From Black Box to Balance: A Systematic Review and Framework for Sustainable AI

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By

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Soni Manocha

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List of Abbreviations

AI – Artificial Intelligence

SPAR- Scientific Procedures and Rationales

SDG – Sustainable Development Goal

IEA- International Energy Agency

GPU- Graphics Processing Unit

ICT- Information & communication technologies

GHG- Greenhouse gas

PUE- Power Usage Effectiveness

VOC- Volatile organic compound

SCAIS- Sustainability Criteria and Indicators for Artificial Intelligence Systems

TOC- Theory of Change

EPA- Energy Policy Act

Abstract

Introduction

Artificial Intelligence (AI) has emerged as a transformative and rapidly evolving technology across numerous domains; however, very little scholarly attention has been devoted to its environmental and public health consequences. The training and inference process of AI involves massive amounts of computational power, leading to carbon emissions, water consumption, and air pollution, while electronic waste is produced primarily because of the short lifespan of hardware. These hidden environmental costs have indirect but notable outcomes on public health.

Methods:

A systematic literature review (SLR) and exploratory bibliometric analysis were conducted to synthesise existing evidence on the environmental impacts of AI as well as the frameworks and regulations addressing its sustainability and implications for public health. Data were retrieved from SCOPUS, PubMed and Embase and analysed using VOSviewer to identify research trends, clusters, and knowledge gaps.

Results:

The analysis revealed four key themes: (1) environmental externalities of AI, including energy use, emissions, and e-waste; (2) Regulatory and policy gaps in addressing sustainability; (3) Despite growing discourse on ethical AI, there is limited integration of the environmental dimension in the current AI framework; and (4) Lack of assessment of AI hardware.

1. Introduction

The rapid growth of AI sectors demands sustainable governance and regulatory scrutiny to ensure compliance with international environmental objectives. The expanding computational demands of AI systems contribute significantly to energy consumption and resource exploitation, challenging global sustainability efforts. Moreover, as AI systems develop into larger and more interconnected networks, so must their potential ecological impact. This is a field of research for which there is little published work at present (1).

As artificial intelligence (AI) becomes more entangled with the advancement of technologies, there is also a significant environmental cost to this change. Global carbon dioxide (CO2) emissions in 2022 were 36.8 billion tonnes, according to data from the Global Carbon Project (2023), marking a critical transition point for climate action. Additionally, the carbon emissions and water usage associated with training and running large AI models enclosed within large data centres have substantially increased, indicating the need for a full-scale environmental impact assessment framework ("Summary Report: White Paper on Global Artificial Intelligence Environmental Impact," n.d.). As AI continues to permeate society and various industries, we need to assess the environmental costs of traditional AI systems (2). The environmental consequences of AI-supported healthcare technologies, such as radiological diagnostics, severely impact the planet, without fully understanding their costs and yet once again pointing out the deficit in our knowledge and with urgency (3). Addressing these knowledge gaps requires a paradigm shift in considering environmental factors in all aspects of AI development and application. For the last several decades, environmental sustainability has been one of the most urgent issues globally, primarily driven by escalating climate change, resource depletion and pollution (4).

This study intends to create a catalogue of environmental sustainability indicators that must be taken into consideration before using AI tools and digital technologies across any sector.

2. Background

Artificial intelligence refers to technology capable of performing human cognitive abilities through algorithm development, including learning and problem-solving. It is capable of making predictions, recommendations, or choices to impact real or virtual environments based on a set of human-defined objectives (5). The technology has been developed to perform abilities such as enhancement of diagnosis to population health initiatives, where AI-based methodologies are utilised to assess large amounts of healthcare data, identify disease patterns, and improve resource allocation (6). Digitisation of health care is promoting AI as the next big thing through sustainable models of health care delivery, in particular for telemedicine applications, where individuals travel less by car, reduce time and money, and save CO2 emissions (7).

It has a double-sided nature by having the potential to transform sustainability, and bringing major environmental and financial challenges that cannot be ignored (8). Four hypotheses are tested, which demonstrate that AI-driven resource efficiency and AI-driven environmental monitoring impact sustainability positively, while AI-driven energy consumption negatively impacts sustainability (4). AI systems, especially deep learning, require large amounts of computation when running. This results in very high energy consumption, with consequential large emissions and hardware wastage. The energy consumption also increases further with data storage and cloud computing (9). In 2020, the International Energy Agency (IEA) reported that data centres accounted for about 1% of global electricity consumption, and this will increase with greater demand as AI and digital services continue to develop. In addition to this, these challenges require the gigantic processing power to train and infer, which further leads to an exponential increase in energy consumption by AI data centres (10).

Artificial intelligence is increasingly recognised for its transformative impact on public health, with positive effects by ensuring disease surveillance to optimisation of clinical workflows. The use of machine learning and data analytics has led to the early detection of infectious outbreaks and to accelerated epidemiological investigations to aid public health authorities in initiating rapid responses to new threats (11). AI-based systems also help optimise healthcare resources to facilitate patient management, infection control, and preventive measures, contributing to improved health outcomes (12). In the area of environmental health, for example, machine learning models can combine large databases to understand links between pollution exposure and health events, thus helping improve the risk prediction process and enhance intervention-oriented toward vulnerable groups (13).

As AI applications continue to evolve, important new sustainability challenges have arisen. Training and deploying complex models in AI requires significant computational power, contributing to increased greenhouse gas emissions and resource consumption (14). This is especially challenging in healthcare contexts where the substantial technical and performance expectations of AI applications often force sustainability into the quiet corners. The entire AI lifecycle, from sourcing raw materials for hardware production until the disposal of electronic waste, presents additional hazards that may exacerbate public health burdens, especially in settings that rely on fossil fuels for energy to support data centres. (15).

Most AI policy guidelines emphasise ethical and social issues; however, they overlook environmental externalities. This omission may result in continuing the environmental harms associated with AI technologies and raises questions about intergenerational justice and planetary health (1). Thus, principles of sustainable development should be integrated into the design and use of AI to ensure that advances in health technology do not come at the expense of planetary health, thereby balancing immediate and long-term well-being (9).

With this backdrop, the objective of this study is to systematically review and synthesise the body of knowledge on the relationship between artificial intelligence (AI) and sustainability, with a particular focus on environmental and public health implications. This review is structured around the following research questions (RQs):

RQ1. What are the environmental impacts associated with the deployment of artificial intelligence as reported in existing literature?

RQ2. How do AI's environmental consequences affect public health outcomes?

RQ3. Which measurable indicators or frameworks have been proposed to assess the sustainability of AI systems?

RQ4. What are the emerging research directions and gaps in AI sustainability?

These research questions provide the analytical foundation for both the bibliometric mapping and thematic synthesis, ensuring that the findings directly contribute to understanding the environmental consequences of AI and pathways toward sustainable adoption.

3. Methodology

This study utilised a systematic literature review (SLR) along with exploratory bibliometric analysis to investigate research situated at the nexus of Artificial Intelligence (AI), environmental sustainability, and public health. This integrated approach of SLR and exploratory bibliometric analysis supported both conceptual rigour through qualitative synthesis of thematic findings and analytical depth, by mapping the intellectual structure, trends and leading scholars in this emerging field of study. In order to facilitate rigour, transparency and replicability, the review was undertaken with the SPAR-4-SLR framework (Paul et al., 2021), which provides a structured framework for conducting evidence-based literature reviews.

It is organised into three chronological stages—assembling, arranging, and assessing, with the purpose of improving the accuracy and comprehensiveness of the systematic review process. In the stage of assembling, appropriate research questions were formed, and relevant sources of data were identified. The identification stage of the process concentrates strictly on the area of AI and environmental sustainability, and is framed by the research question in regard to relevant literature that searches environmental impacts associated with the implementation of artificial intelligence technologies and AI related environmental impacts affecting public health outcomes and exploration of measurable environmental indicators or frameworks reported in the literature to assess the sustainability of AI systems from the peer reviewed journal.

The acquisition sub-stage involved a systematic search using a Boolean strategy on PubMed, Scopus, and Embase, targeting articles published between 2010 and 2025. The search keywords included combinations of terms such as “artificial intelligence”, “machine learning”, “environmental sustainability”, “carbon footprint”, “climate change”, and “public health” applied to article titles, abstracts, and keywords. The initial search query returned 1867 articles. The arranging stage then focused on duplication removal and systematically screening and organising the literature using Rayyan software to ensure a rigorous and structured dataset.

