



## ORIGINAL PAPER

# The Hidden Cost of AI: Carbon Footprint and Mitigation Strategies

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### Abstract:

The integration of Artificial Intelligence (AI) into modern economies holds transformative potential, but its environmental impact, particularly its carbon footprint, is a growing concern. This paper explores the hidden costs associated with AI, focusing on its substantial greenhouse gas (GHG) emissions. Training large-scale AI models, particularly those based on deep learning, is highly energy demanding, resulting in substantial GHG emissions. Operationally, the continued use of AI systems further exacerbates the environmental toll, especially in data centres powered by non-renewable energy sources.

This paper highlights mitigation strategies, including the transition to renewable energy sources for powering AI infrastructures and the development of more energy-efficient algorithms. Techniques such as model pruning, quantisation, and knowledge distillation are identified as crucial in reducing energy consumption during the training and operational phases of AI models. Additionally, the role of AI in sustainability efforts is examined, suggesting that AI could facilitate resource efficiency in industries such as agriculture, commerce, and manufacturing, thereby contributing to the global transition towards a low-carbon economy. While AI promises significant advancements across multiple sectors, it is essential to address its environmental costs through sustainable practices. Failure to do so may result in AI accelerating climate change, overshadowing its potential benefits.

**Keywords:** AI, carbon footprint, climate change, cost, green AI

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## Introduction

There is currently an overwhelming enthusiasm surrounding the potential benefits that Artificial Intelligence (AI) could bring to humanity. However, are we truly prepared for such a profound shift, the full scope of which is only just becoming apparent? A lion cub may seem like an innocent kitten, something we eagerly wish to play with, but when it matures, it can devour us.

Numerous aspects of AI deserve discussion. Artificial intelligence is a technology with immense potential, but also significant risks (European Parliament, 2020; Olimid & Olimid, 2022). AI has the capacity to radically alter our lives, for better or worse. At present, both the enormous advantages and disadvantages of this technology are becoming apparent (Kumar, 2019; Duggal, 2024; IBM, 2024). To utilise AI responsibly and ethically, we require international institutional collaboration and appropriate regulation, which should ensure its benefits while mitigating its drawbacks. Additionally, we need ongoing awareness and education to help us understand and adapt to the impact AI will have on our lives and society. AI is reshaping the future of humanity (Rawas, 2024). However, all of these endeavours must be underpinned by a fundamental objective: cutting-edge technology must not harm the planet, and by extension, people. From this perspective, there are certain issues that are insufficiently discussed, one of which is AI's carbon footprint.

## AI's Carbon Footprint

The carbon footprint represents the total amount of greenhouse gases (GHGs) generated by human actions and activities (Mitu & Stanciu, 2024). Consequently, the carbon footprint is determined by the quantity of GHG emissions, expressed as carbon dioxide equivalent (CO<sub>2</sub>e), associated with the activities of an individual or other entities (e.g., buildings, corporations, countries, etc.). This concept includes both direct emissions, such as those from fossil fuel combustion for production, heating, and transportation, as well as the emissions associated with generating the electricity used to produce the goods and services consumed (Selin, 2024, Stanciu & Mitu, 2024).

Depending on the activity under analysis, distinct types of carbon footprints can be identified, based on the typical GHG emissions of the activities involved (Repsol, 2024):

*Individual carbon footprint:* This is based on a person's consumption habits and takes into account GHG emissions associated with their transportation, energy consumption for heating and cooling homes, dietary habits, goods consumption, recycling practices, etc.

*Product footprint:* This includes the GHG emissions across various stages such as raw material extraction, the production process, energy generation, product transformation for other firms, the customer's use of the product, waste treatment, and transportation between stages.

*Corporate footprint:* This encompasses the GHG emissions inventory related to a company's or organisation's operations. It serves as the primary basis for identifying energy efficiency measures within the organisation, as well as collaborative action with other firms in the sector.

An increasing number of studies highlight that AI consumes large amounts of energy and generates substantial GHG emissions, thereby leaving a significant carbon footprint (Luccioni et al., 2020; Cowls et al., 2021; Cho, 2023, etc.).

