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Integrating Artificial Intelligence and Climate Sustainability for Human Health: A Systematic Review of Natural Resource Challenges, Healthcare Opportunities, and Policy Directions

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ABSTRACT: The field of artificial intelligence (AI) and climate sustainability, climate protection and natural resources management, and health science has become an interdisciplinary research area in which the digital transformation and climate protection are to be assessed together. AI has become a more common feature in medical imaging, aids in clinical decision making, disease surveillance, predictive analytics, drug discovery, health-system management, telemedicine, and population-health monitoring. Such applications can enhance diagnostic efficiency, ensure optimal resource allocation, minimize unnecessary healthcare utilization, reinforce climate-sensitive disease monitoring, and aid in resilient healthcare systems. Meanwhile, AI systems also need significant amounts of computing power, electricity, cooling water, semiconductors, data storage, networking and electronics. This has led to the environmental impact of AI's use being a pertinent issue for sustainable healthcare.

This systematic review explores the connection between AI and climate sustainability in human health outcomes, focusing on natural-resource use, health opportunities, environmental threats, health-system resilience and policy needs. Literature was synthesized in five analytical domains: AI-enabled health applications, climate-sensitive health risks, computational energy and carbon impacts, natural-resource impacts, and governance mechanisms. Healthcare systems have been estimated to be responsible for about 5% of global GHG emissions and data centres are estimated to be responsible for about 180 Mt of indirect CO_2 emissions due to electricity consumption. While this is just a fraction of overall data centre workloads, AI's increasing appetite for compute power has contributed to an increase in strain on electric power systems, water resources, hardware supply chains, and electronic-waste management.

The review points to a two-fold path. Predictive maintenance, energy optimization, precision medicine, telemedicine, optimization of supply chains, prediction of diseases related to climate change, and better resource utilization are just a few examples of how AI can lessen environmental burdens when developed correctly.AI can ease environmental burdens in a variety of ways when designed appropriately, such as: predictive maintenance, energy optimization, precision medicine, telemedicine, optimization of supply chains, prediction of diseases related to climate change, and better resource utilization. A key component of sustainable deployment is lifecycle assessment, along with energy- and carbon-aware computing, renewable electricity procurement, water-efficient data-centre design, hardware circularity, transparent environmental reporting and algorithmic efficiency, plus health-specific governance. It is proposed to develop a policy framework that integrates AI governance with the policy of climate and health. Assessing the performance of sustainable AI for health should not be based solely on clinical performance but also on human-health, environmental, economic, equity, and technological performance.

1. INTRODUCTION

1.1 BACKGROUND

Climate change is a leading driver of population health, health-system performance, food security, water security, infectious-disease transmission, mental health, and social stability. Describes the interconnections between health risks caused by increasing temperatures, extreme heat, floods, droughts, wildfires, storms, ecosystem disruption, and changed vector distributions. Climate change is a key threat to human health, according to World Health Organization, with 3.6 billion people already residing in areas highly vulnerable to climate change. Climate-related hazards impact mortality, noncommunicable diseases, infectious diseases, food systems, water security, health infrastructure, and healthcare delivery.

Healthcare systems are caught in a complex position in this environmental transition. Climate change poses threats to health services through climate sensitive diseases and disasters, and also threatens the environment through energy usage, procurement, transportation, pharmaceuticals and medical devices, water use, waste generation, buildings, and digital infrastructure (Fan *et al.*, 2023). The health industry is estimated to emit around 5% of the worldwide GHGs. Therefore, there is a need for close linkage between climate resilient healthcare and environmentally sustainable healthcare.

In this evolving healthcare landscape, AI has become a significant technological shift. There is a growing use of machine learning, deep learning, natural language processing, computer vision, generative AI, reinforcement learning, and predictive analytics in clinical and public health applications. Medical-image interpretation, early disease detection, clinical decision support, personalized treatment, drug discovery, patient monitoring, hospital operations, resource allocation, disease surveillance, and health research are all areas where AI can be used to support medical imaging. WHO describes AI applications in the areas of diagnosis, health care, drug development, disease surveillance, outbreak response, and health system management.

The task of researching the environmental dimension of AI is massive. AI systems rely on computational infrastructure that consumes electricity and cooling systems, requires water, data storage, networking infrastructure, semiconductor manufacturing, physical facilities, and replacement equipment (Bergquist *et al*., 2024). According to the International Energy Agency (IEA), global data centres account for about 0.5% of global combustion-related CO_2 emissions with around 180 Mt of indirect CO_2 emissions currently generated. Under scenarios of growing demands for data and AI, data-centre emissions are expected to rise significantly in this decade.

Questions of sustainability in healthcare can therefore not be divorced from the environmental impact of AI. While AI can create environmental benefits during its healthcare operation efficiency, it can also create environmental costs in the development and deployment process of the model. This establishes a bi-directional connection between AI and sustainability.

