

The Unequal Cost of Artificial Intelligence Innovation for the Global South

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# Executive Summary (Luiza)

Artificial Intelligence (AI) has revolutionized the world, enabling new efficiencies across a variety of industries. AI technologies depend on stacks of computational hardware and software, called the AI compute, encompassing a lifecycle that poses significant challenges to the development and deployment of environmentally and socially responsible AI technologies. The consequences of the processes involved in this lifecycle primarily affect the Global South, where production materials are sourced through mining and where electronic waste is often disposed of. This report aims to investigate how these developing countries are being affected by the new demands fueled by AI technological developments and the disproportionate costs of innovation for these countries in comparison to developed nations.

The first stage of the lifecycle is production, in which mining processes are required to obtain the materials used to build computational resources that allow AI to operate. Important elements include lithium, cobalt, and rare earth minerals, all of which are sourced in developing nations, respectively, in Chile, the Democratic Republic of Congo, and China. The mining of these materials causes environmental degradation, water pollution and scarcity, loss of biodiversity, and health risks to the local population. The third stage of the lifecycle refers to operating AI Compute to program and utilize AI technology. It requires extensive amounts of energy to power the computational resources, as well as water resources to achieve the cooling process necessary to maintain the functionality of these items. These operations also pose environmental challenges that can lead to social and economic harm of the Global South, since it can contribute to power outages and worsen water scarcity issues in certain regions.

The last stage of the lifecycle accounts for the disposal of electronic waste and has been intensified through an increased obsolescence and disposal process. Due to the complications associated with recycling, developed nations often export e-waste to nations in the Global South to avoid the costs of proper recycling and disposal techniques. In developing nations, dangerous methods are used to extract valuable methods, contaminating soil, water sources, and causing human intoxication.

This report underlines the negative aspects of AI innovation and the reliance of these systems on environmentally harmful practices. These consequences disproportionately impact the countries in the Global South, causing inequalities that fortify and increase the economic and developmental differences between developing and developed nations.

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# The Unequal Cost of Artificial Intelligence Innovation for the Global South

## Introduction (Jaismine)

Artificial Intelligence is a widely developing tool which is being used to drive breakthroughs across sectors in this 21st century: from healthcare and finance to education and infrastructure. In developed nations, AI is widely embraced as an enabler of efficiency, automation, and economic growth. These countries are typically the primary developers and beneficiaries of AI systems, who reap substantial gains from these ecosystems of innovation, data infrastructure, and capital investment (Wall et al., 2021). However, beneath this narrative of progress lies an uneven distribution of costs and benefits, particularly in terms of environmental.

While AI often appears intangible, coded in algorithms and the cloud, it heavily depends on physical infrastructure. From the extraction of critical minerals to the operation of data centers, and the eventual disposal of a variety of hardware, AI systems require vast amounts of energy, water, land, and labor. These demands are frequently outsourced to or absorbed by countries in the Global South (Murdock, 2025). Yet these same countries, despite contributing the resources and labour essential to AI’s existence, often do not fully share in its economic or technological benefits. Instead, they experience increased amount of pollution, strain on their utilities, and suffer from long-term environmental degradation. This geographic and economic separation between AI’s benefits and its harms points to a growing disparity between the regions. For developed nations, the net benefits of AI may appear positive due to efficiency gains and economic returns. Yet for developing countries the environmental toll from resource extraction and energy use to electronic waste dumping is becoming increasingly palpable. As Frimpong, V. (2025) demonstrate in their study of AI infrastructure in Nigeria, the effects of supporting global AI development is financial, infrastructural, and ecological.

This report will endeavor to examine the asymmetrical relationship between developed and developing nations in the context of AI’s environmental impacts. It asks if and how the environmental costs of AI are being externalized onto the Global South and how this enables global technological and ecological disparities. This report analyzes the material footprint of AI systems and traces its utility footprints to study the structural imbalance between the ones who build AI and the ones who bear its onus.

## The AI Compute Lifecycle: Mineral Extraction in the Production of AI (Luiza)

The different layers of hardware and software that support the development and operations of artificial intelligence systems can be referred to as the “AI compute” (OECD, 2022). The lifecycle of the AI compute is directly related to the environmental impacts observed with the deployment of AI technology and it encompasses four different phases: production, transportation, operations, and end-of-life (OECD, 2022). The first stage, production, involves the extraction of different materials that are used to build the foundation that supports the growth of artificial intelligence, which includes cobalt, lithium, and rare earth minerals (OECD, 2022). The rapid development and deployment of these technologies has caused a growing need for expansion of AI compute capacity, resulting in an increasingly rapid process of obsolescence that requires more hardware and software to be built; therefore, increasing the need for the extraction of more of these materials (Crawford & Joler, 2018).

