

# 1. Is AI the Right Tool for the Job? Understanding the Environmental Implications of This Emerging Technology

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**Abstract:** Artificial intelligence (AI) has seen unprecedented rates of adoption and dominates the discourse within our industry. Most of the conversation focuses on the extremes of how it will affect practitioners' careers: AI is the salvation of our profession, or AI will put us all out of work. However, there is notably less attention given to the planetary impact of this powerful, yet energy- and emissions-intensive technology. Research shows that AI has a substantial carbon footprint. The accelerating adoption of AI for mundane content tasks puts us at risk of generating even more emissions at a time when we urgently need to reduce our impacts.

This chapter explores the limited data available regarding emissions impacts of AI technologies and addresses other potential costs to society. These costs must be considered on a case-by-case basis when balancing the merits and drawbacks of incorporating AI in technical communication.

**Keywords:** AI, LLM, carbon footprint, sustainable content, ethics

Artificial intelligence (AI) has become the hottest trend among communications professionals, dominating the discourse within our industry. Conferences, webinars, and newsletters are filled with discussions about how it will affect practitioners' careers and the information is polarized for clicks: AI is either the salvation and future of our profession, or AI will put everyone out of work. However, there is notably less attention given to the planetary impact associated with the use of this powerful, yet energy- and emissions-intensive technology.

I have established that our human-created digital content has an emissions impact (Bonsignore, 2023). That calculation is fundamentally an analysis of clicks—the number of webpage hits or file downloads—multiplied by the page weight or file size. But what is the difference when the content has been created by AI?

This article sought to explore the existing literature to generate similar metrics for AI-generated content. It is perhaps not surprising that the AI industry is moving fast, and the published research into the impacts isn't keeping pace. ChatGPT was released by OpenAI in November 2022, the first of the main-stream AI tools. Given the length of time that it takes to conduct research, gather

data, undergo peer review, and be published, it's no surprise that the publicly available research correlating AI, content development, and emissions is limited.

AI tools have been developed by corporations that have been less than forthcoming with documentation. In an article for *Wired*, Paresh Dave (2024) noted that OpenAI, for example, has apparently scrapped a pledge for operational transparency. However, there is enough publicly available information that we can begin to draw informed inferences about the energy use and related emissions of AI as a whole, and begin to assess the impacts that its use can have on our planet. By looking at the bigger picture, we can begin to understand and balance the significant impact and tradeoffs associated with AI.

## ■ What Is AI?

Any discussion of AI needs to begin with a level-setting: what do we mean when we talk about AI?

Many terms fall under the umbrella of AI. It's important to clarify them upfront.

- Artificial intelligence (AI): The field of study in computer science that develops intelligent machines.
- Machine learning: The branch of AI focused on developing algorithms that make predictions. (e.g. spam filtering in your email)
- Large language model (LLM): An AI algorithm that uses massive data sets to understand and generate content. (e.g. ChatGPT)
- Natural language processing (NLP): The branch of AI that focuses on giving computers the ability to understand human language. (e.g. spell check)
- Generative AI: AI that analyzes data patterns to generate new content, including text, audio, imagery, and code. (e.g. "Write an explanation of a solar eclipse in iambic pentameter")

ChatGPT—the best-known AI tool—is a generative AI LLM that uses machine learning and NLP to interpret user queries and generate conversational, understandable responses. While it was the first tool of significance to go to market, is not the only player in this space, and is competing against Google, Microsoft, Amazon, and Meta for market share.

However, most people are referring to all aspects of these GPT-types of technologies colloquially as "AI" or "ChatGPT" regardless of the actual underlying system, not unlike the genericization of Kleenex, Xerox, or Band-Aid. Therefore, that is the terminology that will be used here.

We should also note that some AI tools have long been used in content, such as spell check and grammar checkers. However, these are relatively basic, low-energy tools that don't have the same emissions impact as the new wave of technology—ChatGPT and the like.

