The Climate Paradox of AI: A Historical Analysis of Academic, Industrial, and Public Narratives

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ABSTRACT

As AI capabilities have accelerated over the past decade, so have the questions surrounding their environmental impact. This narrative review examines how perceptions of AI's environmental impact have evolved across academia, industry, and public discourse between 2014 and 2025. The focus is on three key eras of development. Drawing on peer-reviewed literature, corporate sustainability reports, and public publishing outlets, a qualitative Sentiment Concern Index (SCI) framework was used to interpret shifts in optimism and concern across academia, industry, and publishing houses.

The findings suggest that while early academic and industrial discourse framed AI as a promising but untested tool, more recent years have seen both increased deployment and growing criticism, especially regarding the energy demands of large-scale models. Despite these concerns, the landscape is shifting toward "green AI," carbon-aware infrastructure, and environmentally responsible development practices. The paper concludes with a forward-looking discussion of integrated strategies, emphasizing the need for coordinated policy, technical innovation, public transparency, and cross-sector collaboration. As AI becomes further embedded in society, ensuring that it functions as a climate asset and not an environmental liability will be one of the defining sustainability challenges of the coming decade.

KEYWORDS

Climate Change, AI, Machine Learning, Green AI, Carbon Emissions, Sustainability

INTRODUCTION

Over the past decade, artificial intelligence (AI) has evolved from a specialized research field into a foundational force shaping everyday life. Whether powering virtual assistants, automating vehicles, or enabling scientific research, AI systems have become deeply embedded in work and problem-solving. Simultaneously, the world has grappled with mounting climate pressures: with rising global temperatures and increasing greenhouse gas emissions, there is a growing pressure on governments and industries to transition towards more sustainable systems (1).

As AI systems have become more computationally intensive, questions regarding their environmental impact have also increased. Large-scale models require substantial computational resources in both training and deployment processes, because of their reliance on energy-intensive data centers and specialized hardware such as GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units), which are designed to process large data efficiently but use substantial amounts of electricity to do so (2, 4). The environmental implications of these systems are difficult to evaluate precisely due to these variations in hardware and electricity sources or cooling requirements of data centers, as well as the limited transparency of many AI companies in reporting their energy usage and emissions (2, 3). At the same time, however, AI has increasingly been promoted as a potential tool for climate mitigation through applications such as renewable energy optimization, environmental monitoring, and climate modeling.

This dual role has led to a paradoxical relationship between AI and sustainability. On one hand, AI's increasingly sophisticated abilities hold promise as a powerful tool for accelerating scientific research and supporting climate adaptation efforts, in sectors such as climate modeling, energy grid optimization, and disaster prediction. On the other hand, the rapid scaling of large language models and cloud-based AI models has generated increasing concern regarding its long-term sustainability due to its high electricity consumption and carbon emissions.

Existing discussions surrounding AI and climate change are often fragmented across technical research, corporate sustainability initiatives, and public media coverage. Academic literature tends to emphasize methodological development and environmental measurement, industry discourse frequently highlights efficiency improvements and sustainability commitments, while public publishing outlets often frame AI through narratives of optimism, skepticism, or ethical concern. Examining these perspectives together provides insight not only into the measurable environmental consequences of AI systems, but also into how societal understanding of those consequences has evolved over time.

This narrative review examines how perceptions of AI's environmental impact developed across academia, industry, and public discourse between 2014 and 2025. To organize this evolution, the review first outlines major phases in AI development and infrastructure growth, then examines the corresponding environmental and energy-related concerns associated with these systems, before analyzing how these developments were interpreted across different sectors through an interpretive Sentiment Concern Index (SCI) framework. Through this historical and cross-sector analysis, the review explores the evolving tension between AI's promise as a climate tool and its growing environmental footprint.

HISTORICAL DEVELOPMENT OF AI SYSTEMS

The development of AI can be understood in three key phases, each marking a distinct stage in its evolution. The years 2014 to 2017 formed the "pre-transformer foundation", which saw progress in deep learning but lacked the architectural breakthroughs that would define the next wave. That wave came in 2017 with the introduction of transformers, ushering in what will be henceforth called the "conception of the transformer era," spanning from 2018 to 2021. During this time, AI models became more powerful, more specialized, and vastly more energy-intensive, as new models were generated from the original transformers model. Then, from 2022 onward, the field entered its current phase: the "post-conception era," where transformer-based models such as large language models (LLMs) began to scale rapidly and reach mainstream adoption and widespread use through tools like AI chatbots and productivity assistants.

Looking at AI's evolution through the lens of these three periods is essential as it provides a clear structure for tracking the technological milestones that have shaped AI, such as the introduction of transformer models, which marked an immense turning point in both computational capacity and energy demands. This segmentation of the timeline also allows precise analysis of how energy consumption patterns, hardware advancements, and environmental impacts have shifted with each new wave of innovation. Furthermore, it allows for more detailed review of the literature, as the studies, both academic and industry, can be situated within their relevant context, and enables clearer research into how the public perceptions of AI have shifted as well. Ultimately, organizing AI's evolution into these distinct eras enables a clearer understanding of its dual role as both a driver of energy-intensive progress and a potential tool for climate mitigation.

Together, these concepts of climate change, energy systems, computational infrastructure, and an outline of AI's technical evolution frame the central question of this review: as AI becomes more developed and more widespread, is it exacerbating the very climate problems it might be capable of helping to solve?

Period 1: Pre-Transformer Foundations (2014-2017)

While this period did not see any of the rapid expansion that subsequent eras did in the development or use of AI models, it includes the essential precursors that enable this advancement in the future.

One of the most essential turning points during this era was the introduction of GPUs for use in AI model training. Without them, using only the CPU, it would have been impossible to train any AI model to a useful level of functionality due to the substantial volume of computations that were required to train a model. This is because GPUs were much more specialized than any other existing processing unit, which is essential since specialization allows for incredible amounts of time reduction and energy efficiency in large-scale tasks like AI model training (6). This is why it is known as an AI accelerator.