In the second stage, the organising sub-stage, selected articles were categorised based on metadata such as title, journal, author, country of affiliation, keywords, and citation count to ensure a structured analytical framework. The purification sub-stage used strict exclusion criteria by omitting non-article formats, publications in a language other than English, journals with an impact factor below 1, and studies focusing on topics like AI hardware or investigating

AI's effects on public health or data centres without an environmental sustainability focus. After this process, 100 relevant articles were identified, with each being appropriately aligned with the research questions and addressing aspects of the sustainability trade-offs in relation to AI. The decision to include conference proceedings was deliberate and firm to provide coverage of the intersection of AI's environmental impact and public health outcomes, to document new contributions and evidence of a newly emerging area of investigation within this largely unsystematically covered domain of literature.

In order to make the dataset comprehensive and to minimise bias in the database, multiple bibliographic sources were used to collect articlesIn the Assessing stage, an exploratory bibliometric approach, which is notably useful to explore a less mature domain that has been less researched (Aria & Cuccurullo, 2017; Donthu et al., 2021), , was performed on 100 articles that help to identify the emerging themes, while visualising the conceptual structure on sustainability issues in the deployment of AI technologies. The exploratory bibliometric analysis was conducted using VOSviewer software, with the data retrieved using CrossRef DOIs, which has been purposely chosen for being an open-access database with broad multidisciplinary coverage (van Eck & Waltman, 2017; Hendricks et al., 2020). This methodological decision aligns with emerging bibliometrics research that indicates that the multi-database integration method provides the benefit of reviewing broader literature, and helps to establish the reliability of network analysis (Donthu et al., 2021; van Eck & Waltman, 2017).

Utilising the dataset developed in the previous stage, multiple analytical approaches were used to establish the structure and dynamics of the research field. To clarify, co-citation analysis was used to establish the journals, authors, and references that have been most effective in impacting the field, co-authorship analysis to identify adherence behaviours among researchers and institutions & co-occurrence analysis to determine key themes and locations of keywords as a potential cluster. Based on the analysis performed, a systematic review was conducted by choosing 48 of the articles that were most pertinent to answer the research questions shown in Table 1. This two-step approach helped in analysing the overall depth in synthesising the significant evidence.

4. Exploratory Bibliometric Overview of the Database

The further sections show the bibliometric overview, including "citation," "co-authorship and "co-occurrence". It highlights the thematic structure by providing influential authors and journals, the pattern of research collaboration at the institutional level, and mapping the frequently used keywords.

4.1 Citation analysis

4.1.1 Citations of Sources

Among the 100 documents included in the bibliometric analysis, Figure 1 visualises the source density. Table 2 lists the ten most-cited journals and conference proceedings, along with their total citations, based on a minimum document threshold of two. The Lancet Planetary Health, despite having only two documents, received the highest number of citations (733), indicating its strong influence in the field. Journals like the International Journal of Environmental Research and Public Health and the Journal of Cleaner Production also show significant citation impact. The total link strength suggests varying degrees of connectivity, with the Journal of Medical Internet Research showing the highest network linkage despite a lower citation count. Overall, these sources represent the core literature shaping research in the analysed domain.

Table 2. Top 10 Most-Cited Sources

Source	Documents	Citations	Total Link Strength
The Lancet Planetary Health	2	733	3
International Journal of Environmental Research and Public Health	7	340	3
Journal of Cleaner Production	2	284	0
Journal of the American Medical Informatics Association	3	112	4
NPJ Digital Medicine	2	95	3
Journal of Clinical Medicine	2	63	0
International Journal of Technology Assessment in Health Care	2	62	2
Frontiers in Public Health	2	41	1
Studies in Health Technology and Informatics	2	9	2
Journal of Medical Internet Research	2	2	8

***Source**: Authors' compilation*

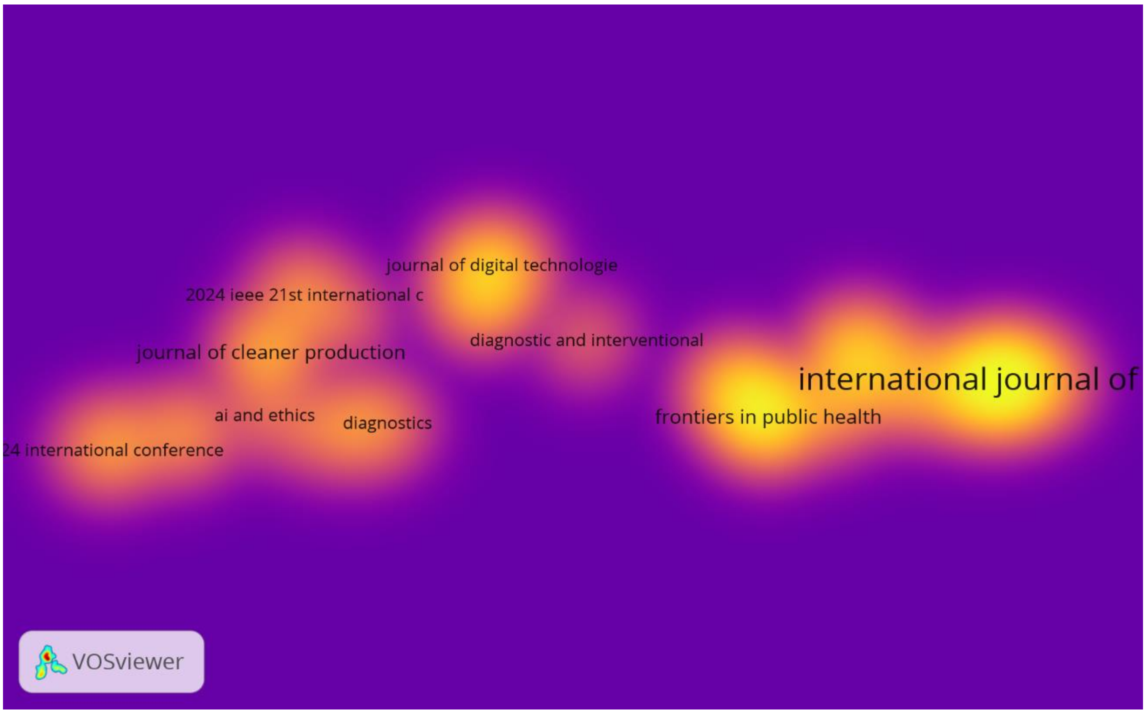


Figure 1. Density visualisation of sources ***Source:** Authors' compilation*

4.1.2 **Citation of documents**

Figure 4 presents the citation visualisation of the 120 articles analysed. Of these, 48 documents have a minimum of 20 citations. Table 4 lists the 20 most-cited documents. Lenzen (2020) ranks first with 663 citations, followed by Van Wynsberghe (2021) with 541 citations (see Table 4 and Figure 4) emerge as the most influential works in the dataset, reflecting high impact in the field. Most of the top-cited papers are recent (2020–2024), indicating a rapidly evolving research landscape. Link counts suggest variable degrees of co-citation or network connectivity, with several papers showing strong links, reflecting collaborations or shared thematic relevance of AI and environmental sustainability issues.

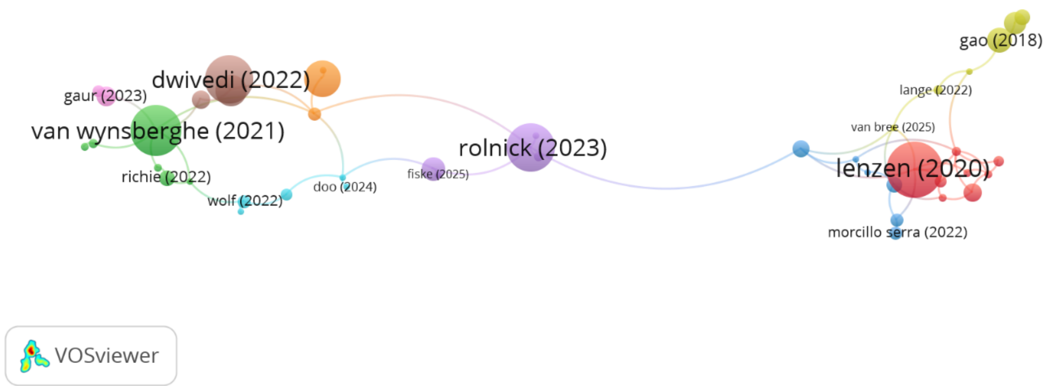
Table 2. **Top 20 Most-Cited Documents**

S. No.	Document	Citations	Links
1	Lenzen (2020)	663	0
2	Van wynsberghe (2021)	541	2
3	Rolnick (2023)	493	1
4	Dwivedi (2022)	487	1
5	Yao (2022)	307	0
6	Galaz (2021)	290	0
7	Fang (2023)	272	0
8	Kar (2022)	208	2
9	Ebi (2006)	202	1
10	Gao (2018)	130	1
11	Rodríguez-jiménez (2023)	122	0
12	Bolón-canedo (2024)	120	1
13	M. bublitz (2019)	119	0
14	Fox (2019)	109	1
15	Xiang (2022)	99	0