These materials are often sourced from countries in the Global South, like Chile, where a region called the Salar de Atacama accounts for 65% of the world lithium market (Agusdinata et al., 2018). The mining of lithium in Chile is sourced from lithium chloride in brine lake deposits, which requires the usage of evaporation ponds; therefore, exposing lithium, which is a highly mobile chemical element, to natural elements (Agusdinata et al., 2018). While the mining process is being completed, there is a high chance that lithium and other chemicals used in the evaporation process will be released into the environment, causing water pollution, which presents a significant challenge to the native population of this region, as the Salar de Atacama is one of the driest deserts in the world and water resources are scarce (Agusdinata et al., 2018). Furthermore, this water scarcity issue is intensified by mining operations not only due to contamination, but also through the large amounts of water required to complete these processes, worsening environmental degradation (Agusdinata et al., 2018). Lithium is needed in the AI compute production stage as it is essential to the production of lithium-ion batteries, which are long-lasting rechargeable batteries especially useful for powering AI devices (Motoma, n.d.).

Another element that is essential to the production of lithium-ion batteries is cobalt, which serves as an electrode in the powering process of these batteries (Clean Energy Institute, n.d.). The Democratic Republic of Congo (DRC) is the largest producer of cobalt, a by-product of the mining of copper, extracting nearly 70% of the world’s supply (RAID & AFREWATCH, 2024). Although the mining industry is of extensive importance in the DRC, creating numerous direct and indirect jobs and representing most of the country’s exports, it also entails a variety of negative consequences to the people and the environment of the DRC (Arvidsson et al., 2022). The mining process of copper and cobalt releases large quantities of these elements, as well as others such as lead, arsenic, and mercury, into the local environments, contributing significantly to water pollution and depletion, damaging wetlands and rivers sedimentation patterns, and causing a loss in biodiversity (RAID & AFREWATCH, 2024). These environmental contaminations and the employment of the Congolese population in the mines have led to an exposure to pollutant metals that have significant health impacts, including pulmonary and skin diseases, cancer, heart and kidney damage, and nervous system deficits (RAID & AFREWATCH, 2024). The lack of government oversight and regulations over mining activities have led to corporations, most of them foreign, causing irreversible damage to the Congolese environment and population (RAID & AFREWATCH, 2024).

The production of AI Compute is also reliant on rare earth minerals that can power magnets and semiconductors in AI hardware (SFA, n.d.). The extraction of these minerals is extremely costly and highly polluting, as over 99% of the earth removed in rare earth mining is discarded, creating pollutants like ammonium, consuming extremely large quantities of water, and generating CO2 emissions (Crawford & Joler, 2018). China is the main producer of these minerals, as it is estimated that a single mine in the inner part of Mongolia contains 70% of the world’s reserve of these minerals, and, in 2009, supplied over 95% of the world’s stock (Crawford & Joler, 2018). Considering the social and environmental impacts that the mining of important AI Compute production materials have on developing nations, there is an indication that the costs of innovation in the artificial intelligence industry are unequal, and developing countries are bearing a disproportionate amount of these costs.

## AI’s Operational Environmental Demands (Jaismine)

Electricity: Training and deploying large-scale AI models consumes vast amounts of electricity. OpenAI's GPT-3, used approximately 1,287 MWh of electricity during training, enough to power an average U.S. household for over 100 years (Patterson et al., 2021). These systems are usually hosted in data centers that require continuous power for computation, along with a requirement for cooling. According to the IEA (2025), data centers consumed approximately 240–340 TWh of electricity in 2022, about 1–1.3% of global final electricity demand, and that share grew to around 1.5% in 2024, with projections suggesting it could increase significantly as AI workloads and innovation increase by the day.

AI infrastructure is increasingly being built in energy-insecure regions, like parts of Africa, where power grids are already overburdened. Frimpong, V. (2025) notes that in Lagos, Nigeria, data centers operated by foreign firms demand over 1 MW of constant power while adjacent communities face daily outages. AI’s infrastructure demands are met through the prioritization of foreign capital over local utility access.

Water: AI demands an intense water usage, primarily for cooling high-density data centers. Li, P., et al. (2023) reveal that training GPT-3 required an estimated 700,000 liters of clean freshwater, mostly through evaporative cooling. As AI adoption grows, so will this “invisible water footprint”. When placed in drought-prone or water-stressed regions of the Global South, these cooling requirements can have serious ecological and social consequences, often competing with basic human needs of the locals.

## The Last Stage: E-waste Disposal (Jaismine)

A major component of AI’s environmental cost is the growing wave of electronic waste generated by its hardware lifecycle. High-performance computing for AI requires rapid hardware upgrades, including GPUs, TPUs, SSDs, and specialized server arrays. Models are becoming increasingly complex and compute-intensive, thus making the hardware obsolete within short timeframes. This creates vast quantities of discarded electronics in short periods of time.