Originally created for use in gaming graphics and 3D graphics rendering in the 1990's, used to output 2D images from a 3D world, GPUs were originally built to handle huge amounts of calculations, especially in contexts such as matrix multiplication (7). Due to this extraordinary computing ability, GPUs were slowly introduced to outside applications starting in 1993, and fully broke free of the graphics industry in the 2000's. By the end of 2017, nearly 28% of the global population had a device that used a GPU, including PCs, smartphones, and gaming consoles, which demonstrates how useful it was and how it radicalized the industry standard, setting the stage for further AI accelerator development in future years.

This era also saw the monumental historical moment of the introduction of the transformer model. But first, it was preceded by the sequence-to-sequence model, or the Seq2Seq model, introduced in 2014, which was the first ever transformer-like model to exist at the time with the use of an encoder-decoder architecture, and it provided the basis for the introduction of the transformer model (8, 9).

This model utilizes LSTM (long short-term memory), working from end-to-end, to read inputs and give outputs that do not have a fixed dimensionality (8). The capabilities of this model are surprisingly similar to those of current-day models, given that it can generate text, albeit to a lesser degree of human-likeness than today's models, and paraphrase or summarize long documents. In other words, it is especially capable of data-to-text generation (9), providing generated text based on a structured input. It was even proposed by some scientists in the field at the time to be used on social-media app algorithms to predict and recommend content to users (10).

Then, in 2017, the Transformer model was first introduced to the world through the paper "Attention is All You Need" written mainly by Google Brain or Research members. This was the first paper that revolutionized the idea of transformers (11). Transformers work according to an encoder-decoder structure. One of its distinguishing features is the self-attention mechanism, which essentially highlights the importance of certain words so that it can only pay attention to the most important ones. It considered not only the individual words as previous models had, but more so their relationship to others. For example, the word "the" held less meaning than the subject of the sentence, rather than the same importance. Thus, it was much more efficient, optimizing the number of operations necessary, and also that it was able to parallelize work, computing multiple inputs at once.

In sum, advancements in Period 1 provided critical foundations for the introduction and growth of AI models. The adoption of GPUs as AI accelerators made large-scale neural networks more feasible, and greatly improved computational efficiency. Similarly, the introduction of encoder-decoder architectures via sequence-to-sequence models, demonstrating early capabilities in tasks such as text generation and summarization. These advances eventually culminated in the 2017 introduction of the Transformer, whose self-attention mechanisms and parallelism transformed the future prospects of subsequent model development.

Period 2: Conception of the Transformer (2018-2021)

After the introduction of the transformer in 2017, numerous different researchers and companies were sparked to develop their own AI model creations. There was also the introduction of pre-trained models in 2018, which made models all the more efficient and well-suited to perform specific tasks.

The overarching name for these models are foundation models, and they began their rise in development in 2021 (12). These foundation models were mainly used for Natural Language Processing, or NLP. They could be easily scaled at this point because of the well-developed hardware, the depth of research into transformers already existing, and increased databases that could be used to train large models more accurately. Even to this day, Google Search relies on foundation models, including BERT, in order to function (12).

The way foundation models work is that they are first trained on large amounts of data across hundreds of GPUs, which can sometimes take months (13). This can create large energy costs and thus carbon emissions, but it is only one time during the initial training process. These models were able to be more specialized, which improved their productivity. However, they also had some negative impacts, such as bias and inequality occurring, which can lead to ethical and legal concerns.

Among the most famous of these foundation models is the GPT model. The first instance, GPT-1, was built in 2018, created specifically in order to overcome the challenges faced by past transformer models on the account of a shortage of labeled data (14). According to Zhang and Li, his model by OpenAI was also able to nearly perfectly recreate human speech patterns, as well as capture information from large, dense texts unsupervised, and complete tasks like text summarization, code generation, and story creation (15). Its main strength was its ability to multitask, and its ability to learn to do tasks proficiently with very few data points. OpenAI continued on to create GPT models 2 and 3, which both surpassed the previous models in their ability to comprehend and produce language (16). The applications of GPT-3 stretched to include customer service chatbots and report summaries, and with the creation of the GPT-3 playground, enabled even inexperienced users to be able to train and create their own downstream models (13).

Another prevalent model is BERT, which was also created using the Transformer model as a basis, using attention layers to utilize the self-attention method (17). It too was built in 2018, developed by Google AI Language, and also operates as a solution to multiple different problems, serving as a general-purpose framework to multiple commonly found tasks language models perform, including sentiment analysis, summarization, and text generation and prediction (18). BERT was made publicly available through open source code, meaning that the pre-trained model was able to be used for an even larger number of purposes, as many developers could use BERT easily and quickly in their own specific models (18).

The development of models like BERT, which were larger and more compute-intense models, requiring the training of billions of texts online, was made possible through the introduction of the TPU, a further specialized AI accelerator from the GPU (18). Models like BERT and GPT had an advantage in that they came pre-trained. This meant they were able to act as a backbone for more specific models with applications in more specialized sectors (17).

In conclusion, Period 2 took the initial idea of transformers and made them into applicable devices. Rapid advancements led to the development of a large range of models, including pre-trained and foundation models. The advancement of hardware, including the TPU, and increased size and quality of datasets led to the abilities of BERT and GPT in strong multitasking capabilities and wide applicability.

Period 3: Mainstream Integration (2022-2025)

In this most modern era, it is clear that AI has now become fully integrated into daily life. Clearly, its benefits are numerous, and only come to grow with each new application that is revealed. While it is true that this rapid integration may have led to underconsiderations in the risks or dangers it poses in the future, this section seeks to focus on the positive implementations AI has achieved.

