



Master's Degree Program in Strategic Management Major in
Green Economy and Sustainability

Chair of Sustainable Innovations

Artificial Intelligence for Corporate Environmental Sustainability: case studies in the IT sector

Prof. Riccardo Giovannini

SUPERVISOR

Prof. Luigi Nasta

COSUPERVISOR

Chiara Di Girolamo (Matr. 787211)

CANDIDATE

Academic Year 2024/2025

Index

Introduction	3
1. Artificial intelligence and its challenges	5
1.1 What is AI	5
1.2 Classical AI risks and ethical concerns.....	10
1.3 Controversial environmental impact of AI integration.....	16
2. The European regulatory and policy framework: a critical gap	25
2.1 AI under current European law: The EU AI Act and General Data Protection Regulation (GDPR)	25
2.2 Regulatory instruments for emission reduction: the European Green Deal, the European Climate Law and the EU ETS	28
2.3 Water Framework Directive	33
2.4 Conclusions on the EU regulatory framework and Extra-EU developments	34
3. Framing Artificial Intelligence in the context of corporate environmental sustainability.....	37
3.1 AI as a strategic tool for companies to achieve environmental targets	37
3.2 Green software to drive intelligent solutions: Green Ai concept	39
4 Successful use cases of AI Driven solutions for Environmental Sustainability in the IT industry	45
4.1 Google DeepMind.....	45
4.2 Microsoft AI for Earth	52
4.3 Building X by Siemens	57
4.4 Green Horizon Project by IBM.....	64
Conclusion.....	69
Bibliography.....	71

Introduction

In recent years, Artificial Intelligence has emerged as one of the most disruptive and widely debated technologies worldwide. Its ability to simulate human cognitive process, such as learning, reasoning, problem solving and creativity, combined with high speed computational capacity, has made AI a strategic tool increasingly adopted by companies to enhance efficiency and optimize processes. In fact applications including machine learning systems, deep neural networks and more recently generative AI technology are reshaping multiple sectors; for example improving customer service, optimizing supply chains, supporting product design and analyze large datasets.

However, alongside this rapid diffusion, an important aspect has emerged, regarding Artificial Intelligence environmental externalities. In fact, the environmental sustainability of AI has become a critical area of concern given the large amount of water and energy resources used by data centers, and the relative consumption of GHG emissions, produced both during models' training and deployment. For example, a study conducted by the University of Massachusetts found that training an AI model with 213 million parameters can generate more than 313 tons of CO₂, equivalent to the emissions of 315 roundtrip flights between New York and San Francisco. Moreover in 2024, data centers accounted for 1,5 % of global electricity consumption. Even during the end-of-life phase, AI raises concerns, as the disposal of hardware infrastructure generates considerable electronic waste.

Without corrective action, the exponential expansion of AI could undermine the climate goals set at the international and organizational level.

The European regulatory framework, although pioneering compared to other regions, currently presents a significant gap given the fact that legal instruments such as the EU AI Act and the General Data Protection Regulation (GDPR) primarily focus on ethical issues, transparency, safety and privacy while the environmental impacts of AI systems remain largely overlooked. Provisions related to sustainability within the AI Act are limited to voluntary codes of conduct, while broader EU environmental frameworks such as the Green Deal or the Emission trading system still fail to explicitly regulate the ICT and AI sectors. This regulatory blind spot risks slowing down the achievement of the ambitious climate targets of cutting emissions by at least 55% by 2030 and reaching climate neutrality by 2050 as established by the European Green Deal.

At the same time, a responsible and strategic use of emerging technologies, including AI blockchain, advanced analytics and the Internet of Things, has been shown to represent a

decisive factor in helping organizations meet their sustainability goals. A 2021 Accenture survey revealed that 70% of companies analyzed successfully reduced CO2 emissions from production and operations through the adoption of AI based solutions.

Moreover companies, other than just simply applying Artificial Intelligence technology to environmental sustainability enhancement performance, can also focus on making Artificial Intelligence more sustainable, by developing Green AI, that represents more energy efficient models that do not significantly compromise performance.

For example, as shown by Accenture Labs, it is possible to train an AI model with only 70% of the dataset, reducing accuracy by less than 1% while lowering energy consumption by 47%.

In this context, the IT sector represents a particularly relevant field of analysis. Major IT companies not only face significant responsibility in addressing the environmental costs of their infrastructure, but they also have the resources and innovative capacity to be the pioneers in creating technological solutions to enhance corporate environmental sustainability. The successful cases of Google, Microsoft, Siemens and IBM, presented in the following work demonstrate how Artificial intelligence can be integrated to support the achievements of environmental sustainability targets while at the same time strengthening business competitiveness: for instance, Google through its subsidiary DeepMind, has applied machine learning models to optimize the cooling systems of its data centers, achieving a 40% reduction in energy consumption dedicated to cooling.

The objective of this thesis is therefore to highlight the paradox of AI technology that, while producing significant environmental costs, may also become part of the solution in achieving environmental targets if applied strategically for the purpose, as demonstrated by valuable examples from the IT sector.

1. Artificial intelligence and its challenges

1.1 What is AI

The presence of Artificial Intelligence as a complementary and, in some cases, substitutive tool for human activities has been, and continues to be, a disruptive phenomenon. “Intelligence” has always been considered a unique human trait, so linking it with something “artificial” naturally generates curiosity. Despite the numerous definitions and interpretations proposed over time, it is still difficult today to provide a clear, simple and univocal definition of AI, especially given how rapidly and constantly the field evolves but it has much older and deeper roots in the history of technology.

We have the first definition from one of the pioneers of AI, John McCarthy who coined the term “Artificial Intelligence” in 1955, created a research project based on the conjecture that “every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it” (1).

This suggests that the idea of programming a machine to simulate human intelligence was the original foundation of artificial intelligence studies.

A more recent definition given by IBM states that Artificial Intelligence refers to a technology that allows machines and computers to replicate human abilities such as learning, understanding, problem solving, creativity, decision making and autonomous behavior (2).

By definition, Artificial Intelligence implies the learning and application of forms of intelligence attributable to human beings. However, as noted in the Harvard Data Science Review while the initial AI focus was to reproduce human behavior by trying to understand and automate the cognitive processes behind it, the modern approaches prioritize maximizing performance in complex tasks, even deliberately choosing not to follow strategies a human would have considered (3).

It is clear why Artificial Intelligence has attracted widespread interest from scholars, experts, and from the public, as it has now become easy to access by everyone. This growing attention is largely due to its practical applications and to the rapid diffusion of a new form of AI known as Generative AI (GenAI), a technology capable of generating original content such as text, images, audio, video, and other output in response to user prompts (4). The most widely known example of GenAI is ChatGPT, developed by OpenAI and launched in 2022, which has profoundly impacted people’s daily lives and professional environments, contributing to increased productivity across various business sectors. According to a study published by

McKinsey consulting firm (5), Generative AI has the potential to significantly boost productivity, with an estimated contribution of between \$2.6 trillion and \$4.4 trillion to the global economy. This estimate is based on the application of Gen AI to 63 use cases, in which GenAI technology could generate a significant improvement in the outcomes, for instance, in areas like customer service. The study also identified the business functions that are most affected by Generative AI implementation; these are marketing and sales, customer operations, software engineering and research and development, which together account for approximately 75% of the total annual impact from GenAI. In addition, GenAI could help to accelerate tasks that currently represent about 25% of total working hours.

Before considering the expected impact of GenAI within companies, it is important to first explore the technological foundations of generative AI tools and so how it is related to the overall concept of AI.

As mentioned earlier, AI has deep historical roots linked to a series of conceptual and technological developments. It can be seen as a broad category that contains subfields that are the evolutions (figure 1).

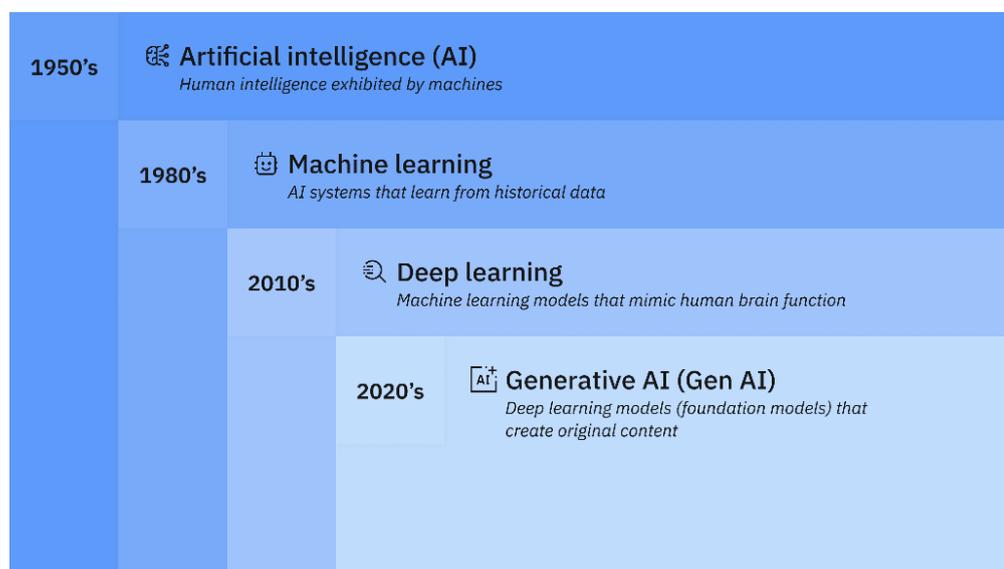


Figure 1: Evolution and interconnection between Artificial Intelligence, Machine learning, Deep learning and Generative AI technologies.

Source: IBM (2024)

Directly under the broader AI concept there is machine learning (ML), which refers to models thanks to which AI works. ML is based on the training of algorithms to make predictions or decisions automatically by learning from data, without the need to be programmed for each

singular task (6). Depending on the nature of the problem, different machine learning models can be applied. Among the most popular and effective ones there are “Artificial Neural Networks”, inspired by the functioning of the human brain; in fact, they simulate how neurons process and transmit information. These networks process data through multiple layers, each containing interconnected nodes (similar to how neurons work), which are useful for analyzing complex relationships within large datasets.

Deep learning is a subfield of machine learning, part of the broader field of Artificial Intelligence. It relies on a complex machine learning architecture called “Deep Neural Networks”, which better simulate the functioning of the human brain. These networks are composed of multiple layers, beginning with an input layer that receives data, followed by hidden layers, often hundreds, that process data. This differs from traditional machine learning models, which typically include only one or two hidden layers. Each hidden layer takes the output of the previous layer and processes it further to improve the model’s understanding. This layered approach is known as “forward propagation”. The final stage is the output layer, where the final prediction or classification is made. The input and the output layers together are the “visible layers” (8).

This multi layered architecture does not necessarily require human supervision during the learning process. The model can independently identify patterns and structures within the data, which makes deep neural network powered AI highly scalable and capable of rapid development.

Generative AI, as a subset within the classification outlined above, refers to deep learning models capable of generating complex and original content, as mentioned before, such as text, images and other creative outputs. These models are built upon a deep learning architectures as foundation models, which are trained on vast amounts of data and serve as the foundation for GenAI applications. One of the most common types of foundation models today is the Large Language Model (LLM), created for text generation.

