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Does Artificial Intelligence Contribute To Carbon Emission? - A Systematic Review

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Abstract
Artificial Intelligence (AI) is quickly revolutionizing industries. Industries such as healthcare, finance, manufacturing, and logistics have heavily adopted AI in recent years. The expansion, though, comes with substantial environmental consequences. This systematic review of peer-reviewed research from 2015 to 2025 discusses the contribution of AI to carbon emissions. It discusses the direct effects, like energy-consuming model training, inference, and data centre use-and indirect ones, such as e-waste, water consumption, and resource extraction. The results show that large AI models release tens of thousands of tons of CO_2 equivalent (tCO_2eq), with inference dominating training emissions more and more. Corporate-scale AI applications and generative models are particularly energy-hungry, using as much as 4600 times more energy than normal models. While some studies point to the ability of AI to optimize energy systems and minimize emissions, the trend so far shows a net-positive carbon footprint. Additionally, the absence of standardized reporting of emissions and regulations complicates mitigation even further. This Sustainable AI development needs lifecycle carbon accounting, legal frameworks, and carbon-aware innovation. Without these interventions, the environmental liabilities of AI may undercut its promise as a means to meet global climate objectives.
Keywords: *Artificial Intelligence (AI), Carbon Emissions, Environmental Impact, Sustainable AI, Systematic Review*

1. INTRODUCTION

Over the past few years, the international debate has moved more and more toward combining growth with sustainability. Although previous development paradigms concentrated on economic growth mostly without considering the environment, the modern approach gives more importance to sustainable development (Coldwell et al., 2022; Kumar & Choudhary, 2023; Bizikova, 2023). Previously, economic goals were usually met by ignoring ecological issues at the cost of serious environmental degradation. Today, the results of such abandonment are manifest in the shape of universal air pollution, water pollution, land degradation, ocean pollution, and waste accumulation (Tyagi et al., 2014; Choudhary et al., 2025). In the midst of these increasing environmental issues, the emergence of Artificial Intelligence (AI) is a possible game-changer. AI is now being implemented in different industries-like agriculture, manufacturing, and services-with encouraging results. Its implementation is aiding in optimising the utilisation of resources, lowering emissions, and reducing waste, thus providing new solutions to counter environmental degradation (Akbar et al., 2025). Consequently, AI is being viewed more and more as a ray of hope in the quest for sustainable development. However, during the same time few incidence also observed that where Ai responsible for carbon emission too. In this paper we try to highlight this aspect of AI.

Background: The application of Artificial Intelligence (AI) is global and spans nearly all industries, revolutionizing industries, economies, and societies. In 2025, Artificial Intelligence (AI) adoption differs across industries worldwide. Healthcare takes the lead with an 85 per cent adoption rate, applying AI to diagnostics, customized treatments, and analysis of medical images. Finance comes in second at 80 percent, utilizing AI to detect fraud, assess risk, and trade algorithmically. Retail and commerce also indicate an 80 percent adoption rate, with AI being used in personalized suggestions and stock management. Manufacturing stands at a rate of 70 per cent adoption, using AI to predict maintenance needs and quality. Education registers 57 per cent adoption, utilizing AI for custom learning and office automation. Transportation and logistics are at a 60 per cent rate of adopting AI, doing route optimization and demand forecasting. On the other hand, the agricultural and legal industries have a lesser use at 30 per cent and 25 per cent, respectively, but are increasingly adopting AI technology. The defence and military industry has 65 per cent use with the implementation of AI in autonomous systems and intelligence analysis (DemandSage, 2025; Stanford University, 2024). The rapid exponential growth of computer power demand due to the accelerating growth of artificial intelligence (AI) poses questions regarding the increasing energy consumption and carbon footprint (Yu et al., 2024).