Projects that would have taken months in the past take less than half the time with the use of AI (19). Furthermore, applications such as AutoML are allowing AI to become accessible to non-experts outside of the field, allowing those outside of the AI field without specific coding capabilities to enjoy its benefits, such as increased efficiency (20).

One of the most prevalent uses of AI is its use in multimodal models, the most well-known of which include ChatGPT, Gemini, and Claude. Furthermore, rather than one specialized task, models are capable of everything from image generation to text generation to summaries to feedback. Generally, most uses today are harmless, especially in the context of simple work-related or personal uses such as the recently popularized “Ghibli-style image” trend (21).

However, there have also been serious problems, specifically when using AI-generated research in professional instances like court-cases. Starting in 2023 and ranging all the way to current-day 2025, courts have been struggling with lawyers as they use AI-generated evidence that is eventually revealed to be untrue, created by AI’s hallucinations. The most well-known is the Mata v. Avianca court case, where lawyers submitted fake, AI-generated extracts and citations from a court case to the court (22). They failed to check whether this case actually existed, and the case turned out to be one that AI fabricated.

Another widespread application is in retail and ecommerce. Used by large-scale companies like Amazon, it aids companies in analyzing customer interests to help them improve ad campaigns and gain more customers, as well as in going through job applications. “Amazon Go” is another famous application, in which Amazon utilized AI in order to establish a chain of cashierless convenience stores in the US (23). This allowed them to streamline the process for customers, making visits even more time efficient and encouraging a larger customer base of regular users (24). Another usage was by Macy’s, a large department store based in the US, who created *Macy’s On Call* with AI, utilizing it to function as a chatbot to answer customers’ questions real time on the company website (25).

It is also used in healthcare, specifically in medical image processing and in monitoring patients. This includes analyzing the hospital scans such as CTs, MRIs, and PETs (26). AI’s ability for pattern recognition allows it to excel in this area. Another healthcare application is known as human activity recognition (HAR) (27), which uses AI to analyze the usual activities and motions of a person in order to predict what an abnormal act for that person may be. The use of AI rather than human analysis improves the accuracy of this monitoring, especially due to AI’s excellent prediction abilities.

Last but not least, another widely known usage is in autonomous vehicles (AVs). Here, AI is required to map out environments using sensors, determine the fastest routes using GPS data, and recognize important elements of the road, such as lanes, pedestrians, and other vehicles. Most importantly, it must be capable of making decisions, especially on when to stop and which direction to go when it faces an obstacle. These AVs are supposed to minimize fuel usage, lower accident rates, and improve traffic flow (28), all while allowing drivers to be more productive, as they may engage in other activities during driving times (29).

While these developments significantly expanded AI’s capabilities and accessibility, they also increased computational requirements, data center activity, and public attention toward AI’s environmental consequences. The following section examines how these technological advances intersected with growing climate and emissions concerns.

AI, ENERGY CONSUMPTION, AND CLIMATE IMPACT

AI’s evolution has led to an increased understanding of its connection to climate change, both as a source of greenhouse gas emissions and as a tool for solutions to combat environmental issues. Early discussions were largely speculative, centered on AI’s potential energy demands and ethical concerns. Over time, assessment methods became more precise, focusing on measurable factors such as the carbon dioxide equivalent emissions from training and deploying large-scale models, the energy consumption of data centers, and the environmental cost of manufacturing and maintaining hardware. At the same time, AI’s contributions to climate action through applications like energy optimization and climate forecasting grew more apparent. As the scope of knowledge on the possible impacts of AI widened, so did the conclusions. This section examines the quantifiable environmental impact of AI over time, detailing how metrics such as carbon output and energy usage have evolved alongside advances in both AI technology and climate measurement practices.

Period 1 (2014-2017)

In this period, rising temperatures coincided with the rapid expansion of AI infrastructure. The global average temperature rose to 0.69° in 2014, becoming the highest recorded global average temperature thus far (30), and temperatures continued to rise afterwards, leading to the years between 2014 and 2017 becoming the hottest in history since 1998 (31).

Most importantly, these accelerating warming trends coincided with the emergence of concern regarding AI's future energy demands. Machine learning models became increasingly computationally intensive in this period due to advances in GPUs and neural network architectures, prompting some early discussion regarding energy efficiency and resource demand.

Most papers and academics interested in AI at this time viewed the relationship between AI and climate change in a relatively positive light, focusing on its areas of possibility (32). AI's high sensitivity meant that it could be used to factor for many unknowns or highly variable factors, making it especially apt at investigating less certain topics like the environment (33).

Nevertheless, several cons of AI had already arisen at this stage. For one, GPU energy efficiency. A paper written by Mittal and Vetter in 2014 already expressed concern about the GPU energy usage of high-computation models (34), showing early awareness that the application of GPUs and rapid growth of AI capabilities had also affected its energy consumption. Another point of concern is the dataset size and training energy (34). In early 2018, just after the tail end of this era, concern was also shown for Deep Neural Networks (DNNs) due to their high use in AI models despite their high computational requirements, and the challenges and complications faced in the process of attempting to create more energy-efficient alternatives (35).

These papers eventually reached out of the tighter circle of AI experts into the field of policymakers and more general academics.

Period 2 (2018-2021)

This period saw climate situations continue to worsen; following the trend of increasingly warm weather patterns, 2018 likewise fell within the rankings as the fourth warmest year in history (36). As AI systems became larger and more commercially integrated between 2018 and 2021 following the publishing of the initial transformer paper, concerns surrounding their environmental cost became more visible in both academic and public discourse.

Notably, in 2019 Strubell et al. published the paper titled “Energy and Policy Considerations for Deep Learning in NLP”, which speaks about the energy consumption in pounds of CO2 for a multitude of different well-known NLP models compared to the consumption of air travel or an entire human life (37). This was the first paper to bring the energy consumption of AI into focus in such a striking way, clearly making comparisons that made it understandable not only to academics but to the average layperson to truly make an impact. According to this paper, while a model like a basic transformer only produces 26 CO2-equivalent emissions, this number increases exponentially to reach 626,115 for BERT models (37).