According to Forti et al. (2020), the world generated over 53 million metric tons of e-waste in 2019. Projections exceed 74 million tons by 2030. Much of this waste is exported to countries in the Global South under the guise of "recyclable goods" or "used electronics." Clearly many of these shipments violate the Basel Convention and result in informal recycling operations where low-income workers, often children, burn or acid-wash components to extract valuable metals. This exposes them to lead, mercury, and other toxins, causing long-term health damage and environmental contamination. The pollution haven hypothesis (Eskeland & Harrison, 2003) stands highly relevant here. It posits that developed countries often "export pollution" to less regulated economies to avoid the environmental and social costs of disposal. In the case of AI, this hypothesis explains the downstream consequences of aggressive innovation cycles: while companies in the Global North reap profits from cutting-edge model releases, the Global South is left with the toxic remnants of the computing systems that powered them.

Dissimilar to traditional IT waste, AI infrastructure components are more specialized and harder to recycle. GPUs used in training deep neural networks contain rare materials, proprietary firmware, and unique cooling setups. These complexities reduce the likelihood of safe, circular disposal, and increase the volume of components simply dumped in landfills, or incinerated in poorly regulated zones.

## Scenario 1: The Consequences of Irresponsible Innovation (Luiza)

The constant and rapid innovation in the artificial intelligence industry is already imposing social and environmental costs on the planet. If no changes are made to the frequency and the extent of mining operations, mineral extraction will be intensified by increasing global demand caused by AI compute needs, which will contribute to a fragilization of ecosystems and loss of biodiversity, predominantly in the Global South, where many of these materials are mined. This enlarged scope of mining operations will cause an exhaustion of resources, and new mining activities will have to be set up in different locations to accommodate world demand as AI compute progresses, possibly affecting regions that are currently protected, such as indigenous territories and other biomes. This will cause severe consequences to the local population of these locations, who often already experience some of the negative impacts of the mining industry, leading to the displacement of these individuals as these areas become uninhabitable due to environmental contamination that causes severe health risks and diminishes availability of potable water and food. Additionally, the devastation of biodiversity in these locations will accentuate the global climate crisis, with different species possibly facing extinction.

Additionally, AI server farms will likely be relocated to countries in developing nations due to the availability of cheaper land resources and relaxed environmental legislations, considering the high energy and water demands to fuel these plants. This relocation will cause power outages and water shortages that may lead to further populational displacement and environmental disruptions. The disposal of e-waste in these locations will pose challenges to sustainability efforts and will undermine advancements in reducing environmental degradation and climate change.

With the growing demand for minerals and resources, and the need of disposal options for hardware of AI compute caused by the rapid obsolescence process inherent in this rapid innovation (OECD, 2022), resources will become increasingly scarce and environmental degradation will be accelerated. Murdock, G. (2025) argues that this phase of AI’s infrastructure reflects a form of “digital primitive accumulation,” in which Global South’s labor and land are exploited to feed digital capital growth in the North. This dynamic closely mirrors colonial patterns, where value is extracted from peripheries to enrich centers; with the difference that now, it is done under the banner of “technological innovation.”

## Scenario 2: Policy Pathways Toward Environmental Justice in AI (Jaismine)

Without coordinated policy intervention AI risks becoming a new layer in an already unequal global system, one where extraction and exploitation are obscured by terms like “innovation” and “efficiency.” One important step can be to enforce extended producer responsibility (EPR) for AI hardware. Rapid turnover of GPUs, servers, and related equipment produces significant electronic waste, most of which is offloaded onto countries with weak environmental protections. EPR policies would hold AI developers and hardware manufacturers accountable for the full lifecycle of their products, including safe disposal (contributing towards a circular economy). These policies should align with international frameworks such as the Basel Convention and made to acknowledge the unique waste profiles of AI infrastructure.

Governments in the Global South can also strengthen border restrictions on e-waste unless manufacturers participate in traceable recycling schemes. The European Union’s WEEE Directive offers a model for implementation (Forti et al., 2020). AI infrastructure placement also demands scrutiny. Governments should implement licensing requirements and social impact assessments before allowing data center construction, especially in resource-constrained settings. Although, regulating AI infrastructure and enforcing environmental safeguards is critical, it is also integral to acknowledge the political and economic dynamics at play here within developing countries. Many governments in the Global South face intense pressure and need to attract foreign direct investment and position themselves as deserving destinations for emerging technologies. In this context, imposing strict environmental or digital sovereignty policies may be perceived as economically risky for them. Some governments may therefore deliberately adopt a looser regulatory stance to secure AI-related infrastructure, jobs, or donor funding, even when these decisions come at an environmental or social cost.