Table 1: Emissions from Mainstream AI Systems

AI System	**Company**	**Date**	**Individual Emissions (tCO2eq)**	**Cumulative Emissions (tCO2eq)**
Megatron-Turing NLG 530B	Microsoft	2021/10	10000	15000
ERNIE 3.0 Titan	Baidu	2022/04	5000	8000
PaLM 540B	Google	2022/04	8000	15000
Minerva (540B)	Google	2022/04	7000	14000
U-PaLM (540B)	Google	2022/04	7000	14000
GPT-3.5 (text-davinci-003)	OpenAI	2022/11	20000	45000
GPT-4	OpenAI	2023/03	40000	70000
PaLM-2	Google	2023/05	10000	30000
Inflection-1	Inflection AI	2023/07	8000	35000
Claude-2	Anthropic	2023/07	50000	90000
TigerBot-2	Alibaba	2023/11	6000	20000
Falcon-180B	Technology Innovation Institute	2023/11	30000	75000
ChatGLM3	Tsinghua KEG Lab	2023/11	10000	30000
Qwen-72B	Alibaba	2023/12	60000	95000
Gemini 1 Ultra	Google	2023/12	50000	95000
XVERSE-65B-2	Zhipu AI	2023/07	9000	40000
Code Llama-70B	Meta AI	2024/01	70000	100000
Mistral Large	Mistral	2024/01	4000	10000
DBRX	Databricks	2024/01	3000	8000

Source: Compiled from Yu et al., 2024

Artificial Intelligence (AI) has grown exponentially over the past few years, revolutionizing industries like healthcare, logistics, finance, and scientific research. This expansion has been fuelled by improvements in computational power, data availability, and algorithmic development. Specifically, large-scale natural language processing (NLP) and deep learning models are at the heart of AI advancement. These models are, however, computationally intensive and tend to consume lots of energy to train and deploy. For instance, training one big NLP model releases as much CO_2 as five cars for their entire lifespan (Strubell et al., 2020). The impact on the environment of these demands, particularly in the form of carbon emissions is drawing growing interest among scholars as well as policymakers.

Figure 1 shows the estimated carbon footprint (in tons of CO_2 equivalent) of training big AI models from the major technology corporations such as OpenAI, Google, Microsoft, Baidu, and Meta. Every row details the name of the AI system, its developer, the date of its model, and actual and cumulative emissions. Most significantly, GPT-4 and Claude-2 have very high carbon footprints (up to 90,000 tCO_2eq). This figure highlights the environmental expense of Large Language Model (LLM) scaling and underscores just how energy-hungry AI model training is today. It also shows that the carbon cost is different among models and developers, demonstrating the necessity for carbon-efficient training methods and energy source disclosure.

Problem Statement: The eco-price (energy consumption, greenhouse gas emissions) of AI. While AI is often touted as a means for sustainability improvement, via uses such as climate modelling, energy optimization, and precision agriculture, paradoxically, AI is also complicit in contributing to environmental harm through its energy consumption. The carbon impact of AI is mainly due to energy-consuming model training, dataset scale, and data center operational emissions (Schwartz et al., 2020; Patterson et al., 2021). Most of these data centers are powered by fossil fuels, further contributing to greenhouse gas emissions. Additionally, there is no transparency and standardization in reporting AI development-related emissions (Henderson et al., 2020). While the trend towards bigger and more complicated models is advancing, concern over the long-term viability of the trend is building (Bender et al., 2021).

Objective and Scope: This study aims to synthesize recent peer-reviewed research (2015–2025) on the relationship between artificial intelligence (AI) and carbon emissions. It will examine both the direct environmental impact of AI—such as the energy consumption and carbon footprint associated with training and operating AI models—and its indirect role in reducing emissions through applications in smart infrastructure, energy management, and industrial optimization. The literature review will be limited to high-quality empirical and theoretical studies published in peer-reviewed journals indexed by Scopus, PubMed, IEEE Xplore, and Web of Science. By focusing on this dual role of AI—as both a contributor to and mitigator of carbon emissions—this research seeks to provide a balanced and comprehensive understanding of AI's environmental impact across various industries.