Shortly after its publication, there was a rebuttal published by Google, with the argument that these numbers were inaccurate considering the efficiency of the materials used, such as highly specialized TPUs and the geographic location, since the proportion of renewable energies used can also vary (38). It is possible that some of these numbers may have been cherry-picked or not necessarily accurate given that Google has Gemini within its products and thus wishes to improve its sales.

This debate was significant because it highlighted one of the central challenges in assessing the environmental impact of NLP models: the difficulty of accurately measuring and estimating their energy consumption. While Strubell et al. emphasized the potentially severe environmental costs of deep learning models, Patterson et al. later argued that such estimates could vary substantially depending on factors such as hardware efficiency and data center infrastructure (38).

Period 3 (2022-2025)

During this period, global climate conditions continued to worsen alongside the rapid expansion of large-scale AI systems. According to NOAA data, 2024 was the hottest recorded year in modern history, with global land and ocean temperature anomalies maintaining a sharp upward trend (39). At the same time, machine learning models were becoming increasingly computationally intensive, requiring larger datasets, more powerful hardware, and energy-demanding infrastructure in their data centers. Despite this growth in energy requirements, early developments in the integration of AI systems prioritized scale and performance over energy efficiency or environmental sustainability. As these systems became more deeply integrated into commercial and industrial applications between 2022 and 2025, their growing electricity consumption and associated carbon emissions emerged as an increasingly significant environmental concern.

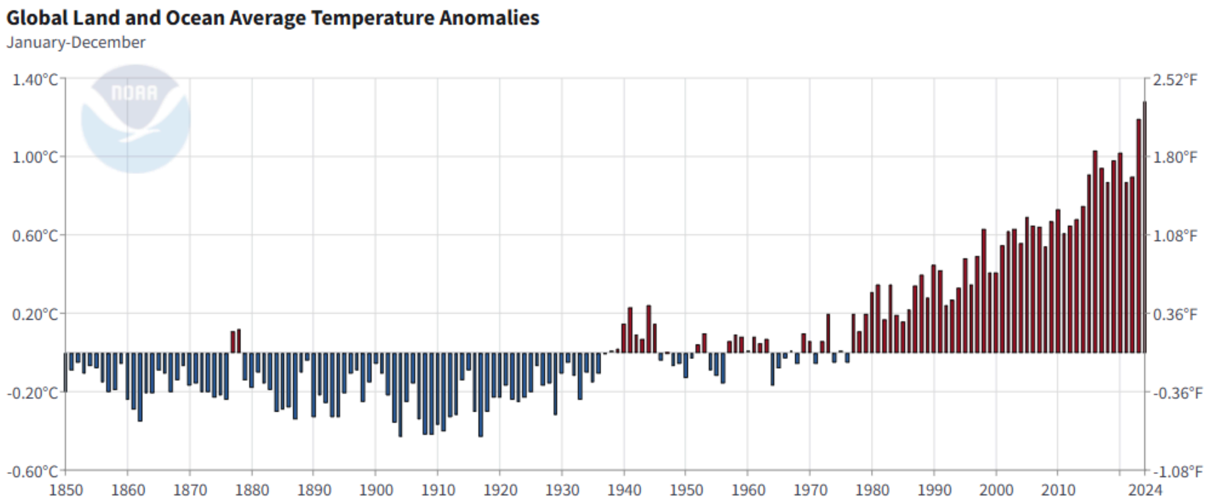

Figure 1: The graph above displays annual anomalies in global land and ocean average temperature from 1850 to 2024. The statistic is measured yearly, with anomalies below 0°C are blue while anomalies higher than 0°C are colored red. The sustained increase in positive temperature anomalies, particularly after 1980, demonstrates the accelerating progression of global warming during the same period in which computationally intensive AI systems expanded rapidly. This provides important environmental context for the increasing energy demands associated with large-scale machine learning infrastructure (40).

The rapid expansion of machine learning systems during this period also led to increased efforts to quantify their environmental impact (41). As models grew larger and AI applications became more widely integrated into consumer technologies and industrial processes, researchers began developing more accurate methods for calculating the carbon emissions and energy consumption associated with training and deploying these systems. This shift in research priorities was influenced in part by the debate sparked in 2019 between Strubell et al. and Google regarding the environmental costs of large-scale natural language processing models. Unlike earlier studies, which focused primarily on improving computational performance with limited attention to energy efficiency, research produced during this period increasingly incorporated sustainability, carbon accounting, and climate mitigation into discussions of AI development (42).

This is also the first period that has seen machine learning actively used to aid climate change mitigation. Its applications fall mostly under the jurisdiction of predictions. According to a paper written in 2024 by Ukoba et al., one of its purposes is helping to optimize renewable energy systems by analyzing complex environmental data and predicting patterns (43). Fluctuations in energy produced by green energy sources, such as solar or wind power, often makes renewable energy systems inefficient, preventing them from being integrated into large-scale power grids. Predicting weather patterns via machine learning combats the unpredictability, allowing them to become more effective, efficient, and reliable. Another example is helping to predict the energy consumption of cars, buildings, or factories to gather data on their impact and reduce emissions as a whole.

Now, articles that are targeted to be read by the general public, such as those by MIT, write about this topic with a high degree of nuance, incorporating both positive and negative elements (44). The conclusion is that more research and implementation is required to see exactly whether AI's climate impact can be mitigated without sacrificing its computational power.