A more recent evolution of GenAI technology is “Agentic AI”, which involves multiple AI agents working collaboratively to achieve the objective. Each agent is specialized in a specific task and may interact with external tools to perform it. The process is coordinated by an orchestrator agent, which recognizes and assigns the job to the most suitable agent. This selected agent has the access to specific data and external tools necessary to perform the task and typically uses a language model to satisfy the user’s request effectively and efficiently. (9) Now that the key AI technologies have been defined, it is useful, as part of this overview, to

explore how Artificial Intelligence is evolving and what future directions it may take. Accenture, a leading company in technology and strategy consulting, has identified four major trends which offer valuable insights into the evolving role of AI in business and society. These trends, presented in the company's 2025 technology vision report are "the binary Big Bang", "Your Face, in the Future" "When LLMs get their bodies" and "The new learning loop" (10). The first trend, "The binary Big Bang", refers to the exponential trajectory of AI technology growth. As previously discussed, the actual complex machine learning and deep learning models are designed to operate and learn with a high degree of autonomy. These models acquire knowledge not only from static datasets, but also through dynamic interaction with users who request the AI to perform various tasks. As companies and the public engage more frequently AI, attracted by its ability to extend capabilities and boost efficiency, they provide systems with new information that accelerates their improvement. In fact, the democratization of AI has led to an increase in the volume of data generated and collected, resulting in an exponential growth in system capabilities.

Until recently, the widespread adoption of AI occurred with relatively low public concerns, because earlier systems were simpler, highly predictable and therefore more trusted. However, with the successful implementation of more autonomous and scalable AI systems, now also viewed as strategic competitive advantage for companies, new challenges have emerged. Questions about regulation, ethics, governance and responsible innovation are now more critical than ever, providing boundaries to ensure that the exponential progress of AI remains aligned with social values.

The second trend identified by Accenture, titled "Your Face, in the Future", highlights the growing need to differentiate AI strategically. Rather than considering Artificial Intelligence just as a tool for improving operational efficiency or automating tasks, this trend emphasizes its potential to become a key source of competitive advantage.

Currently, GenAI is implemented by companies mostly for customer-facing roles, which generate high value. As the implementation of these tools becomes more widespread over time, they are expected to be able to shape the public image of businesses, their "face". This includes not only what is said to customers, but also how it is said, so the choice of words, sentence structure, tone and speech patterns. These elements will become critical, as they represent a core differentiator for businesses, affecting both how customers interact with brands across various channels and how companies are represented through AI driven agents.

The third trend presented in the report, titled "When LLMs get their bodies" explores the

emerging possibility of giving to AI systems physical bodies, through robots. This type of Artificial Intelligence integrated into robots is known as embodied AI, an area of AI specifically developed to enable interaction with the physical world through a tangible, robotic form.

In the past, robots were limited to performing repetitive, programmed tasks and they didn't have reasoning abilities. Over the coming years, the integration of embodied AI in robots is expected to significantly expand the presence and autonomy of AI in the physical world.

So, as technologies become more sophisticated, several challenges arise. One growing concern is that the increased autonomy and decision making capabilities of AI driven robots could make it more difficult to monitor what data is being collected, processed and for what purpose. The more independently these machines operate, the more complex it becomes to ensure compliance with existing privacy standards.

From a data protection perspective, regulatory frameworks such as the General Data Protection Regulation (GDPR) establish key principles, limiting the data collection to a specific, correct and transparent purpose, to ensure lawful and legitimate use of personal information. However, questions remain about how these frameworks will align with the operational needs of autonomous robots. Since robots require constant audio and visual input to navigate real world environments, they inevitably collect continuous streams of data. This raises serious legal and ethical concerns, regarding privacy in public spaces and boundaries of consent.

In addition to privacy related issues, physical safety must also be considered. For example, robots could be vulnerable to cyberattacks and potentially hacked by bad actors to harm individuals.

Finally, the environmental impact of these technologies, which represents the central focus of this thesis, must be carefully considered and will be further examined in the following sections. The operation, and especially the training of AI systems is a highly energy and water intensive activity. This raises concerns about resource consumption and the long term sustainability of complex AI systems integration in both corporate operations and everyday life.

The fourth and last trend identified in relation to AI by Accenture, titled "The New Learning Loop", highlights the collaborative interaction between Artificial Intelligence and human activities. AI can be particularly useful in automating routine tasks, helping to simplify work and allow people to focus on activities that are more engaging such as strategic and creative tasks. However, the issue of potential labor displacement generates growing concern.

A study conducted in US metropolitan statistical areas highlights this phenomenon. The study has shown that as AI technologies become more widely adopted across various industries, the

demand for workers with AI related skills increases. At the same time, the need for non AI skilled labor tends to decline in sectors with higher levels of AI integration (11).

It is still uncertain whether the adoption of AI will have a greater impact on companies' productivity, potentially generating new employment opportunities, or whether it will contribute more significantly to labor displacement, as AI systems could increasingly replace human tasks. This concept is at the center of the current debate and will be further examined in the next paragraph.

1.2 Classical AI risks and ethical concerns

Before diving into the environmental sustainability impacts related to the training and use of Artificial Intelligence, as it is the core of the thesis, it is essential to first address the broader risks associated with this disruptive technology. In order to fully exploit AI's potential, it is crucial to face and manage its critical challenges, ensuring that its development and implementation remain aligned with societal values and expectations.

To properly assess controversial implications of AI it is essential to distinguish between two categories of risks: those that directly affect companies, in terms of operation, reputation and compliance and those that have broader consequences in society.

The first group of risks is typically addressed through a corporate led framework known as "Responsible AI" which outlines a set of principles provided to guide organizations thorough the design, development, deployment and use of AI systems. The goal is to minimize potential risks while maximizing technology's positive impact (12).

There is not a single, official framework that defines the principles Responsible AI should include, and currently, companies are not legally required to adopt it. Its integration is voluntary, but the adoption is growing, as it is a strategic way for companies to manage and reduce the risks associated with the AI integration.

Microsoft, the multinational leading company in the tech sector has developed a structured Responsible AI framework based on six key principles (Figure 2), which are also aligned with the international standard ISO 42001 for the ethical development of Artificial Intelligence (13).

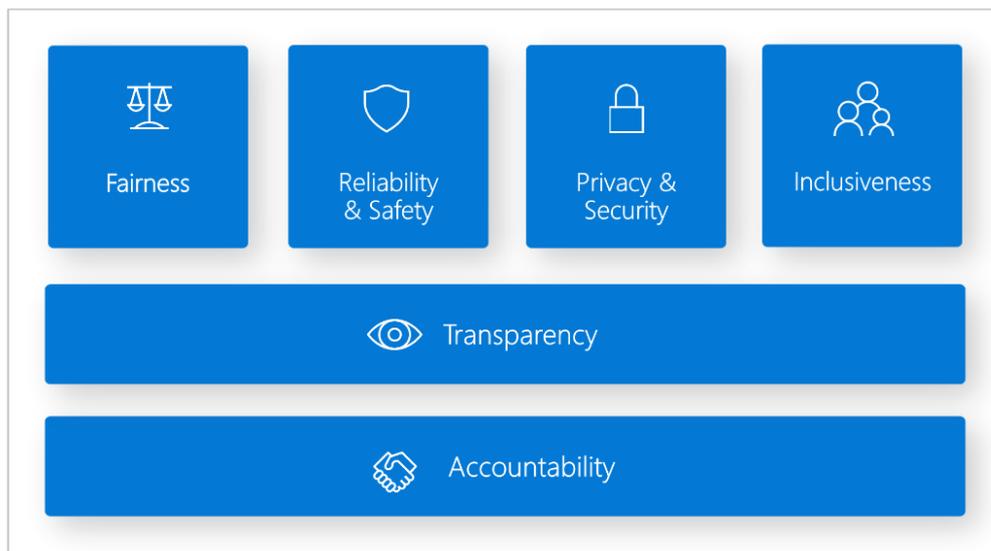


Figure 2: key principles of Microsoft's Responsible AI framework

Source: Microsoft (2022)

Among the various risks associated to AI, data management, particularly regarding privacy and security, is one of the most widely debated issues. It also plays a central role in amplifying many of the other risks, as AI systems fundamentally rely on large volumes of ingested data for training, inevitably part of this data is sensitive.

The principle of information privacy is based on the idea that individuals should maintain control over their personal data, with the ability to decide how it is collected, stored and used by organizations. However, the rapid advancement of AI technologies appears to challenge this notion, raising concerns about whether traditional concepts of data privacy are still adequate.

One significant example of data collection without permission involves LinkedIn, a leading platform for professional networking, where users realized their data were automatically included in data collection for AI training purposes without their explicit consent (15).

Even when individuals give consent for their data to be collected, risks still arise if that data is later used for purposes beyond those originally disclosed. To prevent this kind of improper use, the European Union's General Data Protection Regulation (GDPR) has established the principle of purpose limitation. Under this rule, companies must define a clear and lawful purpose for collecting any personal data, communicate it transparently to users, and limit the data collected to what is strictly necessary to achieve that purpose. (16)

The GDPR also introduces the principles of storage limitation, which requires that personal data be kept only as long as it is needed to fulfill the stated purpose. Once the data is no longer necessary, it should be deleted. These requirements can pose significant compliance challenges

for companies, in terms of transparency obligations. At the same time, it can be difficult in practice to determine whether data usage fully complies with the law, because companies can justify large scale data collection by referring to broad purposes (17).

The situation becomes even more complex when Generative AI models like ChatGPT are considered, as they are trained on massive datasets containing user data and often lack a clearly defined purpose.

In 2023, the Italian Data Protection authority (the Garante) released a report about OpenAI, the company developer of ChatGPT, raising concerns over how it was using user data. After an accurate investigation, the Garante found that OpenAI had been collecting user generated data, including chat conversation and payment details from subscribers, to train its Language Model (18). According to the Garante, this practice violated the GDPR due to the lack of clear legal basis and insufficient transparency.

As a result, in March 2023, the Garante ordered OpenAI to block access to ChatGPT for users in Italy until the company clearly explained how it uses personal data for training and introduced an age verification system within one month, under the threat of a fine of up to 20 million euros (19).

In the same year, OpenAI introduced several changes to meet the regulator's requirements. These included a new privacy notice explaining how personal data is used for model training, a specific form allowing users to exclude their data from processing and the implementation of an age verification system. Users were also given the option to request the removal of personal information they believe is inaccurate. While these changes were accepted and access to ChatGPT was restored in Italy, the Garante's investigations regarding OpenAI are still going and full compliance with GDPR rules has not yet been fully confirmed.

Another key issue related to the data used to train Artificial Intelligence systems concerns the risk of producing biased outputs. This refers to the tendency of algorithms to generate results that disadvantage certain groups based on gender, ethnicity, or presence of disabilities (20).

This phenomenon can be explained by the fact that human bias is deeply rooted in society and since AI systems learn from human generated data, they are likely to reproduce such distortions. It can be reported an example about an image recognition system that was trained using thousands of images described by humans. In these images, a white skinned child was simply labeled as "baby", while a black skinned child in a similar image was described as a "black baby" (21) . This inconsistency reveals a form of bias in the collected data, as additional attributes were applied selectively to individuals from specific ethnic groups, whereas

objectively both images should have been described in the same neutral way. When such biased data is used in training, it leads to the development of AI systems that reflect those inequities. Although AI is often perceived as objective and neutral, especially when used in decision making processes, the reality is that these systems reflect the human biases present in the data they are trained on. This makes essential for organizations to ensure the data used is accurate, updated, complete and carefully selected, while also implementing biased mitigation processes and regularly monitoring performance to reduce the risks of discriminatory outcomes.