16	Gaur (2023)	80	1
17	Wang (2024)	78	0
18	Alzoubi (2024)	76	2
19	McALister (2022)	70	0
20	Bush (2011)	69	1

Source: *Authors' compilation*

Figure 2. Citation visualisation of documents



Source*: Authors' compilation*

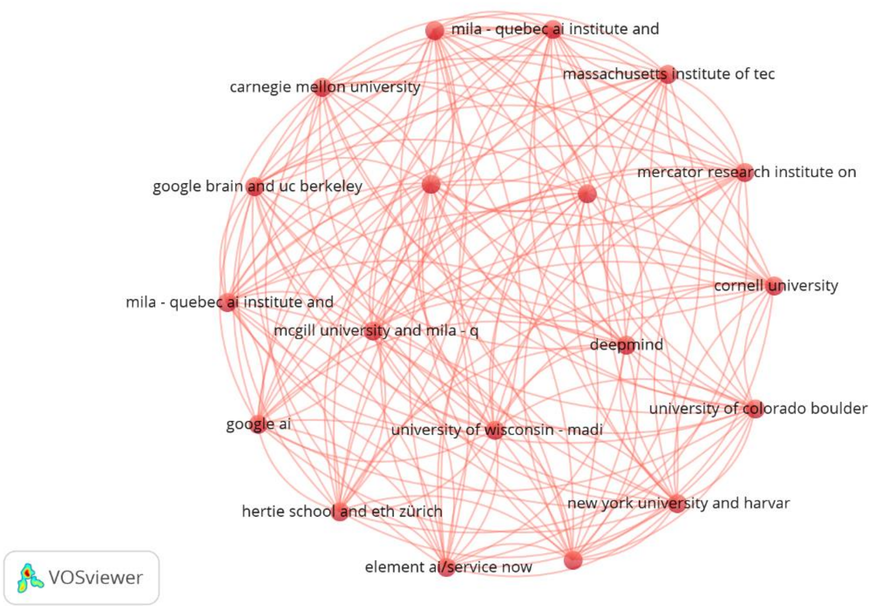
4.2 Co-authorship analysis

4.2.1 Co-authorship of affiliations

Of the 169 affiliations of the authors, 112 have a minimum of 10 citations, and only 36 associations have 100 or more citations.

Figure 3 presents a co-authorship map of the affiliations with at least 1 citation. The affiliations in the network map belong to a single cluster (red), which means that the related affiliations have worked on similar topics within AI and sustainability.

Figure 3: Co-authorship network map of affiliations



Source: *Authors' compilation*

4.3 Keyword Co-occurrence Analysis

Table 3 presents the keyword occurrence analysis outcomes generated through bibliometric analysis in VOSviewer, illustrating six clusters of related keywords along with their occurrence frequency and total link strength. The clusters are determined by two quantitative measures: link strength, which refers to the total number of co-occurrences a keyword shares with others and provides insight into its network connectivity and thematic relevance within the group; and occurrence, which measures the frequency of a keyword, indicating prevailing research directions.

The most frequently occurring terms in this analysis are “artificial intelligence,” “environmental impact,” “technology,” and “sustainability,” highlighting strong linkages and intellectual cohesion within the research domain. Cluster size was further assessed by the number of keywords, as larger clusters with denser internal linkages typically represent well-developed and mature areas of research.

Figure 4 depicts the co-occurrence network map of key terms, where node size represents keyword frequency and connecting lines demonstrate the strength of associations between keywords.

Table 3. Keywords’ occurrences

Cluster 1 (11 items)	**Link**	**Total link Strength**	**Occurrence**
AI system	20	27	4
Challenge	32	58	8
Deep learning model	14	17	3
Efficiency	28	53	7
Energy Consumption	30	49	7
Environment	31	80	11
Environmental impact	31	79	13
Green artificial intelligence	19	23	4
Process	15	20	4
Research	33	79	10
Strategy	30	52	9
Cluster 2 (11 items)			
Carbon emission	19	35	7
Data	14	19	4
Electronic waste	13	19	3
Health	30	67	9

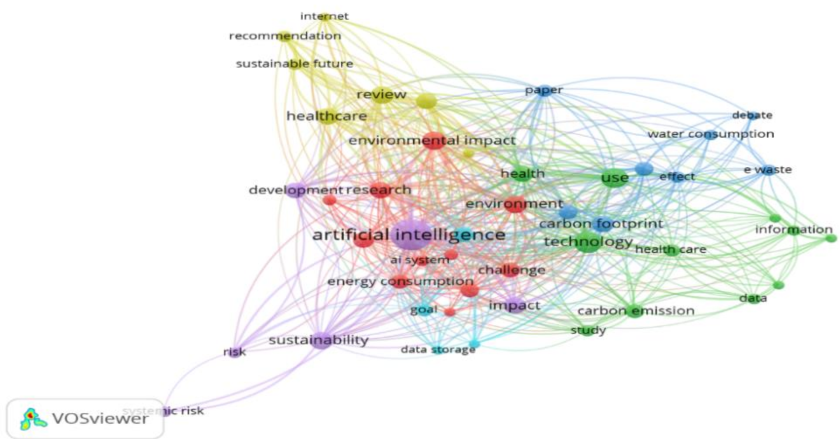
Healthcare	21	31	6
Health technology assessment	11	15	3
Information	14	23	4
Production	9	17	3
Study	17	28	5
Technology	39	123	17
Use	35	105	15
Cluster 3 (8 Items)			
Carbon footprint	33	66	10
Debate	9	18	3
E-waste	17	30	5
Effect	23	37	5
Energy	23	50	7
Environmental sustainability	30	44	7
Paper	26	53	6
Water consumption	17	26	4
Cluster 4 (7 Items)			
Climate change	28	55	9
Field	18	20	3
Healthcare	24	74	10
Internet	14	28	3
Recommendation	12	28	5
Review	31	84	11
Sustainable future	15	31	5
Cluster 5 (6 Items)			
Artificial intelligence	44	217	37
Development	25	60	9
Impact	31	60	10

Risk	11	23	4
Sustainability	31	54	11
Systemic risk	3	9	4
Cluster 6(4 Items)			
Application	24	52	8
Data storage	13	21	3
Goal	25	39	6
Relationship	16	24	3
Total	**524**	**1111**	**47 items**

Source: *Authors' compilation*

Figure 4 shows the co-occurrence map of key terms. The node size shows the occurrence of keywords, and lines demonstrate the connections between the keywords.

Figure 4. Network analysis of major themes



Source*: Author's compilation*

Based on the findings of the bibliometric analysis, considering citation counts, network linkages, keyword co-occurrence clusters, and institutional and author-level influence, an evidence-informed approach was used to select 48 highly relevant articles, grouped into six thematic clusters. These 48 relevant articles formed the foundation for a focused systematic literature review (SLR).

This structured approach, shown in Figure 5.

Figure 5. The methodology of reviewing data on Systematic reviews on AI, Environmental Sustainability & Public Health using the SPAR-4-SLR protocol

Assembling

Identification

Domain: Artificial intelligence, environment
Research question: RQ1. What are the environmental impacts associated with the deployment of artificial intelligence as reported in existing literature?
RQ2. How do AI environmental consequences affect public health outcomes?
RQ3. Which measurable indicators or frameworks have been proposed to assess the sustainability of AI systems?
RQ4. What are the emerging research directions and gaps in AI sustainability?
Source quality: Only peer-reviewed journal articles and reputable conference proceedings directly addressing AI, sustainability, or related environmental and public health impacts
Source: Scopus, PubMed, Embase

Acquisition

Search material and acquisition: PubMed, Scopus, Embase, hand-searching, cross-referencing
Search period: January 2010 to August 2025
Search keywords/strings: ("artificial intelligence"[Title/Abstract] OR "ai"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning AND ("environment sustainability"[Title/Abstract] OR "carbon footprint"[Title/Abstract] OR "carbon emission"[Title/Abstract] OR "climate change"[Title/Abstract]" AND ("public health"[Title/Abstract]
Search results: 1867

Arranging

Organization

Organizing codes: In this study, descriptive codes based on their source database, year of publication, and type of publication (journal article, conference proceeding, or report) is organised for systematic arrangement of the literature &facilitated exploratory bibliometric analysis and ensured comparability across studies.

Purification

Duplicate removed: 56 through Rayyan software
Title/abstract screening → 278
Applied inclusion criteria - must directly address AI + sustainability, written in the English language
Exclusion criteria- Impact factor <1
Full-text screening(n) → 100 relevant papers.
Publication stage: Final
Language: English

Assessing

Evaluation

Analysis method: Exploratory Bibliometric followed by SLR on 48 articles
Quality appraisal using Exploratory Bibliometric analysis: Co-authorship, Co-occurrence, citation analysis
Agenda Proposal Method: Thematic Analysis

Reporting

Reporting conventions: Tables, Figures
Limitations: Database and Indexing Bias:
Despite using multiple sources, some relevant studies may have been missed due to indexing gaps of the research field.