Summary

In some ways, the impact of AI usage on the climate may be viewed as positive. One of the most common uses is in modelling, especially in situations that require processing large amounts of data. AI has been used to model for situations like weather patterns or natural disasters, to help mitigate their consequences. Datasite collections like the Climate Data User Guide (45) have also been established due to this effort, which aided the development of accurate climate models and predictions. An example of this is research done in 2024, where machine learning was used to predict the effect of climate change on US heat waves (46). The results agreed with human-processed data, demonstrating the AI's usefulness in this context. Other than natural phenomena, modelling is also useful when used for predicting emissions from engines or buildings, which are huge contributors to global emissions. Outside of simply predicting emissions produced, models can also predict how new biofuels or eco-friendly fuels may perform, leading to accelerated introduction of fossil fuel alternatives (47).

However, these advantages come at a cost: according to OpenAI themselves, AI models require substantial energy demand in order to function, and this amount has only been growing as systems grow more complex and powerful in order to process increasing amounts of data (48). In fact, it is estimated by an MIT Technology Review article that a one-time training process for GPT-4 consumed 50 gigawatt-hours of energy, which is roughly equivalent to the energy required to power San Francisco for three days (49). The increase in function quality required the use of AI accelerators such as GPUs, which also contributed to the general increase in energy usage over time, as the more advanced a model became, the more components and computational resources it required (42). Furthermore, not only do they require actual energy to power all of the necessary components, but also, as the servers begin to run they generate a large amount of heat, leading to the need of cooling systems that use up even more energy (50).

In light of these shifting energy demands and effects on the environment, perceptions of AI's environmental role also evolved substantially across different sectors. Academic institutions, technology companies, and public media often interpreted these developments differently, shaping broader discourse surrounding AI and sustainability.

CROSS-SECTOR SENTIMENT AND NARRATIVES

Following the quick development of AI, discourse surrounding its environmental impact has also grown. This section specifically examines how AI's relationship with climate change has been perceived in each of the three eras. This evaluation will focus on three main publication fields: academia, industry, and online publishing houses. By analyzing sentiment trends and categorizing proposed solutions, this section shows the evolution of views surrounding AI's environmental footprint.

Literature Selection and Interpretive Framework

Media Sampling

Academic analysis was based on articles accessed through platforms such as Google Scholar, IEEE Xplore, and arXiv. Papers were selected based on relevance to AI's environmental impact, using search terms like "AI and energy consumption," "AI and climate change," and "green AI." For each era, at least five papers were chosen to ensure there were a wide range of views represented.

Industry sentiment was assessed using over 25 publicly available sources, including whitepapers, annual ESG reports, and technical blogs from companies such as Google, Microsoft, IBM, DeepMind, and smaller climate AI startups. Only documents that explicitly addressed AI's energy use or climate applications were included.

The view of public publishing houses was determined by choosing 10+ articles for each period from some of the most visited English-language news outlets when measured by web traffic as of March 2025 (51), as well as more genre-specific sites. The most visited sites were *The New York Times, BBC, CNN, The Guardian,* and *News18*. The countries represented here are the US, the UK, and India. However, the NYT, BBC, and CNN are often read outside of their "host" countries, seen more as global networks. For example, BBC reaches around 318 million people according to their official website, updated recently, which far surpasses the number of people just in the UK (52). More genre-specific sites include *Scientific American* and *MIT Technology Review*.

Interpretive Framework

To facilitate effective comparative discussion between sectors on their perception of AI's impact on the climate, a Sentiment Concern Index (SCI) was developed. Rather than functioning as a quantitative metric, the SCI serves as an interpretive framework which will be used to organize broad tendencies and trends observed across reviewed sources, reflecting the level of concern or optimism toward AI's environmental impact.

Score	Interpretation
+3	Strongly optimistic (AI significantly helps climate)
+2	Moderately optimistic (AI helps climate significantly more than harms)
+1	Slightly optimistic (AI helps climate slightly more than harms)
0	Neutral/mixed (AI helps and harms climate equally)
-1	Slightly concerned (AI harms climate slightly more than helps)
-2	Moderately concerned (AI harms significantly more than helps)
-3	Strongly alarmed (AI significantly harms climate)

Table 1: Interpretive Sentiment Concern Index (SCI) framework used to categorize narrative tone across sectors of academic, industrial, and public discourse.

Period 1: 2014-2017

Academia (+1)

In the field of academia, AI was explored as a tool for climate modeling and energy optimization, although this mainly took place towards the end of this era, in 2017 or the early months of 2018. Research was cautiously optimistic, highlighting theoretical benefits. This includes papers such as a paper written by Yang et. al in 2017, which used AI techniques such as the artificial neural network (ANN) to predict the inflow levels of reservoirs based in the US and China (53). A paper written by Amasyali and El-Gohary in early 2018 also developed a machine learning-based method to optimize HVAC systems, displaying this early academic interest in applying AI to energy efficiency (54).

However, the energy use of training models was already being flagged in parallel research, laying early groundwork for “Green AI” discourse. This occurred as early as 2016, where a paper by Li et al. examined the energy consumption of training then-popular neural network models on computer vision tasks, containing one of the first deep-dives and breakdowns of the energy used during training and inference for models utilizing GPUs (55).

Still, with the lack of concrete evidence or research at the time, there was not much that could be said on the topic.

Industry (0)

On the other hand, few common real-world applications had been implemented at the time throughout various industries.

From environment reports from Google, Samsung, and IBM, it can be seen that corporate interest was nascent. In the Environmental Report by Google (2016), AI was discussed primarily in terms of data center automation, not environmental applications (56). IBM's 2017 Corporate Responsibility Report mentioned AI-driven enterprise solutions but lacked reference to climate or environmental targets (57). As can be seen, most conversations within these companies were centered on automation, not sustainability, leaving environmental effects largely absent from discourse.

Similar effects happened within startups in the AI sector, which focused on innovation narratives with no significant sustainability viewpoint. In a list of 25 rising startups in this period written for Forbes magazine, on which the detailed missions and purposes of each startup focus most on solving problems such as improving datasets and engines, and aiding manufacturing companies, without a hint of any startup working towards solving a climate-based problem (58).

