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Environmental After Effects of Artificial Intelligence Technologies: A Review

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ABSTRACT

Artificial Intelligence (AI) has marked a significant change as transformative technologies globally. This review explains the environmental consequences of AI development. Under the surface of this digital revolution lies a growing ecological crisis which goes unnoticed, this paper focuses on aftereffects of artificial intelligence technologies and algorithms and how the manufacturing of GPU, water consumption by data centres and e-waste affects biodiversity. The study reviews findings from peer-reviewed literature and data reports from 2022 to 2025. This analysis also reviews some policies and key points for economic principles and how there can be a paradigm shift towards Green AI with a steady growth.

Key words: artificial intelligence, water consumption, carbon emissions, sustainability, data centres, e-waste, Green AI

1. INTRODUCTION

The rapid increase in the usage of artificial intelligence across various industries has seen a transformative shift in global digital infrastructure, marked by the escalating deployment of large-scale machine learning models that requires an unavoidable surge in computational power. This surge in demand is primarily driven by complex training, testing and inference workloads, which compel massive high-performance data centres to operate at sustained high utilization levels [1], [2].

Over this the immediate energy demand required to power these processors, these facilities also require substantial water consumption for cooling, a critical resource extraction often overlooked in climate impact assessments [1], [3]. The enormous dependence on computational resources forges an environmental burden like the cooling systems need cooling from high density server racks, often drawn from local water resources already under significant stress [1], [4]. Furthermore, the transition to high performance GPUs and specialized hardware has accelerated this footprint, as the training of large language models requires lengthy computing cycles that raises both electrical and hydrological demands [1]. The water wastage in the data centre is something many are not aware of. Recent estimates show that the expansion of AI infrastructure could generate an annual water footprint of up to 1,125 million m3 in the US alone by 2030, highlighting the severe tension between model scaling and environmental sustainability [5]. Through the advancement of Green AI, these costs and benefits can be mitigated by adopting architectural optimisations such as model pruning and quantisation, enabling computational requirements to be reduced by up to 50% [6]. Moreover, carbon emissions can be further reduced by 30 to 40% through the transition of data centres to renewable energy sources and implementation of advanced site-specific cooling designs [2], [6]. However, achieving a net-zero target remains challenging, as the widespread adoption of these efficiency measures is controlled by the continued reliance on carbon offset initiatives and water restoration mechanisms across the industry [5]. To address these challenges, a paradigm shift is required in the way environmental externalities are quantified, moving beyond simple carbon metrics to include spatial and temporal assessments of water scarcity. In this study, the effectiveness of these interventions is demonstrated, and a policy roadmap is proposed to ensure that the ecological cost of intelligence does not exceed societal utility [1], [5]. Ultimately, the development of a sustainable framework requires that the increasing demand for large-scale computation be balanced with the biological constraints of the ecosystems on which digital infrastructures depend [1], [7].

1.1 Rapid Surge in AI Adoption

The current trend of machine learning integration implies a transition from specialized research applications to imperative utility, driving a vertical expansion in data centre utilization [1]. As algorithmic complexity grows, the dependency on intensive training cycles and persistent inference tasks tethered this expansion to significant environmental risks, including aggravating regional water stress and rising carbon emissions [1], [5]. This upward trend is further complicated by the Jeavons Paradox, wherein improvements in operational efficiency inadvertently stimulate higher total consumption, thereby counteracting potential gains in resource conservation. [8]. Consequently, current sustainability efforts must transition from purely efficiency focused optimization to systematic strategies that integrate hardware software co design with mandatory environmental impact reporting [9]. Such structural adjustments are vital to restraining the disproportionate contribution of AI specific workloads to total electricity demand and provide long term ecological viability [1]. Furthermore, the lack of standardized transparency about direct water consumption and cooling methodologies complicates the attempts to examine the true effectiveness of these mitigation strategies [10]. Addressing these data discrepancies is critical, as nearly two third of new data centres in the United States have been established in regions already experiencing acute water scarcity [11]. To address this, future policy frameworks must advocate for spatially responsible site selection and the adoption of multi-dimensional ecological metrics that account for the integrated energy water material land nexus [3].

1.2 Computational Intensity of Training and Inference

The massive integration of high-density GPUs for deep learning architectures transforms informational processing into significant material throughput, as these processors necessitate constant, high-power electricity loads and intensive, continuous thermal management [3]. This credence on high performance hardware generates a feedback loop where the heat generation inherent to intensive matrix multiplications authorizes even greater quantities of water for cooling, often surpassing the resource availability of the surrounding region [1], [12]. Likewise, the manufacturing of these specialized computing components includes the eradication of the rare earth minerals like lithium and cobalt, which adds a significant yet repeatedly ignored upstream ecological debt to the hardware lifecycle [12]. Beyond these manufacturing effects, this rapid turnover of hardware swifts to keep pace with evolving model architectures raises electronic waste and creates a constant cycle of resource deficiency [13], [14]. Thereupon, the development of more sustainable AI systems must consolidate the circular economy principles, such as enhancing hardware lifespans and improving component recyclability, to relieve these long-term environmental burdens [15].

