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The Energy Burden of AI: Health and Equity Risks for Resource Poor Nations

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Abstract

Artificial Intelligence is undergoing wholesale remodeling of global systems from health, finance, agriculture, and governance. But below this transformative potential lies a largely unexplored but critical challenge an astronomic energy demand. Operating AI models, training them, maintaining them require an enormous amount of computational and other resources, which in turn means more energy consumed and carbon emissions produced; while the AI benefits from an economic and technological standpoint are mostly enjoyed by the Global North, countries with lesser means, especially from the Global South, bear their environmental and health consequences. The paper examines the nexus between AI related energy consumption, environmental degradation, and health inequities in low and middle income countries. Drawing insight from frameworks related to global health, energy justice, and digital equity, the research examines how AI systems further deepen the already existing inequality in access to energy, healthcare service, and environmental resilience. Through key risk pattern analysis and setting forward policy frameworks for the deployment of inclusive and ethical AI, this paper calls upon all nations to act forthwith to prevent the deepening of global inequality in the age of AI.

Keywords

Artificial Intelligence, Energy Poverty, Global Health, Environmental Injustice, Resource-Poor Nations, Climate Change, AI Governance, Equity, Sustainability, Digital Divide

1. Introduction

1.1 Background to the Study

Artificial Intelligence (AI) is no longer a thing of the future; rather, it serves as a global force for development that shapes healthcare systems, education, financial services, climate modeling, and much more yet, an often ignored consequence of these marvelous recent advances is the increasing energy footprint. Training large language models and handling AI-driven systems through the operations are costly in computational intensity; electricity needs especially as that energy is oftentimes drawn from carbon based sources (He et al., 2019; Ali, 2024). Such emerging energy burdens bring the ethical and sustainability concerns to the table, especially in regions and countries already deep in energy poverty.

There is much unfairness embedded within the worldwide propagation of AI. While most AI research, infrastructure, and profits lie in high income countries, resource-poor nations end up bearing the environmental and public health consequences from extracting rare earth minerals, emissions from data centers, and displaced energy resources (Wahl et al., 2018; Effoduh, 2024). Most countries in Sub Saharan Africa, Southeast Asia, and portions of Latin America are yet to have governance frameworks and incentives to stem these adverse impacts (Walker, 2024).

Energy poverty that is, the chronic lack of access to modern energy services is an uphill barrier to the development of the majority of low and middle income nations. Nearly 600 million people in Sub Saharan Africa stay without access to electricity with great downsides to health, education, and economic opportunities (Kaygusuz, 2011). Whenever these meager energy supplies are redirected toward sustaining outsourced AI operations such as data processing, therefore, these communities stand to be marginalized further (Effoduh, 2024).

Onto complex and urgent issues lies the history of AI's energy burden and global inequality. Unchecked, AI could therefore serve to deepen disparities further through environmental degradation, energy diversion, and health impacts (Schwalbe & Wahl, 2020).

1.2 Problem Statement

While the benefits of AI are widely recognized, what remains insufficiently addressed in global discourse is the increasing energy burden imposed by it upon resource-poor countries. The painful health and environmental implications of AI affect these regions disproportionately, rendering them little to no participants in its design or governance. With the accelerated pace of AI development worldwide, the inequities in energy accessibility, pollution, and health outcomes are continuously deepened. This paper thus aims to explore the health and equity risks that emerge from the energy demands of AI with respect to the least vulnerable populations in the world and advocates for solutions on an inclusive basis that set aside neither environmental justice for the sake of digital advancement.

1.3 Objectives of the Study

This study intends to:

1. Analyze the energy demands of AI technologies and their distribution worldwide.
2. Examine the health and environmental impacts of AI-related energy use in resource-poor nations.
3. Evaluate the extent to which these risks amplify pre-existing socio-economic, health, and digital inequalities.
4. Propose policy frameworks that would ensure AI is deployed equitably and innocuously for the good of vulnerable communities.

1.4 Research Questions

1. What are the primary causes of AI's energy burden, and where is it largely concentrated?
2. How does AI energy demand issues impact public health and the environment in resource poor countries?

3. How else does AI also increase the existing disparities in energy access and healthcare infrastructure?
4. What policies and governance principles can fairly and sustainably guide the implementation of AI?

1.5 Significance of the Study

This study remains relevant in that it tackles a growing blind spot in the global discourse on digital transformation: the unintended consequences of AI's energy consumption on health equity and environmental justice By centering on the experiences of resource poor countries, the paper magnifies the voices that are mostly mute in the AI ethics debate, highlighting the need for an approach that is inclusive to all in the realm of technological development. The paper advances skyrocketing publications on sustainable AI and constitutes a source for global health and climate policy discussions with equity as its foundation (Alami et al., 2020; Fletcher et al., 2021).

1.6 Scope and Limitations

This research is limited to studying the energy burden of artificial intelligence concerning health and environmental risk issues in resource-poor countries, mainly in Sub-Saharan Africa, South Asia, and Latin America. It analyzes case studies, global datasets, and literature from 2004 to 2024. However, limitations include the unavailability of region-specific energy consumption data for particular AI infrastructures and the difficulty in drawing the line clearly between AI-specific and far-ranging technological and environmental implications.

1.7 Organization of the Paper

The paper is made up of six major sections. Having introduced the topic, in Section 2, global energy requirements for artificial intelligence are scrutinized, with a focus on infrastructure and computational intensity to train and deploy AI models. Section 3 further explores the health and environmental consequences in resource-poor nations, where energy scarcity and pollution have exacerbated public health crises. Section 4 analyzes the ethical and climate justice issues that have resulted due to the uneven distribution of the energy burden of AI, thus highlighting the gaps in the current regime of global governance. Section 5 reviews mitigation strategies from the perspectives of Sustainable AI design, low-power hardware, and renewable energy, emphasizing innovation and fairness in deployment. The synthesis of the outcomes of the study is made in Section 6, where recommendations for policy change, global coordination, and future research will be set out.