News Media (-1)

In more scientific articles, such as those from Scientific American, AI was being viewed positively throughout 2015-2017. This includes articles like "Springtime for AI: The Rise of Deep Learning", which highlights the new applications of deep learning and neural networks that had arisen (59). In 2015, it even published an article titled "Deep Learning is the AI Breakthrough We've Been Waiting For", stating clearly that the possibilities of the newly developed deep learning, allowing computers to be autonomous, could suggest positive consequences (60). With the introduction of AI being so recent at the time, these articles focus primarily on the small developments made at the time like photo recognition and the ability for computers to autonomously play video games.

But for some, rather than actual concrete information or data points about AI, skepticism about "AI hype" was common. The New York Times published such articles in 2014, for example, such as "Artificial Intelligence as a Threat", which speaks about how it may not take long for AI to "spiral out of control" (61). An article from The New York Times in 2016 spoke on the topic of AI's "great awakening" in regards to its use in Google Translate, and showed clearly how the integration of AI into multiple Google products had changed the entire landscape of the market, also did not mention anything about its possible environmental impacts (62). At the time, celebrities like Elon Musk and books had been published about the grim outlook of AI usage. However, this article, and many others in common, mostly speak to general AI ethics rather than concerns with its environmental impact.

Period 2: 2018-2021

Academia (+2)

Academic consensus grew around AI’s potential to enhance energy forecasting, emission tracking, and climate modeling. Major development occurred in 2019, with an influx of papers. For instance, Rolnick published “Tackling Climate Change with Machine Learning,” a landmark survey outlining 13 domains where ML could accelerate sustainability (63). A paper by Campos et al. explored the uses of neural networks in making simulations of the Gulf of Mexico, specifically for the long-term predictions of weather and wave patterns (64). Wang et al. (2019) proposed hybrid models combining deep learning with Earth system science to better simulate climate (65). These signaled growing consensus that AI could support decarbonization, despite simultaneously ongoing ethical debates.

It is true that ethical debates on AI fairness and environmental equity also intensified. Most notably, the publishing of the paper analyzing carbon outputs of different AI models, written by Strubell et al. (37). Overall, these were overshadowed by the mounting potential being discovered.

Industry (+1)

AI adoption in climate tech expanded greatly. Some applications were smart grids and precision agriculture. Microsoft’s “AI for Earth” program, launched in 2017 and matured by 2019, provided open-access tools for land cover mapping and climate modeling (66). IBM launched AI-powered energy management platforms, called Watson IoT for smart buildings (67), as well as deployed a site through which companies without coding experience could easily design and deploy their own AI models (68).

However, OpenAI's GPT-2 and similar models triggered controversy due to their high energy demands, signaling tension between utility and emissions, as noted in an article in a business article by Wired, titled “AI Can Do Great Things—if It Doesn’t Burn the Planet” (69). Growth in data centers and compute-heavy AI models led to further mixed perceptions. Because the growth in uses and overall need for AI drastically increased in this time period of initial deployment, there was a larger focal point on distribution and development for speed and effectiveness over a focus on environmental impacts or energy efficiency.

In 2020, for instance, Microsoft wrote a study on the carbon benefits of cloud computing, showing how large-scale companies were interested in promoting a healthy environment and were attempting to balance efficiency of models alongside the growing need for carbon efficiency, making ambitious zero-carbon or zero-emission goals by 2025 and 2030 (70).

Public Publishing Houses (0)

In comparison to the fearful or overtly negative tones of previous years, coming from the concern about “AI hype”, a more balanced tone emerged in news articles and media in this era. Overall, the tone balanced critique with cautious endorsement, showing rising literacy and awareness from writers and from the public about AI’s environmental tradeoffs.

Highlighting this change were stories which praised AI for its profound positive impacts, such as tracking deforestation or improving disaster prediction. Scientific American, while it largely focused on AI’s other applications in this era, contributed to this growing concept of climate change and AI with the article titled “What AI Can Do for Climate Change, and What Climate Change Can Do for AI” (71). The New York Times first wrote on this concept in 2019, writing an article titled “How A.I. Can Help Handle Severe Weather” (72).

Still there existed some articles that critiqued AI’s environmental tradeoffs, particularly surrounding NLP model energy use. In 2019, MIT Technology Review’s article titled “Training a single AI model can emit as much carbon as five cars in their lifetimes” (73) spotlighted the famous GPT-2 study by Strubell et al. (37), which had also shaken the academic world in the very same year.

The debate surrounding AI-related emissions also began extending beyond academic journals and traditional news media into broader online discourse. Discussions sparked by the estimates presented by Strubell et al. and later challenged by Google researchers such as Patterson et al. contributed to increased visibility of AI’s environmental impact across social and professional media platforms. This helped shift concerns surrounding the sustainability of large-scale AI systems into more mainstream technological discussions rather than remaining confined to specialized academic literature.

Period 3: 2022-2025

Academia (+1)

Recent academic work emphasizes responsible AI, defined by IBM as a set of principles used to guide AI’s design, development, and uses, ensuring that AI solutions do not cause damage but are able to aid organizations and stakeholders involved (74). This includes papers written on green AI design, promotion of carbon-aware training, and AI for adaption strategies to the ever-changing climate. In a paper by Liu and Yin, green AI is discussed in detail, not only including facts on their carbon footprints but specifically emphasizing mitigation strategies, with a specific section dedicated to experimental setup on determining the best ways to mitigate the environmental impact of LLMs (75).

More and more studies have been committed to accurately measuring the energy costs of AI models. This first began with a paper by Samsi written in 2023, which was one of the first to analyze the computational and resources required by LLMs (76). Although not focused on the environmental impacts that energy-intensive LLMs had, this was still a step forward in uncovering accurate data, past the simple estimations proposed in Strubell's 2019 paper.

