Review Article

Adverse Environmental and Public Health Effects of Artificial Intelligence: A Narrative Review

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The rapid global expansion of artificial intelligence (AI), particularly generative models, drives energy-intensive data centers with substantial environmental and public health costs. This narrative review synthesizes information obtained from the scientific literature confirming contributions of AI to greenhouse gas emissions, freshwater depletion, e-waste, and air pollution from fossil-powered grids. Public health risks include algorithmic bias exacerbating disparities, AI-generated misinformation/deepfakes eroding trust, privacy loss, mental health harms, and job displacement impacting social determinants. These burdens disproportionately affect marginalized communities via environmental justice failures and biased algorithms. While acknowledging that certain AI applications, particularly in climate modeling, medical diagnostics, and energy optimization, may offer net benefits under appropriate governance, this review focuses on the documented adverse impacts of current large-scale, commercial AI deployment patterns. Mitigation demands life-cycle assessments, renewable energy mandates, circular hardware economies, bias audits, and policies prioritizing health equity. Sustainable AI requires coordinated action across stakeholders. Implementing these mitigation strategies is constrained by major obstacles in cost, technical infrastructure, and governance. Overcoming these barriers requires the development of comprehensive economic analyses and structured strategic roadmaps.

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1. Introduction

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a dominant technological force of the 21st century. Following the release of advanced generative AI models in late 2022, technology has experienced exponential growth[1]. The computational demands of training and deploying large language models (LLMs) and other AI systems require substantial, energy-intensive infrastructure primarily housed in hyperscale data centers[2], which have become one of the fastest-growing ICT (Information and Communication Technology)-related sources of emissions globally[3][4].

While dominant narratives frequently highlight the potential of AI to address global challenges such as climate change, comparatively little attention has been paid to the technology's substantial environmental footprint and its broader public health implications[5][6]. The present review examines the adverse environmental and public health impacts associated with prevailing large-scale, commercial AI deployment patterns, particularly energy-intensive generative models and large language models. It is recognized that smaller-scale, public-interest AI applications operated under different governance structures, may present distinct risk-benefit profiles. These impacts are multifaceted and extensive, spanning energy consumption, greenhouse gas (GHG) emissions, freshwater depletion, electronic waste (e-waste) generation, ecosystem disruption, and air pollution[7][8]. Moreover, the public health implications extend beyond these direct environmental pathways to include algorithmic bias in healthcare, proliferation of health misinformation, impacts on mental health, and erosion of social determinants of health, such as employment stability[9][10][11].

The AI life cycle involves mining rare earth materials that damage the environment and harm communities in the Global South, producing energy-intensive hardware, running data centers that often depend on fossil fuels, and dumping e-waste in poorer regions, creating a chain of inequalities[1][12][13][14]. Marginalized communities frequently bear the brunt of environmental degradation and health risks without reaping proportional benefits, a pattern that repeats within nations along lines of race and class, and between the Global North and South[15][16].

While prior reviews have examined carbon footprint of AI[9][13], or also algorithmic bias in healthcare[10], this is the first comprehensive review to explicitly connect the full AI lifecycle (from rare earth mining to e-waste dumping) with both environmental degradation and public health harms through an environmental justice lens. The present review adopts an integrated, planetary health lens to synthesize

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and critically evaluate the evidence on adverse environmental and public health effects of AI. It connects the dots between hardware supply chains, energy systems, algorithmic governance, and social determinants of health. It is argued that a truly sustainable AI future cannot be achieved through computational efficiency alone. Rather, sustainability must be redefined to encompass ecological integrity, public health protection, and health justice. The prevailing techno-optimistic narrative, which frames AI as a net environmental or social benefit, obscures a growing body of evidence on its externalized costs. By integrating insights across environmental science, public health, and environmental justice, this review offers a planetary health–centered synthesis of adverse impacts of AI and calls for a paradigm shift in how its costs, benefits, and governance are conceptualized and distributed. In relation to this, Figure 1 presents a conceptual framework illustrating how environmental and public health impacts occur across the AI lifecycle, from resource extraction through e-waste disposal, with particular emphasis on environmental justice concerns and the disproportionate burden placed on marginalized communities and the Global South.