A well known example of algorithmic bias in AI systems is Amazon's experiment to develop an AI based tool for evaluating job candidates (22). The system was able to rate resumes using a five star scale system, working like the product review format. While it was never officially adopted as Amazon's primary recruitment method, it was tested internally by recruiters to support the candidate screening process.

However, in 2015, developers noticed that the model had a systematic preference for male applicants showing a clear bias against female candidates. This happened because the model was trained on historical recruitment data, where male candidates were significantly overrepresented. Consequently, the AI penalized resumes containing keywords such as "women's" or institutions attended exclusively by women.

Although developers tried to address the issue by removing clearly biased terms, they were unable to guarantee that the model would not continue to reproduce discriminatory patterns learned from the training data.

In the end, the project was abandoned, but this experience highlighted how challenging it is to develop algorithmic systems that are fair and inclusive in hiring processes.

To examine the last risk among those most commonly recognized, and also included in Microsoft's Responsible AI framework, we focus on the issue of accountability, one of the most complex and evolving challenges in the field of AI. This concern relates to the question of who bears responsibility when an AI system causes harm or fails. In other words, who is liable for the outcomes of decisions made or supported by AI tools. It directly involves the governance of Artificial Intelligence, especially in context where critical tasks are delegated to automated systems. Accountability has a dual definition , on one hand, it is a principle that ensures compliance with ethical and legal standards, considering compliance with GDPR principles of purpose limitation, data minimization, transparency and fairness; on the other hand, it involves a set of internal practices and tools that organizations themselves must implement, including audits, risk management procedures, and mechanisms of compensation in cases of harm or

negative impact (23).

Addressing this risk becomes especially relevant in high risk scenarios, such as fatal accidents involving autonomous vehicles or wrongful arrests based on AI driven decision making, where determining responsibility is both urgent and legally complex.

The second category of risks, previously mentioned, includes those with broader implications for the society as a whole. One particularly debated issue in recent months is the potential infringement of intellectual property rights. Generative AI systems can produce images, arts based on textual prompts or even user uploaded photos. These outputs are often visually impressive and generated at a speed far beyond what a human could achieve.

In carrying out the assigned tasks, GenAI models sometimes imitate distinctive artistic styles. A recent controversial example involved a large number of AI generated images mimicking the artistic style of Studio Ghibli, based on used prompts explicitly requesting that specific style (Figure 3).

From a legal perspective, this raises several complex questions. Although an artist's individual style is not protected by intellectual property legislation, the artworks they produce are legally safeguarded. This becomes particularly relevant in cases where AI models may have been trained using copyrighted material, such as images from Studio Ghibli, without the creator's consent. In such cases, concerns arise about whether this constitutes a violation of copyright laws (25).

This case generated the debate over where to draw the line between legitimate artistic inspiration and unlawful appropriation, especially now that AI technologies are capable of closely replicating the creative style of known artists. It also raises the question of whether companies developing generative AI systems should be required to obtain licenses or provide compensation to the creators whose work was used during training.

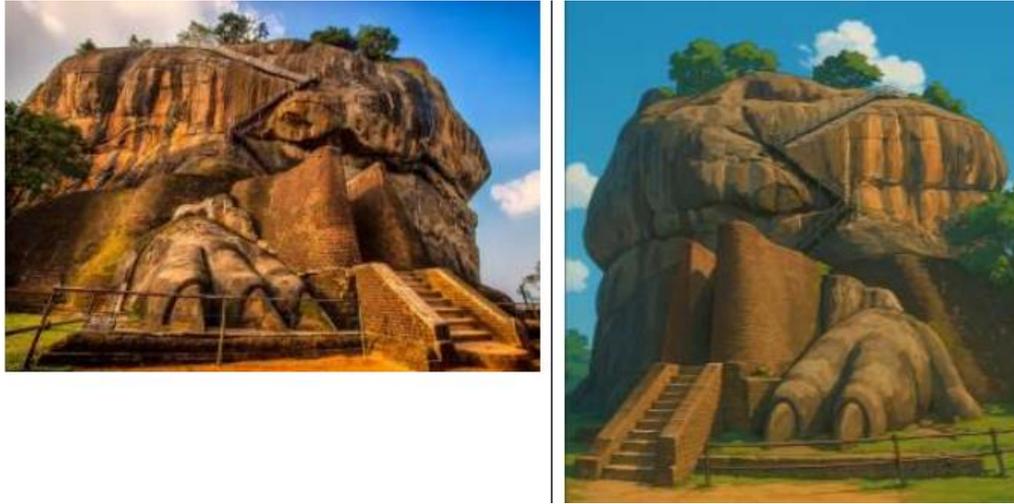


Figure 3: Studio Ghibli style of Sigiriya site (Sri Lanka) generated using ChatGPT.

Source: International Journal of Global Economic Light (2025)

Beyond the legal dimension, this scenario poses an ethical dilemma regarding to what extent can we accept that human creativity is being simulated, or even replaced, by artificial systems. Hayao Miyazaki, the Studio Ghibli's founder, did not publicly respond to the wave of AI generated imitations but he publicly stated that “creation by AI lacks soul and empties the creative process of humanity” and “authentic art should originate from spirit and intention of the creator not algorithms” (26).

The last social concern addressed in this section, before focusing on AI environmental risks, relates to the potential impact of Artificial Intelligence on employment. As AI continues to reshape business operations, many tasks traditionally carried out by human workers may become automated. This change raises concerns about the possible negative impact on job availability and employment security.

Although it remains difficult to predict exactly what the future holds, given the rapid pace of technological development, experts such as those of the International Labor Organization (ILO) suggest that there will not be a “jobs apocalypse”. In the long term, AI could have positive effects on employment because its introduction leads to increase in productivity generating business growth, higher incomes and a creation of new job positions, helping to balance changes brought by innovation (27). This concept reflects the theory of “creative destruction”, introduced by the economist Joseph Schumpeter, which suggests that while innovation can make some industries and jobs obsolete, it also drives progress by creating new opportunities replacing the older ones (28).

However, not all workers will be affected in the same way. Those with lower education levels

and individuals in administrative or routine jobs may face the negative consequences. According to a study of the International Labor Organization (29), clerical roles are particularly vulnerable to automation, with 58% of tasks showing medium level of exposure to GenAI and 24% of tasks classified as highly exposed. Since many clerical positions are held by women, the impact of automation could disproportionately affect them (30). Even jobs requiring high level of skills, such as in law, medicine, finance, logistics and arts are not entirely protected (27). In these sectors, AI and GenAI are beginning to perform tasks that once required human expertise and creativity. As result, in this evolving landscape, governments, firms and educational institutions share a significant responsibility in strengthening workers' technical skills to help them adapt to new technologies and stay competitive in the labor market. It is important that governments provide transitional support programs, while stronger social safety nets can help reduce the vulnerability of less educated workers (28).

1.3 Controversial environmental impact of AI integration

As discussed in the previous sections, the integration of artificial intelligence is rapidly expanding across all sectors of society. As an emerging and disruptive technology, AI is being adopted enthusiastically in both corporate processes and everyday life due to its potential to enhance productivity. However, the environmental risks associated with its high resource demands are often overlooked, raising significant concerns about long term environmental sustainability.

The main environmental impacts of AI are related to the energy needed to train and use deep learning models, which produces large amount of CO₂, and the significant use of water, especially for cooling data centers. At the same time, because of the great potential of AI, as part of the global production system, it can help to address environmental challenges, if its negative environmental aspects are properly recognized and mitigated. This possibility will be explored in more detail in the final chapters of the thesis.

A report published by the OECD focuses on the environmental impacts of AI thorough its entire lifecycle, considering Production, Operations and End- of- life phases (31).

For what concern the first phase of Production, the report focuses on the wider ICT sector, since specific data on AI is still limited. Still the findings are relevant as producing the hardware needed for AI like chips, CPUs and GPUs depends on the extraction of natural resources. Many

of these components require rare earth elements, which are expensive to extract and cause serious environmental damage. A clear example of this is the fact that only 0.2% of the clay mined contains rare earths. The remaining 99,8% becomes waste called “tailings” that is dumped back into the environment. These tailings are usually contaminated with chemicals used during processing and can release pollutants such as ammonium into soil and water (32). It is also estimated that refining one ton of rare earth produces about 75000 liters of acid water and one ton of radioactive waste (33).

Considering the carbon footprint related to the production of data centers, it contributes significantly to global emissions. In 2015, it was estimated that around 20 megatons of CO₂ equivalent (CO₂e) were generated during the production phase, accounting for approximately 15% of total greenhouse gas emissions from data centers (34). In 2022, Meta reported that emissions from the construction of its data centers represented about 30% of the company’s total emissions (35).

In the operation phase, AI systems have an environmental impact mainly due to water usage, energy consumption and related GHG emissions, both during training and deployment.

Recently, energy consumption linked to AI has gained attention because of its environmental and economic costs. A study by the University of Massachusetts assessed the emissions generated while training several large AI models. The study showed that a training process could produce over 626,000 pounds of CO₂e which is nearly five times more than the total emissions produced by an average American car over its lifetime, including its production (36). For what concern Generative AI models, such as virtual assistants like ChatGPT, also use more energy compared to traditional digital tools. The International Energy Agency (IEA) estimates that a single ChatGPT query uses about ten times more electricity than a standard Google search (37). As AI usage increases, energy demand is expected to rise as well, making the transition to low carbon energy sources essential to limit emissions.

A study by James O’Donnell and Casey Crownhart for MIT Technology Review investigated the energy used by each specific request to GenAI systems, focusing on the inference stage, when the model is used to generate text, images or videos. Their findings show that measuring the AI energy consumption is complex because it is effected by many variables like the type of AI model, the number of parameters, type of expected output, the data center where the task is processed, the time of day when the request is made, the local electricity grid and whether the power source is mainly renewable or fossil based.

Another issue is the lack of transparency. Most widely used models, such as Gemini (Google)

or ChatGPT (OpenAI) are closed source, meaning that information like the number of parameters, energy consumption per request, or data center locations are not publicly available. Moreover, AI data centers require a continuous and stable energy supply to operate. Since renewable sources like solar and wind are intermittent and these facilities need electricity 24/7, data centers often rely on more stable but more polluting energy sources, such as fossil fuels. To address this problem, tech companies like Meta, Amazon and Google have proposed nuclear energy as a low carbon alternative. However, nuclear power currently represents only 20% of electricity generated in the US (38), and building new nuclear plants requires many years. Furthermore, the environmental issues associated with nuclear waste disposal remain a serious concern.

Delving into the energy consumption associated with different AI outputs, whether text images or video, the energy required varies significantly depending on the task.

Since it is not possible to measure the energy use of closed source models like OpenAI's ChatGPT or Google's Gemini the study made by O'Donnell and Crownhart for MIT Technology Review focused on open source models, which are publicly available and widely used. In April 2025, META reported that its LLaMA model had been downloaded over 1.2 billion times (39), highlighting the open source model popularity among organizations seeking greater control and transparency.

The table below (Table 1) summarizes the energy required to generate text using two versions of Meta's open source model LLaMA 3.1 8B (8 billion parameters) that consumes 57 joules per response, or 114 joules, when accounting also for cooling and other operational loads. This is equivalent to running a microwave for one tenth of a second. While the larger 405B version (405 billion parameters) requires 3.353 joules or 6.706 joules including system loads to generate a text, comparable to powering a microwave for eight seconds.

In general, models with more parameters produce more accurate responses but also require substantially more energy.

While the energy per response for text generation appears modest, the cumulative impact becomes significant given the widespread and frequent use of these models. It is also important to mention the fact that Chat GPT-4 is estimated to contain over 1 trillion parameters, suggesting much higher consumption. Additionally, the complexity of the prompt can heavily influence energy use considering simple questions consume far less energy, up to nine times less, than creative or elaborate prompts such as storytelling or recipe generation (40).