Positive framing continues, but is now paired with accountability frameworks. Leal Filho et al. (2022) discuss in their paper how AI can help enhance and enforce government and policy coherence (77), showing a shift in the fact that AI has expanded its boundaries and can now be used to aid outside of academic or research uses, in the society and community. This reflects its more widespread use by the wider community through the creation of multiple AI chatbots, as well as its continual integration into widely used products such as Siri (78).

Industry (+2)

Recently big tech companies such as Google or Microsoft have made climate pledges (e.g., "net-zero AI," "sustainable ML"). In the case of Google, their dedication to this climate pledge was demonstrated through the creation of a specific environmental report just for its AI usages starting from July of 2023 (79). Within, they feature multiple environmental sustainability strategies and targets, specifying both past and present metrics to show how they are working towards these goals (79).

One commonly referenced metric in industry sustainability reporting is Power Usage Effectiveness, or PUE, which measures how well a data center converts energy into useful computational work (80). Lower PUE values generally indicate greater infrastructural efficiency with respect to factors such as cooling. The formula goes as follows:

$$PUE = \frac{Total\ Facility\ Power}{IT\ Equipment\ Power}$$

In their 2024 environmental review Google reported a low PUE score of 1.10, implying that most of the energy used is used directly by necessary equipment and thus suggesting evidence of their improving data center efficiency. They also developed the TPU, and showed their use of AI prediction in projects like cool roofs, implementing reflective roofs to save energy from heating and AC, and to reduce emissions (81). Google's website also provides supporting information, having written multiple articles on their research on the uses and effects of AI's sustainability (82). For instance, a recent article explains Google's implementation of AI in farming, greatly boosting crop productivity (83). They also specify that they are working together with the government and NGOs by providing them with climate data, and have even written an article on how AI can help advance progress on UN SDG goal number 7, clean energy, in the future (84). This shows how large tech companies want to create an image of being dedicated to this climate movement of improving sustainability.

Startups have also chosen to focus more on finding solutions to mitigate the climate impact of AI, deploying AI in emissions tracking and carbon market validation. Some famous companies include Anthropic, known for its Claude models, and Mistral AI, known for models such as Mistral and Mixtral. Google has aided this shift by choosing to fund AI startups which have a focus on climate change aid or mitigation purposes, such as tackling deforestation or ecosystem conservation (85).

News Media (+1)

Unlike covering AI's effects or possible damaging outcomes, coverage shifted more towards solutions, including carbon-efficient algorithms, open-source climate datasets, and climate AI competitions. While some criticism persists, it is increasingly constructive.

For instance, in the Scientific American, the article "AI Needs to Be More Energy Efficient" discusses the solution of urging the public to be more involved in promoting the development of energy-efficient methodologies and models in the industry, ending the article with a clear call to action that clearly displays the shift towards constructive criticism (86). In the New York Times, articles from 2022 onwards have consistently been published on the topic of AI's usages in climate prediction and control, as well as its energy efficiency, such as "Will A.I. Ruin the Planet or Save the Planet?" (87). Dealbook newsletter, which mainly focuses on finance, showing how AI and climate issues have managed to catch the attention of other sectors (88). Most recently, the article "Can You Choose an A.I. Model That Harms the Planet Less?" by Mulkey in 2025 reflects this same sentiment (89).

EMERGING TRENDS, RESPONSES, AND FUTURE DIRECTIONS

As concern regarding the environmental impact of AI systems has expanded across the sectors of academia, industry, and public media, a growing range of mitigation strategies has emerged. These efforts reflect increasing recognition that the long-term sustainability of AI development depends not only on technological advancement itself, but also on improvements in computational efficiency, infrastructure transparency, environmental accountability, and interdisciplinary collaboration. Although perspectives differ across sectors, proposed responses generally gather under several recurring themes, including Green AI, climate-oriented applications, standardized emissions reporting, and broader coordination between stakeholders.

Computational Efficiency and Green AI

Recent shifts in both academia and industry demonstrate increasing recognition of AI's carbon footprint, leading to a push toward "green AI", low-power model design, and carbon labeling. As transformers become ubiquitous, their environmental impact could be mitigated by integrating carbon-aware scheduling, leveraging renewable-powered data centers, and prioritizing efficiency in model design.

For instance, Google Cloud has committed to powering its global data centers 24/7 with carbon-free energy by 2030 by employing its DeepMind AI to manage data cooling systems most efficiently (90). Microsoft Azure has also set targets to achieve 100% renewable energy supply by 2025 and to become carbon-negative by 2030, integrating advanced cooling and resource optimization while addressing supply chain emissions. In parallel, hardware and GPU providers such as Nvidia have transitioned their controlled facilities to 100% renewable electricity, coupling infrastructure decarbonization with efforts to improve chip efficiency and lower energy demands for AI workloads.

Another major response to highlight here is “Green AI,” a framework which emphasizes computational efficiency, as well as transparency and sustainability in machine learning development. Rather than focusing exclusively on maximizing model performance, Green AI initiatives encourage and often incentivize researchers and companies to consider energy consumption, hardware efficiency, and environmental cost as further factors of evaluation. This shift reflects broader recognition that improvements in AI capability must be balanced against its environmental demands.

Much of the existing literature surrounding Green AI has focused on reducing the computational intensity of model training and deployment. Proposed strategies have included model pruning, sparse architectures, parameter sharing, and the development of smaller task-specific systems which achieve performance while lowering energy consumption.

There are also suggested motivations for this initiative, with cash prizes often being deemed to be the most useful. Google has highlighted this as early as their 2016 sustainability report, where they mention they will provide most of a project’s cashflow given that the developers choose to use sustainable energy sources (58). In media and public publishing papers, more instances of these cases are being highlighted, such as Meta’s low-carbon data center infrastructure through the use of more sustainable materials (91) and DeepMind’s use of AI to reduce data center cooling costs (92).