Source: *Authors' compilation*

5. Key Findings

To answer the research questions, insights from the bibliometric cluster analysis were integrated with the findings of the systematic review.

Cluster 1: Environmental Impact of AI: Carbon emission, water and energy consumption, and E-waste (RQ1)

Cluster 1 emerged as a dominant thematic cluster encompassing keywords such as AI system, environmental impact, energy consumption, green artificial intelligence, and efficiency. The cluster reflects the scholarly focus on understanding and mitigating the ecological and resource demands stemming from the lifecycle of AI technologies. A substantial body of research addresses the high energy consumption of AI training and deployment, particularly with compute-intensive deep learning models (9). Research also stresses a pressing need for green AI strategies which seek to reduce carbon emissions while retaining or improving model performance (2). The challenge is in assessing environmental impacts accurately because of the complexity in energy sourcing, hardware production, and system operation (16). The literature shows that many AI technologies have significant environmental impacts, including carbon emissions, water and energy consumption, and e-waste.

During training and inference phases, the energy demands of AI produce considerable carbon emissions. For instance, large-scale models such as deep learning-based language models utilise considerable computing power, resulting in greater electricity demands and GHG emissions. Estimates suggest that training a single large language model produces emissions equivalent to 300,000 kg of CO_2, an alarming figure that illustrates the environmental burden of AI (17). This is amplified in health AI applications where a complex model is performed on health datasets, such as for radiology or to assist in diagnosis, which not only requires significant amounts of computational power, but also puts pressure on data centres and energy infrastructures as a function of the energy required (14).

As the architecture of AI models becomes more complex, the amount of energy they consume grows exponentially. Data centres serve as the physical foundation for AI compute, but are themselves substantial sources of carbon emissions due to their high electricity requirements. Their energy usage is comparable to the annual consumption of small countries (9). To counteract the heat generated by hardware, data centre cooling systems require water, imposing risks on local ecosystems, especially in water-scarce regions where their operations can compete with domestic and agricultural water needs. Moreover, this water usage is significant and geographically uneven, with some small data centres in developed countries consuming water volumes thousands of times greater than individuals living in less developed regions (17). However, strategic placement of data centres in cooler climates can lessen cooling needs, aligning infrastructure design with environmental sustainability goals (2) . Such disparities highlight environmental injustices tied to AI infrastructure. As AI requires more power, many energy grids that depend on fossil fuels face increased load and delays in decarbonization efforts, which poses a negative feedback mechanism (15). Therefore, though AI can be advantageous for advancing energy efficiency in other areas, it paradoxically contributes to higher overall energy demand and emissions.

This phenomenon has been documented in several case studies, reinforcing that a significant proportion of worldwide carbon emissions is driven by data centres and AI compute platforms.

AI's carbon emissions extend beyond operational energy use. It encompasses its hardware, including raw material extraction for the manufacturing of GPU (graphics processing unit) chips and their eventual disposal. These components are heavily dependent on the extraction of specialised materials, including rare earth elements such as neodymium, tantalum, and cobalt, alongside various metals and plastics, all of which can contaminate local water sources. Mining and refining these materials may jeopardise the natural ecosystems, including wildlife habitat destruction, chemical pollution, and heavy energy consumption (18). These supply chains emit considerable GHGs and contribute to resource depletion, laying an often-unseen foundation for AI's environmental costs. Additionally, large-scale AI installations may also impact animal navigation systems and breeding patterns through their electromagnetic emissions (19).

Owing to advances in technology, these electronic devices have exploded across the globe and become an enormous environmental concern called e-waste (20). It is estimated that by 2025, there will be 42 billion IoT devices, with carbon emissions and electronic waste (e-waste) contributing to the growing challenges for e-waste in information & communication technologies (ICT) (21). The underlying challenge with AI hardware lies in its composition of non-biodegradable materials. Many superabsorbent polymers and electronic elements are often non-biodegradable and non-biocompatible (22). These discarded components show potential harm to ecosystems and human health through leaching heavy metals and persistent pollutants when handled improperly (3).

Lifecycle assessment (LCA) methodologies have been employed to quantify such impacts, yet their application to AI systems is nascent and requires refinement. Comprehensive LCAs incorporate the embodied carbon emissions across their manufacturing, transport, and disposal stages, illustrating the totality of AI's hidden carbon footprint (22). his has led to examples where operating and training AI systems sometimes emit carbon as much as other heavy industrial processes. A lifecycle methodology is, therefore, essential in advancing sustainability across the AI ecosystem (23). These findings address Research Question 1 (RQ1) on the environmental impacts of AI, forming a critical evidence base for guiding sustainable AI development.

Analysis of Cluster 2: Intersection of AI environmental impacts and public health systems

Cluster 2 has a focus on carbon emissions, health, healthcare, electronic waste, and health technology assessment, constituting a specialised subfield at the intersection of AI environmental impacts and public health systems. Specifically, researchers within this cluster study the carbon footprint associated with running AI applications in healthcare contexts, including the energy intensity of medical AI tools and their ecological footprints across the product lifecycle (18). The cluster also comprises research on the electronic waste and associated toxicities produced due to hardware obsolescence, and environmental risks associated with informal electronic waste recycling (24). The entire lifecycle of AI, from manufacturing, transport to disposal, has the potential to result in emissions of criterion air pollutants, e.g., fine particulate matter (PM 2.5), nitrogen oxides (NOx), carbon monoxide (CO), and volatile organic compounds (VOCs). Evidence indicates that these pollutants are found in higher concentrations near large data centres and semiconductor manufacturing facilities, contributing to poor air quality specifically within those regions. Further, pollutant outputs from AI infrastructures are equivalent to, and often greater than, other major industrial sectors, raising serious concerns about environmental justice and public health, especially for nearby communities (15) (25) (26).

Additionally, emissions of pollutants and e-waste exposures related to AI have been empirically associated with higher rates of respiratory and cardiovascular diseases in communities. Higher rates of asthma, chronic bronchitis, arrhythmias, and heart failure demonstrate spatial correlation in relation to clusters of data centres and locations of informal e-waste recycling. The elderly, children, and people from low-SES households have even greater risk and vulnerability due to physiological and social factors.

There are also regional inequalities, with some locations experiencing far greater health burdens related to AI pollution, indicating an urgent need for more focused interventions and allocation of resources to alleviate the situation (15) (27) (28). E-waste substances such as lead, cadmium, and brominated flame retardants are potent neurotoxicants, and the literature from informal recycling communities reveals associations between heavy metal body burdens and cognitive impairments, hormonal imbalances, and other neurodevelopmental disorders in exposed individuals. Chronic exposures further increase the risk of cancers and systemic toxicity, and these effects are often challenging to establish a clear causal attribution, due to limited or conflicting data and methodological challenges. Therefore, increasing trends of pollution-related respiratory, cardiovascular, and neurological diseases increase the demand for services in both primary and specialised care. The health systems are expected to manage greater patient volumes for chronic conditions, acute care, and rehabilitation. This creates further pressure on limited health care personnel, health infrastructure, and budgets, particularly in resource-constrained countries. Economically, there will be higher treatment costs associated with a growing burden of possible lost productivity and more disability-adjusted life years, highlighting the need for a systemic response to these emerging burdens associated with AI-driven environmental health risks (15) (50).

.The presented health effects demonstrate the need for improved e-waste management processes and continued studies focused on long-term health risks associated with pollutants produced by AI waste (29) (30).

Moreover, studies in the area of health system sustainability emphasise the need to incorporate comprehensive environmental metrics into health technology assessments in order to optimise decision-making (31).

Although vigorous academic discussions are underway in Cluster 2, the extent of exploration regarding healthcare-specific environmental challenges is moderate (18). While linkages among technology, use, and healthcare are strong, they have led to the formation of some very highly linked hubs, but in terms of the number of occurrences, there is still room for further exploration using metrics that concern lifecycles and systemic environmental impacts within health infrastructures (32). In addition, the necessity of extending health technology assessments to fully reflect environmental dimensions, including e-waste and carbon emissions, also poses critical tasks to be addressed (33).

This cluster sets the stage for RQ2, which looks at how AI-related environmental consequences affect public health outcomes (17). It also contributes empirical evidence to RQ1 by documenting carbon emissions as a critical component in AI's environmental impacts (14). Additionally, the cluster highlights sector-specific research gaps, thereby shaping RQ4's inquiry into emerging challenges and unexplored domains, especially within the healthcare industry (34).

