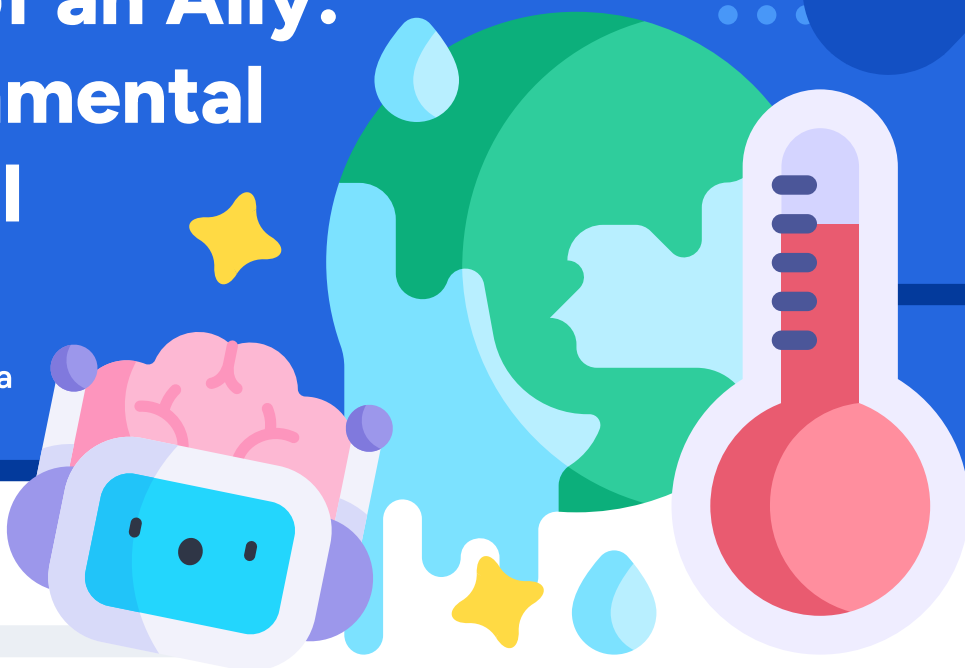


A Fig Leaf of an Ally: The Environmental Impact of AI

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The contribution of AI technologies to climate change has drawn the attention of academics and scientists, particularly amid the growing trend of utilizing AI as reliable and accurate tools for assistance and production. Payar Dhar's (2020) report highlights that AI is likely to have a role in aggravating the climate problem, which experts must consider urgently addressing.

AI technologies embody a dual role: as an aid to mitigating the climate crisis and a significant contributor to climate change. On the one hand, the power of AI to access and process high-quality datasets via sophisticated computational programming allows it to be employed as a transformational problem-solving tool across various areas, including efforts to address climate change. Yet, beneath the facade of collusion in tackling climate change, AI itself significantly contributes to carbon emissions, making it, in effect, a driver of climate change aggravation. The dual role in which AI embodies climate change calls for a thorough analysis in order to identify the core issue and formulate appropriate mitigative steps.

Meanwhile, Kate Crawford and Vladan Joler in *Anatomy of an AI System* inferred that AI—and contemporary technologies as a whole—is rooted in human exploitations, implying the presence of environmental impact associated with the human-driven inputs required to create AI systems. These inputs may include metal extractions straight from the Earth and sweatshops of programmers maintaining the system operation. Moreover, researchers at the University of Massachusetts Amherst estimated that training a single big language model costs roughly 300,000 kilograms of carbon dioxide emissions, equivalent to 125 round-trip flights from New York and Beijing. Yet, this is only a fraction of the problem. Dhar reported that so much is still to be investigated, studied, and analyzed, particularly regarding the infrastructure necessary to deploy AI technologies.

Obscurity of Data Limits Comprehension

Although the message about AI's climate impact was formally communicated to the public in 2019, the obscurity of data, especially about the carbon costs and material details, largely prevents it from conveying the urgency the issue requires. At the social level, Crawford and Joler contended that, in terms of its training and general operationalization, the currently existing data are either vague or non-existent. This leads to a widespread assumption, particularly among laymen, that building AI systems is a simple task. Meanwhile, the direct opposite of this assumption is deemed more truthful; the development of AI requires a complex and meticulous process.