Table 1:

Text	AI Models	Energy per request	Total estimate*
	LLaMA 3.1 8B	57 joules	114 joules
	LLaMA 3.1 405B	3.353 joules	6.706 joules

*Including cooling and other operational loads

Source: adapted from MIT Technology Review (2025). *We did the math on AI's energy footprint. Here's the story you haven't heard.*

For images generation, energy consumption depends less on the prompt itself and more on the model size and image resolution (Table 2). In this analysis, the open source model called Stable Diffusion 3 Medium (with 2 billion parameters) was tested. To produce a standard quality image (1024x1024 pixels, 25 diffusion steps) the model used approximately 1141 joules of GPU power. For a higher quality result using 50 steps, the energy requirement doubled to about 4.402 joules, equal to running a microwave for about five and a half seconds.

These models generate images through a gradual process, where each step is a computational phase that incrementally adds detail to the final image.

Table 2:

Images	AI Model	Image quality	Energy per request	Total estimate*
	Stable Diffusion 3 Medium	25 steps** 1024x1024 pixels	1.141 joules	2.282 joules
		50 steps**	-	4.402 joules

*Including cooling and other operational loads

**The image is generated progressively, and each step is a computation phase that adds more detail to the final output

Source: adapted from MIT Technology Review (2025). *We did the math on AI's energy footprint. Here's the story you haven't heard.*

Among the outputs analyzed, video generation had the highest energy demand (Table 3). The model tested was CogVideoX, an open source video generation system developed by the Chinese startup Zhipu Ai in collaboration with researchers from Tsinghua University. The latest version of the model can produce 5 second videos at 16 frames per second, requiring 3.4 million

joules, enough to power a microwave for over an hour. A lower quality version producing 8fps consumes approximately 109.000 joules.

However, closed source models such as OpenAI’s Sora, which generate longer and higher quality videos, consume even more energy. At the moment, it is not possible to estimate this due to a lack of transparency.

Table 3:

Videos	AI Model	Video quality	Energy per request	Total estimate*
	CogVideoX	8 fps (low quality)	-	109.000 joules
		16 fps, 5sec	-	3.4 million joules

*Estimate including cooling and other operational loads

Source: adapted from MIT Technology Review (2025). *We did the math on AI’s energy footprint. Here’s the story you haven’t heard.*

As previously discussed, the water required for the operational phase of artificial intelligence systems is a topic that remains relatively underexplored despite its importance. This phase involves the use of millions of liters of freshwater, primarily for server cooling and for electricity generation. The large volumes of water required raise significant sustainability concerns and may also contribute to social tension, given the limited availability and uneven distribution of freshwater resources.

To illustrate the scale of the issue, in 2023 Google’s company owned data centers withdrew approximately 29 billion liters of freshwater, of which over 23 billion liters was consumed, so lost through evaporation for on site cooling processes; nearly 80% of it was potable water (41). To contextualize the scale, this amount of water corresponds to roughly 315 million 10 minute showers, based on an average usage of 73 liters per shower, as estimated by the Philadelphia Water Department (42).

Moreover, the 2024 U.S. Data Center Energy Report estimated that by 2028, the total annual on site water consumption by American data center could double or even quadruple compared to 2023 levels, potentially reaching between 150 and 280 billion liters (43). On a global scale, projections indicate that by 2027, the total water withdrawal linked to Scope 1 (direct water withdrawal for on site cooling) and Scope 2 (off site water withdrawal for electricity generation)

could range from 4.2 to 6.6 billion cubic meters, even under more “optimistic” assumptions. The estimate surpasses the total annual water withdrawal of 4 to 6 times that of Denmark, or half that of the United Kingdom (44).

Despite the heavy environmental and social consequences, the growing water footprint of AI technologies has attracted little scholarly or policy attention. This lack of focus poses serious barriers to the development of truly sustainable AI systems. A critical aspect to consider is that water and carbon footprint, while interconnected, are not mutually substitutable, because improving carbon efficiency does not necessarily translate into lower water use.

A recent study conducted by Li et al. introduced a methodology for estimating the water footprint of Artificial Intelligence systems. Taking GPT-3, having 175 billion parameters, as a practical example, the authors demonstrated that the training process alone can lead to the consumption of around 5.4 million liters of water (45). Furthermore, even during its use phase, the inference, GPT-3 is estimated to consume the equivalent of a 500 ml bottle of water for every 10 to 50 medium length responses, depending on the time of the day the request is processed and the geographic location where the model is deployed (45).

Before delving deeper into how AI systems use water and how the use can be reduced, it is essential to clarify the distinction between water withdrawal and water consumption. The term water withdrawal refers to the process of extracting freshwater from surface or groundwater sources, either temporarily or permanently, for various uses¹. On the other hand, water consumption refers to the portion of that withdrawn water that is not returned to its original source, as it has evaporated or been incorporated into a product, making it unavailable for reuse².

When assessing the water usage of data centers, it is useful to distinguish between three levels of impact, commonly referred to as scopes. The first, Scope 1, refers to the direct onsite use of water for cooling the servers. Scope 2 includes offsite water use for the generation of electricity. Lastly, Scope 3 is related to the water consumption along the supply chain, particularly during the manufacturing of servers and related hardware components.

As illustrated in figure 4, in Scope 1 the electricity powering the servers is converted into heat, which must be removed using water-based cooling processes. In cooling towers, part of the water evaporates as part of the heat dissipation process. The non-evaporated water is directed

¹ Definition retrieved from the OECD website, available at: <https://www.oecd.org/en/data/indicators/water-withdrawals.html#:~:text=Definition,to%20a%20place%20of%20use>.

² Definition retrieved from World Resources Institute web site, available at:

<https://www.wri.org/insights/whats-difference-between-water-use-and-water-consumption>

through the heat exchanger, where it continues to absorb heat from the system. However, the remaining water can only be reused a limited number of times, typically 3 to 10 cycles, depending on water quality, before being discharged to avoid mineral and salt accumulation. Continuous freshwater input is necessary to prevent pipes obstruction and bacterial proliferation. It is estimated in Scope 1 that approximately 80% of the water evaporates during the cooling process, and is therefore classified as consumed.

Scope 2 water usage, as shown in figure 4, is linked to the electricity consumption of the data center, as water is also used in off site cooling systems to dissipate heat generated during electricity production.

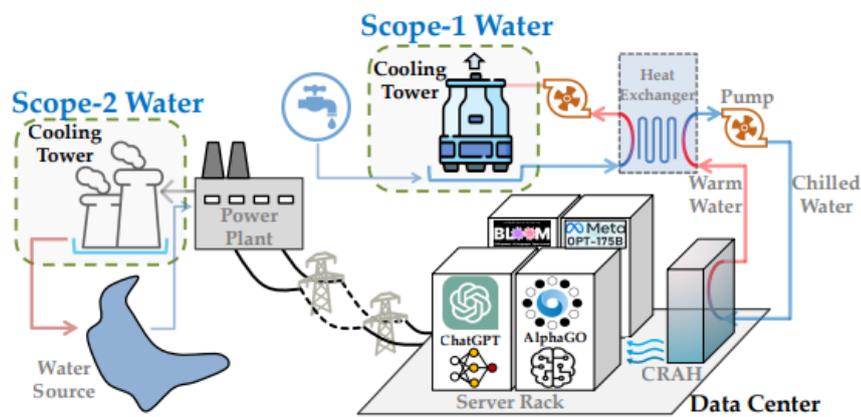


Figure 4: Illustration of the operational water usage in a typical data center

Source: *Making AI Less “Thirsty”: Uncovering and Addressing the Secret Water Footprint of AI Models* (2025)

Scope 3 water consumption is also significant. For example, ultrapure water is essential for wafer fabrication, necessary for the manufacturing of chips and semiconductors. Additionally, water is required to cool semiconductor fabrication plants and wastewater discharged from these facilities often contains toxic chemicals and hazardous substances.

Several factors must be considered in managing water usage for data centers. First, timing and location matter. On site water efficiency depends on weather conditions, in fact cooler temperatures reduce cooling needs, while off site water efficiency is influenced by the energy mix of the grid, which changes through the day. For example, renewable energy sources like solar and wind are intermittent, affecting when electricity is cleanest. In this context, it may be beneficial to schedule AI training during the night, when temperatures are lower and electricity demand on the grid is reduced, potentially allowing for cleaner energy mix depending on local

renewable availability (45).

This consideration leads to a strategic dilemma, that is if it is more sustainable to adopt a “follow the sun” approach, locating data centers where solar energy is abundant, or an “unfollow the sun” approach, favoring cooler climates that require less water for cooling. The paper by Li et al., upon analyzed, leaves this question open, calling for further research to develop balanced strategies that maximize both carbon efficiency and water conservation.

It is important to highlight, however, that Northern Virginia, currently the leading global hub for data centers, is neither characterized by abundant solar heat nor by low ambient temperatures. This indicates that environmental criteria such as energy or water efficiency, including approaches like “follow” or “unfollow the sun” are not yet primary factors in choosing site location. Instead, decisions appear to be predominantly influenced by elements such as early investments in fiber optic infrastructure, advantageous tax regimes and access to a large, specialized workforce (46).

Regarding the end of life stage of technological products, this typically results in electronic waste (e-waste), which is now considered the fastest growing category of solid waste worldwide (47). E-waste poses serious concerns due to its content of hazardous materials and its potential to release toxic substances if improperly recycled. A big portion of the world’s electronic waste is exported to developing countries, including China, India, Bangladesh and several regions of West Africa, where it is processed by informal workers using manual and unsafe techniques. These recycling activities often take place in open air dumping grounds, which are usually situated within residential areas (48). Such conditions represent a serious threat to the environment but also to human health, especially when children and adolescents are involved. The informal processing of e-waste leads to extensive contamination of air, soil and water, and causes a wide range of adverse health outcomes (49). Exposure to toxic substances released during unregulated recycling practices are linked to endocrine disorder, neurodevelopmental deficits and cancer (50). Young individuals are especially vulnerable due to the sensitivity of their developing nervous system, which is more susceptible to neurotoxic elements like mercury. Additionally, exposure to hazardous chemicals commonly found in electronic waste may compromise lung development and respiratory health, potentially resulting in irreversible health issues (51).

Considering the challenges outlined above, it is essential to recognize that artificial intelligence holds the potential to improve business performance, including in terms of environmental sustainability, as we will explore in the following sections. However, these benefits must not

overshadow the critical environmental issues linked to the development and lifecycle of AI systems.

The next chapter will examine the current regulatory landscape concerning AI and environmental sustainability, highlighting how existing legal frameworks often fail to address the environmental challenges posed by these technologies. While much attention has been given to topics such as algorithmic ethics, transparency and privacy, the environmental dimension, especially regarding resource consumption, remains underestimated, revealing a significant policy gap.

2. The European regulatory and policy framework: a critical gap

2.1 AI under current European law: The EU AI Act and General Data Protection Regulation (GDPR)

As discussed in the previous chapter, the development and deployment of Artificial Intelligence systems has important environmental implications, due to its intensive energy demand and considerable water consumption. More sophisticated models, such as the widely used ChatGPT or Gemini, tend to have an even greater impact, as they are more complex and process vast number of daily requests.

Because the use of Artificial Intelligence will increase and the models will be even more complex and resource hungry, a solid regulatory framework is essential to balance the beneficial applications of AI with climate change mitigation strategies. This will ensure both the long term sustainability and feasibility of AI adoption.