Existing governance platforms, such as the OECD’s Global Partnership on AI, should include representation from the Global South and require environmental transparency from AI firms. This includes disclosing compute usage, energy and water consumption by location, and the disposal of discarded hardware.

## Conclusion (Jaismine)

Environmental consequences of artificial intelligence are foundational to how the global AI economy functions today and may evolve tomorrow. This report has shown that while AI is celebrated as a symbol of modern efficiency, it rests on an extractive and exploitative infrastructure where economically marginalized nations bear the ecological burden while technologically advanced countries accumulate the benefits. The Global South plays an integral role in sustaining AI’s material and operational demands, yet remains peripheral in decision-making, ownership, and gains. As AI development accelerates, this imbalance becomes more entrenched rather than less. The imbalance is not inevitable or inherent, but is being structurally reproduced, and until it is addressed, AI cannot claim to be truly “intelligent,” let alone equitable.

References

Agusdinata, D. B., Liu, W., Eakin, H., & Romero, H. (2018). Socio-environmental impacts of lithium mineral extraction: Towards a research agenda. *Environmental Research Letters, 13*(12), 123005. <https://doi.org/10.1088/1748-9326/aae9b1>

Arvidsson, R., Chordia, M., & Nordelöf, A. (2022). Quantifying the life-cycle health impacts of a cobalt-containing lithium-ion battery. *The International Journal of Life Cycle Assessment, 27*(8), 1106–1118. <https://doi.org/10.1007/s11367-022-02084-3>

Clean Energy Institute. (n.d.). *Lithium-ion battery*. University of Washington. <https://www.cei.washington.edu/research/energy-storage/lithium-ion-battery/>

Crawford, K., & Joler, V. (2018). *Anatomy of an AI system*. SHARE Lab & AI Now Institute. <https://anatomyof.ai>

Eskeland, G. S., & Harrison, A. E. (2003). *Moving to Greener Pastures? Multinationals and the Pollution Haven Hypothesis*. International Journal of Energy Economics and Policy. <https://www.sciencedirect.com/science/article/abs/pii/S0304387802000846>

Frimpong, V. (2025). *Artificial Intelligence Investment in Resource-Constrained African Economies: Financial, Strategic, and Ethical Trade-Offs with Broader Implications.* World, 6(2), 70. <https://doi.org/10.3390/world6020070>

Forti, V., Baldé, C. P., Kuehr, R., & Bel, G. (2020). *The Global E-waste Monitor 2020: Quantities, flows, and the circular economy potential*. United Nations University. <https://www.itu.int/en/ITU-D/Environment/Documents/Toolbox/GEM_2020_def.pdf>

International Energy Agency. (2025, April). *Energy and AI: Energy demand from AI [Analysis report]*. IEA. <https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai>

Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). *Making AI Less “Thirsty”: Uncovering and Addressing the Secret Water Footprint of AI Models*. arXiv. https://arxiv.org/pdf/2304.03271v4

Motoma Power. (n.d.). *The role of lithium batteries in advancing AI devices*. <https://motoma.com/industry/the-role-of-lithium-batteries-in-advancing-ai-devices.html>

Murdock, G. (2025). *Artificial intelligence as primitive accumulation: Enclosure, extraction, exploitation*. Communication and the Public, 1(6). <https://doi.org/10.1007/s44382-025-00004-1>

OECD. (2022). *Measuring the environmental impacts of artificial intelligence compute and applications: The AI footprint* (OECD Digital Economy Papers No. 341). OECD Publishing. <https://doi.org/10.1787/7babf571-en>

Patterson, D. A., Gonzalez, J. E., Le, Q. V., Liang, C., Munguia, L.-M., Rothchild, D., So, D. R., Texier, M., & Dean, J. (2021). *Carbon emissions and large neural network training* (arXiv preprint arXiv:2104.10350). arXiv. <https://doi.org/10.48550/arXiv.2104.10350>

RAID & AFREWATCH. (2024). *Beneath the Green: A critical look at the cost of industrial cobalt mining in the DRC*. <https://raid-uk.org/report-environmental-pollution-human-costs-drc-cobalt-demand-industrial-mines-green-energy-evs-2024/>

SFA (Oxford). (n.d.). *Critical minerals in artificial intelligence*. <https://www.sfa-oxford.com/knowledge-and-insights/critical-minerals-in-low-carbon-and-future-technologies/critical-minerals-in-artificial-intelligence/>

Wall, M., et al. (2021). *Artificial Intelligence in the Global South (AI4D): Potential and Risks*. arXiv. <https://arxiv.org/pdf/2108.10093>