## ■ What Was AI Designed For?

AI was designed to analyze massive datasets and generate conclusions that would either be too time-consuming or outside the scope of one human's analytical grasp. For example, AI tools are increasingly used to forecast hurricane intensity and landfall; they can simulate and predict the long-term durability of a knee implant; or they can run time-intensive physics simulations to understand how buildings will perform in earthquakes. As noted by Lynn H. Kaack, et al. (2022), AI excels at information gathering, forecasting, and predictive simulations, delivering comprehensive results in accelerated timeframes.

## ■ How Does AI Work?

There are two primary aspects of AI:

- Training: the volumes of datasets that the tool uses to “learn” its skills; this can be anything from a specifically developed dataset to the collected works of Shakespeare
- Inference: making predictions using the trained models

While significant research is emerging regarding the impacts of AI training, there is less public understanding of the impacts of AI inferences. I'll examine them separately below for clarity, but researchers ultimately need to look at the full scope of the process to understand the impact in its entirety.

## ■ Literature Review

This paper began by investigating existing research into the environmental impacts of using AI tools as content tools. Given the novelty of these systems, the information does not exist. Therefore, it was necessary to take a step backward: if we can't measure the impacts of specific instances, we need to take a look at the development and use of AI tools as a whole.

## ■ AI and Energy

Generative AI tools have broken records for technology growth and adoption. Research by Andrew A. Chien, et al. (2023) noted that it uses extensive computational resources and can infer that there is a corresponding increase in energy use and carbon emissions.

Our use of digital technologies is ever-increasing, and every byte is energy. As I noted in previous literature, energy—at least for the foreseeable future—has a carbon footprint (Bonsignore, 2023). We power our electronic devices and data centers primarily by burning fossil fuels, such as petroleum, natural gas, or coal. These energy sources turn turbines that generate electricity, which is then

distributed to our homes and businesses through the local or regional power grid. We use a lot of energy. Our digital footprints are ever-increasing, and every byte has a carbon cost.

According to *Our World in Data* (Ritchie, 2023), humanity has doubled its energy consumption in the past four decades, from roughly 87,000 terawatt hours in 1980 to approximately 174,000 terawatt hours in 2019. Increases in renewable energy generation are not meeting our increased demand. Our increased overall consumption limits the amount of headway that we're making on a true green energy transition. Our expanding use of information and communication technologies (ICT)—including AI—is driving a significant amount of that consumption.

## ■ AI and Energy: Past and Future

Even prior to the emergence of ChatGPT, AI technologies were known to be energy intensive. Between 2012 and 2018, Mariarosaria Taddeo and team (2021) reported that the computing power required for machine learning models increased by more than 300,000 times, doubling every 3.4 months.

Data centers were reportedly consuming more than 2% of the world's energy in 2020, and it was estimated that energy use would increase to “somewhere between 8% (best case) and 21% (expected)” by 2025 (Stein, 2020). Further, according to the International Energy Agency (IEA) (2023), these numbers would account for approximately 1% of global emissions.

Nicola Jones (2018) pointed out that data centers were responsible for 0.3% of the overall annual carbon emissions. However, when examined as part of the entire information and communications technology (ICT) ecosystem—adding digital devices and related networks used to create, store, transmit, and consume data—the impact of our data-hungry lifestyle accounts for roughly 2% of global emissions. That's comparable to the annual emissions from the aviation industry (Environmental and Energy Study Institute 2022).

Those working deep in the climate space are deeply aware of the added consumption that AI will bring. At a panel discussion during NYC Climate Week 2023—specific details restricted by Chatham House rules—the panelists discussed how AI is causing computational demand to skyrocket. Jonathan Koomey (2011) and NVIDIA (2021) agreed, and this means more computing hardware. This need for more hardware means more data centers (Shao et al., 2022), which Sebastian Moss (2021) notes will lead to increasing water and energy use to keep those data centers cool. The panelists believe AI to be roughly seven times as energy intensive as a standard data center because the nodes are constantly working at maximum capacity and requiring significant energy for operations and cooling. Consider that in traditional data centers—already known to have significant environmental impacts—most of the data is stored, not active. Whereas conventional data centers operate more like a car idling at a traffic light, AI requires the all-out effort of a Formula 1 racecar.