Besides these measures, shifting toward the localized inference models can extensively diminish the requirement for constant, energy-intensive data transfers across the global network infrastructures. This paradigm shift toward edge-based computing minimizes the dependency on centralized, high-latency cloud clusters, thereby alleviating the stress placed on regional power grids and local aquifers. [16], [17] Integrating these systemic changes requires the development of an "AI Environmental Impact" inventory, which would quantify site-specific transformations in biodiversity and local water tables to inform more responsible infrastructure planning [18].

Table 1: AI Environmental Cascade Summary

Cascade Level	Trigger	Ecological Effect	Time horizon
Level 1	Model training/ inference	Electricity demand, water cooling	Immediate
Level 2	Data centre construction	Grid strain, fossil fuel revival, land use	1–3 years
Level 3	GPU/chip procurement	Mining, semiconductor water use, e-waste	2–5 years
Level 4	Geographic concentration	Thermal pollution, biodiversity loss, groundwater depletion	5–15 years

This multi-tiered analytical study in table 1, establishes a compatible foundation for realizing the complex environmental significance of AI, thereby informing the development of targeted policy recommendations and engineering interventions discussed in subsequent sections [44], [45]. This structured breakdown grants us a granular examination of environmental burdens, revealing how upstream technological decisions manifest as downstream ecological superficialities, such an understanding is critical for identifying potential points of interference across the AI lifecycle to promote more sustainable practices and lighten the adverse ecological consequences [46], [47]. Indeed, it focuses on the need for a "greening AI" approach that implants sustainability at the core of AI development and deployment by adopting a multi-level, system dynamics perspective biforked with design thinking [48]. This includes a paradigm shift from viewing AI as a truly computational endeavour to identifying its essential role within expansive socio-technical-ecological systems, which demands an evaluation of its correlated and mostly entangled sustainability impacts [44], [49]. This comprehensive aspect highlights the requirement of moving beyond segregated deliberations of energy consumption to surround a full life-cycle assessment which includes aspects such as e-waste, water usage, and the broader systemic environmental risks which are associated with AI development and deployment [45], [48].

1.3 GPU Utilizations and Energy consumptions

Modern high-performance accelerators, such as the NVIDIA HGX H100, demand unprecedented power densities that drive significant carbon footprints and accelerate the degradation of cooling infrastructure [3]. These workloads translate into sustained; high-throughput demands that are distinct from standard cloud usage, as they remain compute-bound and rely heavily on specialized hardware that lacks true energy proportionality [19]. Therefore, this divergence between peak performance and idle power consumption requires the adoption of hardware-aware model pruning and precision reduction for obtaining the energy-to-accuracy ratio [20]. Furthermore, shifting the design focus toward energy-proportional architectures can reduce the hidden costs of dark silicon, assures that hardware utilization scales more gracefully with the actual computational requirements [21]. In addition to these hardware-level optimizations, researchers are increasingly exploring neuromorphic computing and permissive architectures that imitate biological neural structures to achieve substantial gains in energy efficiency [4]. Also, the implementation of model compression techniques such as quantization and knowledge distillation grants the deployment of lighter, task-specific architectures that drastically consumes lower power without compromising model performance [11]. Beyond these techniques, accepting the geographically aware load balancing can further reduce the operational impacts by routing workloads to regions where renewable energy availability and ambient cooling conditions align with seasonal environmental constraints [22]. Depending on this spatial intelligence, data centres can be operated as active grid participants by modulating compute intensity in response to real-time grid signals, thereby supporting frequency regulation and enhancing overall power system reliability [11].

2. ENVIRONMENTAL IMPACTS OF DATA CENTRES

These facilities periodically apply the pressure on regional power grids through the clustering of high-demand workloads, which leads to provoked localized grid instability and necessitates advanced power electronics to mitigate the resulting voltage fluctuations [23]. Simultaneously, the continual extraction of substantial water volumes for evaporative cooling systems continues to the depletion of local aquifers, which negatively affects the nearby aquatic biodiversity and escalates the regional water insufficiency [23]. Moreover, the thermal discharge resulting from these cooling processes modifies the ambient temperature of local watersheds, thereby creating delicate conditions for temperature-sensitive flora and fauna that depend on stable aquatic ecosystems for their continued existence. These localized disturbances are further compounded by the accumulation of chemical additives within cooling water effluents, potentially introducing the synthetic toxins into vulnerable biological corridors [24], [25]. Such ecological degradation is frequently intensified by the physical footprint of infrastructure expansion, which necessitates land clearing and habitat fragmentation that irreversibly alters local biodiversity [1].