Nevertheless, today the environmental concerns of AI remain overlooked in current technology regulations, including major instruments such as the Eu AI Act and the GDPR.

The European Regulation 2024/1689, better known as the EU AI Act, constitutes the first comprehensive legislative framework on AI worldwide. It sets as priorities that AI systems must be transparent, safe, traceable, environmentally sustainable, and cannot assume discriminatory behaviors (52).

The act establishes a risk-based approach, given that the obligations of providers and users vary according to the level of risk assigned to the AI systems (Figure 5)

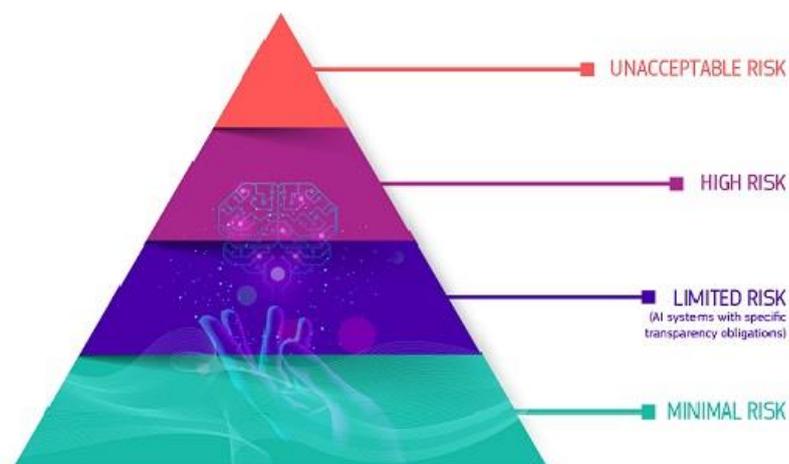


Figure 5: four levels of AI systems risk identified by the EU AI Act

Source: European Parliament (2025)

Unacceptable risk systems are those that pose a serious threat to individuals' safety or rights and are strictly prohibited. This category includes practices such as social scoring and emotion recognition in the workplace or educational institutions.

High risk systems are those with the potential to provide severe negative impact on health, safety and fundamental rights of people. Examples include AI safety components integrated into critical infrastructure whose malfunction could endanger lives, and recruitment tools such as automated CV screening software. These systems are not banned but they are subject to stringent requirements for the market entry; such requirements include risk assessment and mitigation measures. Once in the market, high risk AI must be subject to market surveillance by authorities, human oversight by deployers and continuous monitoring by providers.

Limited risk systems are AI systems that have to comply with transparency obligations and EU copyright law. Generative AI applications, such as ChatGPT, are in this category so, to be permitted to work, they must clearly disclose when content is AI generated, their measures against the production of illegal material and disclose summaries of training data.

Most of AI applications currently in use within EU are classified as minimal risk systems, for which the AI Act does not impose specific regulatory obligations.

For what concerns the sustainability of AI systems, the regulatory approach of EU AI Act is limited because it mainly encourages voluntary codes of conduct to improve environmental sustainability.

The current version of the Act includes, in the general objectives of the regulation, the environmental sustainability topic but it fails to establish binding measures to incentivize concrete action. Also, the provision encouraging the development of more sustainable AI systems through the access to research funding and sandboxes for AI doesn't provide effective mechanism for implementation to promote the objective.

In addition, article 40 focuses on the promotion of harmonized standards that could, in principle, reduce the resource consumption of AI systems. However, as demonstrated in previous research, even though transparency tools such as documenting and reporting the greenhouse gas footprint represent a step forward, such disclosure often fails to effectively reach their intended audience (53). Nevertheless, this information can still be valuable for non governmental organizations and regulatory agencies to collect reliable data on the environmental impacts generated by AI models.

Therefore, while this framework represents an initial step, it does not sufficiently address the environmental risks posed by AI systems.

Another EU legal framework that can be applied, at least indirectly, to the environmental implications of AI is the General Data Protection Regulation (GDPR). The GDPR defines the conditions under which personal data in the European Union may be collected, processed and transferred, safeguarding privacy and security. It imposes strict obligations on data controllers and processors, requiring them to implement adequate technical and organizational security measures (54).

While the GDPR was never designed providing specific rules related to environmental protection, data processing itself has both direct and indirect environmental effects. On the one hand, large scale AI operations, such as model training and deployment, as we have seen in the last chapter, have a direct impact on environment, consuming significant amounts of electricity and water, contributing to GHG emissions and resource depletion. On the other hand, the production, use and disposal of the machinery required for data processing create further indirect emissions across their lifecycle. Given that, some of the GDPR's fundamental principles can be reinterpreted through an environmental perspective in order to encourage more sustainable practices (55).

One example concerns the principle of legitimate interests and purposes of processing. Under the GDPR personal data may only be collected and used for legitimate purposes. If environmental costs were taken into account as part of this GDPR assessment, direct impacts such as high levels of energy or water use could be considered as factors in determining the legitimacy of the processing. A cost benefit analysis could demonstrate when environmental negative impact of data processing is greater than the benefits it brings to society. For example, training an AI model that consumes large amounts of energy might be acceptable if it supports goals in the public interest, such as advancing medical research or improving renewable energy. By contrast, it is harder to justify such high resource use for entertainment purposes, where the cultural or recreational values does not clearly balance the environmental cost.

Another issue arises with the interaction between sustainability and individual rights. The right to be forgotten, contained in Article 17 of the GDPR, allows individuals to request, under certain conditions, the erasure of their data. If, however, a large number of requests were exercised under the article 17 (1) (a) GDPR after the training of a foundation model, retraining might be required, generating significant additional emissions. A possible solution would be to reinterpret the Article 17 (3) (c) and (d), which currently provide exceptions to the right of erasure when processing is necessary in the public interest, for scientific, historical or statistical purposes, allowing also limitation to the right to be forgotten for sustainability considerations.

Transparency requirements raise further challenges. Article 15 (1) (h) GDPR impose obligations for controllers to provide information on the logic behind automated decision making. Many modern AI systems are deep learning models, functioning as opaque black boxes, due to the large amount of parameters involved. Amsterdam Court of Appeals in the Uber and Ola case (56), have confirmed that post hoc explanation algorithms may be required to meet transparency standards. However, these algorithms consume vast amount of resources, increasing emissions.

For highly complex tasks, such as medical diagnosis, black box models may be indispensable. This creates the need for a balance between the risks caused by opacity and the environmental costs of ensuring transparency. From a doctrinal perspective, the balance could take place within the access provision, in particular under Article 15(1)(h) GDPR. In this framework, transparency requirements could, for sustainability reasons, be satisfied by providing a general explanation of the overall functioning of the model rather than detailed explanation of each individual output, where the model provides significant social benefits.

Finally, fairness and non discrimination requirements illustrate the same dilemma. Post hoc fairness algorithms are introduced to mitigate bias in machine learning systems (57). They also demand additional computational power, raising emissions. Yet unlike opacity, discrimination has immediate and severe impacts on individuals, denying opportunities, access to resources or exposing them to harm. From a normative perspective, the social damage caused by unfair algorithms generally takes priority over relatively modest environmental costs of fairness interventions, especially since such algorithms typically do not generate significant GHG emissions (58).

In conclusion, the GDPR does not explicitly link data protection to environmental sustainability. However, its principles can be reinterpreted by policymakers to incorporate climate considerations without altering the fundamental structure of the GDPR.

2.2 Regulatory instruments for emission reduction: the European Green Deal, the European Climate Law and the EU ETS

The significant climate impact of Artificial Intelligence systems raises an important question about how current European environmental laws take these costs and risks into account. Within the EU framework there are already rules that deal with issues relevant to AI's footprint, mainly greenhouse gas emissions and water use. Key examples include the EU Emission Trading

System (ETS) and the Water Framework Directive. However, as we will see, none of these instruments specifically mention or directly regulate the training and deployment of AI systems. The European Green Deal (59) sets the ambitious goals of cutting emissions by at least 55% by 2030 and reaching climate neutrality by 2050, objectives that are now legally binding through the European Climate Law. But the climate risks linked to AI, as a fast growing technology, are still being underestimated and it could undermine the EU's ability to meet the established climate neutrality targets.

At the same time, the European Commission in the Green Deal highlights how digital technologies, including AI, can support sustainability. Data analysis, high performance computing and AI tools are seen as ways to improve environmental monitoring and resource management. Examples include AI systems that track air and water pollution or optimize energy use. These applications show the positive potential of AI, but to make it possible, sustainability must become a crucial point of the digital transition. Despite these opportunities, there is uncertainty in the Green Deal regarding how urgently and to what extent AI's environmental dimension should be addressed by law.

This ambiguity is particularly evident in the Green Deal Industrial Plan (60), a strategy designed to strengthen the competitiveness of Europe's net zero industry and to accelerate the transition towards climate neutrality. The plan aims to create a more favorable environment to boost the EU's production capacity using net zero technologies, which are essential to achieve Europe's ambitious climate goals. Within this framework, the plan identifies Artificial Intelligence as both a driver of digital innovation and a key enabler of green transition. While this recognition is justified and reflects the transformative potential of AI, the plan nevertheless overlooks the environmental costs and emissions associated with the training and deployment of AI models. This omission reveals an important gap in the current regulatory frameworks.

The European Climate Law (61) strengthens the Green Deal by making the goal of climate neutrality by 2050 legally binding, being aligned with the UN 2030 Agenda for Sustainable Development (62) and the Paris Agreement (63).

Achieving climate neutrality means that EU member states, as a whole, must reach net zero GHG emissions, primarily by cutting pollution, investing in clean energy technologies and protecting ecosystems. For the achievement of the intermediate target of reducing emissions by at least 55% by 2030 and the final 2050 target it is crucial that all EU policies contribute to the goal and that every sector of the economy plays its part.

To comply with these commitments, the EU relies on a variety of legal and financial tools (64).

The Emission Trading Scheme (65) functioning on a cap-and-trade basis proved to be the most prominent in reducing emissions. It works by EU that sets a cap that is a maximum limit on total emissions, expressed in allowances, where each allowance permits the emission of one tonne of CO2 equivalent. If a company exceeds their allowances in emissions, it will face financial penalties. An entity can obtain allowances, generally, by European public auctions or buying them from other companies, but some are allocated for free to certain industries. If a company manages to reduce its emissions, it may choose to sell the surplus allowances or save them for future uses (Figure 6)

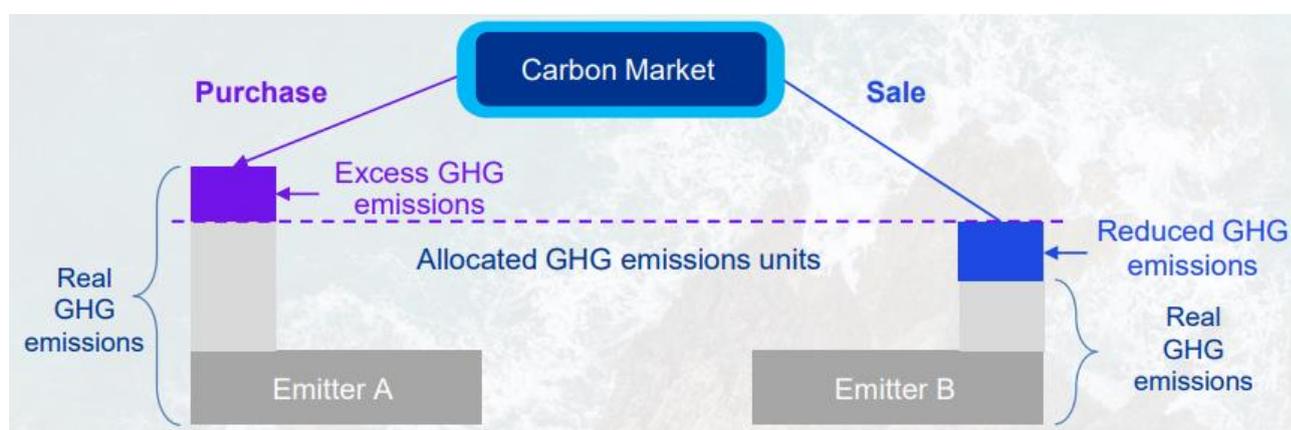


Figure 6: visual representation of how Emission Trading System works.