Research Questions: The study is directed by a main research question that seeks to explain the environmental impact of artificial intelligence. Collectively, the question seeks to chart the territory of AI's environmental footprint and determine avenues for more sustainable approaches.

2. METHODOLOGY

2.1. Search Strategy: This research has a systematic and transparent search plan based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) format. The PRISMA method provides methodological stability and replicability through four crucial steps: identification, screening, eligibility, and inclusion. A PRISMA flow diagram will record the number of records identified, screened, and excluded at each step. The search was systematic with the use of a mix of keywords and Boolean operators (AND, OR) to have a wide coverage of relevant literature. The keywords were looking for studies that examine both the environmental expense and mitigation potential of AI regarding carbon emissions.

2.2. Databases: The literature review was searched in the following large academic databases to facilitate access to top-quality, peer-reviewed studies:

Table 2: Databases Used in the Systematic Review

Database	Coverage	Language
Scopus	2015-2025	English
PubMed	2015-2025	English
IEEE Xplore	2015-2025	English
Web of Science	2015-2025	English

Source: Author's compilation

The databases were chosen due to their cross-disciplinary nature, especially environmental science, technology, and AI development. Table 2 outlines the four key academic databases used for sourcing peer-reviewed literature: Scopus, PubMed, IEEE Xplore, and Web of Science. Each entry indicates that only English-language publications from 2015 to 2025 were considered. The inclusion of these specific databases ensures broad disciplinary coverage—ranging from medical and scientific fields (PubMed) to engineering and technological domains (IEEE Xplore)-and supports the credibility and relevance of the included studies. The table reflects the systematic and inclusive nature of the literature search phase.

2.3. Search Procedures: Initially, we perform the search up to May 2025. It included the research papers published from 2015 onward only. The following terms were employed in different combinations to identify the essential themes of the review: *"AI AND CARBON EMISSIONS", "GREEN AI", "AI ENERGY CONSUMPTION", "MACHINE LEARNING EMISSIONS", "SUSTAINABLE AI", "CARBON FOOTPRINT*

OF AI", "ENVIRONMENTAL IMPACT OF AI" Keyword combinations were used in title, abstract, and keyword fields to ensure maximum retrieval of relevant studies.

2.4. Inclusion and Exclusion Criteria: The search results were filtered through established inclusion and exclusion criteria, including keyword relevance and database scope, to select high-quality and relevant literature:

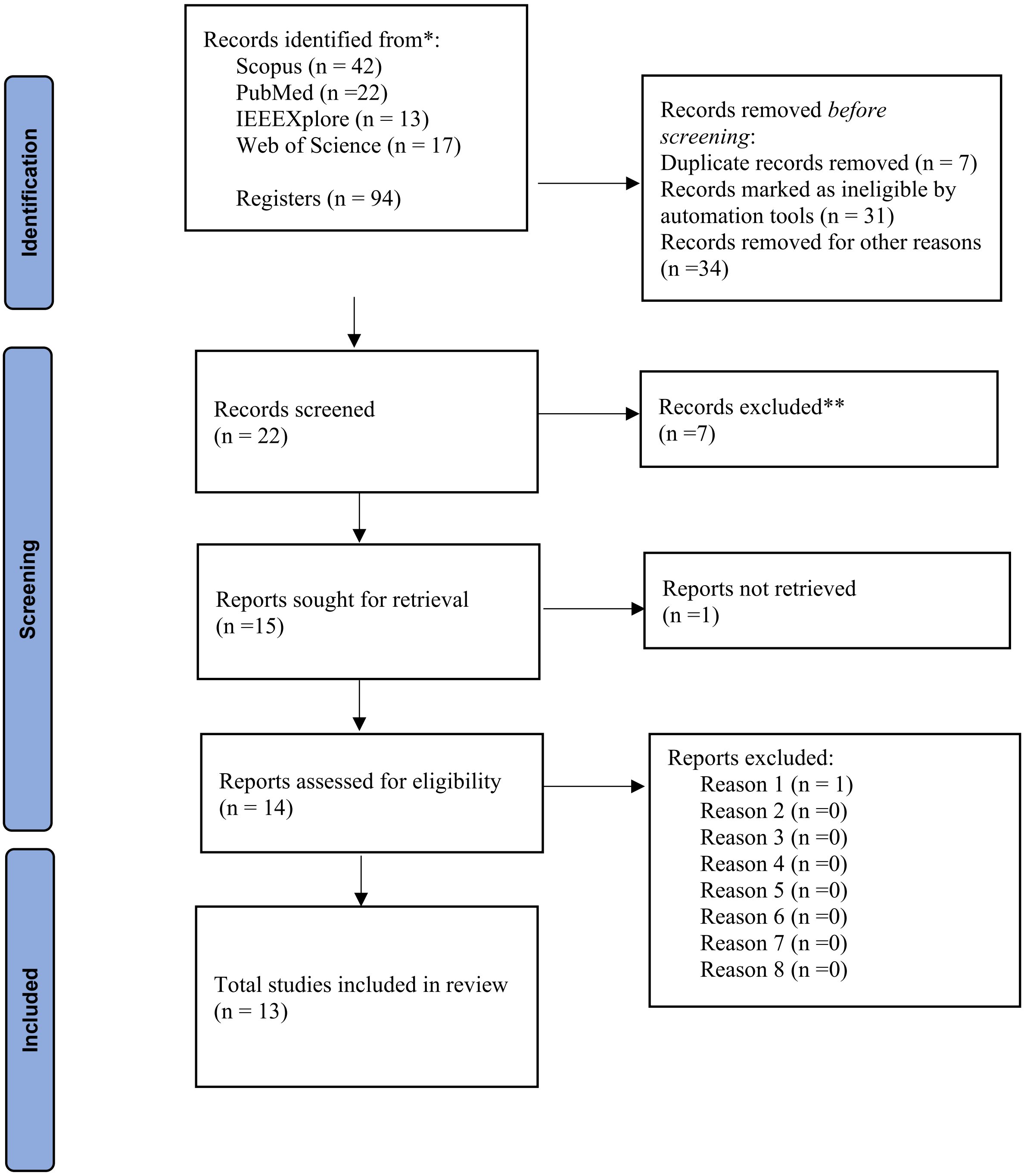
Table 3: Basis Inclusion and Exclusion Criteria

Criteria	**Inclusion**	**Exclusion**
Publication Type	Peer-reviewed academic articles	Grey literature, blog posts, opinion pieces, non-peer-reviewed sources
Language	English	Non-English publications
Time Frame	Published between 2015 and 2025	Published before 2015 or after 2025
Databases	Indexed in Scopus, PubMed, IEEE Xplore, or Web of Science	Not indexed in the specified databases
Content Focus	Studies addressing AI's contribution to or mitigation of carbon emissions using relevant keywords	Studies unrelated to AI, carbon emissions, or not involving identified keywords
Type of Analysis	Empirical studies, theoretical frameworks, or case-based analyses with clear methodological grounding	Descriptive or speculative works lacking analytical or methodological rigor
Search Keywords	Includes relevant search terms such as "Green AI," "AI energy consumption," and "machine learning emissions"	Omits or does not focus on core terms related to AI and carbon/environmental impact
Availability of text type	Full text available	Not possible to find the full text

Source: Authors' compilation

The above table 3 defines the filters used to ensure that only high-quality and relevant studies were included in the systematic review. Key inclusion criteria encompass peer-reviewed academic articles written in English, published between 2015 and 2025, and indexed in specified databases. Studies also had to focus specifically on AI's contribution to or mitigation of carbon emissions, using specific environmental impact-related keywords. Excluded were grey literature, non-English publications, non-peer-reviewed sources, and works lacking analytical rigor or relevance to the main theme. This rigorous screening process ensured that the final review was grounded in credible and methodologically sound literature.