1.2 THE AI–CLIMATE–HEALTH NEXUS

The AI–climate–health nexus is a multi-dimensional system where technologies and environmental resources, as well as health services and population health, affect each other. Climate change could drive up health service needs and provide new demands for surveillance, prediction, preparedness and emergency response. The requirements can be addressed using computational tools that can be provided by AI. But the electricity, water, minerals, and manufactured hardware needed for computing power can also be used up.

This connection may be described in four ways that are linked together. The first track is climate change and health risk. Exposure to heat, air pollution, infectious agents, allergens, food insecurity, water contamination and exposure to extreme weather are altered by environmental change (Ueda *et al*., 2024). The second pathway relates to AI-driven adaptation, which involves predictive analysis and monitoring tools enhancing preparedness. The third pathway relates to the environmental impacts arising from the use of AI, such as electricity usage, carbon emissions, water needs, hardware production, and e-waste. The fourth path is related to mitigation, where artificial intelligence systems work to make optimal use of energy, transportation, supplies, hospital processes and resources.

Sustainable health-AI must thus be measured in tandem with the health impact and environmental cost.

1.3 PROBLEM STATEMENT

Recent studies in AI for healthcare have focused on diagnostic precision, predictive accuracy, clinical impact, cost-effectiveness, and patient results. The evaluation of technology is less consistently in the use of environmental indicators. Previous studies on AI and the National Health Service revealed a lack of standardisation in quantifying climate impacts caused by AI. There is also a need to assess both emissions produced by AI and the potential for AI to decrease emissions resulting from healthcare processes.

There is a methodological challenge because of the lack of uniform environmental assessment. Two same level-performing AI systems could require drastically different amounts of computation (Han *et al*., 2025). This larger model might generate a much higher footprint than a smaller one with similar clinical performance if it has a significant training and inference infrastructure footprint. Likewise, an AI system operating in a carbon intensive electricity system can have a different environmental footprint to the same AI system operating in a low-carbon electricity system.

1.4 OBJECTIVES

- To examine the integration of artificial intelligence and climate sustainability and its implications for human health.
- To assess the natural-resource requirements, environmental impacts, and healthcare-system risks associated with the application of artificial intelligence.
- To evaluate the potential of artificial intelligence in climate adaptation, sustainable healthcare, disease surveillance, resource optimization, and health-system resilience.
- To review existing governance mechanisms and propose policy directions for sustainable AI deployment based on clinical, environmental, economic, and social considerations.

2. LITERATURE REVIEW

2.1 ARTIFICIAL INTELLIGENCE IN HEALTHCARE

AI has moved beyond its status as an experimental decision support tool to become a part of the clinical and public-health infrastructure. Medical imaging is one of the oldest applications, which is playing a significant role in radiology, pathology, ophthalmology, dermatology, cardiology and oncology (Al-Raeei, 2024). Computer-vision models can be used to handle massive amounts of image data, and can help with classification, detection, segmentation, and prioritization. Another huge application is in predictive analytics. Machine-learning systems have the potential to incorporate EHR, lab results, demographic data, physiological parameters and environmental factors to predict disease risk and healthcare utilization. These systems can be used for early intervention and population-health management.

AI is also becoming more and more popular in drug discovery and development. Machine learning can help in molecular screening, target identification, protein-structure analysis, compound optimization, and trial design. Applications can help to decrease the amount of time and resources needed at specific steps in pharmaceutical research. Additional opportunities are available in public health. Epidemiological, climatic, mobility, environmental, and health-service data can be analysed with the help of AI-powered surveillance systems to identify emerging disease patterns. Models using temperature, rainfall, vector distribution, land use, and population characteristics can be used to monitor climate-sensitive diseases. WHO has highlighted the possibility of AI to solve workforce shortage and resource constraints and has also outlined governance, ethical, safety, and equity needs.

2.2 CLIMATE CHANGE AND HUMAN HEALTH

There are direct and indirect effects of climate change on physical health. Exposure to heat can pose risks of cardiovascular diseases, respiratory diseases, renal diseases and other health-related conditions (Kosna, 2025). Trauma, displacement, damage to infrastructure and disruption to medical services are a result of floods and storms. Drought impacts on agricultural productivity and food availability. Vector-borne diseases and zoonotic transmission are affected by changes in ecological conditions. Health risks associated with these climate conditions are especially high for populations that are less likely to have access to healthcare, clean water, nutritious food, stable housing, and climate-resilient infrastructure. Evidence from WHO shows that for vulnerable regions, death rates from extreme weather events are significantly higher than for regions with relatively low historical emissions. So, there is a need for both mitigation and adaptation strategies for health systems. While mitigation is intended to lessen the environmental stressors caused by health care systems, adaptation aims to build health services and communities' resilience to climate threats.