Analysis of Cluster 3: **Ecological costs arising from AI**

Cluster 3 encompasses themes such as carbon footprint, e-waste, water consumption, and debates about environmental sustainability. The cluster reflects sophisticated discussions on ecological costs arising from AI computational processing, including both direct emissions and indirect environmental trade-offs (19). It also engages with broader discussions about sustainability practices that involve concepts such as Jevons' paradox and rebound effects, which caution that efficiency gains may paradoxically escalate overall energy use (35). Emerging concerns centred on water consumption during AI operations and the environmental burden of electronic waste further enrich this discourse, underscoring the complexity of environmental sustainability assessments (36).

The status of research in Cluster 3 is positioned as moderately active, but fragmented, characterised by a dialogue that has not yet fully coalesced into standardised sustainability metrics (3). The literature reveals an urgent need for indicators that integrate diverse environmental resources and integrate lifecycle thinking. (23). Water consumption and circular-economy concepts are relatively less developed topics, thus providing opportunities for further work (37).

Cluster 3 aligns closely with RQ1 through offering critical viewpoints on measurement challenges and environmental impact evaluations in the AI domain (19). It identifies shortcomings in indicators that account for resource consumption beyond carbon emissions, supporting RQ3's focus on sustainability frameworks (38).

Analysis of Cluster 4: **AI within broader environmental health and policy contexts**

Cluster 4 integrates climate change, healthcare, review papers, and sustainable future perspectives, thus situating AI within broader social, ecological, and policy contexts. This cluster looks into how AI can mitigate climate change in healthcare, such as optimising energy use and enhancing environmental resilience in clinical settings (14). Notably, the cluster highlights future-oriented discourse emphasising the integration of AI technologies into climate strategies while maintaining healthcare priorities consistent with sustainable development principles (32).

Research in Cluster 4 exhibits a well-developed yet evolving interdisciplinary focus. High keyword occurrence within this cluster indicates growing scholarly attention; however, the intersection of AI, environmental health, and climate science calls for deeper interdisciplinary collaboration (16). The corpus includes evaluative reviews that synthesise sustainable AI development trajectories and recommend policy measures aligned with planetary health objectives (16). In recent years, there have been substantial advances in the creation and evaluation of frameworks addressing environmental sustainability in artificial intelligence (AI). The systematic framework, developed by Rohde and colleagues, is a noteworthy example, given that it describes 19 sustainability criteria and 67 indicators, in an interdisciplinary approach, to allow a comprehensive and organised framework for considering AI systems' environmental consequences (39). In practice, national agencies in countries like Denmark, Ireland, and the Netherlands are starting to identify and make available granular data on the environmental impact of AI-specific information and communication technology (ICT) infrastructure, while private-sector environmental, social, and governance (ESG) reporting has also gained traction, albeit often on a voluntary basis (40). New integrative frameworks now emphasise linking ESG disclosure with responsible AI (RAI) policies to improve transparency and to foster sustainable leadership among corporations (41).

China has the most consolidated international efforts and is dedicated to energy management and national security, but there are no detailed standards even regarding the energy efficiency and environmental impacts of AI data centres (40). The European Union is progressing toward more comprehensive regulatory options with legislation such as the Energy Efficiency Directive and the AI Act, and the expansion of the Eco-design Directive to cover AI hardware; nonetheless, timelines and enforcement have somewhat hampered effectiveness (19). The United States primarily relies on the private sector and voluntary guidance, with limited federal regulation at the national level (40). Other countries, such as India, are beginning to convene discussions on the role of AI as an environmental policy matter, though the bigger questions of policy frameworks remain absent (3).

All regions and sectors still have major gaps. Current measurement frameworks are still incomplete and lack a common standard for tracking the overall environmental sustainability impacts of AI. Widely used metrics such as Power Usage Effectiveness (PUE) are insufficient for capturing lifecycle emissions or the upstream and downstream effects of AI infrastructure (10). The majority of research and policy initiatives focus on operational carbon emissions or energy consumption of AI and overlook broader environmental impacts, especially e-waste implications, biodiversity issues, and natural resources (42). Disparities exist within countries at the regional level, especially visible in large economies like China, where differences in AI development and carbon impacts are evident among various regions (43). Weak regulatory enforcement, inconsistent voluntary disclosures, and the absence of transparent, comprehensive data impede global comparisons and progress. Most frameworks do not account for the entire lifecycle of AI systems and fail to consider direct trade-off analyses between technological advances with respect to risks to the environment and sustainability, thereby limiting utility in achieving integrated goals and solutions (35) (44).

There is a significant opportunity to enhance the translation of this knowledge into actionable policy frameworks and operational recommendations, indicating some key areas for future research (17). Additionally, tools to integrate research findings into practice remain limited (38).

Cluster 4 primarily contributes to RQ4 by identifying gaps in sustainable future planning and encouraging research at the nexus of AI, climate change, and health (17). Moreover, this cluster supports RQ3 through reviews that reflect the need for sustainability indicators and evaluation frameworks for AI (16).

Analysis of Cluster 5: **AI's environmental implications**

Dealing with subjects that include artificial intelligence, development, impact, risk of applications, sustainability, and systemic hazards, Cluster 5 provides an overall survey of AI's possible environmental consequences, including its potential dangers and challenges. The majority of studies here are focused on analysing environmental sustainability trade-offs implied by AI system development and deployment

(35). It also looks at systemic risks, addressing AI as a double-edged sword that, on the one hand, can help achieve environmental sustainability and, on the other, introduces new vulnerabilities (45). These effects of Artificial Intelligence (AI) vary considerably between developed and developing countries and are closely associated with energy infrastructure and data centre locations. Developed countries host energy-intensive AI infrastructures that are historically powered by fossil fuels, resulting in these locations having the highest carbon footprints. For instance, demand for electricity from all new AI servers deployed during a single year could potentially equal that of annual energy consumption in countries like Argentina or the Netherlands, with contrasting environmental consequences depending on regional energy mixes (17).

Conversely, developing nations may experience reduced direct AI carbon emissions due to lower infrastructure concentrations, yet they may face greater ramifications associated with environmental injustices. These disparities also exist with regard to the use of water and energy resources associated with AI and the offshoring of environmentally adverse extraction activities associated with hardware production (43). This unequal distribution of burdens and benefits raises significant concerns regarding climate justice and equitable technology deployment, necessitating policies that address these imbalances to prevent widening systemic inequalities (22)

Certain populations bear disproportionate health and environmental risks from AI's ecological footprint. Vulnerable groups, including marginalised communities and low-income populations, often face increased exposure to air pollution, water scarcity, and contaminated e-waste sites associated with AI-related activities (15). These exposures exacerbate pre-existing health and social inequities, underscoring the intersection of technological and societal vulnerabilities (46).

As the largest cluster by occurrence, Cluster 5 reflects the emphasis in academic research on AI development life-cycles and their associated sustainability (47). However, an isolated placement of keywords like systemic risk and sustainability suggests that these topics remain underexplored. This presents an opportunity to expand research (44). Additionally, existing sustainability trade-off analyses often lack thorough empirical validation, indicating an essential research frontier (16).

The cluster informs RQ1 by providing further details of how the AI development phases affect environmental implications (35). It substantially supports RQ4 by highlighting the current inadequacies in risk governance mechanisms and advocating for comprehensive sustainability assessments (48). Furthermore, it contributes to RQ3 through discussions of frameworks that integrate sustainability and risk mitigation within AI systems (1).

***Analysis of Cluster 6:* AI deployment**

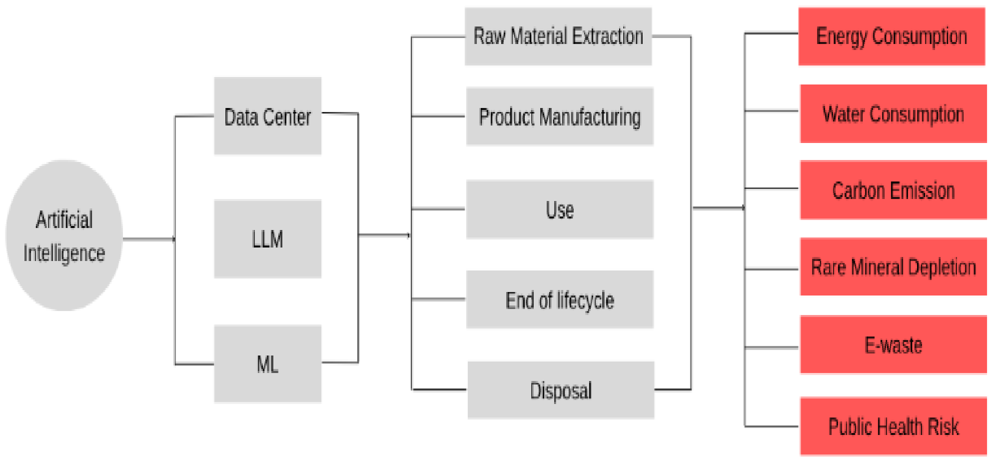
Cluster 6 addresses emerging themes focused on AI applications, data storage infrastructure, and goal-oriented sustainability research. It investigates how AI deployment can be strategically oriented toward defined sustainability objectives, encompassing optimisation of data processing and storage to mitigate environmental impacts (49). This cluster's literature explores the environmental effects of data centres and cloud computing, emphasising the importance of energy-efficient design and operation (40). Additionally, discussions here revolve around aligning AI development with planetary health and global sustainability goals (50).