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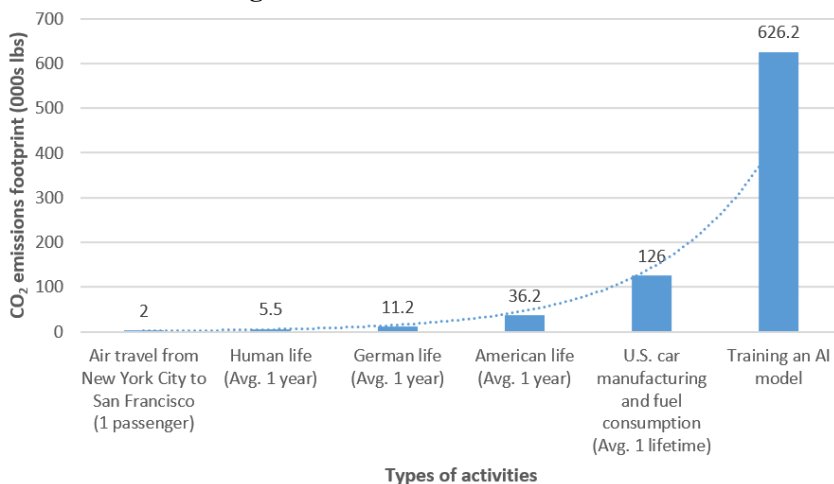
According to Williamson (2023), the carbon footprint of AI is a composite indicator, which equals the total GHG emissions, or carbon dioxide equivalent (CO<sub>2</sub>e), produced during the manufacture of computing technology (e.g., chips, semiconductors, etc.), combined with the emissions from training AI models and the CO<sub>2</sub>e emitted during the operational lifetime of AI systems.

### Carbon Footprint of AI = Carbon Footprint of Computing Technology Production + Carbon Footprint of Training AI + Carbon Footprint of Operating AI (Usage)

Most analyses of AI's carbon footprint focus on the latter two categories, as they are unique to AI (Williamson, 2023). However, each of these components significantly contributes to AI's overall environmental impact, necessitating a detailed analysis to understand their implications and potential mitigation strategies.

1. *Carbon Footprint of Computing Technology Production* - The production of computing technology is a critical factor in determining the carbon footprint of AI systems. The manufacturing processes for hardware, such as graphics processing units (GPUs) and data centres, are energy-intensive and often reliant on fossil fuels. The industrial sector, including the production of computing hardware, is a major source of global carbon emissions, accounting for nearly 36% of total emissions (Chen et al., 2022). This is further exacerbated by the increasing demand for advanced computing technologies, which require energy-intensive processes. The amount of GHGs generated by electricity production varies significantly across regions, with some areas producing energy with a far larger carbon footprint than others. In regions where coal and gas dominate the energy mix, the carbon emissions associated with computing technology production can be substantial, contributing to AI's overall carbon footprint (Lannelongue et al., 2021). The relationship between economic activity and environmental degradation is well-documented; as energy consumption increases with economic growth, so too do CO<sub>2</sub>e emissions (Ojaghlou et al., 2023). Moreover, the extraction of raw materials for hardware production, or the use of plastics, also adds to the environmental burden, as the mining and processing of these materials often lead to significant GHG emissions (Panagiotopoulou et al., 2021; Mascarenhas, 2023).

**Figure 1 – CO<sub>2</sub> emission benchmarks**



Source: Authors' processed, based on Nord (2020)

2. *Carbon Footprint of Training AI* – The training of AI models, particularly large-scale deep learning models, is a highly energy-intensive process that significantly contributes to the carbon footprint of AI. Training state-of-the-art models requires extensive computing resources, leading to high electricity consumption (Xiao, 2023). There is a wide range of emissions depending on the model, with some sources indicating that training a large language model can result in 200 to 600 metric tonnes of CO<sub>2</sub>e (Williamson, 2023). For instance, training models such as OpenAI's GPT-3 has been estimated to produce approximately 552 metric tonnes of CO<sub>2</sub>e emissions (Cooper, 2023; Tomlinson, 2024). This one-time cost is often amortised over the many queries processed by the model, but the initial energy demand remains a critical concern. The environmental impact of AI model training is exacerbated by the increasing complexity and size of these models, which require even more computational power and consequently more energy (Liu et al., 2023). The inefficiency of current hardware and algorithms further aggravates energy consumption during training, creating a situation where the growth rate of AI computational power outpaces improvements in energy efficiency (Liu et al., 2023). As such, the GHG emissions from AI training represent a growing concern, necessitating a shift towards more feasible practices in AI development (Xiao, 2023).

3. *Carbon Footprint of Operating AI (Usage)* – Once AI models are trained, their operational phase also contributes to the carbon footprint. Emissions per query during the usage of AI systems can vary depending on several factors, including the efficiency of the underlying hardware and the energy source powering the data centres. Continuous use of AI applications, especially those requiring real-time data processing and decision-making, leads to sustained energy consumption. The GHG emissions associated with electricity used for AI operations can vary significantly depending on the energy sources utilised (e.g., fossil fuels versus renewable energy). AI systems deployed in data centres using renewable energy sources may have a substantially lower operational carbon footprint compared to those powered by fossil fuels (Panagiotopoulou et al., 2021). However, the rapid expansion of data centres, which are projected to contribute up to 2% of global CO<sub>2</sub> emissions, highlights the urgent need for sustainable practices in the Information and Communications Technology (ICT) sector (Avgerinou et al., 2017).

### **Mitigation Strategies and AI Sustainability**

The carbon footprint of AI is an increasing concern, necessitating the implementation of effective mitigation strategies and the promotion of Green AI initiatives. These strategies aim to reduce the environmental impact of AI technologies while leveraging their potential to contribute positively to sustainability efforts.

