going beyond life cycle analysis and eco-design requirements[19].

The direct environmental impacts of AI, including the manufacture of equipment, fresh water use, abiotic materials, rare earth elements and energy consumption, or greenhouse gas emissions, are starting to be investigated. With this knowledge, scientists will be able to develop methodologies and key performance indicators for assessing the environmental footprint of an AI system, provided that they have the information and physical quantities characterizing its operation.

Open-sourcing models can encourage the sharing of resources and avoid the repetition of model training for similar uses, thus ensuring more efficient consumption of energy and resources.

The key issues we face in meeting this challenge are:

- ➔**Defining significant parameters**[20] which can then be used to construct metrics and indicators to quantify the environmental impact of AI. It is essential to take into account the end-to-end impacts -from client terminals that use networks to cloud servers-, during all stages of the AI process (learning, inference) and with a complete vision of the life cycle of hardware and software resources[21].
- ➔**Encouraging more data sharing from companies,** as most data on the environmental impacts of AI systems currently comes from AI providers, such as large-scale data center operators, or their customers. This can be achieved through different methods, such as voluntary disclosure or

19 T. Duke, P. Giudici, P., *Responsible AI in Practice: A Practical Guide to Safe and Human AI,* Apress L.P., 2025

20 We can think of data such as: the size of the system, the learning process, the volume of inference, the update frequency, the energy performance of the processors and their lifespan.

21 A. Berthelot, E. Caron, M. Jay, L. Lefevre, Estimating the environmental impact of Generative-AI services using an LCA-based methodology. CIRP LCE 2024-31st Conference on Life Cycle Engineering, Jun 2024.

data declaration (e.g., the European Data Centre Declaration Scheme[22]). Standardization is also necessary to ensure that data reports are easily comparable and actionable.

→ **Offering software-based energy consumption measurements** with levels of abstraction capable of adapting to the heterogeneity of technologies and architectures used by manufacturers. This includes defining approaches to understanding the most optimal hardware and software combination in terms of environmental performance.

→ **Quantifying the likely or possible positive impacts of AI in specific sectors.** This could be incredibly useful for inspiring sustainability-minded individuals and organizations to explore new applications of this technology for the public good. Estimating the effects of AI systems on alleviating the environmental footprint of other economic sectors is a major undertaking. To succeed in doing so, we first need to limit ourselves to specific use cases and applications or to a few well-defined sectors, for instance agriculture, transport, telecommunications or housing.

Challenge 4

Scaling Circular Economy Principles for hardware used to power AI

Over the past few decades, there has been progress in implementing circular economy principles and improving recycling within the digital industry.[23]. Regarding the legislation, one noteworthy example is the adoption of the Eco-design for Sustainable Products Regulation (ESPR) at the European Union level.

This regulation establishes a general regulatory framework to adopt new and more ambitious eco-design standards for energy-related products, Information and communication technologies (ICT), and other electronic goods.

However, **this does not imply that all technical and societal challenges have been resolved when it comes to generalizing circular economy approaches across AI supply chains.** This section of the paper suggests that, that while we are not starting from scratch, this challenge remains to be solved.

The main hurdle is that **AI deployment is likely to lead to an increase in the flow of electronic waste,** which could reach a total accumulation of 1.2 to 5 million tons over the period 2020–2030, depending on the different scenarios for the development of generative AI[24]. One of the explanations is that hardware and software need to be adapted to accommodate new AI technologies. Identifying and implementing circular economy strategies early—as it is already the case for some classic electronic and electric technologies and devices—and throughout

22 Commission adopts EU-wide scheme for rating sustainability of data centers

23 Chersan, Ionela-Corina & Paunescu, Mirela & Nichita, Mirela & Dumitru, Valentin & Manea, Lidia. (2023). *Circular Economy Practices in the Electrical and Electronic Equipment Sector in the European Union.* Amfiteatru Economic. 25. 80-100. 10.24818/EA/2023/62/80.

24 P. Wang et al. *The challenges of generative artificial intelligence in electronic waste,* Nature Computational Science, 2024

the AI value chain is thus essential and could reduce e-waste generation by 16 to 86%.

In addition, strategies that increase the modularity and reparability of equipment—whether terminals or connected equipment— by allowing the replacement of individual components rather than of entire units **will boost the circular economy dynamic.** They will also simplify the integration or addition of embedded AI solutions (Edge AI, Tiny Edge) into industrial equipment, enabling it to harness AI advantages, such as improving predictive maintenance, for example. This, in turn, could increase the life span of hardware components that are used to power AI technology.

While AI can help extend the lifespan of hardware, it is essential to consider the environmental impact of the hardware itself. Some research has already been conducted on this topic, and certain industries have worked on strategies to reduce the environmental footprint of mainstream digital technologies—not just those specific to AI. Although these issues are not unique to AI, they are becoming increasingly important with the rise of AI, particularly generative AI.

The growth of AI systems may also increase the demand for certain metals. Strengthening equipment collection and recycling strategies can reduce the environmental impact of the hardware used by the AI systems, providing a secondary source of critical metals and helping ensure a more reliable and sustainable supply of these essential minerals[25]. The main challenge of recycling lies in the complexity of recovering the rare metals present in electronic components. Therefore, in addition to creating a market for recovered spare parts, we must support research and development efforts to establish an industry focused on the treatment and recovery of components that cannot be directly reused in new equipment.