Principally, nebulousness in data is rooted primarily in the absence of standardized ways of quantifying the total emissions for which AI is responsible. This lack of transparency is further compounded by tech companies' reluctance to disclose data or take any initiative toward greater openness. Meanwhile, according to Alexandre Lacoste et al. (2019), the carbon costs of AI training are determined by a number of elements, including geographical location of training, types of energy grid, duration of training and procedures necessary, and hardware models. Lacoste and the team developed an emission calculator designed to estimate the energy consumption of an AI training model to connect the various elements altogether and quantify the cost of AI development.

The screenshot shows the 'ML CO2 Impact' website. At the top, there's a navigation bar with links: 'Compute', 'Publish', 'Learn', 'Act', and 'About'. The main heading is 'Machine Learning Emissions Calculator'. Below it, a subheading says 'Choose your hardware, runtime and cloud provider to estimate the carbon impact of your research.' A paragraph explains that the calculator provides 'raw' carbon emissions and an 'offset' carbon emissions estimate, which depends on the grid used by the cloud provider. Another paragraph notes that the estimate does not take datacenter PUE into account and advises users to find their datacenter's PUE or consult documentation. A link to 'Missing a Hardware or a region? Open an issue or a PR on Github' is provided. The form has four input fields: 'Hardware type' (dropdown menu showing 'A100 PCIe 40/80GB'), 'Hours Used' (input field with '100'), 'Provider' (dropdown menu showing 'Google Cloud Platf'), and 'Region of Compute' (dropdown menu showing 'asia-east1'). A red 'COMPUTE' button is at the bottom.



Estimation, however, is a key issue. Unfortunately, the emission calculator could only do so much to predict the energy consumption of AI development, which already demonstrates the significant environmental impact of AI models. Still, precise data that originates directly from tech companies and AI developers is necessary to address the issue adequately. Ultimately, the vagueness of these costs functions as a fig leaf that conceals the complexities and shortcomings that are embroiled in AI technologies.

Red versus Green AI

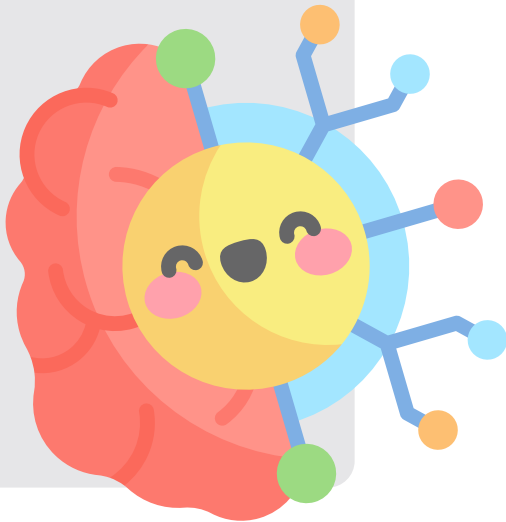
Under the overarching process of AI development, AI training acts as its problematic layer that aggravates the already-vague data, which pertains to what Roy Schwartz called the 'red AI' trend. This trend refers to an approach that tech companies employ to enforce a linear gain in AI performance by using more computational power. Three factors that are tweaked around in red AI include (1) the cost of processing a single example through the model, (2) the size of the training dataset, and (3) the number of hyperparameter experiments. Researchers at OpenAI analyzed computational trends and revealed a staggering 300,000-fold increase, driven by a doubling of computational training every 3.4 months—far surpassing the initially predicted interval of 18 months. Without precise data, it could still be determined that the linear increase of computational costs is proportional to the linear escalation of carbon emissions. Again, however, while computing is arguably quantifiable—more so than innovation and data—there is a significant knowledge gap regarding the amount of computing being put into AI training.