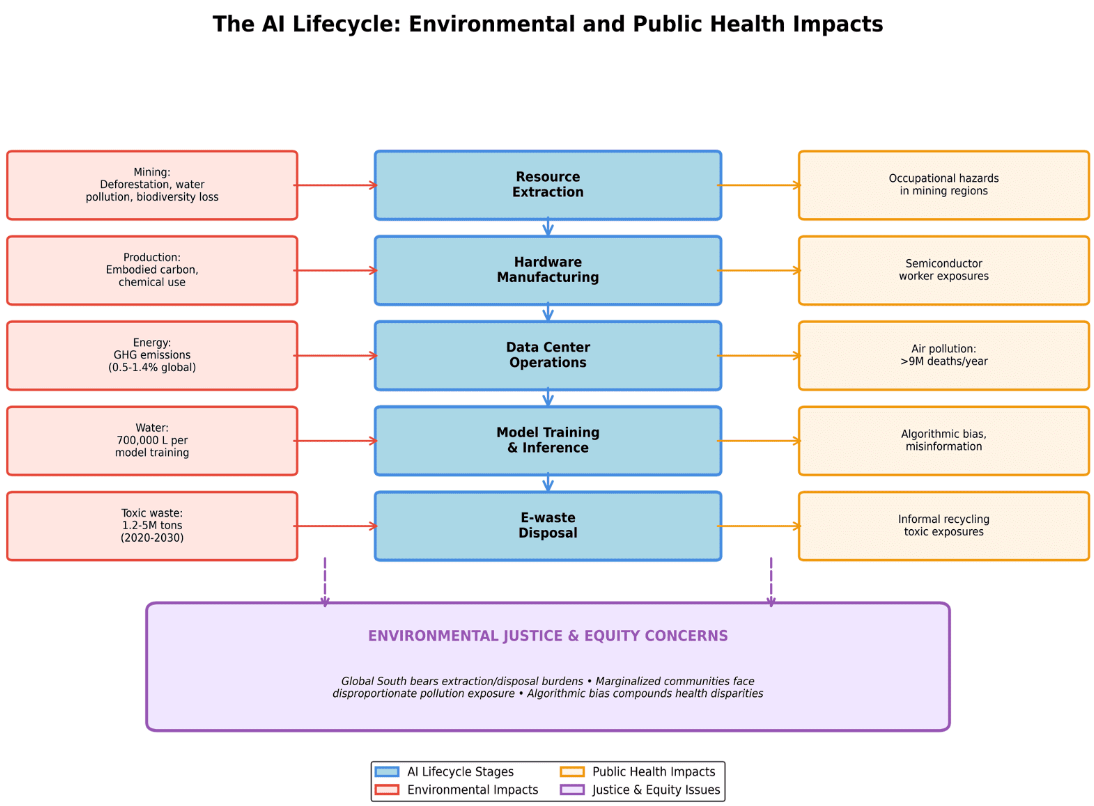

Figure 1. Conceptual framework of AI lifecycle showing environmental and public health impacts across stages, with emphasis on disproportionate burden on marginalized communities and the Global South.

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2. Methods: Search strategy

For preparing this narrative review, a systematic scientific literature search was employed. The primary databases searched were PubMed, Web of Science, Scopus, and Google Scholar. These databases were used to capture both biomedical/health-focused literature and broader interdisciplinary research from environmental sciences, computer sciences, and social sciences. Studies were screened based on title and abstract for inclusion in this narrative synthesis. Other specific sources were also consulted (e.g., IEA, UNEP). This review does not follow a formal PRISMA framework. While it could enhance methodological rigor, the narrative synthesis approach was selected to allow for the integration of diverse, interdisciplinary evidence spanning environmental science, public health, and social justice, which is often not captured within a single systematic review protocol.

The search strategy combined keywords and Medical Subject Headings (MeSH) terms related to two core concepts: 1) Artificial Intelligence, and 2) Environmental or Public Health impacts. Key search strings included: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("carbon footprint" OR "energy consumption" OR "environmental impact" OR "sustainability" OR "e-waste" OR "water consumption"); "AI" OR "algorithm") AND ("public health" OR "health equity" OR "algorithmic bias" OR "health misinformation" OR "mental health" OR "privacy" OR "occupational health"); ("large language models" OR "foundation models" OR "generative AI") AND ("environment" OR "health" OR "ethics").

Peer-reviewed journal articles, systematic reviews, meta-analyses, and significant conference proceedings published in English between January 2015, and December 2025 were considered for inclusion. To support some specific statement, references published before 2015 were occasionally included. Studies that provided quantitative or robust qualitative analysis of the environmental impact of AI (e.g., life-cycle assessments, emission projections) or its adverse public health effects (e.g., studies on algorithmic bias outcomes, health misinformation spread), were prioritized. The reference lists of key review articles were also hand-searched for additional relevant publications.