These high-intensity data centers use water for efficient cooling. However, many are in water-stressed areas such as Arizona and Utah, reducing the amount of fresh water available for residents. Mél Hogan (2015) estimated that one data center in Utah used 7 million gallons of water per day.

Jeffrey Daston (2024) reporting for Reuters noted that at a *Bloomberg* event at the World Economic Forum in Davos, Switzerland, Sam Altman—the on-again, off-again CEO of OpenAI—suggested that AI is so energy-intensive as to require the development of entirely new sources of electricity to accommodate the technology’s needs. “With the ever-growing adoption of artificial intelligence (AI)-based systems, the carbon footprint of AI is no longer negligible,” (Verdecchia et al., 2023, p. n.p.). While Emily M. Bender and her collaborators (2021) discussed the rapid expansion of model sizes, noting that this expansion brings with it a corresponding increase in environmental impacts.

The growth of AI and cloud-based services are driving record growth in the data center sector, which is being touted as a win for tech. However even those that are bullish about data center growth admit to their sustainability drawbacks. “Data centers are massive power users and require significant efforts to keep cool,” said Matt Landek. “Given hyperscaler and colocation provider sustainability goals, the data center industry will need new innovations to improve cooling and energy efficiency for AI uses” (qtd. in Steele, 2023, n.p.).

As mentioned previously, AI is best at analyzing massive data sets for forecasting and predictive simulations. In those contexts, there is some amount of operational efficiency that reduces the time required for large-scale modeling of pharmaceutical drug development or Amazon deforestation simulations. There is an element of learning as it goes. It is less efficient when developing a conversational chatbot or a user journey because the experiences are human and therefore less predictable. Humans do not use consistent wording to request necessary information. Because generative AI is based on patterns, these variations in inputs require unique searches and can generate different results.

## ■ Measuring The Impact of AI

Measuring the impact of AI is complicated. There’s legacy data on older technologies (insights as to the operational costs of smaller, less developed models), but the pace of growth for AI is rapidly accelerating, with newer tools being released regularly. And, as with any emerging technology, there is a lag between the launch of the new product, and the measurement of the impacts.

Research tends to approach measurement from the back door: If Company X is known to be developing AI models, and they have publicly reported that they have purchased a known number of servers or graphics processing units (GPUs) from Company Y, estimates can be made about the energy draw and related emissions associated with that hardware. Similarly, the acquisition of a new data center can result in a generalized inference based on square footage, rack space, and energy

draw of the contained hardware. But the statistics will vary among OpenAI, Meta, and Google because no two systems are configured exactly the same way.

Alex De Vries (2023) estimated that Google's AI alone is on track to consume as much energy as the entire nation of Ireland. But the major tech companies like Google, Meta, and X (formerly Twitter), are hardly the only entrants into the AI race; these major organizations are competing against venture-funded startups that are incentivizing massive, rapid growth with even less transparency than publicly traded corporations.

Within the industry, there are calls to require energy and emissions costs explicitly, such as those by James O'Donnell and Casey Crownhart (2025). According to David Patterson et al (2021), this would stimulate competition among providers and help everyone understand the true costs,

Fortunately, these questions are also penetrating the mainstream consciousness. Chris Stokel-Walker (2023) argued that “the race to build high-performance, AI-powered search engines is likely to require a dramatic rise in computing power, and with it a massive increase in the amount of energy that tech companies require and the amount of carbon they emit” (n.p.). As noted earlier, there are two primary phases to AI: training and inference. There is uneven analysis of the impacts of each. While there is greater transparency on the impact of training, there is less attention paid to the impacts of individual queries.

## ■ Impacts of Training

The training phase is the aspect that's most studied (Verdecchia 2023). Processing human language is one of the most energy-intensive uses of AI. Estimates for the impact of training a single model to handle human language is equal to approximately five times the lifetime emissions of the average car in the US (Stein 2020).