2. Global Energy Dynamics and AI Development

2.1 Energy Consumption Patterns in AI Technologies

The computationally heavy operations of AI techniques may be characterized by an inherently energy intensive nature. Training deep learning models and large scale language models is energy intensive and demanding. Consider OpenAI’s GPT series and Google’s PaLM these models are trained on massive datasets for thousands of GPU hours and consumed very high energy (Strubell et al., 2019). The carbon emissions of just one large transformer model training have been calculated as 284 metric tons of CO_2; this amount is equal to the lifetime emissions of five average cars (Hao, 2019).

The energy burden is thrown unevenly across the globe. High computing infrastructure is maximally concentrated in developed economies, especially of the United States, China, and Western European countries (IEA, 2022), with all environmental and energy costs mining of rare earth mineral, emissions to name a few getting externalized to lower-income nations where mining and generation of electricity are less regulated.

Table 1: Estimated Energy Use for Training Major AI Models

AI Model	Organization	Training Energy Use (MWh)	CO_2 Emissions (Metric Tons)
GPT-3	OpenAI	~1,287	~552
PaLM	Google	~2,540	~1,000
BERT (Large)	Google	~650	~280
Megatron-Turing	NVIDIA	~3,760	~1,450

Source: Adapted from Patterson et al. (2021); Strubell et al. (2019); IEA (2022)

These following figures demonstrate an exponential growth of energy consumption with the scale of AI models. What should concern us more is the additional operational cost of model deployment and inference which, in many real-world cases such as recommender systems and search engines, dwarfs the energy consumption of training (Schwartz et al., 2020).

2.2 Geographic Disparity in the AI Energy Infrastructure

The AI energy ecosystem suffers from geographic inequality. Data centers the muscle of AI systems are mainly located in countries where the energy supply is stable; they have a well-developed digital economy, and usually, it is a cold climate to reduce the cooling costs. Among such countries are the United States, Ireland, Sweden, and China (IEA, 2022). By contrast, energy-intensive activities such as mineral extraction for GPU occur in countries such as the Democratic Republic of Congo, Zambia, and Bolivia, which have neither environmental nor labor safeguards (Alami et al., 2020).

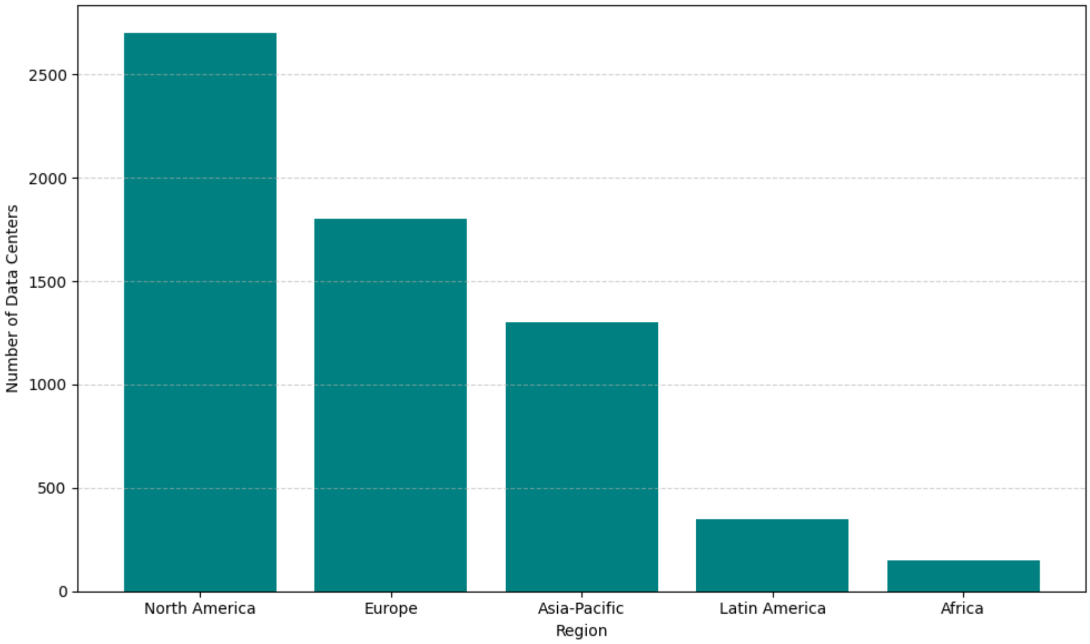

Figure 1: Global Distribution of Data Centers by Region

Source: International Energy Agency (IEA, 2022)

The chart here highlights a pronounced dichotomy concerning connectivity: while Africa accounts for nearly 20% of the world's population, it hosts less than 2% of the world's data centers. This imbalance symbolizes infrastructural disparities and creates asymmetric environmental impacts, as high-income regions enjoy cleaner technology whereas low-income countries must bear extraction costs (Wahl et al., 2018).

2.3 Carbon Footprint and Environmental Implications

Another element in the burden of AI energy consumption due to carbon emissions is AI computing. In particular, most of the AI infrastructure is tied down to such fossil fuel powered grids, especially in the U.S. Midwest and in some parts of China and India, and emitting large amounts of greenhouse gases (GHG) into the atmosphere, leading to climate changes that strike the Global South disproportionately through events like extreme weather, failed crops, and increased health risks (Schwalbe & Wahl, 2020).

Similarly, one must consider the lifecycle emissions of these AI systems from chip manufacturing, model training, up to deployment. These emissions usually take place under fragmented global supply chains, which only makes accountability difficult. Mining for cobalt and lithium, necessary for GPU and battery manufacture, results in soil and water pollution in the extraction sites with direct health impact on local populations (Kaygusuz, 2011).