Articles focusing solely on the beneficial applications of AI, without a critical examination of associated risks or externalities, were excluded. The present review specifically analyzed adverse impacts to provide a necessary counterpoint to dominant techno-optimistic views and to focus on documented harms. Future research should evaluate the overall risk-benefit profile of AI across various governance models to complement this analysis. Non-English publications and opinion pieces or commentaries that did not present original data or a novel systematic analysis were also excluded. The selected literature was synthesized thematically, with findings organized into environmental footprint, public health implications, and overarching issues of equity and justice.

3. The environmental footprint of AI

The environmental impacts of AI across its lifecycle are summarized in Table 1, which presents key quantitative estimates for energy consumption, water use, e-waste generation, air pollution, and resource extraction.

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Impact category	Key findings and quantitative estimates
Energy consumption and carbon Emissions	*Training GPT-3: approx. 1,287 MWh electricity, approx. 552 metric tons CO_2 *80-90% of AI system energy use occurs during inference phase *Global data center electricity projected to exceed 1,000 TWh by 2026 *Data centers currently account for about 0.5% of global CO_2 emissions; projected to reach 1-1.4% by 2030
Freshwater depletion	*Training GPT-3: approx. 700,000 liters of freshwater for cooling *35-40% of major data centers located in regions with moderate-to-high water stress *Thermal discharge (10-15°C above ambient) impacts aquatic ecosystems
Electronic waste (e-waste)	*Projected 1.2-5.0 million tons of AI-related e-waste accumulated 2020-2030 *Of 62 million metric tons global e-waste (2022), only 22.3% formally recycled *Contains heavy metals (Pb, Hg, Cd), flame retardants (PBDEs), dioxins/furans, among other toxic substances
Air pollution	*Fossil fuel-powered grids emit PM2.5, NOx, SO_2 for data center electricity *On-site diesel backup generators create localized pollution in communities *Total air pollution burden: > 9 million premature deaths globally/year; AI's marginal contribution: poorly quantified, estimated in tens of thousands
Resource extraction	*70% of global cobalt from Democratic Republic of Congo, often under conditions with human rights concerns *Rare earth elements (REEs) essential for semiconductors and high-performance computing *Mining causes deforestation, water pollution, biodiversity loss

Table 1. Summary of environmental impacts of AI development and deployment

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3.1. Energy consumption and carbon emissions

The computational power required to train and operate state-of-the-art AI models, particularly large generative models, requires substantial energy and carbon costs that are frequently underestimated[17]. Training complex models is exceptionally energy-intensive[18]. Early estimates even suggested that training a single large AI model could, under specific assumptions, emit CO_2 equivalent to the lifetime emissions of five average passenger vehicles[19]. However, such figures are highly sensitive to model architecture, hardware efficiency, and the carbon intensity of the electricity grid, and more recent life-cycle assessments emphasize this variability[20][21]. For example, training the GPT-3 model has been estimated to consume approximately 1,287 MWh of electricity and emit around 552 metric tons of CO_2, which would be equivalent to the annual electricity use of roughly 120 USA households[2][21]. As models grow to trillions of parameters, these demands escalate significantly[20]. Critically, the dominant energy burden occurs not during training but during the inference phase, the operational use of AI to respond to user queries. Studies indicate that 80–90% of an AI system's total lifetime energy consumption occurs during inference, as models process billions of requests daily[21][22]. A single query to a generative AI chatbot can consume 4 to 10 times more energy than a standard web search[23][3]. Integrating generative AI into all Google searches, for instance, could add 10–30 TWh of annual electricity demand, which would be comparable to the total annual consumption of a country like Ireland (29.3 TWh)[23].

Global data center electricity demand, driven significantly by AI workloads, is projected by the International Energy Agency[3] to exceed 1,000 TWh by 2026, surpassing current annual consumption of Japan. This growth has been already reflected in corporate emissions. Thus, Google reported a 48% increase in its total GHG emissions between 2019 and 2023, explicitly attributing this rise to "the greater intensity of AI compute," while Microsoft reported 30% emissions increase from 2020 to 2024.

