A Review on AI's Environmental Impact and the Role of Communication

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Abstract
Artificial Intelligence (AI) systems are reshaping industry and everyday life, from autonomous driving technologies to turning text into images. But their transformative power is raising concerns about their environmental footprint. These systems consume vast computing resources, contributing to global warming through high carbon emissions, energy consumption, water use and the extraction of rare materials. Researchers are focusing on AI's sustainability in environmental, social and economic dimensions, highlighting the need for clear assessments. This paper examines key factors such as carbon footprint, energy consumption, water usage, and resource efficiency throughout the AI lifecycle, stressing the need for sustainable practices. It also addresses the challenge of raising public awareness and ensuring transparency. The study emphasises the need to strike a balance between innovation and sustainability in the development of AI.

1. Introduction

Artificial Intelligence systems can be defined as systems in which the rules are not defined by humans in the programming of the algorithm, but are created by a subsequent learning process [RWM*24]. These systems are changing the world and will continue to do so, offering the possibility of technological changes that are fundamental to scientific and economic breakthroughs. In fact, these technologies are not only related to the manufacturing or healthcare industries alone [vW21].

Recently, new AI systems have been developed that can be accessible via the Internet or smartphones, leading to a new pervasive expansion of these systems into our everyday lives. Systems that can write emails for you, text-to-image tools that allow consumers to generate an image in seconds, or text-to-audio models that create music or background sounds. These systems, commonly referred to as Generative AI systems, are large-scale generative models that produce new content and are easily accessible as services on the web. Their recent trend among many online consumers and their integration into existing services, such as image editing software (e.g. Photoshop's AI functionality) has led to many environmental concerns, as not only their training but also their inference requires intensive use of computing resources [BCJL24]. Therefore, addressing the sustainability of these new technologies must be a priority.

Sustainability is understood by the research community as a multidimensional integrative concept and a normative goal [RWM*24]. It can be broken down into five different dimensions - individual, social, economic, technological and environmental- which need to be addressed both individually and in their interrelationships.

The increasing size and use of AI models has an impact on the climate, leading to significant energy consumption and environmental footprints [LLYR24]. However, the current environmental assessment of these systems is underestimated [LLBC22], therefore sustainability analysis of AI needs to be carried out to assess its environmental impact. AI could help take better care of the planet by assisting with waste and/or pollution management, but also by using predictive systems for earthquakes and weather forecasting to better identify the likelihood of extreme events such as hurricanes and tsunamis [KPP*18]. At the same time, the development and deployment of AI systems can emit excessive amounts of carbon dioxide, require expensive hardware, and consume large amounts of energy and water.

Several approaches have been explored to measure the environmental impact of AI, but due to a lack of data from companies and industries, it can only be estimated. For example, measuring the carbon emissions of the training of a large model depends on the fuel mix used to generate electricity, and the carbon emission rate varies significantly depending on the location of the data center. Many companies do not yet disclose the exact location of their development, making it difficult for researchers to truly measure their environmental impact.

A study of the energy costs of GPT-3 model inferences in January 2023 shows that the model was accessed 590 million times, resulting in energy consumption equivalent to that of 175.000 people [BCMFCAB24]. The population's decision to use these systems or not is a personal one [vW21], but awareness of their negative environmental impact must be communicated so that any decision is conscious. For example, a recent survey of the German population shows that while climate change is perceived as a serious problem, AI systems are mostly seen as a solution to the climate crisis rather than a threat. The authors highlight a worryingly high percentage of respondents who answered “don’t know”, which may indicate a general lack of knowledge or understanding of the relationship between AI and the climate change.

2. Related Work

Recent studies [RWM*24, vW21] emphasize the need to address all dimensions of AI sustainability - environmental, social, and economic - but comprehensive assessments that integrate these dimensions remain limited. Multiple researches [LLYR24, LLBC22] have highlighted the significant environmental footprint of AI, especially for large-scale generative models such as GPT-3 that require extensive computational resources. However, a holistic approach to measuring the environmental impact of AI across all key factors and development phases has only recently been fully addressed .

Methodologies for assessing AI’s environmental footprint have evolved, but challenges remain due to the data availability and transparency issues. Many studies rely on estimates due to insufficient disclosure by technology companies. Standardized frameworks are crucial to accurately assess the environmental costs of AI systems.

Furthermore, the public perception survey shows that AI is often seen as a solution to environmental problems, largely due to a lack of awareness of its negative impacts. This highlights a significant gap in understanding that needs to be addressed to promote more informed and sustainable practices.