As the smallest cluster in terms of keyword occurrence and linkage, Cluster 6 signifies an incipient research niche with substantial potential (51). The relative scarcity of publications suggests that sustainability in AI applications and data infrastructure remains ripe for exploration, with a particular opportunity to develop standardised evaluation and monitoring frameworks (10).

This emerging domain substantially informs RQ3 by offering insights into sustainability indicator development tailored to AI infrastructure assessment (10). It impacts RQ4 by defining novel research agendas aimed at integrating AI's practical applications with overarching sustainability objectives (49).

To synthesise the findings from the SLR, a visual summary has been developed (Refer to Figure 6)

Figure 6. AI system and environmental sustainability: SLR Insights



Source: *Authors' compilation*

6. Discussion

6.1 Emerging research directions and gaps in AI sustainability

Current studies tend to isolate carbon emissions without integrating multiple sustainability indicators, such as ecological footprint and energy transition measures. There is an absence of research into multi-dimensional and multi-criteria evaluation of sustainability, while simultaneously taking into consideration emission, ecological impact, circular economy, and energy system transformations, such as measures to transition from fossil fuel-based energy systems to renewable energy systems, both at regional levels and global levels. Filling the gap will facilitate a more accurate way to measure the true contribution of AI technology's trade-offs. Future research must leverage multi-dimensional frameworks to capture AI's environmental footprint holistically, while expanding geographical scope beyond the dominant country-focused studies to global and diverse regional contexts (47) (42).

6.1.1 Regulatory and Policy Gaps

A central issue connected to AI sustainability research and governance is the absence of standardised terminology, metrics, and reporting frameworks to accurately measure and communicate AI's environmental impacts. Currently, there is no universally accepted set of indicators to quantify the ecological footprint of AI compute processes and applications. This negatively affects our ability to benchmark, develop policies, and industry responsibility to mitigate the sustainability of AI performance.

Industries in the U.S., EU, and China play a key role in implementing regulations, aligning with laws like the EU AI Act and China's Energy Conservation Law to ensure energy efficiency and sustainability in data centres [47]. They also play a significant role in developing innovations for clean energy use and emissions reductions. The U.S. lacks a comprehensive federal framework for AI infrastructure and data centres, leaving gaps in specific standards for development and ethical AI deployment. While laws like the Energy Policy Act of 2005 reference guidelines for energy use, there is no strict reference for the specifics of energy used by data centres. China is concerned with the security and control aspects of its AI plan, but lacks ethical and energy efficiency-related standards of practice, especially with data centres [51]. In the EU, legislation like the Energy Efficiency Directive and AI Act faces delays in implementation and lacks enforcement mechanisms, particularly for energy integration and ethical AI practices [52]. Altogether, to have a standardised reporting mechanism, a concerted Global cooperation between multiple stakeholders, including policymakers, researchers, and industries, is needed to enable evidence-based policy initiatives and harmonise frameworks, and foster innovation to facilitate a sustainable AI ecosystem (40) (10) (9).

Table 4 presents the existing regulatory landscape and extent of integration of sustainability in the US, EU, and China. It highlights the notable gaps and inconsistencies in governance.

Table 4. Comparative overview of AI sustainability

Parameter	US	EU	China
Regulatory Approach	Regulations like the Energy Policy Act only set broad guidelines and are not tailored to the unique needs of AI or data centres [58].	EU AI Act: Implementation delays and a lack of strong enforcement mechanisms fail to mandate energy integration standards [58].	The regulatory approach to AI prioritizes control and cybersecurity [58].
Integration of Sustainability	Existing executive orders (e.g., October 2023 Executive Order on AI) mention sustainability goals but do not enforce the development of green algorithms or energy-efficient practices in AI deployment (23).	Eco-design Directive have been extended to cover some AI hardware through energy efficiency requirements, but these focus mainly on hardware, not on the broader AI lifecycle or model deployment practices (19).	No strict requirements for carbon accounting or mandates tied to energy sources for AI deployment (23)

Source*: Authors' compilation*

Building on the regulatory landscape, the healthcare sector represents one of the most sensitive domains, as there is a growing application of AI for diagnostic support, optimising treatment pathways, and healthcare management; however, there is concern about AI's environmental impact. During and after the deployment stage, systematic assessments of their environmental impacts are limited. Future research should establish sustainability evaluation frameworks for e-Health solutions that consider technological, economic, social, and organisational dimensions. This might include considerations for regulatory frameworks, international collaborations, and other important factors to ensure environmental costs do not exceed healthcare benefits (9) (52) (14).

6.2 Conceptual framework: The AI Sustainability–Theory of Change (AIs-TOC) Model

Drawing from the bibliometric analysis and systematic literature review (SLR) findings, particularly the insights from Cluster 1 on the environmental impact of AI, a conceptual framework titled the AI Sustainability–Theory of Change (AIs-TOC) model has been developed**.** This framework is designed to guide future research, policy formulation, and practice by focusing on how targeted interventions in AI design, governance, and implementation can lead to measurable sustainability outcomes.

Based on the stages of the theory of change, we propose a framework (Figure 7) to bring together environmental, technological, social, and governance elements. Connecting the evidence from SLR, such as carbon emissions, water and energy consumption, and e-waste associated with AI systems, this AIs-TOC framework provides a useful, strategic roadmap for researchers and policymakers to assess, implement, and scale sustainable AI systems in diverse sectors. In this phase, experts from various fields, such as researchers, AI developers, and policymakers, will participate to provide policy context, technical expertise, and knowledge for responsible governance in the implementation of AI systems. Equally central at this stage is to have comprehensive data across all AI models for analysing lifecycle impacts. These data allow for action steps which include improving lifecycle assessments (LCA), enhancing energy efficiency, and strategically relocating data centres into colder climates. Robust stakeholder participation ensures that their decisions incorporate a broad spectrum of perspectives, essential for both local and global contexts.

The results from these efforts entail the creation of sustainability dashboards, reporting transparently on AI resource utilisation and related health effects, and conducting equity audits that assess the impacts of AI deployment across regions.

he expected outcomes specifically aim for sustained systemic change such as increased transparency and accountability in AI sustainability monitoring and reporting. Furthermore, the framework is also concerned with integrating circular economy principles in AI infrastructure and supply chains to recover resources and reduce environmental harm. Enhanced equity is addressed by reducing disparity between developed and developing nations, as well as integrating health considerations directly into AI design and policy development. Resultantly, the impact of the framework extends to healthier planetary systems, improved public health, and equitable global adoption of AI that aligns with the United Nations Sustainable Development Goals (SDGs 3, 6, 7, 12, 13), supporting the broader transition to a resilient circular economy

Figure 7. AI Sustainability- TOC Model

Inputs	Activities	Outputs	Outcomes	Impacts
• Stakeholders (Researcher, Policymaker, AI developers) • Data related to all type of AI models	• Lifecycle assessment (LCA) of AI models • Energy efficient practices • Equity- placement of data centers at colder region, relying on renewable energy source • Facilitate stakeholder participation	• Sustainability dashboards & reports on AI resource use and health impacts • Equity audits comparing impacts across regions (developed vs developing	• **Reduced energy, water, and e-waste footprint** of AI • **Improved transparency and accountability** in AI sustainability reporting. • **Increased adoption of circular practices** in AI infrastructure and supply chains. • **Enhanced equity in AI deployment** (less disparity between developed and developing nations). • **Integration of health considerations** into AI design and	• Healthier Planetary Systems • Better Public Health • Equitable Global AI Adoption • AI development and deployment aligned with UN SDGs (3, 6, 7, 12, 13) • Resilient Circular Economy

Source: *Author's compilation*

6.3 Proposed indicator to address gaps in the SCAIS framework

Recent work, such as the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) framework by Rhode et al, has produced a comprehensive set of 67 indicators organised into 4 dimensions: social, economic, ecological, and governance (39). To begin with, the SCAIS framework does not capture all dimensions of Socio-Technical-Ecological Systems (SES). AI does not affect the community or the environment separately. It affects the whole system, where every aspect is interconnected.

Second, many indicators are qualitative, and the measurement or assessment methods are not standardised, which limits comparability among studies. Underexplored are the interdependencies among categories and potential trade-offs among indicators (e.g., ecological benefits versus economic concentration). The SCAIS framework does not yet provide a clear mechanism for systematically identifying or managing cross-dimensional trade-offs.