Although data centers currently account for about 0.5% of global energy-related CO_2 emissions[3], projections suggest this share could rise to 1% by 2030, and up to 1.4% under accelerated AI adoption scenarios. This places data centers among the few sectors (alongside aviation) where emissions are expected to increase rather than decline in the coming decade. Moreover, the embodied carbon from data center construction and AI hardware manufacturing, spanning raw material extraction, semiconductor fabrication, and global transport, can constitute one-third to two-thirds of a system's total lifetime footprint[24]. The production of advanced semiconductors alone is highly resource intensive. Over two decades ago, Williams et al.[25] estimated that manufacturing a single 2-g microchip required 1.6 kg of

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fossil fuels, 72 g of chemicals, and 32 liters of water, baseline values that probably underestimated the current demands for high-performance AI chips[26].

3.2. Water resource impacts

AI data centers consume vast quantities of freshwater, primarily for cooling systems that prevent server overheating[27][28]. Water use occurs through two main pathways: direct on-site consumption in cooling towers, and indirect consumption associated with off-site thermoelectric power generation. Li et al. [29] estimated that training the GPT-3 model required approximately 700,000 liters of clean freshwater for cooling alone, an amount that would be sufficient to fill an Olympic-sized swimming pool to a depth of about 30 cm. This volume is approximately equivalent to the total freshwater use of an average American household over 20 years[29].

Such water demands are increasingly problematic in a world facing growing climate-induced water scarcity[30]. An estimated 35–40% of major data centers are in regions experiencing moderate-to-high water stress, including for example, Arizona, Nevada, and Texas in the southwestern United States[31]. The concentration of data center expansion in these watersheds raises legitimate concerns about competition with agricultural, residential, and ecological water needs. Beyond quantity, data center operations also affect water quality. Thermal discharge from cooling systems, typically 10–15°C above ambient temperature, can reduce dissolved oxygen levels and harm aquatic ecosystems[32]. Additionally, chemicals used in water treatment (e.g., biocides, corrosion inhibitors) pose contamination risks if they are not rigorously managed[33].

3.3. Electronic waste generation and life-cycle impacts

The rapid pace of innovation in AI hardware, driven by the need for greater computational power, has led to accelerated obsolescence and a growing stream of e-waste[34]. The specialized hardware required for AI training and inference has a relatively short lifespan in cutting-edge data centers before being replaced by newer, more efficient models[35]. A computational power-driven material flow analysis by Wang et al.[36] reported that AI-related e-waste could accumulate to a total of 1.2 to 5.0 million tons during the 2020-2030 period under different development scenarios. Lannelongue[37] estimated that the development of generative AI, and particularly of large language models (LLMs), might mean 1.2-5 million tons of accumulated e-waste between 2020 and 2030.

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E-waste contains a cocktail of toxic and hazardous substances, including heavy metals such as lead, mercury, cadmium (among others), as well as organic compounds like flame retardants (polybrominated diphenyl ethers (PBDEs)), polychlorinated dibenzo-*p*-dioxins and furans (PCDD/Fs), chlorofluorocarbons, and polycyclic aromatic hydrocarbons (PAHs)[12][38]. When e-waste is disposed in landfills or informally recycled, these materials can leach into soil and groundwater or be released into the air through burning, creating significant pathways for human exposure and environmental contamination[38][39][40]. The global management of e-waste is currently profoundly inadequate[41]. The Global e-Waste Monitor[42] reported that of the 62 million metric tons of e-waste generated in 2022, less than 22.3% was formally collected and recycled. A substantial portion is exported from high-income to low- and middle-income countries, where informal recycling under hazardous conditions exposes workers and nearby communities to toxicants[43][44].

The life-cycle impact begins long before disposal. AI hardware relies on critical minerals like cobalt, lithium, and rare earth elements (REEs). Over 70% of the world's cobalt, essential for batteries and electronics, comes from the Democratic Republic of Congo, often mined under conditions associated with human rights abuses and severe ecological damage, including deforestation and water pollution[13]. In turn, REEs play a pivotal role in AI hardware, particularly in semiconductors, magnets, and optical components, which are essential for high-performance computing[45]. However, scientific understanding of human exposure pathways and associated health risks from REEs has not kept pace with their surging industrial demand[46]. Toxicity primarily stems from oxidative stress, mitochondrial dysfunction, and multi-organ damage, particularly affecting the respiratory, hepatic, and reproductive systems. While chelation therapies show promise in mitigating exposure (especially to radioactive isotopes), robust clinical evidence and comprehensive regulatory frameworks remain lacking[47]. The extraction and processing of these materials are carbon-intensive and contribute to biodiversity loss and ecosystem degradation in mining regions[48].