The key issues we face in meeting this challenge are:

- ➔ **Identifying and implementing the strategies and levers that will strengthen efforts to maintain the momentum of extending the lifespan of equipment** (servers and terminals) and reduce premature obsolescence[26], notably through software optimization, hardware eco-design -to improve modularity, upgradability, and end-of-life dismantling-, or the reuse of previous-generation equipment for less energy-intensive applications such as running small and medium-sized models, specialized projects, etc.;
- ➔ **Identifying strategies to prevent the components (such as boards, chips, etc.) from becoming waste,** particularly by improving the dismantling equipment used to recover components that can be repurposed for new uses when they are no longer compatible with AI system operations;
- ➔ **Strengthening metal recovery activities** so that when components can no longer be reused and become e-waste, we can increase the circularity of the raw materials thereby reducing our reliance on critical metals sourced from mining. We must also collectively continue to address structural and technical hurdles, including ensuring that recycled metal maintain the same performance characteristics as their original counterparts.

25 https://www.iea.org/reports/recycling-of-critical-minerals

26 According to the EU regulation establishing a framework for the setting of ecodesign requirements for sustainable products, ‘premature obsolescence’ means a product design feature or subsequent action or omission resulting in the product becoming non-functional or performing less well without such changes of functionality or performance being the result of normal wear and tear. Ecodesign requirements should also address practices associated with premature obsolescence. Such practices have an overall negative impact on the environment, in the form of increased waste and use of energy and materials, which can be reduced through ecodesign requirements while contributing to sustainable consumption.

Challenge 5

Changing the Image of AI to Promote the Development of Frugal AI Tools and Their Rational Use

Many scientists are working on developing AI systems that are frugal, economical and even low-tech. It is vital to stimulate this work, reward it and make it visible. To achieve this, we need to change the way we measure and value performance.

The development of very large-scale AI systems is partly due to the criteria used to evaluate the performance of algorithms and technologies in the scientific community. Such performance criteria currently give priority to quantitative performance, for instance through general benchmarks, to the detriment of "specialized" benchmarks or benchmarks "centered" on a few problems that would enable the advantages of "specific" AI to be highlighted.

For users to act responsibly, frugal AI models must exist and be actively advertised. Through public-private partnerships or labels, for example, AI providers should be encouraged to develop such targeted, task-specific AI models and advertise them to B2B customers and the public.

The key issues we face in meeting this challenge are:

- ➔ **Giving visibility to scientific work on frugal and sustainable AI on an international scale,** in particular through the development of new journals or conferences that make it easier for researchers and practitioners working on AI and the environment to publish and present their work;
- ➔ **Developing training in AI, both initial and continuous.** Educational content must incorporate green skills and tools and solutions designed for a constrained world. The speed at which new AI concepts are emerging underscores the importance of lifelong learning;
- ➔ **Developing educational content (e.g. under the lead of UNESCO or the OECD) such as MOOCs,** to help people understand how AI works, highlighting its strengths and weaknesses, and encouraging the sensible use of AI tools. Concrete numbers and examples help the general audience to understand the environmental and other impacts of AI.

Appendix

There are profound links between AI and the environment. Broadly speaking, they can be divided into three categories:

AI that models the environment, the climate, as well as natural and environmental hazards;

AI as a tool to decarbonize certain industries (agriculture, mobility, industry, housing and construction);

The environmental footprint of AI, and more specifically the impact of the hardware and software components on which AI tools are based.

This document focuses on the last point. In the following, we will briefly outline the contributions of AI to the first two points.

Environmental Modeling—Understanding, Simulating and Predicting

The digital simulation of mechanistic models made it possible to understand and anticipate geophysical phenomena (meteorology, oceanography, climate, natural and environmental hazards, etc.). Nevertheless, the size of the models, their parameterization, and their cost (computing time and associated environmental cost) are becoming obstacles to scientific advances. At the same time, there is an abundance of data (sensors, satellite data, surveys carried out over many years) enabling the use of data science and AI in particular. These new technologies enable major advances[27], sometimes with hybridization between traditional models and AI techniques.

Climate services (the provision and use of climate data, information and knowledge to support decision-making play a key role in many sectors of our economy.

AI's Contribution to Decarbonization and the Ecological Transition - Mitigation

Digital technology and AI are transforming a wide range of sectors and often provide a lever to help reduce the environmental footprint of these sectors. There are particularly notable advances in the following sectors: agro-ecology (mixed crops, decision-making tools for farmers, genetic diversity, flexible robotics, etc.), mobility (multimodality, planning tools, etc.), industry (eco-design, optimization of data centers, digital twins), energy (smart grids, renewable energies). This list is not exhaustive, and at this stage, few quantitative results are available.

It should be emphasized that the use of AI in this field is not just about optimizing existing processes. AI can have a transformative effect, proposing a wholly different trajectory (radical innovations or creative breakthroughs).

27 V. Eyring, W.D. Collins, P. Gentine et al. *Pushing the frontiers in climate modeling and analysis with machine learning.* Nat. Clim. Chang. 14, 916–928 2024. GenCast.
G. Couairon, C. Lessig, A. Charantonis and C. Monteleoni, *ArchesWeather:* An efficient AI weather forecasting model at 1.5 deg resolution 2024.

The position paper was coordinated by the National Institute for Research in Digital Science and Technology (INRIA), the Digital Department, and the Innovation Laboratory of the French Ministry of Ecological Transition, Biodiversity, Forest, Sea, and Fisheries.

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The creation of this position paper was a collaborative effort that could not have been achieved without the insights from researchers, industry leaders and AI experts. Note that contributors do not necessarily support the position paper in its entirety.

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