Third, lifecycle impacts associated with hardware, e-waste, and embodied carbon are still underrepresented. Finally, pathways associated with deployment are not associated strongly, which limits their usefulness as a decision-support tool.

To address these gaps, this study proposes a streamlined set of quantifiable, deployment-oriented environmental indicators derived from a systematic literature review. These indicators prioritise measurability, comparability, and trade-off evaluation. Table 5 summarises the indicators along with their measurable parameters. It encompasses the environmental dimensions of AI. Starting with energy consumption, which reflects the amount of energy utilised per training in kilowatt-hours (kWh), to compare the efficient models in the AI system and to measure its dependency on renewable or non-renewable sources. Carbon emissions, calculated in kg of CO_2 or total greenhouse gas emissions per training cycle, provide a standardised measure to assess climate change. Assessments often overlook water consumption, which quantifies the amount needed to cool down the data centre operation. Hardware lifecycle and e-waste indicator assesses efficiency, contribution of AI components to the circular economy, and reliance on rare metals for their production. To maximise the benefits of AI and address the major limitation of the SCAIS framework, we propose the Socio-environmental Impact Ratio to calculate the gains achieved relative to its environmental cost. For instance, in public health, it can be represented by the number of patients diagnosed via teleconsultation. Additionally, economic returns can be calculated by cost reduction or revenue generated to capture broader societal value. Finally, the air pollution indicator is the most significant one as it not only measures the pollutants emitted from the data centres but also indirectly helps in estimating the disease burden linked to environmental pollution. Together, these parameters enable the quantification of the AI environmental impacts and assist in trade-off evaluation.

Table 5. Addressing gaps in the SCAIS framework through Proposed Indicators

SCAIS Limitation	Proposed Indicator	Parameters
Lack of standardised measurement for energy use: Focuses on energy efficiency, but not quantifiable	Energy consumption (53)	Kilowatt-hours (kWh) per training/inference task; Breakdown into Renewable and non-renewable energy share

Mentions CO_2 emissions qualitatively	Carbon Emission (54)	Kg CO_2 Total GHG emission/training
Limited attention to Water consumption	Water consumption (55)	Litres of water used in cooling and data centre operations
Resource efficiency and recycling: Hardware lifecycle impacts are not mentioned explicitly	Hardware lifecycle & E-waste (24)	Kg or tons of hardware recycled/reused; rare-earth mineral dependency
Trade-offs: Identifies potential conflicts, but no assessment mechanism	Socio-environmental impact ratio	Benefits received (patients served per AI application/reduction in emission due to teleconsultation/time reduced in diagnosis/revenue generated) per unit environment cost (CO_2 emission, water, and energy consumption)
Pollution & Health impact: Measuring Pollutants in data centre regions	Air pollution (15)	µg/m³ Emissions of PM2.5, NOx, SO_2 relative to operation

***Source**: Authors' compilation*

7. Future implications

7.1 Life Cycle Assessment of AI Systems

To effectively tackle this challenge, it is important to extend impact assessments beyond operational energy demands and also to consider the complete lifecycle of artificial intelligence (AI) systems. Lifecycle considerations would include environmental costs associated with the production of hardware, transportation, deployment, maintenance, and disposal or recycling of systems at end-of-life. Although methodologies for evaluating lifecycle carbon footprint of AI and hardware have not been developed to the extent that we can understand its full environmental burden.

Such assessments are essential for holistic sustainability evaluations and for identifying hotspots where interventions like hardware design optimisation or circular economy strategies could yield significant benefits. Advancing research on life cycle inventories, impact modelling, and sustainability indicators tailored to AI infrastructure and software is therefore needed. These efforts would help public health decision-makers to balance operational efficiencies against their environmental impacts (47) (10) (9).

7.2 Policy and Industry Recommendations for a Sustainable AI Future

Achieving sustainable AI requires stakeholders to adopt a circular economy approach as well as practices associated with green AI. This includes promoting energy and water-efficient algorithms, powering infrastructures with renewable energy, and designing hardware for reuse and recycling (56). Policymakers should strengthen regulations by incorporating enforceable sustainability indicators and supporting equitable technology dissemination to reduce disparities and social harms (41).

Collectively, these efforts can shape an AI ecosystem that promotes ecological sustainability while creating social justice by ensuring that all contributions from AI benefit both people and the planet (57).

8. Conclusion

AI plays as both a tool for environmental stewardship and a source of environmental burden, which makes this an area of concern. Our systematic review indicates that although AI has been implemented broadly to optimise resource utilisation, facilitate outbreak prediction, and improve monitoring capabilities, the range of sustainability issues associated with the energy consumption, computational demands, and electronic waste of AI system use is significant and growing (8). The literature is converging on the fact that the lifecycle impacts of AI across the spectrum, from extraction of raw materials for hardware to training, model, and use, need to be more thoroughly assessed and managed (4).

Research shows that the environmental impact of artificial intelligence is not linear: as deployment increases, its energy and carbon footprint also increase, although if appropriately deployed on renewable energy, AI can attenuate its environmental impact. However, the environmental harms of AI, such as pollution, electronic waste, and greenhouse gas emissions, are documented, but their translation into health outcomes or health equity implications is largely unaddressed in the literature. To ensure sustainable use of AI, an interdisciplinary approach is required, along with strategies across the lifecycle stages of AI.

Appendix

Table 1. Key Findings of the Studies

S. No.	Title	Author	Journal	Publication year	Key Findings
1.	AI-driven cloud sustainability: Accelerating the path to net-zero digital infrastructure	Shravan Kumar Amjala	WJARR	2025	Intelligent workload/time/geographic scheduling and renewable alignment optimize AI cloud energy use.
2.	Artificial Intelligence Impact on the Environment: Hidden Ecological Costs and Ethical-Legal Issues	A. Zhuk	Journal of Digital Technologies and Law	2023	Stresses legal/ethical necessity of energy efficiency, responsible e-waste management, and renewable energy in AI.
3.	AI-enabled ChatGPT's carbon footprint and its use in the healthcare sector: a coin has two sides	Chiranjib Chakraborty et al.	Journal of Stroke and Neurointervention	2023	Shows telemedicine and AI can reduce patient travel and lower the carbon footprint of healthcare delivery. However, AI-enabled ChatGPT might increase the carbon footprint in general cases. Need to develop energy-efficient hardware
4.	AI-Driven Data Analysis of Quantifying Environmental Impact and Efficiency of Shape Memory Polymers	Mattew A. Olawumi et al.	Biomimetics	2024	Uses AI to optimize sustainable 4D printing of SMPs for efficient, eco-friendly biomedical use.
5.	Aligning With the Goals of the Planetary Health Concept Regarding Ecological Sustainability and Digital Health: Scoping Review	Mathea Berger, Jan Peter Ehlers, Julia Nitsche	J Med Internet Res	2025	Telemedicine reduces carbon emissions significantly compared to in-person consultations, especially in hospital settings.
6.	Artificial intelligence for carbon emissions using system of systems theory	Loveleen Gaur et al.	Ecological Informatics	2023	Proposes integrating AI in smart energy grids and building management to reduce energy consumption and improve sustainability.

7.	Artificial intelligence for waste management in smart cities: a review	Bingbing Fang et al.	Environmental Chemistry Letters	2023	AI enables automated waste collection/sorting, improving efficiency and safety in municipal and construction waste management.
8.	Artificial intelligence, systemic risks, and sustainability	Victor Galaz et al.	Technology in Society	2021	Examines AI's diffusion in biosphere-relevant sectors, outlining potential systemic risks and need for governance.
9.	Balancing Progress and Responsibility: A Synthesis of Sustainability Trade-Offs of AI-Based Systems	Apoorva Nalini Pradeep Kumar et al.	IEEE ICSA	2024	Reviews trade-offs in applying AI to sustainability, noting both energy efficiency gains and social, economic impacts.
10.	Environmentally sustainable development and use of artificial intelligence in health care	Cristina Richie	Bioethics	2022	AI in healthcare can reduce costs and improve outcomes but must address issues like bias, resource use, and equitable access.
11.	Environmental Sustainability: Can Artificial Intelligence be an Enabler for SDGs?	Gyandeep Chaudhary	NEPT	2023	AI is vital for monitoring biodiversity and ecosystem services and can help in SDG achievement.
12.	Climate change and artificial intelligence in healthcare: Review and recommendations towards a sustainable future	Daiju Ueda et al.	Diagnostics & Interventional Imaging	2024	Explores climate impacts of AI in healthcare, focusing on energy use, carbon footprint, and mitigation strategies.
13.	Climate change and health: the next challenge of ethical AI	Amelia Fiske et al.	Lancet Global Health	2025	Examines the intersection of AI, climate, and health, calling for ethical frameworks addressing climate justice in AI.
14.	Development and Deployment of Green Artificial Intelligence	Dr. Anil Kumar Pandey	IJMCR	2023	Efficiency in AI and data center operations (cooling, location, collaborative learning) can cut carbon footprint.
15.	Disruptive Technologies for Environment and Health Research: An Overview of	Frederico M. Bublitz et al.	IJERPH	2019	Proposes an IoT-based surveillance architecture for environmental and health monitoring,

