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THE IMPACT OF AI ON THE ENVIRONMENT

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Annotation. Artificial Intelligence (AI) transforms environmental sustainability, serving as both a catalyst for resource optimization and a major driver of ecological strain through intensive energy and material demands. This work examines AI's environmental footprint, analyzing emissions from data centers and hardware alongside water consumption. The study highlights critical challenges and pathways toward sustainable AI deployment.

Keywords: Artificial Intelligence (AI), environment, carbon footprint, water usage.

Introduction. Artificial intelligence (AI) currently has significant negative impacts on the environment through rising energy demand, greenhouse gas emissions, water consumption, material use, and e-waste. Studies emphasize that understanding these impacts across the full life cycle of AI systems is essential in order to limit ecological damage and align AI with climate and resource-protection goals. As AI becomes more deeply embedded in economic and social systems, concerns are growing about its potential environmental consequences, especially in the context of already escalating sustainability challenges and transgressed planetary boundaries.

Main part. Modern AI workloads are concentrated in large warehouse-scale data centers that have become extremely energy-efficient at the level of individual facilities, but this total electricity demand is nonetheless growing rapidly. One study notes that global data center electricity use increased by about 6% between 2010 and 2018 even though the number of compute instances grew by 550%, and the International Energy Agency (IEA) projects data center electricity demand to rise from 460 TWh in 2022 to more than 1,000 TWh by 2026. Between 2017 and 2021, the electricity consumption of Google, Meta and Microsoft more than doubled or tripled, with AI identified as the most important driver of this growth [1]. The life-cycle assessment of a 3.6 MW AI data center points out that such facilities are essential for training and running models like ChatGPT, but their operation leads to significant energy consumption and associated CO_2 emissions. The Greenpeace report adds that newly built, AI-oriented "hyperscale" data centers can have connection capacities of several hundred megawatts and occupy areas of up to four square kilometers. Estimates cited there suggest that, excluding cryptocurrencies, the share of AI-specific hardware in data center electricity use could increase from 14% in 2023 to 47% by 2030 [2]. For example, one referenced analysis reports that training the GPT-3 language model resulted in around 552 tons of CO_2-equivalent emissions on a relatively carbon-intensive grid [3].

Several sources stress that focusing only on operational energy consumption overlooks a major part of AI's environmental impact, namely embodied emissions from hardware manufacturing and data center construction. One study characterizes AI's total carbon footprint as the sum of emissions from manufacturing infrastructures and hardware (embodied carbon) and emissions from training and using models (operational carbon). For a multilingual language model examined there, the ratio of operational to embodied carbon is roughly 2:1, and embodied emissions add about 50% on top of the operational emissions over the model's life cycle [4]. The Meta sustainability data cited in the same paper show that, between 2019 and 2022, the share of data center construction and hardware manufacturing in Meta's Scope 3 greenhouse gas emissions rose from 41% to over 60%, and similar patterns are observed for other large cloud providers. The life-cycle assessment of an AI data center architecture finds that, over a 20-year period, about 70% of total CO_2 emissions are associated with manufacturing (including IT hardware, cooling, power and building infrastructure), while around 29% come from the use phase. This study also shows that electricity mix has a strong influence on operational emissions: operating the same AI data center in France rather than Germany can reduce total CO_2 emissions by a factor of about 3.7, mainly because of France's lower-carbon electricity system.

While most environmental studies have focused on energy and CO_2, the systematic review identifies significant but understudied impacts of AI on water, material use, pollution and biodiversity. Summarizing existing evidence, it reports that training a single large language model can use more than five million liters of freshwater, and that inference can require on the order of 500 milliliters of water for every 10–50 user responses, depending on cooling technology and location. Data centers themselves are described as energy- and water-intensive infrastructures that are often built on carbon-intensive grids or in regions facing water stress [2].

The same review notes that semiconductor fabrication for AI-critical chips consumes millions of liters of ultrapure water per day and generates hazardous waste. Mining for key materials such as lithium, cobalt and rare earth elements leads to water depletion, pollution and biodiversity loss in affected regions, and these upstream impacts are rarely captured in narrow energy-only assessments. The authors highlight that embodied emissions from hardware and infrastructure may account for roughly 30–50% of the life-cycle carbon footprint of AI, and they argue that water, material, land use, non-carbon pollutants and biodiversity impacts should be systematically integrated into environmental assessments of AI [2].

The Greenpeace-commissioned report provides additional quantitative indications of water and resource use. It states that global data center water consumption was around 175 billion liters in 2023 and could rise to 664 billion liters by 2030, more than tripling in seven years, with particular risks in regions suffering from water scarcity.

The same source estimates that the expansion of data centers and AI capacity could generate up to five million tons of additional electronic waste by 2030, amplifying issues around e-waste management and toxic pollution.

Efficiency gains in AI are triggering the rebound effect: efficiency improves, yet aggregate electricity use continues to grow. AI-driven efficiency gains in other sectors may induce sectoral rebound. AI-driven personalization and advertising may intensify consumption. Lower costs may increase demand for AI services, while efficiency savings are often reinvested in more computationally-intensive models or hardware.

Where AI is used to improve efficiency in sectors such as transport, logistics, or manufacturing, similar rebound effects may occur in these sectors.

Technological advances alone will not eliminate the environmental impacts caused by technology. Efficiency improvements lower costs, leading to increased AI usage that negates savings – this is known as the rebound effect or Jevons Paradox. Across the reviewed literature, 31% of systemic impact studies explicitly address rebound dynamics, while 40% examine impacts arising from AI-led shifts in consumer behavior. Such effects often reinforce environmental burdens rather than reduce them [2].

Conclusion. Escalating computing requirements are driving increasing energy use and CO_2 emissions. Inference emissions may exceed training emissions at deployment scale. Embodied emissions from hardware and infrastructure may account for approximately 30–50% of the life-cycle carbon footprint.

Training a single LLM can use over 5 million litres of freshwater, while inference can require approximately 500 ml for each 10–50 responses.

Data centers are energy– and water-intensive and are often sited on carbon-intensive grids or in water-stressed regions. Mining for AI-critical materials such as lithium, cobalt, and rare earths causes water depletion, pollution, and biodiversity loss. AI accelerates hardware turnover, contributing to global e-waste. Evaluating AI's overall impact requires accounting for computing-related, application-level, and systemic impacts, while integrating both environmental and social dimensions.

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