Source: KPMG (2023)

The cap decreases annually, in line with the EU’s climate targets, ensuring a continuous reduction in emissions. Over time, the ETS has proven highly effective, in fact, by 2023 it had contributed to reducing emissions from European power and industry plants, by around 47%, compared to 2005 (66), establishing as one of the EU’s most successful climate instruments.

In relation to AI, the ETS does not provide specific coverage. The Emission Trading System currently applies only to well defined high emission sectors, such as power generation, energy intensive industries such as steel, oil, iron, chemicals, minerals, aluminum and pulp and paper production, as well as commercial aviation within the EEA and maritime transport. It also applies to activities involving the combustion of fuels in installations with a total rated thermal input exceeding 20 MW (67).

Emerging technologies like AI are not covered directly, unless deployed within one of these regulated sectors. As a result, the environmental costs of AI could remain outside the system’s scope.

One possible solution would be to extend the ETS to cover the ICT sector, specifically AI (55). Of course, pretending to include the entire ICT sector in the Emission Trading System may be misleading and overly generic, as most of the emissions involved are in Scope 3, not directly under companies' control. Instead, the data center infrastructure, on which Artificial Intelligence technologies rely, could be introduced into the ETS, specifically the data processing segment that is a highly energy intensive activity directly controlled by data center owners. This activity consist in converting raw data into valuable information through structured stages including data collection, preparation, analysis and storage (68).

Including Data centers in the ETS could help bring down AI's emissions in the same way the system has successfully reduced emissions in European power and industry plant.

In line with the reductions already achieved, the effective inclusion of the datacenters within the ETS would require initial emission caps to be sufficiently strict to encourage allowance trading, increase their market value and so create strong incentives for reducing GHG emissions (55).

Another important measure that could be implemented to strengthen environmental protection, while also considering the positive implication of AI technologies would be create a taxation framework based on the final purpose of data processing for Artificial Intelligence. In fact, AI systems are employed in areas such as environmental protection, healthcare, education, security and entertainment, sectors that vary a lot in their importance for basic social and environmental functions. Regulators could therefore establish "social usefulness classes", reflecting the expected social benefits of AI applications. Taxation could then be adapted to those classes. For example, more emission flexibility could be given to medical diagnostic systems, which can save lives, than to entertainment purpose models, which have limited social benefits. Such an approach would encourage innovation where it is most needed while also ensuring that AI's climate costs are not ignored.

EU initiatives have already begun to address the environmental footprint regarding energy consumption of the digital infrastructure on which AI depends, through measures targeting data centers. The most relevant instruments in this regard are the Energy Efficiency Directive (69) and the Commission Delegated Regulation (70), which impose obligations on reporting and monitoring the energy use of such facilities. Although not designed specifically for AI, these measures are crucial because data centers are the backbone of AI training and deployment.

Directive (EU) 2023/ 1791 requires data centers with an installed IT power demand of at least 500 kW, including even small sized facilities, to monitor and report their energy performance.

The data will be collected in a European database, making it possible to assess and compare the energy efficiency and water footprint of data centers across the EU. This instrument is totally aligned with EU's climate ambitions on emission reduction.

The Delegated Regulation provides further details identifying information to be reported and performance indicators to be used. Among these, the most significant is the requirement to measure IT related energy consumption using the Power Usage Effectiveness (PUE) methodology. PUE expresses the ratio between the total energy consumed by a data center and the energy used exclusively by IT equipment (Figure 7). For instance, if a facility consumes 1300 kWh overall, of which 1000 kWh is used by servers and IT devices, its PUE would be 1.3. This means that for every 1 kWh required by IT operations, an additional 0,3 kWh is consumed by cooling, power distribution, or other support systems. The lower the PUE, the higher the efficiency of the facility is.



*A lower PUE ration indicates greater energy efficiency

Figure 7: PUE calculation to measure data center energy efficiency

Source: Nlyte Software (2025)

While these transparency and reporting measures represent progress, the Energy Efficiency Directive still does not establish binding efficiency thresholds or renewable energy requirements for data centers (71). As a result, facilities continue to consume vast amounts of electricity without making any improvements in sustainability performance.

Germany, however, offers a useful example of a stricter approach that could inspire broader EU action (72). The country has introduced a national reporting scheme combined with concrete efficiency and renewable energy targets for data centers. Operators are required to maintain a PUE between 1.5 and 1.2 depending on the age of the facility, achieve an Energy Reuse Factor³

³ Metric that measures the portion of a data center's total energy consumption that, instead of being wasted, is captured and repurposed for external uses, such as supplying heat to nearby buildings. Source: <https://www.nlyte.com/blog/energy-reuse-factor-a-key-metric-for-sustainable-data-center-operations/>

of 10% to 20% and ensure at least 50% of their electricity supply comes from renewable sources, a percentage that must rise to 100% by 2027. In addition, it requires data center operators to provide their clients with annual reports detailing the share of energy consumption directly attributable to their activities (73).

2.3 Water Framework Directive

The environmental concerns linked to Artificial Intelligence extend beyond energy use generating greenhouse gas emissions, also involving the significant issue of water consumption, as discussed earlier.

Through the AI production cycle, large volumes of water, most of the time fresh water, are withdrawn and consumed. This occurs in several stages such as cooling servers, generating the electricity that powers data centers and manufacturing the hardware on which AI relies. It is estimated that approximately 80% of water withdrawn by data centers is consumed through evaporation (74). Even in cases where water is only withdrawn and later returned, its immediate availability for other critical purposes such as drinking water supply or irrigation is reduced; so it also contributes to water stress.

The Water Framework Directive (75) could, if revised, can represent a relevant regulatory framework to limit the overall volume of water used by data centers and to prevent potential deterioration in water quality. Since its adoption in 2000, the WFD has been the cornerstone of European water law. It recognizes water as a shared heritage that must be protected and safeguarded. Its objective is to prevent any further decline in the condition of European water bodies and to achieve a “good status”. To reach this goal, the Directive promotes actions to reduce pollution and ensure that water supplies are sufficient to sustain both biodiversity and human needs.

However, today, the Water Framework Directive only touches the negative AI water implication in an indirect way. Its scope extends to rivers, lakes, transitional and coastal waters, as well as groundwater, focusing on preserving water quality. This creates a clear misalignment because the main water related challenge posed by AI and other emerging technologies is not contamination, given the fact that it doesn't seem to pollute more than other industrial sector (55), but rather the risks related to water quantity.

Unlike the Emission Trading System, which sets explicit caps on greenhouse gas emissions, the WFD does not impose binding limits on the withdrawal or consumption of water.

Recital 19 of the WFD, explicitly deals with water quantity as an “ancillary element to water quality”. Nonetheless, the Directive does provide some indirect mechanisms for addressing the water quantity concern. Article 5 (1), for example, requires an economic assessment of water use, while Article 8 (1) obliges Member States to monitor both surface and groundwater volumes. These provisions, however, remain ancillary to the central goal of safeguarding water quality.

The Court of Justice of the European Union has added important clarification to the interpretation of the WFD, making clear that water quantity is an important part for the evaluation of the ecological status. In the well known case of the Weser river, the Court made clear that even a deterioration in a single parameter of the water status, including quantity, is sufficient to constitute a violation of the WFD regarding the prevention of degradation of water status rule, even when the overall classification of the water body remains unchanged (76).

The case occurred from the German project to deepen sections of the Weser River to facilitate the passage to larger ships. The environmental association BUND went against the project, arguing that it would damage the ecological and chemical condition of the river, and so was against the Directive 2000/60/EC.

The Court examined the Case and stated that Member States are legally required, unless a derogation is granted, to refuse projects that could worsen the condition of a water body. The Court clarified that deterioration occurs even when one element listed in Annex V of the WFD, including those relating to water quantity, deteriorates by one class, regardless of whether the overall classification of the water body remains unchanged.

The resolution of the case made the Directive’s non deterioration principle much stricter and turned it into a stronger legal obligation for Member States. It also confirmed that water quantity, previously treated as a secondary concern, must be considered a key factor in assessing the status of water bodies and consequently, the feasibility of a project.

2.4 Conclusions on the EU regulatory framework and Extra-EU developments

This chapter has highlighted the European regulatory framework concerning AI technologies, both in terms of current technology regulations and environmental considerations. Instruments such as the EU AI Act and the GDPR establish a robust system, particularly with regard to transparency and data privacy, while the environmental impacts of AI systems remain largely overlooked. Similarly, the main regulatory tools for emissions reduction, such as the European

Green Deal, the Climate Law, and the EU ETS, as well as frameworks like the Water Framework Directive, do not specifically address strategies to minimize the environmental footprint of data centers.

Some progress has been made through the Energy Efficiency Directive and the Commission Delegated Regulation, upon mentioned, which impose obligations on reporting and monitoring the energy use of such facilities. Although not designed specifically for AI, these measures are strongly related to this technology, as data centers are the backbone of AI training and deployment.

However, Europe appears less competitive in the global race for AI development, partly due to the strict requirements of the EU AI Act and GDPR, and the emerging concern on the environmental sustainability of data centers. Faced with these costs, companies often relocate facilities to locations with less stringent regulations.

Outside the EU, different approaches are emerging. United States, in the last year, started to move in the opposite direction. The country already hosts the largest concentration of data centers in the world, whose energy use accounts for about 4.4% of national annual electricity consumption.

In this contest, recently, the Trump administration has chosen to focus on competitiveness and rapid AI development, even if this means weakening environmental safeguards.

In fact, in July 2025, the White House presented “Winning the Race: America’s AI Action Plan” (77), a program designed to reduce regulatory barriers concerning environmental sustainability topics, that slow down the construction of new data centers and related infrastructure.

One of the most important recommendations of the plan is the introduction of new categorical exclusions under the National Environmental Policy Act (NEPA) specifically for data centers. NEPA, passed in 1970, is one of the cornerstones of US environmental law and requires federal agencies to carry out detailed environmental impact assessments before approving large projects (78). These assessments look at how a project might affect land, water, biodiversity, air quality and even the health of communities. While essential for environmental protection, they are often long, costly and bureaucratically complex, and it can delay new construction for years.

The plan also includes the Clean Water Act of 1972, which regulates discharges into water bodies. Under the current system, any project that affects these areas must obtain a specific permit issued by U.S Army Corps of Engineers, under the supervision of the Environmental

Protection Agency, in accordance with Section 404 of the act. This process involves extensive environmental studies, public consultations and often legal disputes, which means that obtaining such permits can take months or even years, creating significant construction delays. To overcome this obstacle, the administration has proposed the creation of a national standardized permit for data centers, designed to avoid case by case evaluations.

The plan also suggests simplifying the procedures required under the Clean Air Act (CAA) and CERCLA (Comprehensive Environmental Response, Compensation and Liability Act). Both laws play a vital role in protecting air quality and ensuring the safe use of contaminated land, but their lengthy and costly procedures are often seen as obstacles to the rapid expansion of digital infrastructure.