2.3 AI AS AN ENVIRONMENTAL BURDEN

The impact of AI on the environment extends beyond power usage during model training. The entire life-cycle involves hardware production, extraction of raw materials, data collection, model development, model refinement, inference, data storage, cooling, networking, hardware replacement, and end-of-life disposal. In some cases, large-scale computational models might need significant computational resources during the development process. When models are used in millions of users or across a large healthcare network, there's also the potential for significant cumulative demand through continuous inference. All data centres need to have cooling equipment since all computers produce heat. Water can be used directly for cooling or indirectly via electricity generation (Volf *et al.*, 2024). The environmental impact will then vary according to the geographical location, the mix of electricity generation, the cooling technology used, the weather conditions and the efficiency of the operation. This is followed by the concern of e-waste. The hardware components used for AI infrastructure include high-speed processors, accelerators, servers, storage solutions, networking gear, batteries, and other hardware parts. The high rate of technology change can decrease equipment lifecycles and generate a greater amount of e-waste. The 2024 overview of climate change and AI in healthcare highlights energy usage, carbon footprints, impacts of data centres, e-waste, and energy-efficient AI, green computing, renewable energy, resource optimisation, and sustainable healthcare workflows.

2.4 AI AS AN ENVIRONMENTAL ENABLER

AI can help with sustainability in the environment by optimizing. Healthcare facilities have complex energy systems including HVAC, lighting, refrigeration, sterilisation, medical equipment, IT systems and building management systems. Patterns in energy demand can be recognised by predictive algorithms and equipment operation optimised. Optimization of the supply chain can minimize transport distances, stock out, losses and overbuying (Sirmaçek *et al.*, 2023). Predictive maintenance can increase the lifespan of equipment and save materials. Demand forecasting can help enhance pharmaceutical and medical-supply management.

Selected forms of patient and staff transport can be avoided by telemedicine and remote monitoring. The environmental value is nevertheless dependent on digital infrastructure, substitution of travel, device lifespan, and actual physical health care activity reduction.AI can enhance environmental monitoring too. Machine-learning models can incorporate air quality data, temperature, humidity, pollution, land use, and clinical data to help determine who is at a higher risk.

2.5 SUSTAINABLE HEALTHCARE FACILITIES

The World Health Organization (WHO) framework on climate resilient and environmental friendly health care facilities recognizes the sustainable health-system development as having six key elements: health workforce capacity, water and sanitation, healthcare waste management, sustainable energy, infrastructure, technology, and products.

For these components, AI can be a helpful companion in managing them intelligently and predicting their behavior (Miller *et al.*, 2025). The data from the sensors can be used by building-management systems to optimize energy usage. Abnormal consumption and leakage can be detected by water-monitoring systems. Waste-management analytics can play a part in waste-disposal trends and segregation. Predictive maintenance can minimize equipment breakdowns and replacements. This is why it's crucial for digital infrastructure to align with environmental infrastructure for the integration of AI in sustainable healthcare facilities.

3. METHODOLOGY

3.1 STUDY DESIGN

A systematic literature-review framework was created to investigate the relationship between Artificial Intelligence (AI), climate sustainability and natural resources, health and human health (Subramaniam *et al.*, 2022). The methodology is based on the concept of systematic evidence synthesis and literature has been classified based on the technological application, environmental burden, healthcare opportunity, health outcome, and policy implication. The search strategy was designed based on five conceptual areas: (1) Artificial Intelligence; (2) Healthcare; (3) Climate change and Sustainability; (4) Natural resources and Environmental impact; (5) Governance and Policy.

3.2 SEARCH STRATEGY

The literature search framework included peer-reviewed biomedical and interdisciplinary literature as well as authoritative institutional evidence from WHO and IEA. Artificial intelligence, AI, machine learning, healthcare, health systems, climate change, sustainability, green AI, carbon footprint, energy consumption, water consumption, electronic waste, natural resources, climate resilience, health policy, etc. were among the search concepts (Anwar and Sakti, 2024).Peer-reviewed studies, systematic and scoping reviews, major international institutional reports and studies directly relevant to AI in health, climate or environmental sustainability and resource use were prioritized.

3.3 ELIGIBILITY CRITERIA

Research was deemed relevant if it dealt with one or more of the following relationships: AI and Healthcare; AI and Environmental Sustainability; AI and Climate Change; AI-related Energy/Carbon impacts; Environmental impacts of the Healthcare sector; Climate-resilient Healthcare systems; and Governance of AI and Sustainable Health technologies (Adedayo *et al.*, 2023).Studies that did not have any health or environmental relevance were not included, as they were just related to unrelated computational applications. Themes were not identified for publications that did not have substantive content related to AI, healthcare, climate sustainability, or resource use.

3.4 DATA EXTRACTION AND THEMATIC SYNTHESIS

The data was retrieved based on the following categories: publication year, application domain, environmental dimension, health-system dimension, resource requirement, sustainability opportunity, risk, and policy relevance. This evidence was then clustered in five analytical areas: environmental burden, climate-health adaptation, healthcare optimization, resource efficiency, and governance (Mumtaz *et al.*, 2022).The direction of effects was compared using an evidence matrix. Positive sustainability impacts described were reductions in energy, travel, resources, waste, and climate preparedness. The negative impacts were computer energy use, water use, hardware needs, carbon emissions, and e-waste.