Climate-Oriented AI Applications

In order to counter the possible adverse effects of AI, another suggestion is to utilize AI in aiding environmental intelligence efforts. Researchers, governments, and private companies have explored AI-driven approaches for renewable energy optimization, environmental monitoring, emissions forecasting, precision agriculture, transportation efficiency, and climate modeling. These applications contribute to the argument that AI may function not only as a source of environmental concern, but also as a potential tool for addressing complex climate-related challenges.

Such instances of applied usage include climate modeling, satellite image analysis, biodiversity mapping, and disaster response optimization. Case stories about real-time wildfire detection (93) or glacier monitoring (94) have also been shared across public news media. Additionally, it may be able to aid in insurance risk assessments, precision agriculture, and supply chain monitoring, especially for worldwide companies such as Amazon.

Regulation and Government Intervention

As concern surrounding AI-related emissions has increased, the need for increased governmental regulations and governance in this sector is also increasingly mentioned. This includes the call researchers and policymakers make for the need for greater transparency regarding computational energy usage and environmental reporting. Estimating the carbon footprint of AI systems remains challenging due to differences in hardware efficiency, data center infrastructure, cooling requirements, regional electricity sources, and limited public disclosure from private companies. As a result, many existing emissions estimates vary substantially across studies.

Metrics such as Power Usage Effectiveness (PUE), discussed previously in relation to industry sustainability reporting, have become increasingly central to conversations surrounding AI infrastructure efficiency and emissions accounting. However, researchers have noted that PUE alone does not fully capture the environmental impact of data centers, since overall emissions also depend on electricity sources, hardware lifecycles, cooling systems, and operational scale.

Several researchers have argued that greater standardization in emissions reporting may improve the comparability and reliability of environmental assessments related to AI systems. Existing estimates often rely on incomplete information regarding training duration, hardware utilization, or electricity sourcing, making it difficult to evaluate the true environmental costs associated with large-scale models. In response, some researchers have proposed standardized reporting frameworks aimed at improving transparency regarding energy consumption, carbon emissions, and computational requirements.

At the same time, public discussion regarding AI sustainability has increasingly expanded into broader regulatory and governance debates. Policymakers and advocacy groups have raised questions regarding data center expansion, energy infrastructure demand, water usage, and the environmental responsibilities of large technology companies. While formal regulation remains limited in many regions, recent discussions suggest growing interest in sustainability standards and environmental accountability within AI development.

Improved transparency and standardized reporting may become increasingly important as AI systems continue expanding into energy-intensive commercial and public applications. Existing literature increasingly emphasizes that meaningful evaluation of AI sustainability requires not only technological innovation, but also more consistent methods for measuring and communicating environmental impact.

Public Engagement and Cross-Sector Collaboration

The evolving relationship between AI and climate change has increasingly become not only a technical issue, but also a societal and interdisciplinary one. Academic researchers, technology companies, policymakers, journalists, and public media outlets often seem to frame AI's environmental role differently, contributing to competing narratives which can lead to confusion as these perspectives directly influence public understanding and institutional responses to AI-related environmental concerns.

The findings of this review suggest that future strategies should move beyond single-sector solutions. Effective climate-aligned AI development may rely on combining regulatory policies and market incentives requiring carbon reporting paired with credits or tax benefits for low-carbon AI development. Technical innovation is also essential, as in advancing in the creation of sparse models and efficient training protocols, learning to reduce the amount of data movement and computation required per model.

Market-based and social incentives are important. For instance, giving carbon credits for efficient code or models, having AI-enabled ESG investing platforms, and public awards for climate-conscious innovation like green-buildings do could all incentivize researchers and industries alike to target energy efficiency.

Lastly, multiple sources suggest a solution related to education, aimed at the public, in order to garner increased engagement from the wider community. This includes pushing for transparency in revealing AI's environmental costs from researchers in academia, or hosting climate-related AI hackathons or open-data challenges to crowdsource solutions and ignite further interest or passion into this topic, accelerating developments.

Current literature increasingly suggests that the long-term relationship between AI and climate change will depend not only on continued technological advancement, but also on how societies choose to evaluate, regulate, and prioritize the environmental consequences associated with large-scale computational systems.

CONCLUSION

This review suggests that the relationship between AI and climate change has evolved into an increasingly multidimensional issue over time; as AI systems have become more computationally intensive and commercially integrated between 2014 and 2025, concerns surrounding its energy-intensive infrastructure have grown alongside recognition of AI's potential contributions to climate mitigation and environmental analysis.

This review found that perspectives surrounding AI's environmental role differed substantially across academia, industry, and public publishing. Academic literature frequently emphasized emissions measurement, computational scaling, and the long-term sustainability implications of increasingly large models. Industry discourse more often focused on efficiency improvements, infrastructure optimization, and renewable energy commitments, while public media narratives alternated between portraying AI as either a transformative climate solution or a rapidly expanding environmental concern. Together, these differing perspectives illustrate how interpretations of AI sustainability are shaped not only by technological developments themselves, but also by the priorities and assumptions of the sectors evaluating them.

The findings of this review additionally suggest that AI's environmental impact cannot be understood through purely optimistic or pessimistic frameworks. Advances in transformer-based systems and machine learning infrastructure have enabled significant progress in climate modeling, energy optimization, environmental monitoring, and emissions analysis. At the same time, the continued expansion of large-scale AI systems has intensified concerns regarding computational resource demands, electricity consumption, and the environmental costs associated with rapidly scaling digital infrastructure.

Because this review is interpretive in nature and based on selectively synthesized literature, its conclusions should be understood as exploratory rather than definitive. Future research may therefore benefit from more standardized approaches to emissions reporting, broader comparative analysis of media and industry narratives, and continued interdisciplinary collaboration between researchers, policymakers, and the public. Ultimately, the long-term relationship between AI and climate change will likely depend not only on technological innovation, but also on how societies are able to regulate and balance the environmental consequences associated with these increasingly large computational systems.

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