In sum, Europe's regulatory framework for AI technology and the U.S. strategy of prioritizing competitiveness represents two opposite approaches none of them fully ensures sustainable AI development. While Europe risks losing competitiveness in innovation, the American trajectory raises serious concerns about environmental conservation. The real challenge ahead is to shape a regulatory framework that can facilitate technological advancement with long lasting sustainability.

In the following sections, we will see how some American and European companies, despite the current regulatory gaps, are already moving in a direction that shows how, when applied to environmentally valuable purposes, Artificial Intelligence can actively contribute to achieving sustainability targets.

3. Framing Artificial Intelligence in the context of corporate environmental sustainability

3.1 AI as a strategic tool for companies to achieve environmental targets

As seen in the last chapters, the green and digital transition of our society, and in particular the rise of Artificial Intelligence systems, represent both an opportunity and a challenge in the context of environmental sustainability. On one side, training and deploying AI models have a clear environmental cost because they require large amounts of electricity, water for cooling activities and generate electronic waste. As we have seen in past paragraphs, today environmental risks of AI are still largely overlooked, especially by current regulations that do not address the problem with binding rules to reduce emissions and resource consumption of the AI systems. Without stronger safeguards, the expansion of AI could undermine climate goals that Europe is trying to achieve (79).

At the same time, as the following section will show, AI can also be a transformative instrument for sustainability in companies. When applied strategically, it can support a more efficient use of natural resources (for instance, monitoring consumption of water, electricity or natural gas), help to reduce polluting emissions through the optimization of industrial processes, improve circular economy practices through, for example, smarter waste management, and even contribute to disaster prevention with advanced monitoring and alert systems.

So, if combined with other technologies like blockchain, digital twin and Internet of Things, AI can be an important driver for sustainability strategies in businesses. Across different industries, AI is already proving that it can bring positive environmental results, especially in managing emissions, making supply chains more efficient, also addressing human rights and ethical topics.

It is important to clarify that while this thesis does not address the social dimension of sustainability, as it falls outside the chosen scope, true sustainability doesn't consider only the environmental perspective. Ethical issues, human rights and responsible sourcing remain crucial for building a sustainable future.

Evidence from companies shows they are moving in this path. Figure 8 presents results from a 2021 Accenture survey involving 560 large firms from multiple sectors and regions, all with revenues above one billion dollars. The study found that 70% of these companies are using AI technology solution to reduce emissions from their operations (80).

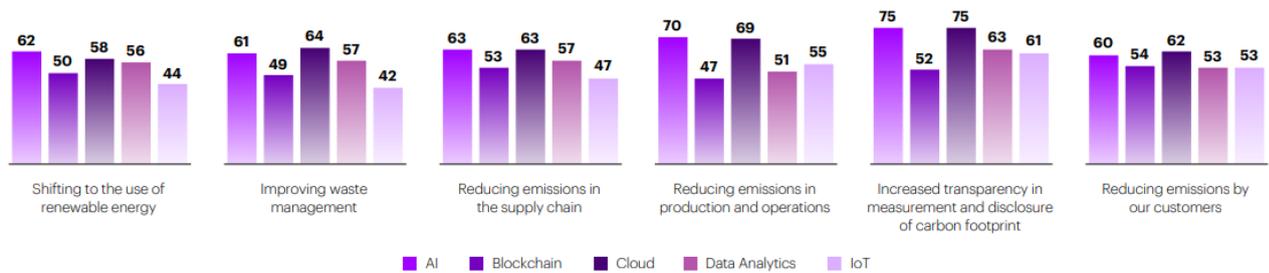


Figure 8: Technologies adopted by companies to meet emission targets (% of companies)

Source: Accenture (2021)

A practical case comes from a global building materials company that worked with Accenture to launch a machine learning app capable of predicting cement strength in real time during production. This data driven innovation allowed the company to produce more eco friendly cement without additional costs to consumers. The results are that up to 13.000 tones of CO2 were reduced per plant, for a total of around 3 million tones, and cost savings of \$150 million across all facilities (81).

The improvement comes from a better management of clinker production, the most energy and carbon intensive phase of cement manufacturing. Clinker, produced by heating limestone and clay at 1450 °C, is responsible for most emissions in the cement industry, due to both the burning of fossil fuels and the chemical breakdown of limestone (82). Real time predictions allow producers to use only the necessary amount of clinker and adjust furnace conditions, avoiding unnecessary energy waste. This reduces fossil fuel use and lower emissions, while keeping cement quality intact.

Another example comes from the IT sector, where companies are increasingly investing in sustainable technologies. Microsoft for instance is committed to becoming carbon negative by 2030 and removing all emissions generated from its founding in 1975 (83). Part of its strategy includes launching the Microsoft Sustainability Calculator, a tool powered by AI that helps clients analyze the carbon footprint of their Azure cloud workloads. By offering transparency on IT related emissions, including the once in Scope 3, the tool allows companies using Azure cloud to better manage and report their climate impacts (84).

Addressing sustainability, however, requires more than optimizing individual processes, it demands action along the entire supply chain, which accounts for 60% of global emissions (85). The challenge is of course difficult because of the interconnections between modern supply chains that make complex to measure and track ESG performance.

A promising solution is the use of digital twin technology that is a virtual replica of a physical

system, resource or process, continuously updated with new data from, for example, sensors and telemetry data. With integrated AI, digital twins can simulate and test different scenarios, predict performance, find inefficiencies and suggest optimized operational strategies.

The pharmaceutical company Sanofi provides a concrete example. By combining real time data with digital twins and AI technologies has developed AI powered yield analytics platform that learns from current and past performance, ensuring the optimization of the company's manufacturing process and increasing yields. Another AI based application of Sanofi, called Plai, helps the company to predict up to 80% of potential stock disruptions, improving manufacturing efficiency and supply chain resilience (86).

AI can also play an essential role in measuring and monitoring environmental sustainability metrics. By processing vast datasets from sensors, satellites and other sources, AI improves the companies' ability to track their impact on ecosystems and public organizations, thanks to AI, can anticipate environmental threats and have early warning systems for natural disasters (87). According to a survey conducted by Accenture in 2021, 75% of companies that increased transparency in reporting, and measurement of their carbon footprint did so with the help of AI tools (88).

Therefore, integrating Artificial Intelligence into corporate sustainability strategies can represent a key element in achieving environmental objectives. However, this approach also raises questions about its overall effectiveness, particularly when AI's benefits are weighed against its energy and resource costs. To address this challenge, as discussed in the following section, attention can be directed to the design of AI systems focusing on the concept of Green AI, which refers to developing more energy efficient Artificial Intelligence without significantly compromise model quality.

3.2 Green software to drive intelligent solutions: Green Ai concept

As previously discussed, both the green and digital transformation of society, including the growing adoption of Artificial Intelligence systems, represent a twin challenge that combines opportunity with risk. In early chapters, the environmental costs of AI training and development have been examined; these processes demand large amounts of electricity and cooling water, while also generating electronic waste. Yet, on the other hand, AI has the potential to act as a tool for addressing environmental challenges, both when it is applied directly to sustainability goals, as discussed in the previous paragraph, and when it is designed to be greener itself. This requires organizations to view sustainability of their software strategy as a central element of

how AI systems, and all their digital infrastructure, are conceived and developed.

Software is the backbone of nearly every technological system. To make real progress in sustainability, companies must look closely at the entire software lifecycle, so, how it is designed, built, deployed and used, and analyze how each step can be optimized to reduce environmental impact.

Software cannot run without hardware so every increase in software activity generates greater demand on the servers, devices and networks powering it; this amplifies energy consumption and emissions. Green software practices can reduce resource consumption in different ways, depending on the impact area (figure 9).

	Impact area	Green software practices	Did you know?
1	Green Software development lifecycle	Adopting energy efficient and green practices across the software development lifecycle - from selecting platforms, programming languages, to designing software architecture and DevOps, to save energy, reduce emissions, and develop carbon-efficient software	Interpreted languages can consume 10x more energy than semi-compiled and 48x more energy than compiled
2	Green UI/UX	Driving user friendly digital experience with effective accessibility - easier navigation and therefore lower screen time reducing emissions; optimizing performance by selection of screen color, evaluating screen's processing power and compressing content and images	By modifying UI to support dark mode, an app can reduce the UI carbon emissions by -60%
3	Green AI	Evaluating the trade-off between energy efficiency and accuracy of the AI/ML models based on the criticality of the use case. Repurposing existing models for a different task called transfer learning can further cut down energy and time and in turn emissions	With a responsible target accuracy, the carbon emissions of your ML models can be reduced by -80%
4	Green Cloud & data centers	Encouraging data center to cloud migrations , right hosting decisions and green application development on cloud for hardware and energy efficiency; further evaluate implementation of edge computing - inherently a low energy technology - storing and using data near the device or end-user	By migrating GCP cloud location from asia-east-1 to europe-north-1, the project can save -66% of emissions
5	Green Data	Focusing on efficient data processing throughout the data lifecycle by eliminating storage waste, data compression, effective utilization of networks and data transmission, improving efficiency in workload management can reduce dark data from the ecosystem reducing emissions	Green Data Mgmt, can reduce the costs incurred on transmission & storage of "dark data" which accounts for 70% -90% of all data
6	Green Distributed ledger technology	Using energy efficient DLT algorithms and green blockchain design principles including decisions on number of nodes in the network, size of transaction data, compression strategy, data storage, computing and network infrastructure	Consensus algorithm, network design, increased transaction frequency, etc. have a huge impact on emissions
7	Green Infrastructure	Driving reduction in environmental impact of IT infrastructure - end-user devices, networking components and data center by considering both usage emissions and the lifecycle emissions associated with manufacturing and end-of-life. Encouraging responsible procurement and end-of-life management amongst others	Currently, only about 17% of e-waste collected is recycled. And most organizations recycle less than 10% of their hardware

Figure 9: Green software priority areas

Source: Accenture (2024)

Adopting green software practices means placing sustainability at the core of digital transformation strategies and integrate environmental considerations into every phases of development, from the definition of user needs, technical requirements and maintenance of applications.

Accenture's research provides insight into where businesses currently stand on this journey. In the survey, they asked companies whether they integrate sustainability principles into the

software development lifecycle stages. Out of 560 organizations interviewed, only two reported consistently taking care of every step; most answered to taking just one or two actions (88). (Figure 10).

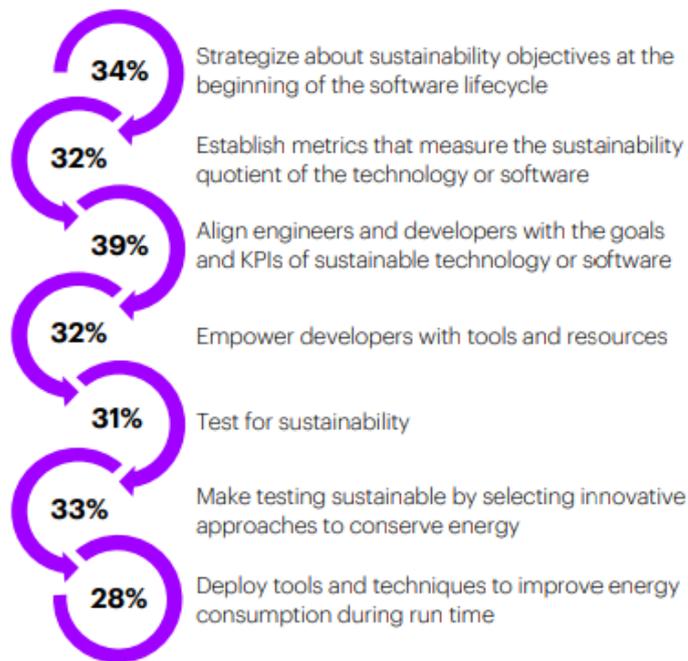


Figure 10: Sustainability principle adopted in the software development lifecycle

Source: Accenture (2021)

The findings also suggest that to truly leverage modern architecture, companies need to rethink how software is designed, giving energy efficiency the same weight as traditional priorities like security, scalability and functionality. Yet half of the respondents still do not set dedicated sustainability goals within their software development agenda, a choice probably linked to the absence of binding regulatory frameworks, as previously discussed.