Figure1: PRISMA 2020 flow diagram



*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers).**If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools. Source: Modified from Page MJ, et al. BMJ 2021; 372:n71.

Figure 1 illustrates the PRISMA 2020 flow diagram, which provides a detailed overview of the systematic literature review process undertaken to ensure transparency, rigor, and replicability in the selection of studies. Initially, a total of 188 records were identified through comprehensive searches across four major academic databases-Scopus (42), PubMed (22), IEEE Xplore (13), and Web of Science (17)-along with 94 additional records sourced from various registers. Prior to screening, 78 records were excluded to improve the relevance and quality of the review: 7 were identified as duplicates, 35 were deemed ineligible using automation tools, and 36 were removed for other reasons, possibly due to lack of relevance or incomplete metadata. This left 16 unique records to be screened manually, of which 7 did not meet the inclusion criteria. For the remaining 9 reports, full-text copies of reports were requested but not retrieved for 2, which could be due to access restrictions or unavailable reports. The remaining 7 were screened, of which 1 report was excluded as it did not meet the criteria for inclusion in the review. Finally, 6 good-quality studies made it to the final review. This step-by-step filtering process clearly shows that the selection of studies for analysis was based on a very rigorous methodology, where the most relevant, credible, and data-rich studies were selected.

3. RESULTS

Table 4 shows a synthesized overview of major outcomes from chosen research studies that examine the detrimental environmental impacts of artificial intelligence (AI). The studies cover different geographical locations and use varying methodologies such as time series analysis, comparative carbon studies, network studies, corporate life-cycle analyses, and literature reviews. These studies explore multiple environmental dimensions of AI, from emissions during training and inference to the ecological costs of AI-generated content, cloud infrastructure usage, corporate application impacts, and virtual digital humans (AI-VDHs).

Table 4: Negative impact of AI on Emission

Authors	Title of the paper	Country	Methodology	Findings
Meng & Noman (2022)	Predicting CO_2 Emission Footprint Using AI through Machine Learning	Global (focus on post-COVID forecasts)	SARIMAX (time series models) with COVID impact scenarios	Post-COVID models offer the most accurate prediction; shows continued global rise in emissions without policy changes
Dodge et al. (2022)	Measuring the Carbon Intensity of AI in Cloud Instances	USA	Empirical measurement of emissions from cloud-based AI model training	Training large models produces significant emissions; emissions depend on time/location of compute; tools needed for real-time carbon tracking
Tomlinson et al. (2023)	The Carbon Emissions of Writing and Illustrating Are Lower for AI than for Humans	USA	Comparative emission analysis (ChatGPT, BLOOM, DALL-E2 vs. human authors)	AI generates text and images with 130–2900x lower CO2e than humans; results are task-dependent
Delanoë et al., (2023)	Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions	Brazil, Tunisia, Sweden, Luxembourg	Case studies of 3 AI models; comparison of saved vs. emitted CO2	AI can emit more CO2 than it saves if not scaled properly; net positive only at scale