3.5 ANALYTICAL FRAMEWORK

The Sustainable AI–Health Index, which is proposed, is divided into five dimensions: (1) clinical utility, (2) environmental burden, (3) resource efficiency, (4) health-system resilience and (5) governance readiness. In future empirical evaluations each dimension can be scored on a standardized 0-100 scale.

The framework is represented conceptually as:

Sustainable AI Value = Clinical Benefit + Climate/Health Benefit + Resource Efficiency + System Resilience − Environmental Burden − Governance Risk

This equation is not a clinically validated parameter. Its aim is to not evaluate AI technologies solely based on technical correctness.

4. RESULTS AND ANALYSIS

4.1 OVERALL EVIDENCE PATTERN

The literature reviewed revealed both positive and negative impacts of AI on sustainability. AI creates environmental pressures via computation and infrastructure, and offers tools for lowering resource use and building climate resiliency. The evidence is most robust in the area of clinical applications based on AI, optimizing healthcare outcomes, environmental monitoring, and computational energy use (Alotaibi and Nassif, 2024). There is less evidence available on full life-cycle impacts of AI in healthcare, such as cost of hardware production, water use, e-waste and replacement of systems, compared to other sectors.

TABLE 1. The list below includes major quantitative indicators that are relevant to AI, climate and health. Below is a list of the key quantitative indicators of relevance for AI, climate and health.

Blood urea nitrogen (BUN) 8 to 23 mg/dL The level of nitrogen in the bloodstream.

The health risks from climate change are different globally and 3.6 billion people worldwide are at high risk because of the extreme climate they live in.Climate change affects people at different levels of risk; 3.6 billion people are living in extremely climate-sensitive areas.

TABLE 1. MAJOR QUANTITATIVE INDICATORS RELEVANT TO AI, CLIMATE, AND HEALTH

Indicator	Reported value	Relevance
People living in areas highly susceptible to climate change	3.6 billion	Population-level climate-health vulnerability
Approximate healthcare contribution to global greenhouse-gas emissions	5%	Environmental footprint of health systems
Data-centre indirect CO_2 emissions	~180 Mt CO_2	Current electricity-related emissions
Data-centre share of global combustion CO_2 emissions	~0.5%	Current global emissions contribution
Projected increase in data-centre indirect emissions by 2030, IEA base case	~80%	Growth pressure from digital infrastructure
WHO COP26 recommendations	10	Climate-health policy priorities
Experts and health professionals consulted for WHO COP26 report	400+	Breadth of policy consultation
Organizations consulted for WHO COP26 report	150+	Institutional participation

Digital infrastructure is emerging as a significant environmental infrastructure in the context of the transformation of healthcare, while the quantitative evidence emphasises the population level nature of climate-health risks.

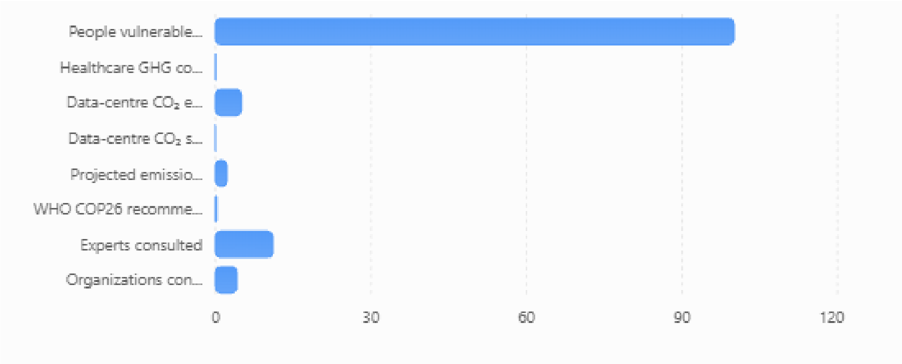

Figure: Major Quantitative Indicators Relevant to Ai, Climate, And Health

4.2 NATURAL-RESOURCE PRESSURES

TABLE 2. Natural-Resource Requirements Of Ai-Enabled Healthcare

Resource domain	**AI-related requirement**	**Principal environmental concern**	**Sustainability intervention**
Electricity	Model training and inference	Carbon emissions and grid pressure	Renewable electricity and energy-efficient models
Water	Data-centre cooling and electricity generation	Local water stress	Water-efficient cooling
Minerals	Semiconductor and server manufacturing	Mining and resource depletion	Hardware circularity
Land	Data-centre infrastructure	Land-use pressure	Efficient facility planning
Materials	Servers, processors, batteries and networking equipment	Resource extraction	Extended equipment lifecycles
Digital storage	Medical images and health records	Electricity and infrastructure demand	Data minimization and efficient storage
Electronic equipment	GPUs, CPUs, servers and networking devices	E-waste	Recycling and circular procurement

The natural-resource dimension explains that a carbon accounting approach is insufficient to assess the sustainability of AI (Reichstein *et al.*, 2025). A technology can be associated with low operating carbon dioxide emissions, but also can have high material and water footprint.