2.1 Water Usage and Wastage in AI Infrastructure

Apart from direct evaporation, these facilities contribute to significant indirect water utilization through the electricity generation at power plants, which frequently depends upon the thermoelectric cooling processes. This "water-energy nexus" signifies that the total liquid footprint of an AI model is much higher as compared to direct site consumption alone, as it encloses the water-intensive life cycles of coal, nuclear, and natural gas power generation [26]. Consequently, the comprehensive life-cycle judgements must report for these embedded water footprints to meticulously reflect the true environmental cost of intensive training sessions [27], [28]. Addressing this systemic inability needs to implement a real-time monitoring of "water-use-efficiency" metrics, which records the ratio of water consumption for cooling process against the total computational output of server farms [1]. Development toward non-evaporative cooling technologies, such as closed-loop liquid immersion or direct-to-chip refrigeration, offers a promising pathway to drastically decouple data centre operations from local water scarcity [1], [29]. Furthermore, aligning data centre deployment with regional water stress indices allows developers to optimize scheduling based on temporal availability, potentially diverting heavy training loads to cooler, water-abundant periods or locations [30], [31].

2.2 AI and Biodiversity Impacts

The rapid procreation of AI infrastructure shows multifaceted threats to global biodiversity, mainly through the degradation of habitats required by large-scale facility construction and the separation of local microclimates. These biological effects are further intensified by the lifecycle management of hardware’s, where incomplete disposal practices direct to the release of heavy metals which are toxic and synthetic pollutants into soil and groundwater systems [14]. Moreover, the massive aggregation of e-waste from rapidly outdated server components enforces a cycle of resource extraction that further extends sensitive ecosystems already nearing critical tipping points [12]. Checking these biodiversity losses needs a transition towards a circular economy model for hardware, which prioritizes a modular design and the implementation of robust recycling protocols to recover the high-value materials. By combining these circularity principles with sustainable material sourcing, the industry can cut down the ecological burden of hardware life cycles while simultaneously mitigating the pressure on vulnerable ecosystems currently crumbled by intensive infrastructure growth. Moreover, the deployment of AI servers is deliberated to create significant annual water footprints, focusing on the urgent needs for industry-wide acceptance of standardized, transparent environmental impact reporting [5]. Specifically, without major technological pivots, global AI demand could reach between 4.1 and 6.6 billion cubic meters of water consumption by 2027, featuring a critical tension between digital extension and the fundamental human right to water [34]. To track these imbalances, researchers are progressively favouring “Green AI" paradigms that prioritize energy and resource efficiency over raw predictive performance [35]. This shift requires a revaluation of hardware lifecycles, as the eradication of rare earth metals—often linked to severe human right abuses and landscape devastation demands that we shift beyond simple energy metrics to combine full-spectrum ecological accounting [36].

3. TOWARDS GREEN AI

Responsible innovation, the Green AI movement advocates for a systematic transition from model-centric optimization to resource-aware development [37]. This shift includes influencing innovations such as solar-powered data centres and wind-integrated operations to mitigate the substantial carbon footprints associated with high-performance computing [38]. Furthermore, algorithmic efficiency often termed "frugal AI"—seeks to reduce the sheer volume of computation required, thereby decreasing both the demand for specialized hardware and the subsequent environmental strain caused by constant infrastructure scaling [38], [39]. To support these efforts, establishing standardized benchmarks for reporting environmental impacts is essential, as current gaps in lifecycle data often hinder the development of fully sustainable hardware [40]. Additionally, adopting circular economy frameworks, such as the implementation of advanced hydrometallurgical recycling technologies, can effectively recover valuable minerals from decommissioned hardware while minimizing the need for further destructive resource extraction [4].

Moreover, enforcing transparency regarding datacentre-specific efficiency metrics—such as Power Usage Effectiveness and Water Usage Effectiveness—is vital for identifying operational best practices and fostering accountability across the semiconductor supply chain [18]. Additionally, policymakers must incentivize the adoption of "spatially responsible siting" strategies, which leverage regional environmental data to ensure that new infrastructure does not exacerbate water stress in vulnerable areas [3]. By coupling these siting strategies with strict energy efficiency certifications, regulators can effectively counteract the Jevons paradox, where efficiency gains are otherwise nullified by increased total consumption [12].