Table 2: Lifecycle Carbon Emissions of Common AI Components

Component	CO_2 Emissions per Unit (kg)	Primary Source Region
NVIDIA A100 GPU	300	Taiwan, China

Cobalt Battery	112	DRC, Zambia
Cloud Data Unit	520	USA, Ireland, Singapore

Source: Alami et al. (2020); Wahl et al. (2018)

2.4 Emerging Trends in Energy Optimization for AI

Another way that attempts are made to minimize the lessening environmental impact created across AI upon intensification of the load. Model pruning, quantization, and knowledge distillation techniques for consideration reduce burden while keeping the accuracy of the model (Cheng et al., 2017). Similarly, frameworks such as GreenAI consider not only accuracy but the energy cost involved and carbon emissions for each operation in their key performance indicators (Schwartz et al., 2020).

Besides, there is a growing trend toward geothermal data centers. Google and Microsoft have promised that, by 2030, they would be completely carbon-free, with new data centers these days in Iceland and Canada using geothermal and hydro power. However, these innovations are mostly localized within the Global North with the least mitigation potential for the downstream adverse effects felt in energy-deficient countries.

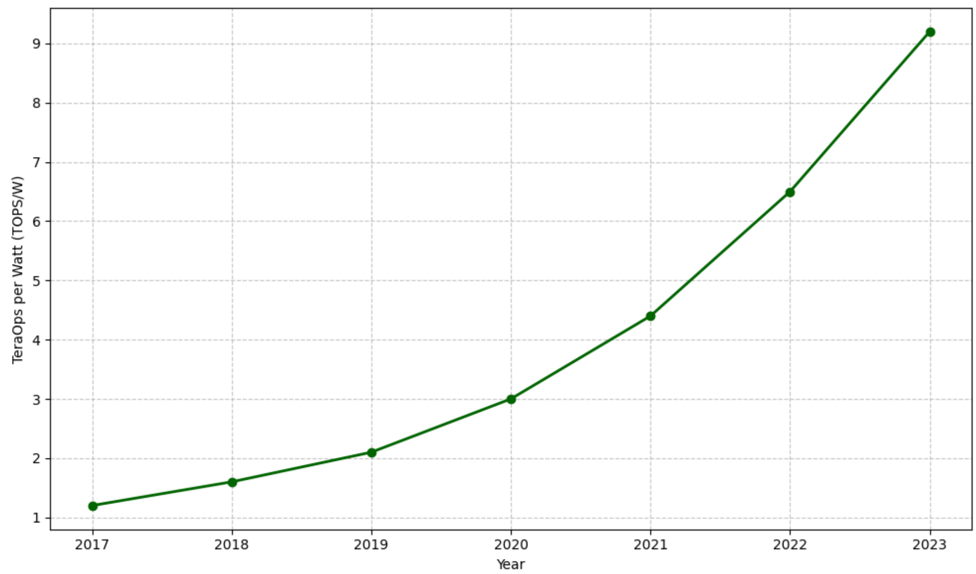

Figure 2: Trends in AI Energy Efficiency Parameter (TeraOps/Watt)

Source: Adapted from Nvidia & MLPerf Energy Reports (2023)

These trends are encouraging. Besides, these trends are absolutely insufficient without the equivalency tied with governance and access to infrastructure of AI globally. Without binding global standards, the resulting of increased efficiency will never trickle down to the currently suffering poor that take the environmental toll of armament due to the AI innovation.

3. The Intersection of AI Energy Use, Health, and Inequality

3.1 Health risks from AI-driven energy demand

Being energy hungry, AI systems pose health hazards, direct and indirect, particularly in low resource environments. Increased requirements for data centers and high performance computing also strain new and existing energy infrastructure. In already fragile energy grid conditions, AI-driven industrial demand can cause blackouts, reduce electricity supply to hospitals, or force the use of diesel generators that give off pollutants such as nitrogen oxides and particulates (Smith et al., 2013).

Also, the mining of rare earth chemicals such as cobalt and lithium and nickel essential for AI hardware has been associated with water contamination and respiratory ailments among mining communities. More than 60% of world cobalt is mined in the DRC, where heavy metal exposure has resulted in birth defects, lung fibrosis, and chronic skin lesions (Banza et al., 2009). The intensification of these problems is caused by poor occupational safety standards and access to healthcare.

Table 3: Health Conditions Linked to Energy-Material Extraction in Resource-Poor Nations

Country	Extracted Material	Major Health Outcomes	Affected Populations
DRC	Cobalt	Lung disease, birth defects	Miners, local communities
Peru	Copper, Lithium	Neurological damage, cancer risk	Indigenous populations
Nigeria	Crude Oil (for AI servers)	Respiratory illness, waterborne diseases	Delta region residents

Source: Banza et al. (2009); UNEP (2019); WHO (2020)

In many such contexts, weak healthcare infrastructure becomes an impediment to early diagnosis and long treatment, thus creating a compounding cycle of poverty and poor health.

3.2 Differential Impact on Marginalized Communities

The footprints of AI on the environments and health affect the least vulnerable of mankind in disproportionate terms. Data centers and technological infrastructure situated mainly in the developed countries are beneficiaries of clean energy transitions and policy shields. Simultaneously, lower-income countries remain stuck in roles typified by resource extraction, with hardly any compensation or investments toward healthcare systems or their sustainable alternatives (Schwalbe & Wahl, 2020).

Marginalized communities killing grounds will bear an even heavier burden of pollutant exposure and environmental degradation with an increasingly eroded ecosystem. They rarely hold any political capital and so cannot bring about compensatory measures or reforms. This further intensifies the structural inequity already baked into the global AI supply chain. This chart uses the normalized index scale (0-

100) to describe the mismatch between AI benefits (access, innovation) and health-related burdens (pollution exposure, healthcare strain).