4.3 HEALTHCARE APPLICATIONS WITH SUSTAINABILITY POTENTIAL

TABLE 3. Ai Applications And Potential Sustainability Effects

Healthcare application	**Primary function**	**Potential health benefit**	**Potential environmental benefit**
Medical imaging AI	Detection and prioritization	Faster diagnosis	Reduced repeat imaging and workflow waste
Predictive analytics	Risk prediction	Earlier intervention	Reduced avoidable resource utilization

Telemedicine	Remote care	Improved access	Potential reduction in travel
Remote monitoring	Continuous assessment	Early deterioration detection	Reduced unnecessary hospital visits
Supply-chain AI	Demand forecasting	Reduced stock-outs	Lower inventory and transport waste
Predictive maintenance	Equipment management	Improved availability	Longer equipment life
Energy optimization	Building control	Stable clinical environments	Reduced electricity consumption
Disease surveillance	Outbreak prediction	Faster public-health response	Better allocation of emergency resources
Climate-health modelling	Risk forecasting	Improved preparedness	More targeted adaptation measures
Drug discovery AI	Molecular screening	Faster development	Potential reduction in research resource requirements

The greatest chance of sustainability is to leverage AI to transform physical health care processes itself, rather than simply add to the computational power (Rane *et al.*, 2024). An AI system that can decrease the number of unnecessary visits to the hospital can make a more positive impact on the environment than an AI system that increases administrative efficiency, but requires significant computing power.

4.4 CARBON AND ENERGY DIMENSION

Electricity is a fundamental need for AI, as the AI computational systems rely on data centres, which are identified by the IEA. Currently, data centres account for around 180 Mt of indirect CO_2 emissions arising from electricity use, and AI is one of the various workloads of data centres.

TABLE 4. Relative Environmental Performance Framework

Dimension	**Conventional digital health**	**High-compute AI**	**Sustainable AI**
Computational intensity	40	100	45
Energy requirement	45	100	40
Potential clinical benefit	55	90	85
Resource optimization	50	70	90
Climate-health prediction	40	85	85
Lifecycle monitoring	30	35	90
Governance maturity	55	45	90
Overall sustainability potential	55	50	90

These scores are not technology-specific scores, but are analytic scores.

The table illustrates the difference between technology and sustainability (Van Hoang, 2024). A high compute AI model can have a high clinical capability, but still have a low overall score when not taking into account any impacts to energy, water, hardware/Lifecyle.

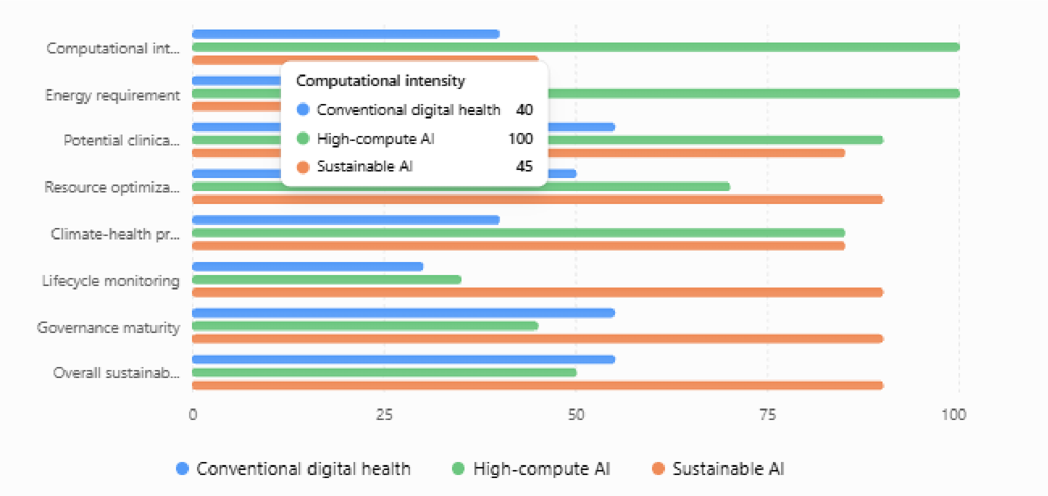

Figure: Relative Environmental Performance Framework

4.5 HEALTH-SYSTEM RESILIENCE

AI can enhance healthcare's ability to thrive in the face of climate-related challenges by complementing the forecasting and resource allocation efforts of the healthcare sector.AI systems can help Health Services better prepare for and react to Climate Change by planning and predicting resource usage (Al-Raeei, 2025). Using heat health prediction can help aid early warning; staffing; emergency preparedness and targeted intervention. Predictions of flood and flood conditions may be used to support Hospital continuity planning and patient evacuation. Monitoring of infectious diseases can be used to incorporate environmental factors that will enable them to detect changing patterns of transmission.