4. E-WASTE GENRATION IN AI MANUFACTURING

The manufacturing of these highly specialized components, which relies on the extraction of rare earth elements and other precious metals, creates a significant embodied carbon footprint and results in various environmental degradation and human rights issues [1], [54]. This pervasive issue is compounded by the fact that the life cycle assessment of AI hardware frequently overlooks the end-of-life phase, leading to an underestimation of its full environmental impact [55]. Consequently, the unchecked proliferation of AI infrastructure without robust circular economy principles exacerbates resource depletion and environmental contamination through improper disposal [3], [56]. As newer generations of AI hardware are developed, older components quickly become obsolete, necessitating their frequent disposal and further exacerbating the issue of electronic waste [1]. This phenomenon contributes significantly to the fastest-growing segment of global solid waste, with only a small fraction formally collected and recycled, leaving hazardous substances to leach into ecosystems [6]. This rapid obsolescence of AI-specific hardware, driven by continuous innovation in computational demands, necessitates frequent upgrades and replacements, further accelerating the accumulation of e-waste and amplifying the associated environmental burdens [1], [57].

5. A PRIMARY STUDY OF AI PERCEPTION AMONG DIFFERENT PROFESSIONALS

In addition to the systematic literature review, a primary survey was also conducted to understand AI usage patterns, awareness of environmental impact caused due to these rapid growing technologies and insight of risks among professionals.

The survey contained structured questions covering AI impact, awareness and future perspective. The tool used here for the survey was google form consisting of different types of question patterns like multiple choice, linear scale and opinion based. There was a total of 82 responses from different professionals like software engineers, professors, students, developers and researchers. The results indicate widespread and regular use of AI tools like LLM Models and AI powered search systems. Also, it is observed from the significant part of responses that familiarity with AI tools was identified late in 2022-2023 with rise in generative artificial intelligence systems.

Despite the adoption of artificial intelligence on a large scale there is very much awareness about how this growing technology also has hidden cost, water wastage and many more like carbon footprint which supports the idea of awareness among the usage of these technologies and how one can shift towards Green AI, and research solutions for energy efficiency. Here in the below figure 1, we can observe the data among different professionals about how much they are aware about this carbon footprint.

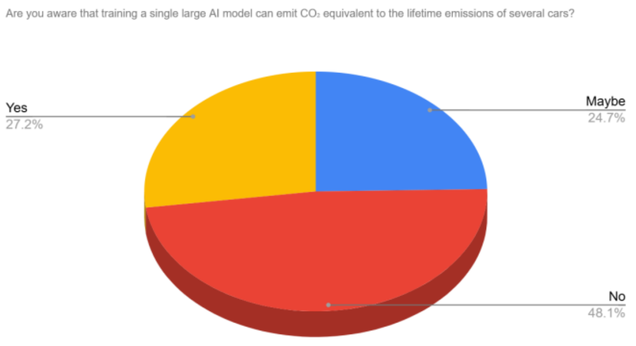

Figure 1: Distribution chart of awareness regarding environmental impact of artificial intelligence technology

The survey in figure 1 indicates that the majority of respondents, likely 48%, are not aware of how much these technologies cause environmental impact due to extensive use of water in huge data centres, which also cause the nearby biodiversity to suffer. So, there should be an awareness among different industries, and industry led AI ethics.

6. CONCLUSION

Certain governments and international bodies are tasked with developing regulated environmental reporting frameworks that mandate footprints [37],[41]. Such mechanisms can help the adoption of specialized hardware accelerators, which offer computational efficiency compared to traditional CPUs, thereby withholding the rapid turnover of computing components [41].

Moreover, implementing institutional reforms that separates model performance from resource consumption can counteract the Jevons' Paradox, where efficiency gains are otherwise invalidated by increased total usage [12].

The unchecked acceleration of AI infrastructure necessitates an immediate transition toward environmental accountability, where sustainability is embedded as a core design principle rather than an external consideration. By formalizing cross-sectoral standards for resource management, the technology industry can move beyond performance-based metrics to achieve a long-term symmetry between computational capability and ecological preservation [41]. Basically, aligning technological progress with planetary boundaries requires a paradigm shift that recognizes environmental supervision as a prerequisite for, rather than a byproduct of, innovation in the intelligence era. Future research must now prioritize the creation of scalable, cross-jurisdictional policy instruments that imply these principles while tending collaborative transparency across global technological ecosystems [42]. Integrating these sustainability metrics into academic curricula and research conferences will ensure that the next generation of engineers is equipped to balance technical advancements with the imperative of ecological restoration [43]. From these review papers we came across different methodologies about how one can shift towards green AI and what are certain measures that can be taken to regulate industry bodies for their advancement in rapidly growing technologies.

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