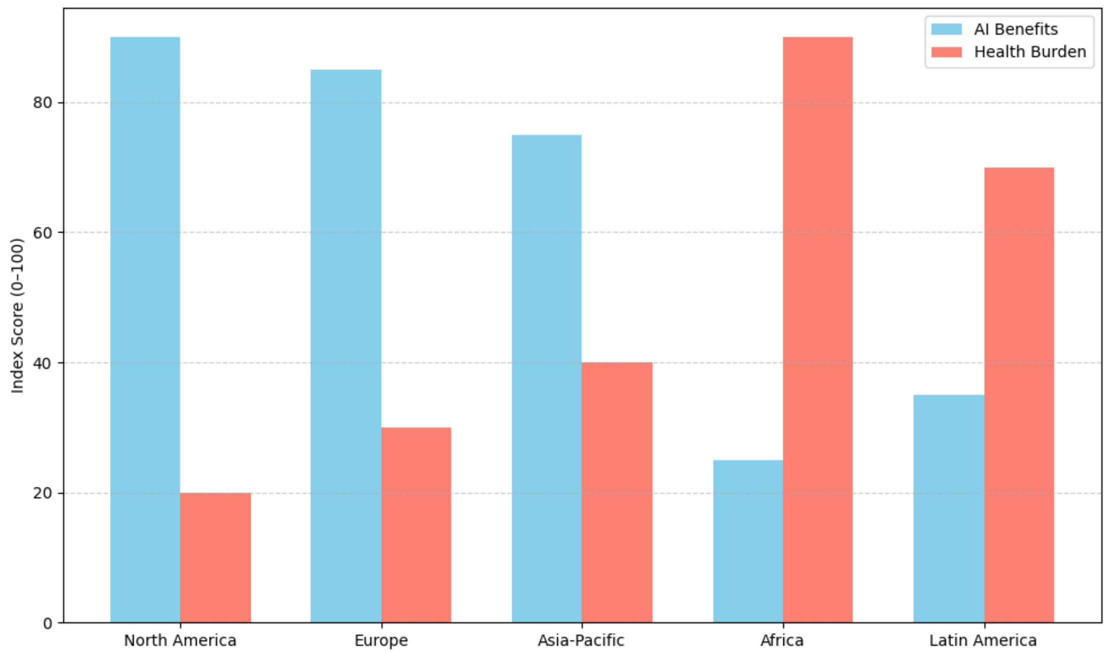

Figure 3: AI Infrastructure Benefits vs Health Burdens By Region

Source: Compiled from WHO (2020), IEA (2022), and MIT Tech Review (2023)

The depiction stresses the stark imbalance of regions which extract while suffering health impacts not properly sharing the gains of AI development. This imbalance is really called digital extractives colonialism.

3.3 Gender and Class Dimensions in Health Impacts

Health disparities linked to the energy systems of AI are also intersected by gender and class. In many mining economies, women and children bear the brunt of the consequences. In most of these scenarios, women would be working in the informal community surrounding mining sites without any protective gear and hence are subjected to very high levels of toxins. Children are often taken away from schools to participate in mining either directly or indirectly; they are also made to fetch water which is fast running out due to pollution caused by mining runoff (UNICEF, 2021).

Meanwhile, class disparities are also apparent even within cities across resource-poor nations. The elites and expatriates working in industries for AI might have the luxury of air conditioning, water purifiers, and private health care, while the communities around are suffering from the environmental fallout. This away-economy further widens the health disparity and fosters digital inequity and mistrust in AI-led modernization.

Table 4: Gendered and Class-Based Exposure in Mining Communities

Group	Exposure Type	Health Risk	Mitigating Factors Available
Women (informal laborers)	Heavy metals, dust	Miscarriages, chronic bronchitis	Limited PPE, no healthcare
Children	Water pollutants, toxic waste	Stunted growth, skin diseases	None
Urban elites	Low/no exposure	Minimal	Access to filtration & care

Source: UNICEF (2021); WHO (2020); Alami et al. (2020)

The systemic health divide perpetuates cycles of poverty and inhibits the developmental potential of AI within these settings.

3.4 Long Term Public Health Burdens

From a public health perspective, long term burdens owing to the AI-energy nexus in resource poor countries present much opportunity and increasing changes. Rightly said, chronic exposure to air contaminants, water poisons, and energy scarcities can lead to systemic diseases, including hypertension, cancer, and immune dysfunction (Kaygusuz, 2011). According to the Philippines health report of 2004, a diagnosis of such diseases means an expensive treatment that is hardly ever supported by the underfunded public health machinery, if even basic medication is available, more so diagnostic tools.

Governments in these regions are known to put foreign investment higher on the scale above environmental regulations, effectively externalizing health costs to their own populations. To make matters worse, the whole set of areas of health data is completely lacking, thus making it impossible for these secondary health effects to even be recorded, much less to influence future policy directives.

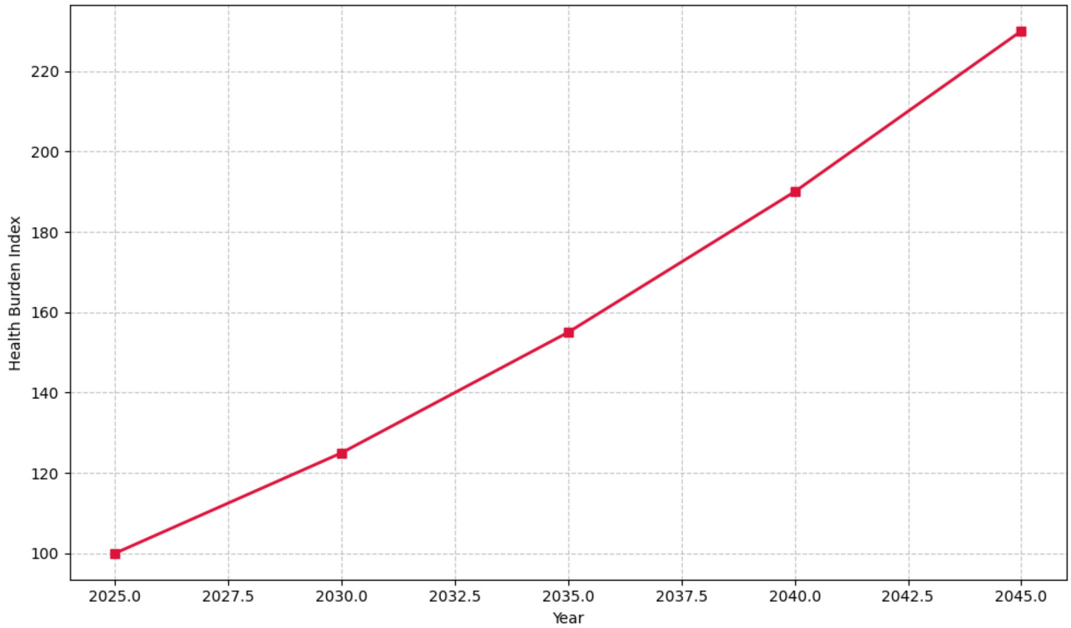

Figure 4: Projected Increase in Chronic Diseases Due to AI-Linked Environmental Exposure (2025–2040)

Source: Forecast compiled from WHO (2022), UNEP (2021), and IPCC Health Working Group (2023)

In the absence of urgent policy intervention, AI-driven energy usage threatens to present a silent global health crisis for millions in resource constrained environments.