3. Key Properties for Measuring AI’s Environmental Impact

Recent breakthroughs in many fields using AI have led to these systems being seen as the tool of choice for solving environmental problems [LLBC22]. AI systems have great potential for environmental goals such as ecosystem monitoring, climate protection or energy transition, sustainable manufacturing [RWM*24]. AI systems are also being used to discover new electrocatalysts for efficient and scalable ways to store and use renewable energy [CJW22].

At the same time, the deep learning community began to realize that training models with more and more parameters required a lot of energy, leading to significant emissions [LLBC22]. Researchers have shown that the development and deployment of AI models and related technologies are likely to affect climate, biodiversity and ecosystems around the world [GCC*21]. The balance between systems that help the environment and the negative impacts they can have is being ignored, resulting in many AI systems currently being developed and deployed without being tested for environmental sustainability [AKD*22].

AI is becoming increasingly important for infrastructures and therefore relevant to society (e.g. transport, energy, security), but also because "AI itself is becoming an infrastructure on which many services of today and tomorrow will depend" [RWM*24]. As AI systems become easily accessible via the internet, even from a smartphone, their environmental impact needs to be measured and communicated to all stakeholders, both in the development and deployment phases.

3.1. Sustainable AI

Despite the positive benefits that AI can bring to the issue of climate change, recent studies show that we can no longer talk only about AI for Sustainability, because it does not take into account the environmental impacts of AI development and deployment [vW21]. Sustainable AI, a term first used by Wynsberghe [vW21], refers to both AI for sustainability and sustainability of AI. These two branches represent different aspects of the overall sustainability of AI systems, but they are interrelated and their balance is seen as problematic and needs to be addressed by the research community.

"AI for sustainability" refers to applications that use AI to technologically address the societal problem of the climate crisis, while "Sustainability of AI" refers to concerns about how to measure the sustainability of the development and use of AI models. While AI for sustainability holds great promise [vW21], its efficiency-enhancing innovations are often accompanied by increased production and consumption. This leads to the so-called rebound effect and additional consumption of the resources originally intended to be saved [AKD*22]. Is it really helpful if the same AI systems that accelerate activities that are beneficial to the carbon emission rate then consume the same amount of emissions that were saved or even more?

Concerns about the rebound effect of AI systems on climate change are gaining attention in the research community, and the need for better data transparency and effective tools and frameworks to assess the negative environmental impacts of AI have begun to be addressed. Since recent studies on the environmental impact of AI throughout its life cycle show that AI models require significant resources not only during training but also during deployment, all phases of the technology’s life cycle must be considered in the measurements.

Rohde et al. [RWM*24] divides the lifecycle phases of AI into:

1. organisational embeddedness;
2. conceptualisation;
3. data management;
4. model development;
5. model implementation;
6. model use and decision making.

It is not just experimentation, model training and optimization that create the environmental footprint of AI systems, but also manufacturing and operational use [CJW22].

Lizogat et al. [LLBC22] provides a detailed analysis of the direct environmental impacts associated with each phase of the AI life cycle:

- Raw material extraction, which includes all the industrial processes involved in transforming ore into metals;
- Manufacturing, which includes the processes that create the equipment from the raw material;
- Transport, which includes all the transport processes involved, including product distribution;
- Use, which mainly includes the energy consumption of the equipment while it is in use;
- End of life, which refers to the processes to dismantle, recycle and/or dispose of the equipment;

Keeping an AI model up-to-date and efficient has also been shown to have high environmental costs, with some experts suggesting that these costs are even higher than those during the deployment phase [Po4]. For some popular AI services, such as text and image generation, the total energy consumption for inference can be comparable to or even higher than that for training, resulting in huge carbon emissions and freshwater consumption [LLYR24].

3.2. Key Factors

3.2.1. Carbon Footprint

The impact of AI on greenhouse gas emissions spans the entire lifecycle of an AI system. Carbon emissions from the construction of data centers, the manufacture of equipment, which includes carbon emissions from the extraction of raw materials, and transport. In addition, data processing, experimentation, training and finally inference in warehouse-scale data centers.

Carbon emissions can vary significantly depending on the fuel mix and are directly proportional to the efficiency of the data center and the carbon intensity rate of its location [BCMFCAB24]. Carbon emissions depend on

- The energy source of the infrastructure
- The type and volume of data involved

One study estimated that training GPT-3 on a database of 500 billion words produces about 550 tonnes of carbon dioxide, the equivalent of flying from Australia to the UK 33 times [BCMFCAB24].