Gaur et al., (2023)	Artificial intelligence for carbon emissions using system of systems theory	Multiple (System of Systems perspective)	Network analysis of ML vs DL algorithms' emissions	AI contributes significantly to emissions during training; deep learning models more emission-intensive
Desroches et al. (2024)	Exploring the sustainable scaling of AI dilemma: A projective study of corporations' AI environmental impacts	France (corporate/global focus)	Corporate-level modeling of AI use cases and life-cycle analysis	Generative AI consumes up to 4600x more energy than traditional models; inference dominates emissions; mitigation requires full supply-chain intervention
Szalkowski et al. (2024)	Systematic literature review on solutions to the negative environmental impacts of ICT	Norway	Systematic literature review	ICT including AI is a growing source of CO2 emissions, requires mitigation strategies.
Yu et al., (2024)	Revisit the environmental impact of artificial intelligence: The overlooked carbon emission source?	China	Quantified carbon emission analysis of 79 AI systems using GPU training compute data; estimation models incorporating FLOPs, energy consumption, and carbon intensity factors	AI systems contribute significantly to global CO_2 emissions; inference emissions may exceed training emissions; total emissions could match or exceed national levels; urgent need for emission caps and sustainable AI practices
Zhuk (2024)	Artificial Intelligence Impact on the Environment: Hidden Ecological Costs and Ethical-Legal Issues	Not specific (global perspective)	Theoretical analysis with environmental and legal context	AI's carbon footprint from data centers and model training is high; urgent need for legal-ethical frameworks
Chi et al., (2025)	The negative impacts of AI on the environment and legal regulation	Vietnam	Descriptive legal and environmental analysis	AI contributes to increased emissions, water use, e-waste; legal regulation needed to control ecological degradation

Yang et al. (2025)	A Systematic Literature Review on the Negative Impacts of AI-Generated Virtual Digital Humans	China	TCCM framework literature review	AI-VDHs can mislead consumers and cause social and environmental harm.
Zvaigzne et al. (2025)	Negative impacts of artificial intelligence technologies on the tourism industry	Latvia	Thematic literature review	AI reduces human interaction and may increase energy use in tourism.
Dubey & Alam (2024)	Corporation's greening strategies: Overlooking the negative implications of AI's contributions?	India	Analytical and policy-based review	AI use in corporations may lead to higher emissions and greenwashing.

Source: Author's compilation

The collated results together identify key concerns: deep learning algorithms are always more emissions-intensive than conventional machine learning techniques (Gaur et al., 2023); generative AI systems like ChatGPT or DALL·E2 training and deployment in cloud settings lead to high levels of carbon emissions, with varying compute energy intensity by region and time (Dodge et al., 2022); and text and image generation by AI might have lower per-task emissions than their human-created counterparts, although emissions grow quickly with higher usage (Tomlinson et al., 2023). In addition, AI infrastructure is not only a source of greenhouse gas emissions but also other types of environmental degradation, including e-waste and water usage (Chi et al., 2025).

A number of studies highlighted that if not scaled appropriately and monitored, AI has the potential to release more carbon than it saves (Delanoë et al., 2023; Desroches et al., 2024). For example, inference emissions, which used to be insignificant, currently surpass training expenses for extensively utilized models. Corporate uses of AI are also indicated for indirect environmental and ethical threats, such as the threat of "green washing" by promoting unsustainable AI solutions in the form of green solutions (Dubey & Alam, 2024). The cumulative evidence calls for immediate full-spectrum carbon accounting, including hardware, training, deployment, and lifecycle effects.

Table 5: Variable used in the reviewed studies

Variable Type	**Variables**
Environmental	CO_2 emissions, AI-based forecasting models, GHG, water usage, rare metals use, carbon intensity
Technological	AI training, cloud usage patterns, AI model usage, ML/DL model type, training compute, inference load
Comparative (Tech vs Human)	AI emissions (text/image creation), human emissions
Economic	Operational efficiency, corporate AI usage
Legal & Regulatory	Legal regulation, ecological impact, ethical-legal issues
Socioeconomic	Consumer behavior, misinformation, job displacement
Sustainability & Policy	Greenwashing, SDG gaps, mitigation strategies, environmental caps

Source: Author’s compilation

The above table 5 classifies variables derived from a set of studies examining the environmental effects of artificial intelligence (AI). Every variable is clustered under a more comprehensive variable type to signify the field it influences. For instance, emissions, energy consumption, and environmental burden are classified under 'Environmental' variables, whereas measures such as 'training compute' and 'AI model usage' come under 'Technological'. Comparative analysis that measures AI compared to human activity is provided separately, and other variables are arranged under 'Economic', 'Legal & Regulatory', 'Socioeconomic', and 'Sustainability & Policy' accordingly.