3.4. Air pollution and local environmental health impacts

The electricity powering data centers largely comes from the grid, which in many regions remains dependent on fossil fuel combustion. Power plants burning coal and natural gas emit harmful air pollutants, including fine particulate matter ($PM_{2.5}$), nitrogen oxides (NOx), and sulfur dioxide (SO_2)[49][50]. These pollutants are well-established contributors to a wide range of cardiorespiratory diseases.

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$PM_{2.5}$, for instance, can penetrate deep into the lungs and bloodstream, and chronic exposure is linked to increased risks of ischemic heart disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and type-2 diabetes[51][50]. Air pollution from all sources, including fossil fuel combustion for electricity generation, has been estimated to contribute to over 9 million premature deaths annually worldwide[52]. However, these figures represent the total global burden of air pollution from all sectors. The marginal contribution of AI-specific data center energy consumption to this total burden remains poorly quantified. With data centers currently representing approximately 1–2% of global electricity demand, and AI workloads accounting for a subset of that consumption, AI's direct contribution to air pollution mortality is likely measured in tens of thousands of deaths globally rather than millions. Anyway, this figure is expected to grow if current trajectories continue without grid decarbonization.

Beyond grid power, data centers rely extensively on on-site diesel-powered backup generators to ensure uninterrupted operation during grid outages. These generators are also regularly tested, often under load. They are significant sources of localized air pollution, emitting NOx, PM, and other pollutants directly into surrounding communities[53][54]. Additionally, the siting of data centers and their associated power infrastructure often occurs in areas with lower property values and less political power, meaning that the resultant air pollution burdens fall disproportionately on low-income communities and communities of color[49].

4. Public health implications beyond environmental pathways

The main public health risks of AI (beyond direct environmental pathways) including algorithmic bias, misinformation, mental health impacts, occupational displacement, and effects on vulnerable populations, are summarized in Table 2.

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Impact area	Key health risks and mechanisms
Algorithmic bias and health inequity	*Commercial algorithms systematically underestimate health needs of Black patients *Dermatology AI shows lower accuracy on darker skin tones due to dataset bias *Pulse oximeters overestimate blood oxygen in patients with darker skin pigmentation *Biases arise from non-representative training data and lack of fairness auditing
Health misinformation and deepfakes	*AI enables scalable, convincing generations of health misinformation *Deepfakes can impersonate healthcare professionals, eroding institutional trust *AI-propagated anti-vaccine content linked to measles outbreaks *Undermines public health messaging and vaccination campaigns
Privacy erosion and mental health	*AI-driven social media algorithms linked to anxiety, depression, body image issues *Engagement-optimized content exacerbates mental health problems in adolescents *Digital phenotyping raises concerns about consent and pathologizing normal behavior *Pervasive surveillance and data collection erode personal privacy
Occupational displacement	*AI automation threatens administrative, clerical, and certain diagnostic jobs *Job insecurity linked to increased mortality, cardiovascular disease, depression *Disproportionately affects low-wage workers, women, and minority groups *Exacerbates existing socioeconomic health inequalities
Vulnerable populations	*Children/adolescents: attention deficits, disordered eating behaviors *Elderly: AI-powered scams, digital exclusion, worsening social isolation

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Impact area	Key health risks and mechanisms
	*Persons with disabilities: AI systems often fail due to non-inclusive datasets

Table 2. Public health implications of AI beyond environmental pathways

4.1. Algorithmic bias and health inequity

Algorithmic bias in AI represents one of the most direct public health risks, as it can perpetuate and amplify existing healthcare disparities, particularly among racial and ethnic minorities[55]. Recently, Joseph[56] confirmed this through evidence of biased training data and deployment practices that exacerbate inequities in diagnostics, treatment prioritization, and outcomes. A previous landmark study by Obermeyer et al.[10] revealed that a widely used commercial algorithm, designed to identify patients for high-risk care management programs, systematically underestimated the health needs of black patients. The algorithm used historical health care spending as a surrogate for underlying health needs, thereby overlooking structural inequities that systematically limit access and reduce expenditures for Black patients and, in turn, embedding racial bias into its risk predictions. [10], This is not an isolated case. Bias has been documented across numerous medical AI applications. Studies have shown that AI models for dermatology condition diagnosis often have lower accuracy on darker skin tones due to underrepresentation in training datasets[57]. Similarly, pulse oximeters, which use algorithmic calibration, have been found to overestimate blood oxygen levels in patients with darker skin pigmentation, leading to potentially dangerous clinical oversight[58]. These biases arise from non-representative training data, flawed problem formulation, and a lack of rigorous fairness auditing throughout the development lifecycle[59].