Climate-resilient and environment-friendly health care facilities are one of the priorities of WHO recommendations for achieving universal health coverage.

When combined with current resilience systems, AI can help achieve this goal. However, using digital infrastructure brings new vulnerabilities. AI-driven services can be affected by power outages, telecom disruption, threats from cyberattacks, excessive heat, flooding and data centre outages. Operating processes that are redundant, off-line, local computing resources, and energy security and disaster recovery facilities are thus critical to resilience.

4.6 GOVERNANCE FINDINGS

Governance becomes a key factor in the context of sustainable AI. WHO highlights the need to consider the critical aspects of governance, ethics, regulation, capacity building, safety, and equity when implementing AI systems (Popescu *et al.*, 2024).

The environmental dimension is a create outgrowth of current AI governance. Environmental disclosure shall be included in the procurement standards. Energy uses and life cycle impacts should be reported by the model developers. The effects on the environment must be taken into account before the mass rollout.

In the 2025 Lancet Global Health discussion, the environmental impact of AI is recognized as a poorly developed aspect of AI ethics, and a focus on the heavy energy and natural resource consumption of algorithmic systems.

5. DISCUSSION

5.1 THE CENTRAL PARADOX OF AI-ENABLED SUSTAINABILITY

The evidence shows an inverse relationship between sustainability and profit. AI can be used to simultaneously provide environmental pressure and environmental improvement tools.

The primary source of the environmental burden is associated with the computational infrastructure. Training and deployment requires electricity, cooling, hardware, storage and networking (Balaska *et al.*, 2023). With the proliferation of AI in healthcare, there could be a significant increase in cumulative demand.

Sustainability opportunity introduced by optimization. Healthcare consumes a lot of resources, such as buildings, laboratories, transportation, pharmaceuticals, medical equipment, supply chains, and human resources. AI can detect inefficiencies throughout these systems.

The goal of the policy should not then be to eradicate the use of AI. What we want to do is to maximize the effectiveness of AI to deliver tangible health and environmental outcomes.

5.2 FROM GREEN AI TO SUSTAINABLE HEALTH AI

Overall, Green AI is more about how to reduce the computing power requirements for building and running AI systems. Sustainable Health AI requires a larger scale.

Energy efficiency, water usage, hardware lifecycle, e-waste, carbon intensity, clinical effectiveness, equity, patient safety, cyber security, and governance are all factors that should be included in a sustainable health-AI model.

The difference is crucial as a fast and efficient AI system can generate an overproduction of health care demands (Balaska *et al.*, 2023). If it is not the case, then a system that has more computational processes can yield a net environmental benefit if it does not have a significant number of resource intensive healthcare processes.

There needs to be a lifecycle view, then.

5.3 AI AND RESOURCE EFFICIENCY IN HEALTHCARE

Healthcare resource efficiency is a key aspect of sustainable AI. Hospitals have a number of processes that are uncertain and experience varying demand. The number of patients admitted to hospital, operating room schedules, demand for diagnostic services, demand for pharmacy services, workload in the lab, energy use, and the demand for medical supplies vary from day to day and month to month.

AI can predict demand patterns and make the best use of resources. Predictive maintenance can help to minimize equipment downtime. Utilization can be enhanced with automated scheduling (Naik and Jagtap, 2024). The inventory models can help minimise overstocking and wastage. Energy-management systems can maximize the efficiency of a building's operation.

The environmental benefit will be dependent on implementation. Optimizing through AI may be minimally sustainable unless there is a reduction in underlying consumptions.

5.4 TELEMEDICINE AND DIGITAL CARE

Reducing the amount of emissions generated by transportation can be accomplished when a patient visits a health care provider is replaced with a telemedicine visit. Selected hospital visits can be cut, and intervention can be earlier, through remote monitoring.

However, digital health does not always go hand-in-hand with 'green'. Electronic devices are produced, data is sent, and electronic infrastructure has environmental implications (Rane, 2023). The difference between digital care lifecycle footprint and the physical care footprint which will be replaced by digital care.

5.5 AI FOR CLIMATE-SENSITIVE DISEASES

AI can aid in the forecasting of diseases that are affected by environmental factors. Machine-learning models can incorporate climatic, geographical, vector ecology, demographic, and clinical surveillance data.

These systems can aid in the work of public-health officials in identifying and distributing these to the appropriate areas (Chen *et al.*, 2024). Climate-health intelligence can then facilitate adaptation by moving health systems from reacting to treating toward predicting prevention.

This change is especially pertinent to areas with fast changing temperatures, rainfalls, urbanisation, and disease ecology.

5.6 WATER AND AI

Water utilization should be less the focus in the realm of sustainable AI research. The cooling in the data centre can be direct, and the generation of electricity can be indirect.