One study by Taddeo, et al. (2021) estimated that a single training run of generative pre-trained transformer 3 (GPT-3) produced more than 200,000 kg of emissions, which is roughly equivalent to driving 49 passenger cars for a year. GPT-3 was the predecessor to GPT-4; the latter provides the backbone of ChatGPT. Each iteration adds additional capacity, more energy, and more emissions.

But of course, AI researchers don't just train a single model; they often train thousands of models before achieving publishable results (Taddeo, 2021). When we see numbers for a single training run, or daily energy use, we need to understand that this is just a small fraction of the total impact.

## ■ The Unknowns of the Inference

It's easy to think that training is the root of the problem because of the massive scope of the datasets used in the initial training. It's a big problem, to be sure, but it's not the whole story. For tools in widespread use—ChatGPT, Gemini, Claude—the inference phase has a significant impact. Inference is where you run

data through a trained model in pursuit of a solution: the query that an individual runs. This is the part of the process that teaches AI systems to interpret and learn from their datasets. Kim Martineau (n.d.) notes in writing for IBM that “because up to 90% of an AI-model’s life is spent in inference mode, the bulk of AI’s carbon footprint is also here, serving AI models to the world” (n.p.). For example, while the training phase would involve exposure to every form of poetry and celestial phenomena, an inference would be the earlier example of asking it to explain a solar eclipse in iambic pentameter.

Alex de Vries (2023) investigated the balance of training vs. inference and saw signs that the impact of inference may be greater than previously assumed. This means that the overall impact of AI is significantly more than first thought. Because the same model is used to perform repeated inferences, the aggregated impact of inference over the lifetime of a model exceeds the impact of training (Patterson, 2022). The challenge comes with measuring that scope.

De Vries looked at a report from research firm SemiAnalysis authored by Dylan Patel and Afzal Ahamad (2023) who suggested that OpenAI required more than 3,600 NVIDIA HGX A100 servers and nearly 29,000 graphics processing units (GPUs) to support ChatGPT. Based on the known energy demand of these components, that suggested an energy demand of 564 MWh of energy use per day. Comparing that to estimates of nearly 1,300 MWh used for a single GPT-3 training run, it is clear that inference demand has a significant energy and emissions impact. This is reinforced by data from Google, which reported that 60% of AI energy consumption stemmed from inference in the period from 2019–2021 (Patterson, 2022). If we extrapolate this per-day use (564 MWh) over a year (365 days) we get 205,860 MWh of energy. Running this data through the U.S. EPA Greenhouse Gas Equivalencies calculator, a year’s worth of inferences generate nearly 90,000 metric tons of emissions annually. (As a reminder, megawatt hours equal 1,000 kilowatt hours.) Analysis from Chien et al. (2023) showed that “for ChatGPT-like services, inference dominates emissions, in one year producing 25x the carbon emissions of training GPT-3” (p. 1).

## ■ Environmental Impacts

It’s important to understand what this consumption means in terms of impacts to the planet. Anthropogenic climate change is expected to have significant impacts on the health and wellbeing of all humans, according to Imogen Tennison and her multinational research team (2021), which Nick Watts et al. (2019) noted will result in more intense heatwaves, higher risks of flooding and damaging storms, and a changing pattern of emerging infectious diseases. We are increasingly racing towards the point of no return. In November 2023, the planet first crossed the threshold of 2.0°C above pre-industrial temperatures (Copernicus, 2023, n.p.). For reference, an increase of no more than 1.5°C was the goal set forth by the Paris Agreement in 2015 (United Nations Framework Convention

on Climate Change, 2023). However, even at 1.5°C, we are facing significant planetary impacts.

For context, the difference between a 1.5°C and 2.0°C increase often results in impacts that are twice as severe, as seen in Table 1.1, based on data from the World Resources Institute (2018). Small temperature differences can have profoundly different effects. This is why there are urgent calls to reduce emissions as much as possible to mitigate the worst of the outcomes.