4.2. Health misinformation, deepfakes, and erosion of trust

Generative AI presents a profound new threat to public health by enabling the scalable, automated, and highly convincing production of health misinformation and deepfakes[60][56][61]. AI can generate tailored text, images, audio, and video that promote unproven treatments, undermine vaccine confidence, or impersonate healthcare professionals[62]. This capability heightens risks in healthcare, where deepfakes falsely attribute endorsements of unvalidated products to experts, potentially misleading patients and

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undermining public trust. For instance, such AI-generated media has been used to advertise bogus supplements by fabricating videos of physicians without their consent[62].

During the COVID-19 pandemic, AI tools were associated with increased dissemination of anti-vaccine content and conspiracy theories[63]. Theoretical frameworks and observational evidence suggest that AI-generated misinformation may contribute to vaccine hesitancy. Adeoye et al.[64] reported an association between AI-amplified vaccine misinformation and recent measles outbreaks, suggesting that automated misinformation dissemination might have contributed to declining vaccination uptake. However, it is still unclear how much AI-generated content, as opposed to other sources of misinformation, pre-existing vaccine skepticism, or broader social factors, contributes to these outcomes, and this question requires more empirical study. AI can create convincing, custom fake information quickly, weakening public health messages and risking years of disease prevention gains[56]. Although these studies strongly suggest an amplification of risk, establishing a direct causal link between misinformation produced by AI and particular outbreak, occurrences remain methodologically difficult, due to the complex interplay of factors influencing vaccine hesitancy and the spread of infectious diseases.

4.3. Privacy erosion, surveillance, and mental health

The data-hungry nature of many AI systems drives pervasive surveillance and data collection, eroding personal privacy. AI-driven social media algorithms, optimized for user engagement, have been consistently associated with negative mental health outcomes, particularly among adolescents[65]. These algorithms can promote content that exacerbates anxiety, depression, body image issues, and sleep disruption[66]. The concept of "digital phenotyping", using AI to infer mental health states from smartphone data, raises significant ethical concerns about consent, pathologizing normal behavior, and increasing health anxiety[67].

4.4. Occupational displacement and social determinants of health

The deployment of AI for automation *has been projected to pose potential risks of* labor market disruption and job displacement, particularly in administrative, clerical, and certain diagnostic tasks. Economic modeling studies suggest that significant job displacement could lead to adverse health outcomes through multiple pathways. Job insecurity and unemployment are powerful social determinants of poor physical and mental health, linked to increased mortality, cardiovascular disease, and depression[68][69][70]. Nevertheless, empirical evidence on realized health outcomes from AI-driven job displacement remains limited, as large-scale workforce disruption is still largely prospective rather than observed. The displacement risk is not evenly distributed. It often disproportionately affects low-wage workers, women, and minority groups, potentially exacerbating existing socioeconomic health inequalities[71].

4.5. Impacts on specific vulnerable populations

Children and adolescents. Algorithmically curated social media content and addictive design features contribute to attention deficits and disordered eating behaviors beyond mental health effects[72][66]. Social media algorithms personalize feeds to maximize engagement, often prioritizing extreme content that vulnerable youth encounter, which heightens risks for poor body image, eating disorders, and impaired attention mechanisms. For instance, platforms like TikTok use AI-driven recommendations that foster addictive scrolling patterns, exacerbating prefrontal cortex changes linked to reduced focus and reward sensitivity in developing brains.

[65].

The elderly. This group of population is particularly vulnerable to AI-powered financial scams and faces barriers due to digital exclusion, which can worsen social isolation and lead to medication or healthcare access errors[73].

Persons with disabilities. Many AI systems, such as voice assistants or facial recognition software, are trained on non-inclusive datasets and fail to work adequately for individuals with disabilities, creating new forms of digital exclusion[74].

5. Environmental justice, social equity, and global inequities

Marginalized populations, including racial minorities, low-income groups, and youth, shoulder amplified AI harms through biased algorithms in healthcare, hiring, and social media that exacerbate existing inequities[10]. Environmental justice principles highlight how the environmental costs of AI infrastructure (air pollution, water depletion, land use) are disproportionately imposed on marginalized communities[75]. It has been shown that data centers and their supporting power plants are more likely to be sited in low-income areas and communities of color, which then experience the localized health impacts without receiving commensurate economic benefits[49][76]. Furthermore, the massive energy demands of data centers drive up electricity costs for nearby residential consumers, effectively subsidizing private technology companies through socialized infrastructure expenses[54].