In light of this, Schwartz proposes the imposition of a 'green AI' trend, which adopts an approach that focuses on reducing carbon emissions in the overall AI development process. Similar ideas are put forward by researchers of the Copenhagen Centre on Energy Efficiency, who underline the necessity to include environmental sustainability as one of the principles in the development and applications of AI. In promoting the concept of green AI, Gabriela Prata Dias, head of the center, and Xiao Wang, the program officer, denoted that beneath the facade of AI as an accessible assisting tool of humans, it is also a "resource demander." Their idea of green AI, therefore, is to ensure that the benefits of AI exceed its drawbacks.



Table 1, a comparison between Red AI and Green AI in terms of its costs, output, and ideation.

	Advantage	Disadvantage
Red AI	● Ensuring that AI serves across various members, elements, and aspects of humanity. ● Methodological leverage of computational methods allow AI to provide better and more accurate results. ● Massive resources meant overall better downstream performance ● In the long run, better models might save more energy.	● Require an exponentially larger model (i.e., higher training data, number of experiments) ● Massive computational works ● Requires large power and supporting infrastructure ● Higher computational and material costs are directly proportional to increasing carbon emissions
Green AI	● The development focuses on reducing environmental impacts. ● Promotes judicious employment of deep-learning systems in AI, especially for simple tasks. ● Less compute-intensive, hence consumes less computational power. ● In theory, green AI is generally a 'cleaner' practice. ● Advocates for government regulations and legislations that demand sustainability and transparency in AI development.	● Yields novel results, though arguably 'less efficient.' ● Spaced out training cycles meant AI solutions are less updated.



Problematic Technicalities



Additionally, the problem in the bigger picture is not limited to the quantification of material and computational costs but rather the domination of global computing infrastructure by major tech companies—Amazon, Google, and Microsoft. According to Roel Dobbe, the co-founder of AI Now Institute, in order to make computing a globally accessible service, data centers must be located in different regions. However, the three dominant tech companies constructing data centers globally rather than limiting them to their home countries are creating a unique complexity that challenges societies to maintain control over vital infrastructure. Precisely, their heavy lobbying efforts to resist domestic regulations that might limit their power. This concentration of power raises a question about the cost of computational resources and its impacts on smaller tech companies that do not share the same degree of energy commitments as these oligarchs.

Re-entering the discussion on transparency, tech oligarchs are not transparent, not only about their energy consumption but also about energy sources. Whilst many have pledged to 100% renewable energy, progress has been slow. In the case of Amazon, which pledged to net-zero emissions by 2014, its carbon emissions increased by 15% in 2017, indicating transgression toward its goal. Not to mention the nexus between Big Data and Big Oil. Major tech companies do not only share relationships with fossil fuel industries but also provide AI solutions to Big Oil companies, implying an indirect line connecting AI technologies with the continuation of fossil-fuel uses.

What is Next?

Since the impact of AI on the climate has been brought to public attention, scholars, experts, and institutions have emphasized the urgency of addressing the issue, especially since it remains relatively new. These insights serve as the foundation for Dhar's report. The table below outlines key ideas and proposed actions.