Table 1.1. Forecasted Differences in Planetary Impacts between 1.5°C and 2.0°C Temperature Increases

Impacts of 1.5°C and 2.0°C Temperature Increases			
	1.5°C	2.0°C	Difference
Global population exposed to severe heat at least once every five years	14%	37%	2.6x worse
Number of ice-free years in the Arctic	At least 1 every 100 years	At least 1 every 10 years	10x worse
Amount of Earth's land area that will shift to a new biome	7%	13%	1.86x worse
Decline in marine fisheries	1.5 million metric tons	3.0 million metric tons	2x worse

Source: *World Resources Institute*.

According to the International Panel on Climate Change (IPCC) (2022), human-induced warming of the climate system is already widespread, as noted by Gabriele C. Hegerl and Francis W. Zwiers (2007). However, the impacts are already being unevenly felt, with more dramatic consequences experienced by women, people with disabilities, those experiencing poverty, and Black, Indigenous, and people of color (Abeygunawardena et al., 2003; United Nations WomenWatch, 2009; U.S. Environmental Protection Agency Press Office, 2022; van Daalen et al., 2020; Yabe & Ukkusuri, 2020).

Although these more vulnerable or marginalized populations have been the first to experience the most severe consequences of climate change, we will all experience the long-term impacts. “Near-term actions that limit global warming to close to 1.5°C would substantially reduce projected losses and damages related to climate change in human systems and ecosystems,” (IPCC, 2022, n.p.). There is a lag time between emissions and their effects. The changes that we’re seeing today are a result of emissions from roughly a decade ago. Even if the entire planet were to change their habits tomorrow, it will be another decade before the tide turns and we start to see improvements. This is why we need to take swift and decisive action today. With that in mind, we all have an ethical obligation—and an enlightened self-interest—to mitigate our climate impacts as quickly and comprehensively as we can (Bonsignore, 2022).

## ■ Additional Ethical Considerations

While environmental concerns are the primary focus of this article, there are many other ethical considerations that need to be weighed when assessing the value of AI in any project. These ethical considerations fall into a few basic categories: bias, legality, privacy, and accuracy. I will address each one briefly.

### ■ Discrimination and Bias

Any model is only as good as the data used in its training and the perspectives of the individuals who review it. Training data bias can emerge when systems are designed with poor data sets, reinforcing structural racism (Zalnieriute & Cutts, 2022). It's easy to blame this on the dataset alone, but as with many social problems, this is exacerbated by homogeneous groups responsible for reviewing the data for social context, oblivious to the implications and harm, notes Gina Lazaro (2023). With AI, we don't know who was in the room formulating and framing the discussions. It's been broadly reported that OpenAI—the parent company behind ChatGPT—hired an outsourcing firm in Kenya to filter the worst violent, harmful, and toxic content for less than U.S.\$2 per hour. While this is economically feasible, Billy Perrigo (2023) discussed that it is also ethically questionable to pay subsistence wages for nine-hour daily shifts reviewing sexual abuse of children and adults, hate speech, and extreme violence. Yet despite the work of these Kenyan workers, the problems with content that promotes discrimination, self-harm, and harm to others persists. Zachary B. Wolf (2023) honed in on the heart of the issue: “AI can be racist, sexist and creepy. What should we do about it?” (n.p.) Unsurprisingly, the article does not solve the problem.

The ethics frameworks used to guide AI development lack geo-cultural diversity and are “primarily framed in the Western context, by researchers mostly situated in Western institutions/organizations, to mitigate social injustices prevalent in the West, using data from the West, and implicitly imparting Western value systems, as noted by Vinodkumar Prabhakaran and team (2022). Additionally, Josephine Seah and Mark Findlay (2021) pointed out that much of the ethics work tends to be male-authored, which is representative of the industry, but not the world as a whole.

Furthermore, even if we're using “good” data, it can have unintended consequences. Data used in one context may not transfer accurately to another. Interpretation bias is always a possibility; Victor Galaz et al. (2021) pointed out that the user may infer something that the designer didn't intend, or the system might not support.