Several strategies have been identified to reduce the carbon footprint associated with AI. A prominent approach is the transition to renewable energy sources for powering data centres and AI infrastructure. By using solar, wind, or hydroelectric energy, organisations can significantly reduce the carbon emissions associated with their AI operations (Mustafa et al., 2022). Additionally, the adoption of energy-efficient hardware and algorithms can further minimise energy consumption during both the training and operational phases of AI systems (Cowls et al., 2021).

Another effective strategy involves optimising AI algorithms to enhance energy efficiency. Research indicates that developing more efficient machine learning models can lead to substantial reductions in energy consumption and, consequently, carbon

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emissions. Techniques such as model pruning, quantisation, and knowledge distillation can reduce the computational resources needed for training and inference, thereby decreasing the overall carbon footprint (Cowls et al., 2021).

The integration of AI into key sectors such as agriculture, commerce, hospitality, industrial manufacturing, etc., can facilitate resource efficiency, leading to lower emissions in these industries (Bhagat et al., 2022; Ahuja, 2024; Ding, 2024; Qi, 2024). Furthermore, AI can enable the transition to a low-carbon economy by enhancing climate monitoring and predictive analytics, which can inform policy and operational decisions (Huang, 2024; Liu, 2024). Of course, these strategies are not exhaustive, their number being limited only by our ability to overcome the barriers of knowledge.

### **The Role of Green AI Initiatives**

The concept of Green AI emphasises the ethical responsibility of AI researchers and practitioners to consider the environmental impact of their work. This includes not only the carbon emissions generated by AI models but also the broader implications of AI technology deployment. The AI community increasingly recognises the need for accountability in the design and implementation of AI systems, leading to the emergence of research focused on environmental sustainability in AI, termed "Green AI" (Verdecchia et al., 2023). Green AI initiatives advocate for transparency in reporting the carbon emissions associated with AI research and applications. This transparency can help stakeholders make informed decisions about the environmental impact of AI technologies and encourage the adoption of sustainable practices. Furthermore, the development of policies promoting sustainable AI practices, such as incentivising the use of renewable energy and energy-efficient technologies, is crucial for fostering a culture of sustainability within the AI community (Cowls et al., 2021). The importance of integrating sustainability into the design and deployment of AI technologies is increasingly recognised, helping to mitigate their environmental impact while harnessing their potential for positive change. Additionally, AI can facilitate the transition to a circular economy by improving waste management and resource efficiency (Yang et al., 2022).

### **Conclusions**

Artificial Intelligence represents one of the most revolutionary technologies of the modern era, with vast potential to radically transform entire sectors of the economy and daily life. From optimising industrial processes to AI-assisted medical diagnosis and the creation of systems capable of offering decision-making support in complex scenarios, AI opens new horizons for innovation and progress.

However, alongside the widespread use of AI, a critical and increasingly concerning aspect is emerging: the enormous energy consumption associated with training and using these models.

The carbon footprint of AI is a complex interaction of various components, including the production of computing technology, AI model training, and operational emissions during usage. Large neural networks, especially deep learning models, require significant computational power, leading to a considerable increase in electricity consumption. The data centres supporting these technologies consume energy equivalent to that of small cities. If this growth is not carefully managed, there is a risk that the benefits brought by AI could be offset by its negative environmental impact, accelerating climate change and diminishing the technological advantages.

Although these factors significantly contribute to the overall environmental impact, AI also offers opportunities to play a crucial role in promoting sustainability. By adopting Green AI practices and optimising energy consumption across all sectors, the AI community can work towards minimising the carbon footprint while maximising AI's potential to address climate change challenges.

Energy consumption is not the only major challenge. AI also raises ethical and governance concerns. As systems become increasingly complex and autonomous, there is a risk that they may escape human control. For instance, decisions made by an AI system in a specific context, without human intervention, could lead to unforeseen or undesirable consequences. Moreover, concerns about transparency and explainability of models are growing, as they become more opaque with increasing complexity. If stringent oversight and accountability measures are not implemented, humanity risks losing control over the technology it has created, which could have disastrous effects.

In conclusion, while AI offers extraordinary opportunities, humanity must remain extremely vigilant regarding the associated challenges. Managing energy consumption and ensuring that AI remains under human control and benefits all people are essential for this technology to reach its potential without causing significant collateral damage.

Thus, the operational carbon footprint of AI is not solely a function of the technology itself but also of the broader energy infrastructure that supports it. In short, AI's carbon footprint is a multi-faceted issue encompassing the production of computing technologies, the energy-intensive training of AI models, and the continuous operational requirements of AI applications. Addressing these components is crucial for mitigating AI's environmental impact and transitioning towards more sustainable technological practices.

#### **Authors' Contributions:**

The authors contributed equally to this work.

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