On a global scale, the inequities are stark. The extractive front-end of the AI lifecycle, mining for cobalt, lithium, and REEs, means severe environmental degradation and health hazards on communities in the Global South, such as in the Democratic Republic of Congo and Chile's Atacama Desert[13]. The back end of the lifecycle sees a massive flow of e-waste from high-income nations to low- and middle-income countries in Africa and Asia, where informal recycling exposes workers and communities to toxic substances[43]. This could be considered a species of "toxic colonialism"[77].

These environmental injustices are compounded by the algorithmic biases in AI healthcare systems, which often disadvantage the same marginalized groups through unrepresentative training data and flawed deployment. Reports describe data centers being in some low-income neighborhoods and communities of color in the USA, where they can expose nearby residents to industrial noise, local heat island effects, and possible air quality impacts[78]. However, there are still few spatial epidemiological studies that systematically compare where these facilities are built with historical redlining patterns and detailed demographic data. Decisions about where to place data centers depend on many factors such as land prices, access to power and other utilities, zoning rules, and tax incentives, so attributing siting patterns solely to environmental injustice is challenging without more rigorous analysis. This creates a pattern of potential double burden on vulnerable populations: enduring the environmental harms of AI's energy-intensive operations while suffering from biased applications in critical services[56][79].

6. Current regulatory landscape and mitigation strategies

The regulatory landscape for AI is fragmented and evolving rapidly. The European Union's AI Act of 2024 represents the most comprehensive attempt to date, establishing a risk-based framework[80]. It mandates fundamental rights impact assessments, transparency obligations, and requires high-risk AI systems (including some used in healthcare) to meet strict standards for data quality, documentation, and human oversight. It also introduces some requirements for reporting on environmental sustainability. In the USA, regulation is more piecemeal, relying on sector-specific agencies like the FDA for medical devices and a growing patchwork of state privacy laws. There is no overarching federal AI law. International coordination, through bodies like the OECD and GPAI, remains largely voluntary and non-binding.

Given the scale of the challenges identified, a multi-pronged mitigation strategy involving all stakeholders is essential:

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1. Transparency, measurement, and standardization. Technology companies must be required to disclose detailed, audited data on energy consumption, carbon emissions, water usage, and e-waste attributable to specific AI models and services. Standardized life-cycle assessment (LCA) methodologies for AI systems need to be developed and adopted[81][36].
2. Accelerated decarbonization and renewable energy. Data centers must transition to continuous, on-site renewable energy sources rather than relying on annual offsetting schemes, which fail to address real-time emissions. This shift demands substantial upfront investments in dedicated solar, wind, or geothermal installations paired with battery storage and smart grid technologies to ensure uninterrupted supply[54]. Facility locations should target areas rich in renewables (like solar-abundant deserts or windy offshore zones), while avoiding water-scarce regions to minimize cooling-related environmental strain. Such planning not only cuts carbon footprints but also alleviates grid pressures that inflate residential electricity costs[10]. Integrating on-site renewables is complicated by high capital costs, extensive land requirements, and energy intermittency. Successfully operationalizing these energy goals will necessitate phased transition plans and public-private partnerships.
3. Efficiency across the stack. Continued research and investment are needed to improve energy efficiency at all levels: hardware (e.g., specialized AI chips), software (e.g., energy-aware model architectures like sparse models, quantization), and data center operations (e.g., advanced cooling techniques)[4].
4. Circular economy for AI hardware. The industry must adopt extended producer responsibility models. This involves designing hardware for longevity, repairability, and easy disassembly, establishing robust refurbishment and remanufacturing programs, and investing in closed-loop recycling systems to recover critical minerals[36]. Transitioning to a circular economy for hardware is currently blocked by designs that prioritize performance over repairability and by the complexities of global supply chains. Essential policy interventions include establishing modularity standards and providing tax incentives for device refurbishment.
5. Health-informed and equitable AI deployment. Public health impact assessments should be mandatory for large AI infrastructure projects[82] For AI applications in healthcare and other high-stakes domains, rigorous, independent bias auditing using diverse datasets must be mandated throughout the development lifecycle. Meaningful community engagement is required in the siting of infrastructure and the development of algorithms that affect public services.

6. Robust policy and "just transition" programs. Policymakers must enact comprehensive legislation that mandates environmental and algorithmic impact assessments. Furthermore, public investment is crucial in education, retraining, and social safety nets to support workers displaced by AI-driven automation, mitigating the negative public health impacts of labor market shocks[83]. Executing "just transition" initiatives demands substantial funding and cross-sector cooperation to retrain workers and secure social safety nets. However, the long-term societal costs of inaction, including public health crises and social instability, are probably to be far more expensive.