### ■ Copyright Issues

There is increasing public awareness that the data used to train ChatGPT (and others) was copyrighted or proprietary. Multiple generative AI systems were

trained on the Books3 dataset that includes upwards of 200,000 copyrighted books (Reisner, 2023). If a content organization is using AI for its content, it may be unwittingly putting the employer in legal jeopardy, generating results that violate copyright law.

## ■ Privacy Implications

The question of privacy violations looms large (Stein 2020). The information contained within the training set may not be used in the same context as intended. For example, OpenAI stores individual data such personally identifiable information (PII), data which is potentially protected in accordance with the General Data Protection Regulation (GDPR). Sunder Ali Khowaja et al. (2023) reminded us that this decoupling is in violation of GDPR because individuals did not explicitly consent to this particular use.

## ■ How accurate is it?

There is widespread reporting of queries that returned incorrect information, known in the industry as “hallucinations.” Tom Carter (2023) reported that Google Gemini—a GPT competitor—was hallucinating answers to even simple questions. In additional work on errors, Myeongjun Erik Jang and Thomas Lukasiewicz (2023) analyzed the errors and inconsistencies that have appeared in ChatGPT when questions are phrased differently. They wrote that “although LLMs are a revolutionary technique that brought an unprecedented era to NLP, such issues should be resolved before ChatGPT is used in real applications, particularly considering the huge economic and environmental costs for training and inference of LLMs” (p. 9). Further investigations on errors, Klaudia Jazwińska and Aisvarya Chandrasekar (2025) compared the eight most prominent AI tools. They discovered that they’re all bad at accurately citing their sources and found chatbot responses wrong. Moreover, upgrading to premium models did not improve results with answers remaining incorrect.

There are ethical concerns associated with using an AI system that delivers factually inaccurate but widely reported misinformation, or one that fabricates information. These tools can put organizations in legal jeopardy. Considering the breadth of known ethical challenges and harms caused by AI—even those above and beyond the planetary impacts—it seems unwise to rely on artificial intelligence as a trusted and viable tool in content development.

## ■ Social-Professional Pressures to Adopt AI

In light of the prevalence of AI discourse within the technical communication community, there is increasing pressure to learn about AI, use it in our work, and be perceived as cutting-edge technology experts by peers and management. This

is not unlike the “mutually reinforcing social norms” that drive teens to use social media, noted Toke Haunstrup Christensen and Els Rommes (2019) even when presented with knowledge of the environmental impacts of their digital choices. Unfortunately, by the time peer-reviewed research is published that directly connects AI, content, and emissions, AI tools will have already become an embedded part of our workflows. It is crucial that we raise awareness of the tradeoffs between new technologies and their harms.

## ■ Conclusion: Balancing Benefits Vs. Harms

Looking at the rapid adoption of AI in content development, it is critical to build awareness of the environmental and ethical impacts of these resources before they become standardized tools in the content toolbox. While we may not have direct emissions metrics due to limited publicly available information, we have more than enough signs that AI is an overpowered tool for a job that could be performed by humans.

Given that we already understand the significant and accelerating climate impact of AI, it seems irresponsible to use it for anything but the most data-intensive simulations that require rapid and comprehensive analysis beyond the scope of what humans can reasonably handle. Using AI for hurricane landfall and intensity forecasting, material fatigue and long-term durability testing of medical devices, or modeling the global impacts of polar ice melt have very different values than chatbots and content generation.

If we are already implementing sustainable content strategies to measure and mitigate the impact of our digital content on the planet, we should also be including the impact of the use of AI in content. Is AI so invaluable to our chatbots, product descriptions, and user journeys to support UX teams that we can't use other, lower-emissions methods for developing content?

All of our work has climate impacts, but we need to decide if the benefits of AI outweigh the harms. I'm inclined to let humans develop content for humans and leave the high-impact, energy- and emissions-intensive queries to areas where humans simply aren't equipped to do the work. These costs need to be considered on a case-by-case basis to balance the benefits and drawbacks of this rapidly growing technology in technical communication.

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