The environmental impacts of a computational workload can be different in different regions, due to differences in water scarcity (Martini *et al.*, 2024). Water-stress indicators should therefore also be included in sustainable healthcare AI planning, in addition to carbon intensity.

A range of factors such as data centre location, cooling technology, availability of reclaimed water and seasonality of water conditions should be considered when planning infrastructure.

5.7 ELECTRONIC WASTE AND CIRCULARITY

The evolution of computing infrastructure is a critical foundation for AI. The evolution of computing infrastructure is an important base for AI. The computational requirements are rapidly increasing and may result in a short technological life cycle for high performance processors and/or accelerators.

Circular procurement, by highlighting re-pair ability, modularity, equipment re-use, refurbishment, recycling and extended service life, can help to solve this problem. Healthcare organizations can incorporate lifecycle requirements into the purchase of technologies.

An environmental evaluation should thus go beyond the operational phase to encompass the manufacturing and disposal phases.

5.8 Equity and the Global South

Engaging in equity goals is a responsibility of sustainability policies in global health. Low-income people and the poorest nations face the greatest impacts of climate change but make the fewest contributions to climate change emissions.

There can also be unequal distribution of infrastructure and healthcare technologies driven by AI. There might be differences in availability of computational resources, reliability of electricity, connectivity, skilled staff, data infrastructure, and financing in high-income settings as compared to low-resource settings (Dankwa-Mullan, 2024).

A sustainable AI policy should, therefore, not become one where the more resource intensive technologies are developed in high resource areas and effects occur throughout the world.

5.9 POLICY INTEGRATION

Climate policy, health policy, digital-health policy, AI governance, energy policy and environmental regulation are often created in different institutional frameworks. All of these are crucial to sustainable AI.WHO's climate-health approach is on integrated actions in health, environment, and policy systems; and the WHO's AI approach is on governance, security, equity, and responsible use of AI (Fuentes-Peñailillo *et al.*, 2024). The necessity to take the health and environmental impacts of AI procurement and utilization into account presents a chance for a new regulatory framework.

6. POLICY DIRECTIONS

6.1 MANDATORY ENVIRONMENTAL DISCLOSURE

Energy usage, estimated carbon emissions, computational needs, water-related effects when feasible, hardware needs, and model life cycle attributes should be made public by healthcare AI vendors (Alahi *et al.*, 2023).In addition to the more conventional measures of performance (accuracy, sensitivity, specificity, latency, cost) and environmental information should be provided.

6.2 CARBON-AWARE AI PROCUREMENT

AI infrastructure electricity carbon intensity should be taken into consideration by healthcare institutions. Energy intensity and clear environmental reporting could be considered in the procurement frameworks.

6.3 RENEWABLE ENERGY INTEGRATION

The adoption of low carbon electricity to power AI infrastructure should be accelerated. By procuring renewable energy, operational emissions of healthcare data-intensive applications can be reduced.

6.4 WATER-EFFICIENT COMPUTING

Water efficient cooling systems should be implemented in Healthcare AI data centres and local water stress assessments should be considered. The use of water should be quantified as part of reports of digital-health sustainability.

6.5 MODEL EFFICIENCY

If there are models that offer similar or equivalent clinical effectiveness, then more efficient and smaller ones are preferable (Senoo *et al.*, 2024). Optimized architectures, transfer learning, efficient architectures, selective computation and model compression reduce resource requirements.

6.6 CIRCULAR DIGITAL INFRASTRUCTURE

Healthcare systems should create guidelines for procurement that encourage hardware reuse, repair, refurbishment, hardware recycling and hardware longevity.

6.7 SUSTAINABILITY IMPACT ASSESSMENT

Because AI systems are energy-intensive, energy use, carbon, water, materials, waste, as well as clinical value, equity and resilience are important factors to consider for the sustainability assessment of the system when implemented in a large scale.

6.8 INTERNATIONAL STANDARDS

International organizations, governments, healthcare institutions, tech companies, researchers, and professional bodies need to collaborate to create a common set of environmental metrics for AI in healthcare.

7. PROPOSED INTEGRATED FRAMEWORK

7.1 THE SUSTAINABLE AI FOR HEALTH FRAMEWORK

There are 5 successive steps that can be used to establish an overall framework.

An environmental baseline assessment is the first step, which involves carrying out a baseline assessment of the existing energy, water, carbon, material, transport and waste (Zatsu *et al.*, 2024).The second phase is the clinical and public health value assessment to ascertain whether AI positively affects health outcomes, access, diagnosis, prevention, preparedness, and/or operational efficiency.

The third stage is lifecycle assessment, which assesses environmental effects of hardware production, deployment and disposal.

It is in the fourth phase, Equity and Resilience Assessment, that it is analysed in terms of distribution of benefits, access, vulnerability, dependence on infrastructure and climate resilience. The fifth stage is continuous monitoring; continuous re-evaluation of environment and clinical performance throughout the technology lifecycle.