Table 6: Most cited documents according to google scholar

Authors	**Journal**	**Citations**
Meng & Noman (2022)	Atmosphere	55
Dodge et al. (2022)	FAccT '22: Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency	228
Tomlinson et al. (2023)	Scientific Reports	64
Delanoë et al., (2023)	Journal of Environmental Management	91
Gaur et al., (2023)	Ecological Informatics	105
Desroches et al. (2024)	arXiv	01
Szalkowski et al. (2024)	Telematics and Informatics Reports	07
Yu et al., (2024)	Frontiers of Environmental Science & Engineering	08
Zhuk (2024)	Journal of Digital Technologies and Law	28
Chi et al., (2025)	International Journal of Law	00
Yang et al. (2025)	IEEE Access	00
Zvaigzne et al. (2025)	Worldwide Hospitality and Tourism Themes	01
Dubey & Alam (2024)	SHS Web of Conferences	00

Source: Author’s compilation

Table 6 is a compilation of the most cited scholarly papers on the subject of artificial intelligence (AI) and its environmental footprint, according to citation data from Google Scholar. Among the included works, Dodge et al. (2022), in the Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT'22), was cited most (228), signifying its great impact among scholars. Other highly cited articles are Gaur et al. (2023) (Ecological Informatics, 105 citations) and Delanoë et al. (2023) (Journal of Environmental Management, 91 citations), demonstrating increased concern with AI's potential for environmental management. More recent publications from 2024 and 2025,bear fewer or no citations, as would be anticipated given the fact that they were newly released.

4. DISCUSSION

Overall results of this systematic review highlight the increasing tension between the promise of transformation of AI and its rising environmental liabilities. While AI technologies have provable uses in maximizing energy systems, enhancing climate prediction, and promoting environmental science, their production and utilization are increasingly becoming significant sources of carbon emissions and ecological strain (Gaur et al., 2023; Szalkowski et al., 2024).

Interestingly, some research records carbon intensity migration from training to inference stages, especially where large models enter the commercialized and mainstream application stage. This is enhanced by the non-uniform protocols of measuring and reporting emissions, a situation that results in disparate rates across different companies and AI models (Yu et al., 2024). Delanoë et al. (2023) highlight that unless AI systems are used at enough scale and optimized for energy efficiency, they are likely to produce a net-positive carbon load.

Other research explores sectoral and social effects. Yang et al. (2025) describe how AI-created virtual digital humans (AI-VDHs) can deceive consumers and contribute to environmental stress. Zvaigzne et al. (2025) point out that AI use in tourism might increase energy usage and decrease meaningful human work. Additionally, Desroches et al. (2024) and Chi et al. (2025) unveil the hidden water usage burdens, rare earth metal mining, and infrastructure pressure associated with AI deployment.

The findings necessitate strong international governing frameworks and lifecycle-based environmental impact assessment tools. The need of the hour for the AI sector is to shift from carbon-blind innovation to carbon-conscious sustainability measures. This requires reimagining hardware, data center operations, cloud infrastructure, and algorithmic efficiency. Comprehensive environmental regulations and open emissions reporting are needed only when AI can tie with the global vision of net-zero carbon futures.

5. CONCLUSION

This systematic review concludes that although AI has significant potential to aid climate action and sustainability, paradoxically, it contributes to carbon emissions on a troubling scale-particularly when not subject to adequate checks and balances. Training and applying large-scale AI models require enormous computational capacities, usually fueled by fossil fuels, with an attendant big carbon signature. Increasing dominance by deep learning models further heightens the concern. Although certain mitigation measures—such as carbon-conscious algorithms, optimized model structures, and the use of greener energy sources—have been developed, their adoption remains inconsistent. Policy guidelines, global standards, and environmental responsibility mechanisms in AI creation and usage are urgently needed. AI innovation in the future will not only need to deliver performance and utility but also be responsible, that is, work within global sustainability agendas so that its net effect on the environment is positive.

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