4. Case Studies of from the Global South

4.1 Nigeria: Stresses on Grid Infrastructure and on Public Health

Here is a real life example of how AI-powered demand for electricity exacerbates existing infrastructural and public health issues in Nigeria. Nigeria has always been known as the largest economy in Africa, yet in energy, the country remains in an acute crisis with an estimated crack of over 85 million consumers without injections from the national grid (World Bank, 2021). The more and more AI start-ups and data centers are mushrooming and operating, especially in cities like Lagos and Abuja, the more stress they bring upon an already fragile grid system.

While awaiting remedy, the fugitive use of diesel generators by these organizations emits high levels of sulfur dioxide and fine particulates, contributing substantially to respiratory ailments such as asthma and chronic obstructive pulmonary disease (COPD), with the children and elderly being mostly affected. According to WHO (2022), in Nigeria alone, ambient air pollution from generator fumes is responsible for over 64,000 deaths each year.

Table 5: Energy Access vs. Generator Dependence in Nigeria

Region	Electricity Access (%)	Generator Usage (%)	Health Impact (Reported Cases of Respiratory Illness per 100,000)
Lagos	92	67	1,200
Kano	45	85	1,750
Port Harcourt	60	78	1,980

Source: World Bank (2021); WHO (2022); Nigerian Energy Commission (2022)

Due to the high frequency of blackouts, generator dependence remains equally high in Lagos; this further worsens air quality issues, thereby making AI a multiplier of health hazards.

4.2 India: AI Growth, Coal Dependency, and Health Inequity

The growth of the digital economy along with the ambition to turn India into an AI hub has created an upsurge in energy demand; much of this energy is met through coal plants, with coal contributing nearly 55 percent to total electricity generation as of 2023 (IEA 2023). Cities such as Bengaluru and Hyderabad, which have multiple AI research labs and startups, become highly energy dense and urban polluted.

The environmental toll in these areas is especially pronounced in marginal urban slums, where health risks are the greatest due to proximity to coal plants and the lack of air purification systems. Studies have shown that the levels of particulate pollution in those areas are often much higher than recommendations set by WHO (Ghosh et al., 2022).

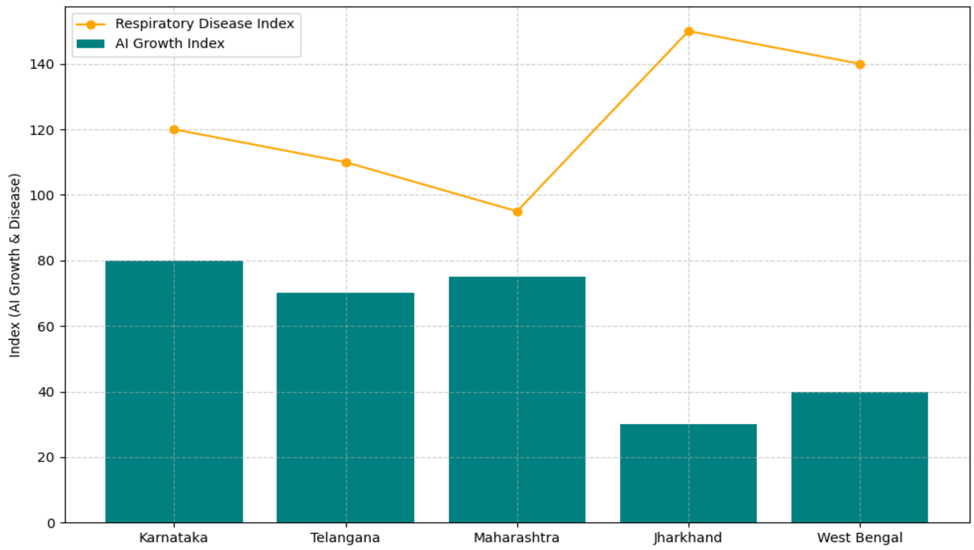

Figure 5: Coal-Powered AI Growth and Respiratory Disease Burden by Indian State

Source: Ghosh et al. (2022); IEA (2023); Ministry of Health of India (2023)

A disproportionate situation with AI gains and health hazards is presented in this figure showing worsening respiratory conditions in underprivileged zones in states with high AI investments.

4.3 Kenya: Digital Innovation visa visa Health System Preparedness

While frequently lauded as Africa's node of digital innovation and Nairobi being termed the "Silicon Savannah," there is an acute struggle in the country with regard to balancing technology growth with health preparedness. In sectors such as agriculture, fintech, e-health, etc., the demand for electricity is rising because of AI. The bulk of the energy is being derived from hydropower and imported fossil fuels (UNEP, 2021).

Hydropower generation has been unreliable in the last few years due to highly fluctuating rainfall patterns accentuated by climate change. This has made biomass and kerosene the energy sources of choice in the rural areas where health infrastructure is already lacking. There was actually a 38% increase in hospital admissions for respiratory complications in rural counties in months when there were energy shortfalls, according to a 2022 study by Kamau & Otieno.