TABLE 5. Integrated Sustainable Ai–Health Governance Framework

Domain	Core indicator	Measurement priority
Clinical	Patient and population outcomes	High
Energy	kWh per model task	High
Carbon	CO_2e per clinical task	High
Water	Water use per computational workload	High
Materials	Hardware/material intensity	Medium–High
Waste	Electronic waste generation	High
Equity	Access and distribution of benefits	High
Resilience	Performance during climate disruptions	High
Governance	Transparency and accountability	High
Economic	Total lifecycle cost	High

The framework incorporates environmental and healthcare performance, rather than sustainability as a stand-alone technology-management problem.

8. RESEARCH GAPS

8.1 STANDARDIZED ENVIRONMENTAL METRICS

The lack of standardized metrics for measuring the environmental impact of AI in the healthcare industry is one of the greatest challenges to consider (Samuels, 2025). Standardized indicators for energy, carbon, water, materials and electronic waste should be developed in future research.

8.2 LIFECYCLE DATA

Research is frequently limited to the use of operational energy and so, does not consider the whole life cycle. More data are required regarding semiconductor production, infrastructure, replacement of hardware, transportation and disposal.

8.3 CLINICAL–ENVIRONMENTAL NET BENEFIT

Not many studies exist that quantify the benefits to the environment from AI beyond the environmental costs of the AI system. Future studies should account for the environmental benefits on a per clinical pathway basis.

8.4 LOW-RESOURCE SETTINGS

There is a need for research on sustainable AI in situations where the power grid is not dependable, there is limited connectivity, limited computing power, and climate variability. Edge computing and lightweight models could apply to these environments in particular.

8.5 WATER FOOTPRINT

The use of water is not as well-known as the use of electricity and carbon (Szpilko *et al.*, 2023). For research, the regional water stress, cooling technology, electricity generation and geography of data centres should be taken into consideration.

8.6 LONG-TERM HEALTH OUTCOMES

AI sustainability research tends to be about technology's sustainability in the long term, rather than population health sustainability in the long term. To assess the long-term health, environmental and economic impacts of AI interventions, longitudinal studies are necessary.

9. LIMITATIONS

The evidence base is also quite diverse as a result of the geographic location, environmental conditions, methods for measuring, computational workload and scope of the systems being studied. AI is also a dynamic landscape, and it's hard to make accurate predictions about how much compute power and infrastructure are required (Raman *et al.*, 2024).The environmental impacts will be quite different depending on how the electricity is generated, the design of the data centre, the size employed, the data centre's utilization rate, the generation of its hardware, the cooling technologies employed, and geographic location. Generalized environmental estimates are therefore not to be interpreted as values which will be the same for all applications of AI.A quantitative framework and analytical scoring of this review are included for structuring of evidence and support in the future for empirical validation. These scores are not to be seen as scores of individual AI systems on their environmental performance.

10. CONCLUSION

AI and climate sustainability are two interwoven elements of the future of human health. AI has the potential to improve patient diagnosis, disease monitoring, clinical decision making, health system management, resource allocation, climate-health prediction and emergency readiness. In parallel, AI has been increasing the electricity, data centre, water, component production, mineral and electronic waste requirements for the environment.

AI is not a question of adoption, but of designing, evaluating, procuring, powering, deploying and governing AI. Healthcare AI should be measured throughout the lifecycle, from clinical effectiveness, through to energy use, carbon footprint, water usage, materials usage, e-waste, equity, resilience and governance.

There is some existing evidence that supports the traditional AI assessment over the sustainable AI assessment. Assessing the environmental impact of an AI system should be quantifiable and part of the healthcare technology evaluation process. IA should be measurable and be part of the healthcare technology evaluation process. Some steps for reducing environmental footprint include energy-efficient models, renewable electricity, water-efficient data centres, and lifecycle assessment, carbon-aware computing and clear environmental reporting, and circular hardware procurement.

One of the most significant applications of AI is as an enabler in the domain of climate resilient healthcare. Predictive disease surveillance, climate-sensitive risk modelling, energy optimization, supply-chain forecasting, remote care, predictive maintenance and resource allocation can help to improve the efficiency of health systems. It is not just digitalization that should be considered to contribute to the environmental value of these applications, but rather comparative lifecycle assessments must be used.

To secure a sustainable trajectory for the future of AI in healthcare, efforts must be made from a collaborative approach among healthcare organizations, governments, tech developers, researchers, environmental agencies, energy providers, international organizations, and communities. As such, the WHO has policy priorities that emphasise the promotion of environmental sustainability in the health system and its planning and governance, and promoting AI safety, equity, transparency and responsible use and implementation.

So the new research trend is going from AI in healthcare towards AI in sustainable healthcare. This transition needs to be measurable and have a link with efficiency, sustainability, clinical outcomes and population health. The sustainable AI ecosystem can help to enable a digitally capable, climate resilient, resources efficient, equity and environment friendly healthcare system.

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