	Artificial Intelligence, Blockchain, and Internet of Things				with privacy considerations.
16.	Efficient Utilization of Energy Consumption in AI Data Centers: Balancing Sustainability and Performance	Tejas Sudhakar Baraskar	IJRASET	2025	Edge and federated learning, renewable integration, and storage can make data center operation more sustainable.
17.	The Emerging Environmental and Public Health Problem of Electronic Waste in India	Veenu Joon, Renu Shahrawat, Meena Kapahi	J Health Pollution		E-waste generation poses serious health/environmental risks; calls for stricter disposal regulations in India.
18.	Energy-Efficient Data Centers: A Supply Chain Approach to Sustainability	Deepika Nathany	IJSREM	2021	Advocates modular, virtualized data center designs for reduced energy cost and environmental impact.
19.	Environmental impact assessment in health technology assessment: principles, approaches, and challenges	Michael Toolan et al.		2023	Reviews methods for including environmental impacts in HTA, focusing on lifecycle and multi-domain analyses.
20.	Evaluation of Climate-Aware Metrics Tools for Radiology Informatics and Artificial Intelligence: Toward a Potential Radiology Ecolabel	Florence X. Doo et al.	JACR	2024	Advocates ecolabeling for radiology AI/datacenters based on comprehensive carbon and energy metrics.
21.	E-WASTE threatens health: The scientific solution adopts the one health strategy	Chiara Frazzoli et al.	Environmental Research	2022	E-waste workers have higher levels of toxic metals; adopting a one health approach can mitigate harm.
22.	Footprints of Artificial Intelligence in Climate Change	Nikita Saklani, Kanchan Bade	IJRASET	2024	AI is applied in climate adaptation and prediction, using supervised and transfer learning for better environmental outcomes.
23.	Integrating Public Health into Climate Change Policy and	Mary Fox et al.	IJERPH	2019	Advocates for integrating complex systems thinking and adaptive management

	Planning: State of Practice Update				in climate/public health planning.
24.	From Efficiency Gains to Rebound Effects: The Problem of Jevons' Paradox in AI's Polarized Environmental Debate	Alexandra Sasha Luccioni, Emma Strubell, Kate Crawford	FAccT	2025	Warns efficiency improvements in AI may be offset by rapid industry growth and lack of environmental regulation.
25.	Green computing: Sustainable Development, Energy Efficiency, and IoT	Sarthak Dongare1, Ayush Lokre2, Ashutosh Khedkar3, Dr. Shagufta sheikh4	International Journal for Multidisciplinary Research	2025	Green computing through AI, virtualization, and workload management reduces energy use and enhances IT sustainability.
26.	Green artificial intelligence initiatives: Potentials and challenges	Yehia Ibrahim Alzoubi, Alok Mishra	Journal of Cleaner Production	2024	Emphasizes energy efficiency in DL, benchmarking tools for green AI, lifecycle assessment, and hardware/software co-optimization.
27.	Healing AI Mental Health to Slash Energy Consumption and Carbon Emissions	Shai Misan et al.	AEIT	2024	Suggests improving AI systems' operational "mental health" can reduce energy use and emissions.
28.	Impact of Artificial Intelligence on the Environment	Surya, Snigdha Sharma		2024	Green AI aims to cut emissions while ensuring performance; weighing benefits vs. environmental costs is critical.
29.	Impacts of artificial intelligence on carbon emissions in China: in terms of artificial intelligence type and regional differences	Mingfang Dong, Guo Wang, Xianfeng Han	Sustainable Cities and Society	2024	Analyzes AI's varied impact on carbon emissions by type and region in China's urbanization context.
30.	Incorporating carbon into health care: adding carbon emissions to health technology assessments	Scott McAlister et al.	Lancet Planet Health	2022	Argues for including carbon impact metrics in health technology evaluations and purchasing.
31.	Industrial Metaverse: A Comprehensive Review, Environmental Impact, and Challenges	Sindiso Mpenyu Nleya, Mthulisi Velempini	Applied Sciences	2024	Reviews environmental and privacy/security risks posed by growing industrial metaverse connectivity.

32.	INTEGRATING ESG AND AI: A COMPREHENSIVE RESPONSIBLE AI ASSESSMENT FRAMEWORK	Sung Une Lee et al.		2024	Presents a framework for assessing ESG impacts of AI applications in real-world business and investment contexts.
33.	May Artificial Intelligence take health and sustainability on a honeymoon? Towards green technologies for multidimensional health and environmental justice	Cristian Moyano-Fernndez et al.		2024	Discusses ecosystem health and the role of AI in environmental justice and biodiversity preservation.
34.	Measuring the environmental impact of artificial intelligence compute and applications the AI footprint	OECD	OECD Digital Economy Papers	2022	Highlights growing AI compute demands and emphasizes the need for efficient and sustainable AI to meet global sustainability goals.
35.	Operational greenhouse-gas emissions of deep learning in digital pathology: a modelling study	Alireza Vafaei Sadr et al.	The Lancet Digital Health	2024	Compares emissions of different DL models in pathology and highlights trade-off between accuracy and climate impact.
36.	Artificial Intelligence and Environmental Sustainability: Insights from PLS SEM on Resource Efficiency and Carbon Emission Reduction	Aman Khan Burki1, Mohamed Normen Ahamed Mafaz2, Zaki Ahmad*3, Auni Zulfaka4, Mohamad Yazid Bin Isa5	American Journal of Open Research	2024	Investigates how AI-driven resource efficiency impacts energy consumption and environmental sustainability.
37.	Radiology AI and sustainability paradox: environmental, economic, and social dimensions	Burak Kocak et al.	Insights into Imaging	2025	Shows renewable integration in radiology AI reduces both operational costs and environmental footprint.
38.	Artificial Intelligence: Towards a more sustainable future	Vernica Boln-Canedo et al.	Neurocomputing	2024	Reviews AI/ML applications for sustainability, including crop yield, soil classification, and efficient hardware.

39.	Strategies of Automated Machine Learning for Energy Sustainability in Green Artificial Intelligence	Dagoberto Castellanos-Nieves, Luis Garca-Forte	Applied Sciences	2024	Hyperparameter optimization can lead to more energy-efficient AI models; multi-objective approaches are effective for sustainability.
40.	Broadening the perspective for sustainable artificial intelligence: sustainability criteria and indicators for Artificial Intelligence systems	Friederike Rohde et al.	Current Opinion in Sustainability	2024	Proposes specific criteria and indicators (e.g., energy use, inclusivity) for sustainable development of AI systems.
41.	Sustainable AI: AI for sustainability and the sustainabi lity of AI	Aimee van Wynsberghe	AI and Ethics	2021	Argues for proportionality in AI deployment, suggesting some high-emission uses should be limited for ethics.
42.	Sustainable materials for artificial intelligence (AI) technology adoption for energy-efficient patient-centric healthcare solutions	Lakshmipri ya Bachina et al.	Journal of Education and Health Promotion	2025	Sustainable/eco-friendly materials are essential for reducing the environmental footprint of AI-driven healthcare.
43.	Sustainable AI in the Cloud	Paul Walsh et al.	IEEE ASEW	2021	Highlights dramatic growth in deep learning compute needs and the need for energy-aware AI development.
44.	The real environment impact of AI: Unveiling the ecological footprint of Artificial Intelligence	Beena Nawghare, Nitin Rane, Soma Kulshrestha, Santosh Gore, Priyanka D. Halle, Roshni S. Golhar, Sujata Gore	Journal of Information Systems Engineering and Management	2025	Potential for emission reduction due to Green AI
45.	Toward Green AI: A Methodological Survey of the Scientific Literature	Enrico Barbierato, Alice Gatti	IEEE Access	2024	Reviews metrics/methods for carbon footprint measurement in AI, highlighting lack of consensus and need

					for dedicated approaches.
46.	The uneven distribution of AI's environmental impact	Shaolei ren, Adam Wierman	Harvard business review	2025	
47.	The Unpaid Toll: Quantifying the Public Health Impact of AI	Yuelin Han et al.		2024	Modeling shows AI lifecycle emissions degrade air quality, with substantial public health impacts from pollutant emissions.
48.	Summary Report: White Paper on Global Artificial Intelligence Environmental Impact	Yunjin Tong	Asia Sustainable Development Foundation1,*1Cambridge, MA, USA	2025	Life-cycle emissions in AI include not just operation but also manufacturing; emphasizes renewable energy and optimization

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