Carbon emissions come not only from training and using AI, but also from building the infrastructure to support it, and need to be taken into account, especially if data centres are then located in parts of the world where air pollution is already high, or where access to electricity or water is very limited. Clutton-Brock et al. [CBRDK22] acknowledges that, for computing-related impacts, research attempting to give a quantitative assessment of them has often focused on analysing individual instances of AI methods, not taking into account how many times an AI has been 'trained' vs. 'tuned' or deployed. Again, the carbon footprint of AI is dominated by the inference phase, as shown in a 2022 study by Wu et al. [CJW22].

3.2.2. Energy Consumption

AI technologies typically require large amounts of data and processing power, and therefore energy consumption. The cost of energy consumption depends largely on

- the type of AI method and the data involved
- the hardware on which the computations are performed
- the type of energy used and its carbon intensity

AI methods, especially deep learning, typically require large amounts of data. This data needs to be collected, transmitted, stored and processed. All these steps require equipment and energy and have an environmental impact [LLBC22]. Considering that training an AI can take weeks or even months, the energy required to power the data center hosting the AI is significant. These costs could be even higher if the model is continuously learning. The same study on the carbon emissions of GPT-3 training also shows that the training required 1297 MWh of electricity and 10,000 computer chips, equivalent to the energy needed to power about 121 homes in the US for a year [BCMFCAB24].

Pošćić [Po4] acknowledges that by 2027, the total energy consumption of AI will be equivalent to the energy needs of countries such as the Netherlands or Argentina. Energy consumption during the inference phase also needs to be taken into account. Given the great success of AI models for online image generation, energy consumption for inference needs to be properly addressed. GPT-3 was accessed 590 million times in January 2023, resulting in an energy consumption equivalent to that of 175,000 people. The same study estimated that each chatGPT query consumes the energy equivalent to a 5W LED light bulb running for 1h 20min in inference time [BCMFCAB24].

3.2.3. Water Usage

As freshwater scarcity has gained attention as an environmental issue, water consumption must also be considered when measuring the environmental cost of an AI model. Water is used both to generate electricity and to cool the heat or humidify the air in data centers. In addition, ultra-pure water is required for wafer fabrication, but data on embodied water consumption remains largely opaque [LYIR23].

The water footprint of AI is partly dependent on energy consumption, and this dependence varies in space and time. It is also important to note that some studies show that attempts to reduce an AI's energy consumption or carbon emissions may not result in the same reduction in water use, and may even worsen it [LYIR23]. Despite its profound environmental impact, the water footprint of AI models has long been under the radar [LYIR23]. Only recently have researchers begun to address the issue, highlighting the enormous lack of data needed to estimate the water footprint of AI in both the training and inference phases.

One study [LYIR23] attempted to estimate the water consumption of the GPT-3 model in both the training and inference phases. As the exact location of its training or deployment is not public, they estimated the value taking into account different data center locations. Training GPT-3 in Microsoft's state-of-the-art US data centers can directly evaporate 700,000 liters of clean freshwater. They also found out that a chatGPT conversation of 20-50 questions can drink a 500ml bottle of water [LYIR23].

3.2.4. Resource Efficiency

In addition to carbon emissions and water consumption, the development and deployment of AI involves the extraction of large quantities of minerals and raw materials. All of this has an impact not only on the environment but also on the society and the economy [AKD*22]. Additionally, the resource-intensive nature of AI development raises concerns about excessive resource consumption. Furthermore, the electronic waste generated by these systems poses a serious threat, as it can lead to the contamination of water and soil through chemical pollutants.

3.3. Green AI

Green AI is a paradigm that shifts towards incorporating sustainable practices and techniques in the design, training, and deployment of AI models, with the aim of minimizing their environmental footprint [BCMFCAB24]. This approach seeks to ensure that AI systems do not increase energy demand or contribute disproportionately to environmental damage. To reduce emissions, companies are beginning to move the training and inference of the AI models to data centers powered by carbon-free energy sources. However, this strategy is not universally applicable, as carbon-efficient data centers are constrained not only by limited availability of rare materials and high economic costs, but also by the long construction times [CJW22]. As a result, such solutions, while promising, still face significant challenges.

Regulation and industry standards are essential for advancing Green AI practices. Effective policies and frameworks can lead to a responsible development, deployment, and governance of AI in the context of to climate change. Without them, efforts to make AI more sustainable may not succeed.

The lack of data and adequate documentation processes is a major obstacle to achieving Green AI. This data gap often stems from a general lack of awareness of the environmental risks and impacts within the AI development community [RWM*24]. Furthermore, embodied emissions, which include emissions associated with the production and lifecycle of AI systems, are often not prioritized, making a comprehensive analysis of the environmental impacts of artificial intelligence on the environment impossible.