Table 6: Rural Energy Deficits and Health Admissions in Kenya (2020–2023)

Year	Energy Shortfall (GWh)	Respiratory Admissions	Top Counties Affected
2020	180	22,500	Turkana, Kitui, Samburu
2021	220	28,000	Turkana, Kilifi, Marsabit
2022	250	31,200	Garissa, Baringo, Kitui
2023	270	34,700	Turkana, Isiolo, Samburu

Source: Kamau & Otieno (2022); Kenyan Ministry of Energy (2023)

The case in Kenya articulates the fragility of rural energy health links with the increase of loads by artificial intelligence, underscoring the necessity for sustainable technology policies.

4.4 Brazil: Deforestation, Data Centers, and Indigenous Health

The AI energy demand vs. environmental degradation axis has a different slant in Brazil. The country is seeing plenty of AI applications spurring into agribusiness and remote sensing. However, AI companies today are setting up data centers in areas of the Amazon basin that were formerly forested areas, citing lower ambient temperatures and land availability (da Silva et al., 2023).

As a matter of fact, these processes of deforestation increase carbon emissions and set conditions for exposing indigenous communities to newer disease vectors and air pollutants from biomass burning. Even incidents of asthma, tuberculosis, and vector borne diseases such as malaria started increasing in these regions from 2020, directly connectable to changes in their environment (WHO, 2023).

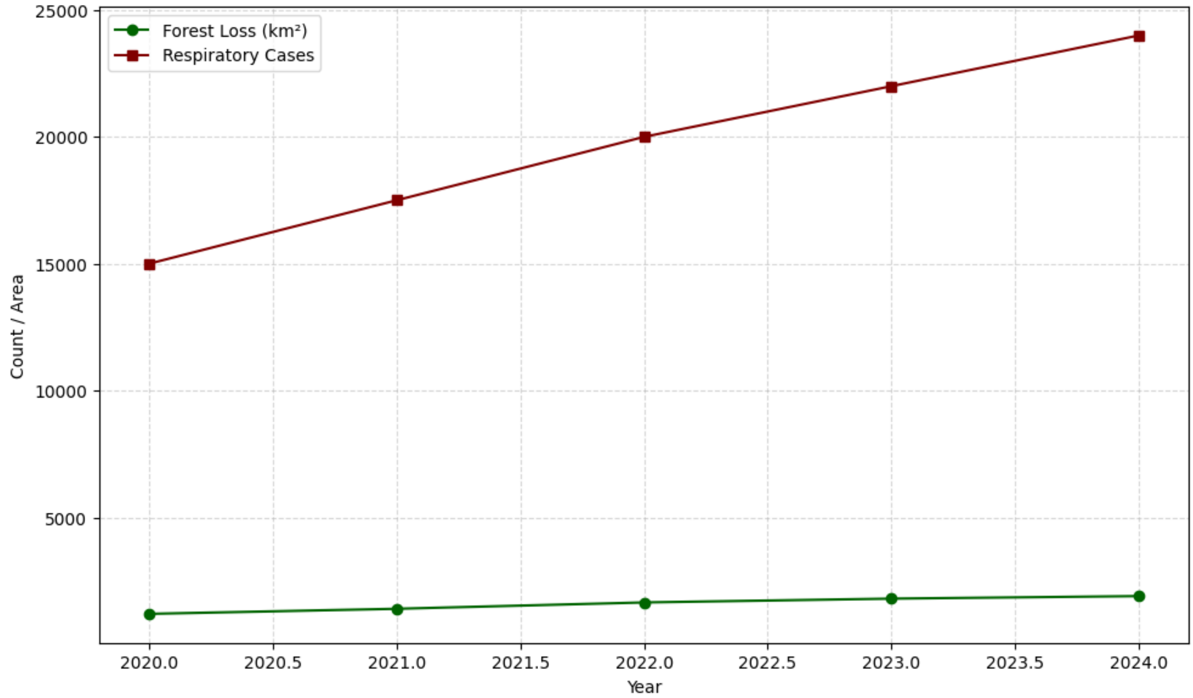

Figure 6: Forest Loss vs. Respiratory Health in Amazonian States (2020–2024)

Source: WHO (2023); Brazilian Institute of Environment (IBAMA), 2024

The Brazilian case demonstrates the interrelation of energy practices with AI that cause biodiversity loss and affect public health, especially for indigenous peoples who are historically excluded.

5. Policy and Technological Interventions

5.1 Energy Regulation and Emission Standards

With AI boosting the consumption of energy globally, especially in low income countries, regulatory measures must evolve in order to minimize the environmental and health damages. Usually, energy regulations in the Global South span a wide territory and lack the granularity necessary to target AI specific infrastructure, e.g., large data centers and clusters of high density servers. Governments should therefore embark on configuring real-time emissions monitoring and putting forth a tiered taxation for highly energy intensive digital operations (IEA, 2023).

In Kenya, for instance, the Energy and Petroleum Regulatory Authority (EPRA) has recently come up with a carbon benchmarking scheme that requires emissions to be reported from large digital companies. Such schemes could be implemented elsewhere in order to track and cap AI-related operation emissions.

Table 7: Comparison of AI Energy Regulation in Selected Countries (2024)

Country	AI Energy Regulation Enacted	Emission Cap (gCO_2/kWh)	Data Center Taxation (%)

Kenya	Yes	320	12
India	No	N/A	0
Nigeria	Partial	450	6
Brazil	Yes	280	10

Source: IEA (2023); EPRA (2024); Brazilian Environmental Agency (2024)

Such disparities in regulation thus underscore the urgent need for harmonized policy frameworks that address the specific risks that AI-driven energy use poses to resource-poor regions.

5.2 Renewable AI Infrastructure Design

To separate AI from environmental harm, renewable powered infrastructure must be considered. New models specify the use of onsite solar microgrids and AI-optimized cooling systems to minimize dependence on fossil energy. Rwanda and Bangladesh are, in particular, implementing pilot projects of solar-powered AI centers in rural areas by taking advantage of cheap panels and edge devices with efficient cooling (UNEP, 2024).