7. Limitations of the evidence base

While the adverse effects outlined are clear and concerning, the research field faces significant limitations that must be acknowledged:

1. Lack of standardized reporting and data opacity. The absence of mandatory, standardized disclosure from AI developers and operators makes precise, comparative quantification of impacts extremely difficult. Most estimates rely on projections, modeling, and incomplete self-reported data[8]. Additionally, some of the quantitative estimates discussed in this review originate from preprints and other forms of "grey literature" (such as arXiv or SSRN). This reliance highlights both the rapid evolution of technological research and the inherent delay associated with conventional peer-review processes. Although these sources are frequently referenced and often methodologically explicit, their results should be interpreted with caution. Peer-reviewed life-cycle assessments and long-term studies should be essential to further verify and improve the accuracy of current estimates.
2. Rapid technological obsolescence. The breakneck speed of AI development means that studies assessing the impact of a specific model or hardware generation can become outdated by the time of publication, challenging researchers' ability to maintain an accurate, real-time understanding[84].
3. Methodological challenges in health impact attribution. Isolating the specific, long-term health effects of algorithmic bias or AI-induced occupational shifts from the myriad other social, economic, and environmental determinants of health is a complex epidemiological challenge[85][56]. Future studies should adopt multifaceted methodologies, such as longitudinal cohort studies and participatory action research with impacted communities. These approaches are vital for isolating causal pathways and accurately measuring specific health outcomes.
4. Geographical research gaps. Most studies on AI's environmental and social impacts focus on the USA, Europe, and China. The consequences in the Global South, where regulatory frameworks may

be weaker, infrastructure less resilient, and data scarcer, are critically understudied[77]. Closing existing research gaps requires financial support for partnerships with institutions in the Global South and localized data collection. Priority must be given to community-led assessments regarding the local impacts of mining, e-waste, and AI infrastructure.

8. Conclusions

The rapid, often unregulated growth of AI is creating serious environmental and health problems that affect people unevenly. Data centers powering AI devour huge amounts of energy, releasing GHG that worsen climate change, while guzzling water for cooling and producing toxic e-waste and air pollution. These technologies also harm public health by embedding biases in healthcare and hiring algorithms that disadvantage Black patients and minorities, generating personalized misinformation to undermine vaccine confidence, and curating addictive social media feeds that fuel attention deficits and eating disorders in youth. Vulnerable groups, such as low-income families saddled with higher electricity bills and underserved communities, bear the heaviest loads, threatening global climate goals, sustainable development, and hard-fought health equity. This review mainly examines the current large-scale commercial deployment of AI, as these patterns are responsible for most of today's environmental and public health consequences. Notwithstanding, specific AI applications including those used for optimizing renewable energy, advancing climate science, or precision medicine with proper oversight, can provide significant net benefits if they are implemented within strong governance frameworks and at sustainable scales. The fundamental task for policymakers and researchers is to guide AI development toward these beneficial uses while simultaneously reducing the risks associated with rapid, unregulated commercial expansion.

Assertions that AI's anticipated efficiencies will ultimately offset its environmental and social footprint remain largely theoretical, constrained by the absence of supportive governance structures, transparent data stewardship, and demonstrable systemic benefits. In contrast, the prevailing trajectory indicates a deepening imbalance of costs and benefits, with a net increase in harm. A decisive course correction is therefore imperative. AI innovation must be steered by precautionary principles and anchored in principles of environmental sustainability and social justice. These priorities should not be relegated to peripheral initiatives or corporate branding narratives but embedded at the core of technical design, regulatory frameworks, and business strategies.

Realizing such a transformation demands urgent, coordinated, and ethical action from researchers, engineers, industry leaders, policymakers, and civil society alike. Progress in AI must be redefined (not by computational scale, model performance, or market dominance) but by its capacity to enhance human and planetary well-being. The time has come for decisive, accountable, and transformative governance of AI. To move from principle to practice, concrete next steps include: 1) developing and mandating standardized sustainability and bias audit frameworks; 2) creating international treaties on mineral sourcing and e-waste accountability; 3) establishing public funding mechanisms for green AI R&D and just transition programs, and 4) fostering multi-stakeholder platforms to translate high-level mitigation strategies into sector-specific implementation roadmaps.

Statements and Declarations

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