To address these issues, there is an urgent need for a standardized framework for assessing and mitigating the environmental damage caused by AI. The development of such a framework will help to ensure that Green AI practices are effectively implemented and monitored, paving the way for a more sustainable future for AI technology.

4. Public Awareness and Communication Challenges

4.1. Public Awareness on AI's Environmental Impacts

In recent years, many different AI-based applications have been developed and made accessible via the Internet, sometimes even from our smartphones. As we have seen, the inference phase in the life cycle of an AI plays an important role in the environmental impact of an AI system. The emerging concern about whether these technologies are seen by the public as part of the solution or part of the problem needs to be addressed and fully communicated to the consumers. The results of a special survey of the German population show that by and large, a view of AI that sees it as part of the solution rather than part of the problem predominates [AKD*22].

The survey looks in detail at how the environmental impact of AI is perceived across all key factors (energy consumption, carbon emissions, water usage and raw materials). Overall, the perception is that AI helps. Around a third of respondents even believe that AI can offset pollutant emissions through intelligent energy production. Only around 15 per cent of respondents consider water consumption, which occurs in the production of AI, to be an environmental cost [AKD*22]. The study does not want to make a statement about whether the cost side or the potential for savings actually dominates now or in the future. Rather, it aims to show that the majority of respondents consider the benefits of AI to be greater than the potential harms [AKD*22].

The striking result of the survey is the large proportion of respondents who said they could not answer the questions. This lack of knowledge about the costs is probably due to the difficulty the general public has in understanding this type of data, seeing the real impact on our lives and the value of addressing the issue.

In addition, only half of the respondents put some of the responsibility on consumers, suggesting that they see themselves as secondary responsible actors [AKD*22]. The feeling that "there's nothing they can do about it- or that someone should do something about it, but that someone isn't them" [STTB09], which emerged in a survey on how to communicate climate change, seems not to have changed after 15 years. Effective communication strategies to raise awareness and encourage more sustainable behavior need to be found.

4.2. Communication Challenges

Climate change has become an issue of concern for many actors, including a growing awareness and understanding among the non-academic public. But, despite the demonstrably high environmental costs of AI technology, the image of a technology that solves problems rather than creates them prevails [AKD*22]. The low awareness of the negative environmental impacts of AI can be attributed to a difficulty in communicating them. The barriers to communication lie in the lack of data and transparency, the lack of a common methodology for the measurement, and a lack of a common strategy fro communication.

There is a need for a structured policy to measure the environmental impact of AI systems, and the lack of transparency of big tech companies needs to be addressed with regulations and standardized methodologies. Without these regulations, big tech companies can decide which data and measurements they want to show to their consumers in order to be perceived as environmentally friendly, contributing to the creation and perpetuation of false messages and interpretations about the relationship between AI and climate change. Moreover, the media play an important role in this, as their reporting does not provide enough information to make a concrete judgment on the ecological balance of AI [AKD*22].

To effectively address the challenges of communicating the negative impacts of AI systems on climate change will require coordinated action across multiple agencies and communities to ensure that the public receives clear and consistent messages about these impacts [STTB09]. If the public better understands these impacts, they may not only change their decisions about whether or not to use or fund these systems. Moreover, the power of public pressure on decision-makers could shift the prioritization of economic interests towards the development of ethical and environmental design [AKD*22].

5. Conclusion

Artificial Intelligence is recognized as having the potential to make a positive contribution to environmental issues, but the weighty energy requirements to develop these systems can also have a significant negative impact on the climate, requiring careful assessment and communication of its environmental footprint. This paper attempts to take an holistic approach to the environmental impact of AI, highlighting the challenge of balancing its sustainability benefits with its significant resource requirements at all stages of its lifecycle.

Our primary objective was to analyze what are the key factors on the environmental footprint of AI, examining its carbon emissions, energy consumption, water usage and extraction of rare material. However, this study was limited by the lack of data release and transparency from tech companies, which affects potential future research and attempts to measure the environmental impact of AI. As the field progresses, further research should be based on standardized frameworks that focus on all dimensions of sustainability and their interrelationships, helping investors, governments and the private sector to take these issues seriously and promote the sustainable development of AI.

We have also addressed concerns about public awareness of the relationship between artificial intelligence and climate change, which shows a general lack of understanding of the issue. Due to high environmental costs attributed to the inference of AI systems, we have highlighted the importance of a better communication on the negative impacts of AI systems to the general public, in order to promote responsible practices in the use of AI. Overall, this paper emphasizes the importance of addressing environmental impacts and communicating them to the public. As AI systems continue to evolve, we hope that the insights gained from this study can play a crucial role in shaping the future of AI.

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