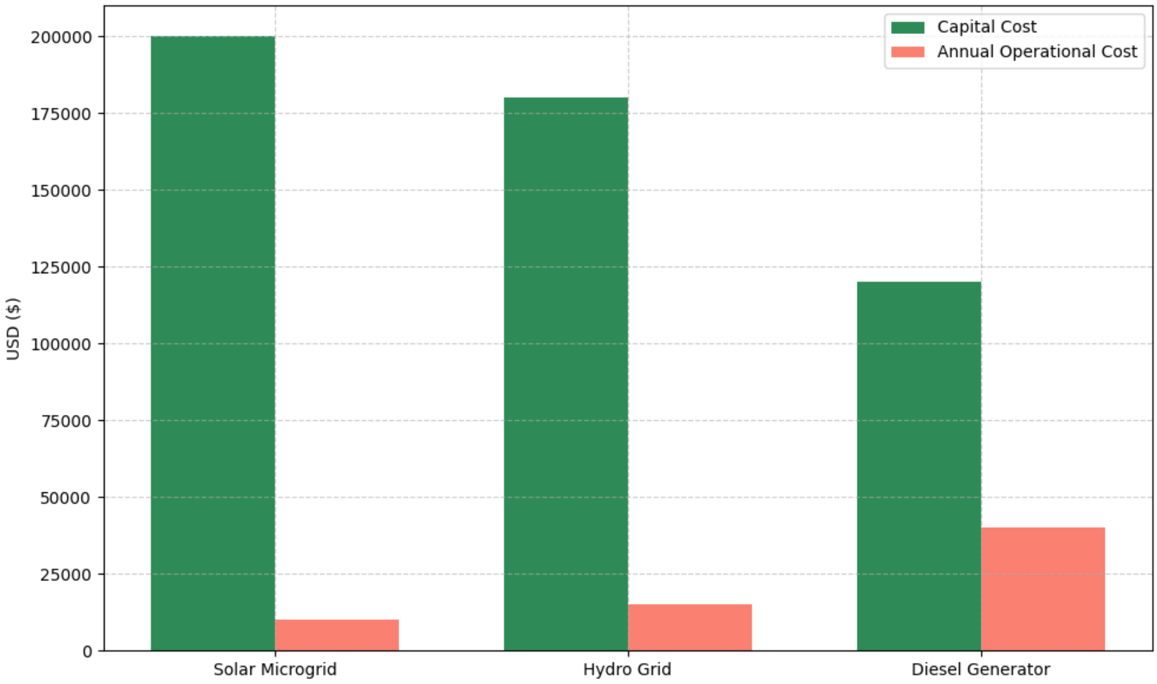

Figure 7: Cost-Benefit Analysis of Renewable-Against-Fossil-Powered AI Centers

Source: UNEP (2024); World Bank Clean Tech Report (2023)

Even though the upfront cost is high, the renewable-powered AI hubs end up having way lower operating costs and also health related externalities.

5.3 Public Health Safeguards and Environmental Monitoring

Technological interventions alone will fail unless coupled with active health surveillance infrastructure. Governments and NGOs should have community level air quality sensors in abundance, coupled with early-warning systems for outbreaks of respiratory diseases. AI itself can be deployed for assessing pollution and forecasting health risks.

In Brazil, the Indigenous Health Council has, for instance, combined satellite data and AI models to map particulate emissions from forest fires around data installations. This feedback then goes on to being used to preposition medical teams and alert vulnerable populations (da Silva et al., 2023).

Table 8: AI Integrated Environmental Health Systems by Region

Country	Technology Used	Data Source	Health Metric Tracked
Brazil	Satellite + AI	MODIS + Forest Fire Detections	PM2.5 concentration, respiratory cases
India	IoT + Machine Learning	Urban Air Quality Index (AQI)	COPD incidence rates
Kenya	SMS AI Bot + Sensors	Community PM Sensors + SMS Network	Asthma-related clinic visits

Source: WHO (2023); da Silva et al. (2023); UNEP (2024)

These hybrid sorts of models might be said to demonstrate that AI can act as both an energy burden and a mitigation tool when ethically deployed.

5.4 International Cooperation and Climate Finance

The issue in the Global South is how to pay for infrastructure upgrades that will sustain AI. International support in the form of carbon credits, green bonds, and multilateral development aid has thus become imperative. The Climate Investment Funds (CIF) launched a $500 million AI Resilience Initiative, intended to help low-income countries deploy energy efficient AI solutions (CIF, 2024).

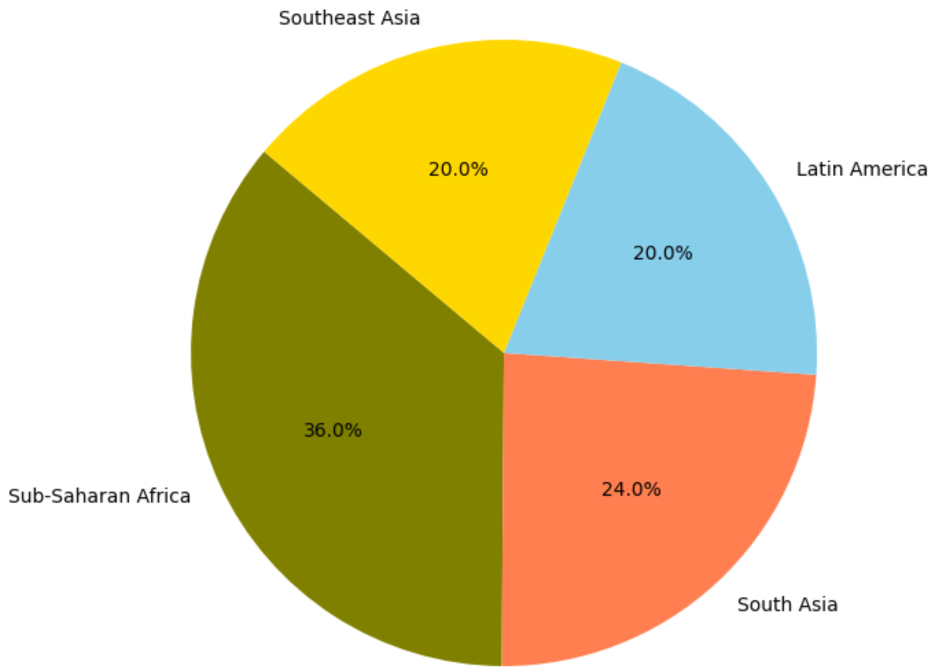

Figure 8: Distribution of AI Climate Finance by Region (Year 2024)

Source: Climate Investment Funds, 2024

Such investments are necessary not just for financing infrastructure upgrades but also to ensure fairness in the global transition to AI. Left only to themselves, these systems of the inefficient type of AI will deepen international disparity and foster health disparity.