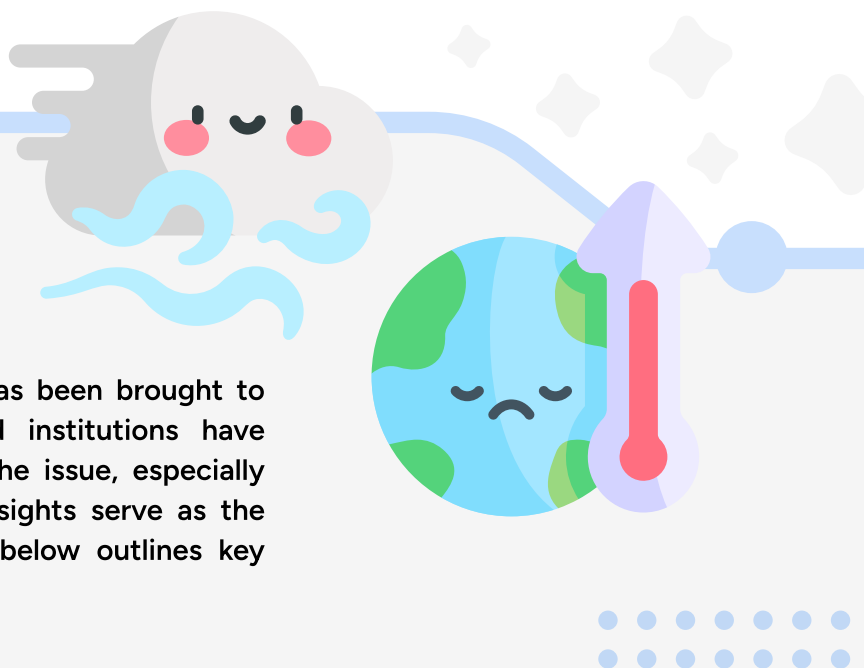


Table 2. A brief breakdown of proposed actions by scholars

Actors	Proposed action	
Roel Dobbe and Meredith Whittaker Co-founder of the AI Now Institute	Compilation of 7-point policy recommendation toward “tech-aware climate policy, and climate-aware tech policy”	Requisite openness and accountability in AI-related practices
		Consider the broader technological ecosystem when assessing AI's environmental impact.
	Compilation of 7-point policy recommendation toward “tech-aware climate policy, and climate-aware tech policy”	Be mindful of unintended consequences that could negate climate benefits.
		Adopt policies beyond energy consumption to address AI's overall impact.
		Align technology and climate policies to ensure they work together effectively.
		Limit the use of AI for fossil fuel extraction to reduce environmental harm.
		Tackle the effects of AI on climate-induced displacement and migration issues.
	The computing industries must reach a transparency level wherein the public could easily find access to reports and information on their carbon footprints.	

Actors	Proposed action
Roel Dobbe and Meredith Whittaker Co-founder of the AI Now Institute	Data centers must be built regionally in order for computing infrastructure to be effective and efficient—not dispersed sporadically whilst being controlled by very few players. At the same time check and balances are necessary to ensure that these players do not operate without restraint over these infrastructure.
Miguel Luengo-Oroz AI strategies and chief data scientist at the UN Global Pulse	Impose an intersection of AI and climate change in studies and conferences, such as in NeurIPS and COP25. This is to simultaneously incorporate AI or tech researchers with experts of climate change in order to attain expertise in both areas.
Alexanda Luccioni Researcher at Cornell University	In promoting a sustainable practice of AI training, a modification of replacing a coal-based energy grid with a renewable energy grid could differentiate emissions by a factor of 40. Another modification could also be as simple as reusing existing models instead of training them from the ground up and utilizing more energy-efficient GPUs
	States could induce mandatory transparency regulation through tax incentives for data centers that operate with renewable energy.
	The environmental impact of AI must enter the mainstream conversation in order to induce more research and investigation to relieve the damages.
Vinuesa et al. Researchers of University of Massachusetts Amherst	Urge researchers to focus on developing computationally efficient hardware and algorithms, report training times and hyperparameter sensitivity in published performance results, and conduct cost–benefit analyses of natural language processing models for comparison.

Actors	Proposed action	
Gabriela Prata Dias and Xiao Wang Headcenter and programme officer at the Copenhagen Centre of Energy Efficiency	Environmental sustainability should be set as one of the main principles in the development and application of AI. In doing so, cleaner practices are necessary.	To ensure that the concept of green AI is thoroughly understood and actionable by all stakeholders in the industry.
		Environmental standards should be established to minimize ecological harm.
		Green AI certifications could be implemented to support the industry's efforts in advancing sustainable AI development.
		To implement practical industry frameworks and guidelines for green procurement in order to help promote environmentally sustainable AI practices.
		Governments must consider long-term impacts when establishing regulatory frameworks and legislation to ensure legal accountability for transparency and sustainability in AI development.

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