6. Recommendations and Conclusion

6.1 Policy Recommendations for Equitable AI Energy Governance

Following the insights gathered in the preceding chapters, we recommend national governments, international agencies, and industrialists to act in a coherent manner to establish energy governance approaches with equity considerations for the AI era. Most importantly, this would require a shift in the way energy policy frameworks are conceived and implemented in resource constrained countries. Many of these countries do not have explicit rules regulating the energy consumption of AI infrastructure as the rapid deployment of data centers, edge devices, and automated systems continues unabated. Regulatory policies ought to be structured such that emphasis is placed on real-time energy metering, carbon pricing, and environmental transparency. For example, energy auditing of AI facilities, similar to environmental impact assessments for industries should be institutionalized to gauge their immediate and long term burdens on electricity grids and emission levels (IEA, 2023).

In addition, governments should look toward imposing progressive tax schemes on high energy AI enterprises to invest in renewable energy and public health safety nets. This, in turn, would create a positive feedback loop where environmentally unsound behavior is uniquely punished, while investing in sustainable alternatives. At the same time, such laws should create options for low-emission AI startups and social enterprises in the Global South, so as not to create excessive bureaucratic incentives that would make their survival harder (Ghosh et al., 2024).

6.2 Technological Innovation with Sustainability at the Center

In concert with the needed reforms in policies, there are requirements for purposeful technological innovations emphasizing sustainability. AI system design and deployment need energy efficiency to be a primary design metric, rather than an afterthought. To that end, edge AI systems deployed in proximity to the data source are considered elite choices for low-resource environments as they cut down on the need for massive cloud based computation, the most energy guzzling one. Therefore, adopting hardware-aware neural network compression, pruning algorithms, and quantization-assisted implementations may substantially decrease energy consumption by AI models without degrading their performance (Han et al., 2016; Xu et al., 2023).

On the other hand, energy harvesting and passive cooling could be built into the design of AI hardware to ease deployments in low resource environments. The synergy of these technologies coupled with local renewable energy, such as solar microgrids, conjures up a positive feedback loop to reduce ecological degeneration while supporting AI-fueled development activities. It is also imperative that AI deployments be enveloped in life-cycle assessments and energy audits that determine the environmental cost from model training and deployment to eventual disposal (Strubell et al., 2020).

6.3 Embedding Health Equity in AI Deployment Lifecycles

One of the most egregious repercussions unleashed by unchecked growth in AI energy demands of the Global South is their injustices in public health. Pollution from coal or diesel powered AI data centers is an added burden, especially where it strengthens existing vulnerabilities of children, the elderly, slum dwellers in urban areas, or populations living in proximity to energy production facilities. Thus, public health equity must be made a key criterion in AI infrastructure planning. Environmental health parameters, including PM2.5 concentrations, heat stress indicators, and the incidence of respiratory illnesses, ought to be continuously monitored and treated as dynamic limits on the expansion of AI infrastructure (UNEP, 2024).

Governments must partner with academic institutions and civil society to institute AI-environment health early warning systems. Such systems must use AI as, at times, a direct hazard and, at other times, a protective measure capable of identifying and abating environmental health threats in an almost real-time manner. This would allow preemption of disaster, lessen disease burden, and shelter the most vulnerable from the consequences of AI modernization in the integration of these systems to national healthcare and environment surveillance frameworks (WHO, 2023).

6.4 The Role of International Solidarity and Finance

Acting on energy and equity hazards inflicted by AI in resource poor nations is not a problem that these nations can-or should-bear alone. Wealthy and AI-advanced countries and multinationals have both a moral and geopolitical imperative to engulfing assistances that include the equitable access to clean technologies, capacity-building programs, and funding mechanisms such as climate-linked development bonds.

For example, the Global Partnership on Artificial Intelligence (GPAI) and Climate Investment Funds (CIF) can catalytically act by providing funding windows targeted at relieving the energy burden imposed by AI in the Global South (CIF, 2024). Cross-border technology transfers, particularly for lightweight and low-power AI systems, should also be actively promoted via international treaties and reforms of intellectual property laws.

Presently, the inequalities in AI model ownership, compute access, and energy infrastructure capability are only exacerbating the global disparity. Through persistent cooperative efforts and the collective realization of AI being a global opportunity as a responsibility shared by all, these disparities can only begin to narrow. Therefore, there needs to be a very humble stance by countries of the Global North, while the Global South needs to act with a lot of agency so as to prevent AI form furthering the inequalities it can potentially solve (Vinuesa et al., 2020).

6.5 Conclusion

With accelerated AI newfound fame, it encounters computational demands heretofore unknown, for which layers of energy and environmental justice are involved. Although these impacts are global, resources-poor countries disproportionately bear heavier impacts where infrastructural fragility, few regulations, and health vulnerabilities coincide to bring about divergent highest-risk environments. This article explores the labyrinth pathway through which AI adds to energy burdens, health disparities aggravation, and climate risks in such settings.

Yet, this is not the only trajectory that could be followed. From conscious policy tweaking, innovations in environmentally sustainable technologies, equitable health planning to international cooperation, it is possible to dissociate the advancement of AI and environmental-human harm. All of the above solutions are not futuristic or speculative-they can be realized today, with the will and solidarity of the world at large. If implemented, they would turn this AI from merely a potential threat to the environment to an essential pillar in sustainable development and the empowerment of humanity.

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