An important dimension of sustainable software practices lies in the development of green AI, as part of the critical points for green software practices (figure 9). The development and training of Artificial Intelligence models, particularly large scale deep learning systems, is one of the most energy intensive activities regarding the AI sphere. Recent estimates indicate that training a single advanced model with 213 million parameters and a neural architecture, can release over 300 tons of CO₂. To put this in perspective, it corresponds to the carbon emissions generated by more than 300 flights between New York and San Francisco (89).

From 2012 to 2018 alone, the computational power used to train advanced AI models increased by more than 300.000 times (90). Often, these massive energy expenditures deliver only marginal improvement in model accuracy. However creating a green AI is possible, by

approaching the problem strategically, it is possible to train models in a more efficient ways; In particular, focusing on three key dimensions of data, model architecture and type of outputs required (Figure 11).

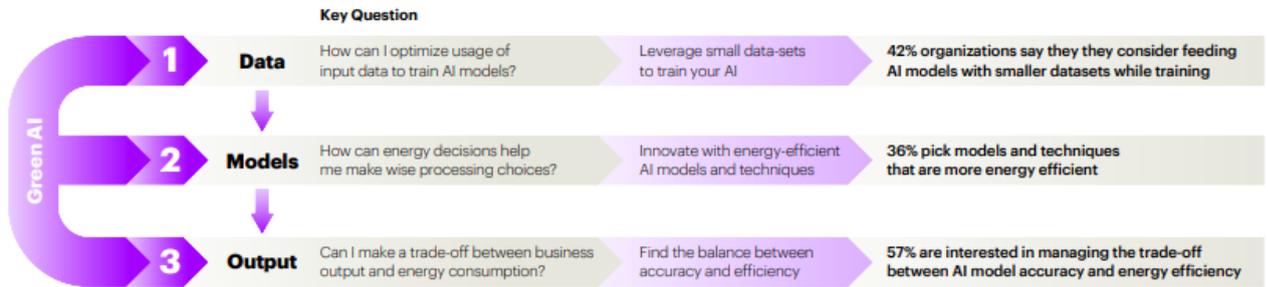


Figure 11: How to make AI green

Source: Accenture (2021)

For what concern data, research has shown that accuracy does not always demand maximum data or compute power. Accenture labs demonstrated that training an AI model on 70% of a dataset makes possible to achieve almost the same accuracy as training on the full dataset, reducing accuracy by less than 1%, and cutting energy use by nearly half (80).

Another experiment with the Iris flower dataset developed by biologist Ronald Fisher, revealed that raising accuracy by just 2.5% required fifteen times more energy than the initial training, so to increase the accuracy from 0% to 96,17% (80). These findings highlight a critical question on whether the pursuit of near perfect accuracy always worth the energy resource cost; the answer depends on the context, but organizations need to consider the explained trade off.

Another way to have a greener AI is to repurpose existing models rather than training a model entirely from the beginning. This approach can significantly reduce energy demand while still delivering high quality results (91).

Ultimately, making AI greener requires a strategic approach towards the accuracy energy efficiency trade off; business must be clear about when added precision of resource intensive models delivers meaningful value and when lighter, more efficient approaches are sufficient.

Cloud computing and data centers represent another dimension of software sustainability. The cloud energy resources need is very high; shifting to the public cloud could cut global carbon emissions by nearly 60 million tons annually. That is equal to removing 22 million cars from the road (91). However, only about 41% of firms currently consider cloud migration as part of their IT sustainability strategies (92). (Figure 12)

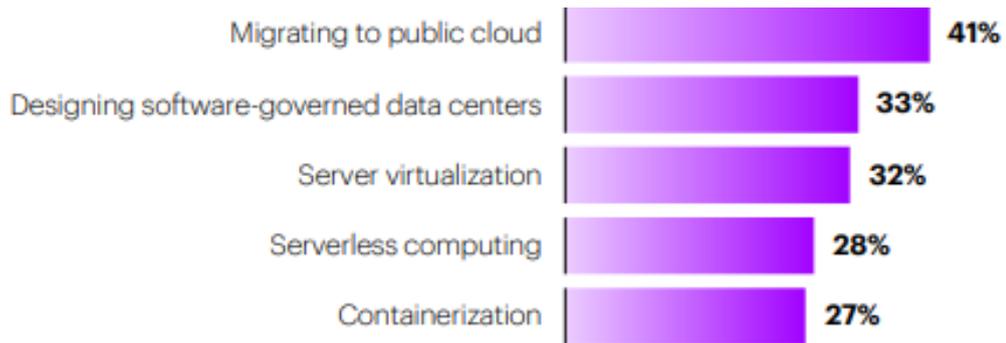


Figure 12: Measures adopted by organizations to lower data center energy consumption

Source: Accenture (2024)

Anyway, public cloud adoption has its own challenges, such as the high energy costs of transferring vast amounts of data.

It is also important for green data centers to pursue decarbonization initiatives, including transitioning to renewable energy and also rethink how cooling system are managed to avoid unnecessary energy waste. An example comes from Google which has applied Artificial Intelligence to optimize the cooling of its data centers (93) and introduced a scheduling system that synchronizes workloads with times of greater renewable energy availability (94). Since this case represents one of the most advanced applications of AI used for sustainable efficiency, it will be explained in greater detail in the last chapter.

The management of data itself also carries significant implications. With AI and digital transformation driving exponential growth in data volumes, companies must be aware of how they store, transmit and use information. Studies show that 70 to 90% of collected data of companies qualifies as “dark data”, information that is stored but never analyzed (95). This represents wasted energy.

Sustainable data management requires a more disciplined approach that implies reducing unnecessary collection and ensuring workloads are intelligently managed.

Finally, there is the infrastructure topic, the physical devices that constitute the foundation of digital services. End user devices like laptops and smartphones, along with cloud and datacenters hardware, contribute to both direct and indirect emissions; and most of the negative effects are related to manufacturing. For instance, the environmental cost of producing smartphones is so high compared to the short time people use them and then change them. In fact, studies suggest that simply extending the typical usage of a smartphone of three extra years, the total emissions generated during production would be largely balanced out over their

longer lifetime (96). To make this possible, both businesses and consumers need to shift from the traditional “take-make-waste” model and move toward a circular system that prioritizes repair, reuse and recycling. However, the current situation is that today, only about 17% of e-waste is recycled and most companies recycle less than 10% of their hardware (97).

4 Successful use cases of AI Driven solutions for Environmental Sustainability in the IT industry

4.1 Google DeepMind

As outlined in the previous chapter, Artificial Intelligence is a powerful technology that can be directed toward addressing climate change and supporting more sustainable practices. At the same time, the infrastructure required to operate AI involves very high consumption of both energy and water.

Google, one of the world's leading technology companies, together with its subsidiary Deepmind, recognized the structural issue of energy intensive computing infrastructure on which AI depends. To respond, it developed a system aimed at optimizing the use of resources within data centers, focusing on the energy used in the cooling process. This initiative is complementary to the company's broader strategy of transitioning to renewable energy in order to significantly cut carbon emissions (98).

Data centers represent some of the most energy demanding facilities globally. They require not only vast computing capacity but also cooling processes to ensure reliable operations; cooling is highly intensive in terms of both energy and water use (99). In 2010, data centers accounted for around 1,1 to 1,5 % of worldwide electricity consumption (100). This share has remained stable, standing at about 1,5% in 2024, but projections suggest it could rise to 3% by 2030 (101). The challenge is therefore evident; it is essential to reduce the energy footprint of data centers. AI technologies here offer a potential and partial solution.

Google addressed this challenge by improving efficiency of its already advanced data centers. In 2016, with the contribution of DeepMind, the company introduced an AI based system to manage cooling operations. The implementation reduced the energy used for cooling by 40% (102).

This achievement represents a significant step forward for the technology industry in terms of environmental sustainability because the gains are not limited to Google itself that will have economic benefit from less energy power used, but the implementation will reduce emission globally and also benefits the many companies relying on Google Cloud, which indirectly improve their own environmental performance.

Google's servers run services such as Search, Gmail and YouTube that generate heat which must constantly be removed to avoid malfunctions. The cooling is provided through large scale industrial equipment including pumps, chillers and cooling towers. However, managing these systems efficiently is challenging, as their operation is influenced by multiple interacting factors

that make it difficult to achieve optimal performance.

First, the way the equipment, operations and environment influence each other is very complex, and traditional engineering models or operator experience alone cannot always capture these dynamics; Second, cooling systems cannot react quickly to sudden changes, such as unexpected spikes in demand or shifts in weather conditions, since it is impossible to plan rules for every scenario. Moreover, each data center has its own design and environment, which means a solution that works in one site cannot simply be applied to another. This is why a more flexible, intelligent and adaptive approach is required.

To deal with these challenges, Google and DeepMind started using machine learning to make cooling more efficient, always under the supervision of trained and expert operators.

Every five minutes, the AI collects information from thousands of sensors inside the data center (figure 13) and sends it to neural networks that simulate different possible actions (figure 14); the system then identifies the combination of actions that would save the most energy while still respecting strict safety limits (Figure 15); these instructions are then checked by the local control system before being put into practice (Figure 16) (103).

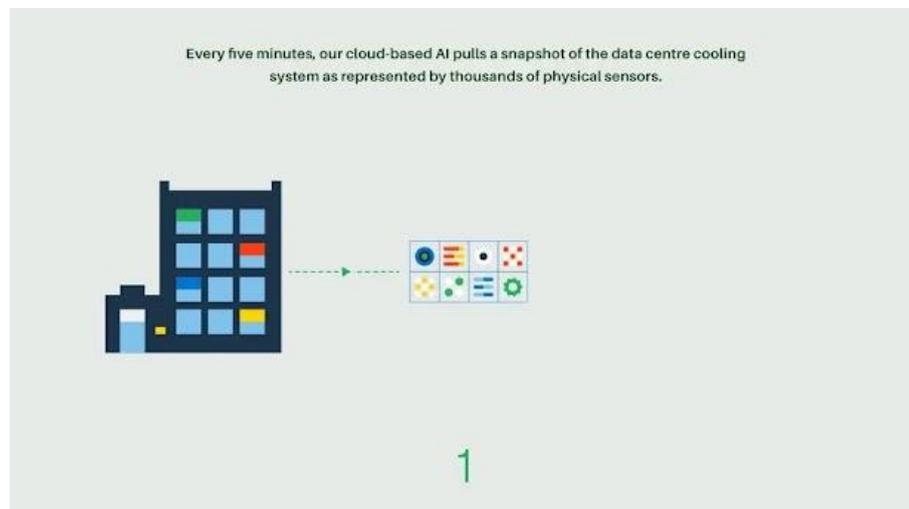


Figure 13: How Google's DeepMind AI works- Step 1

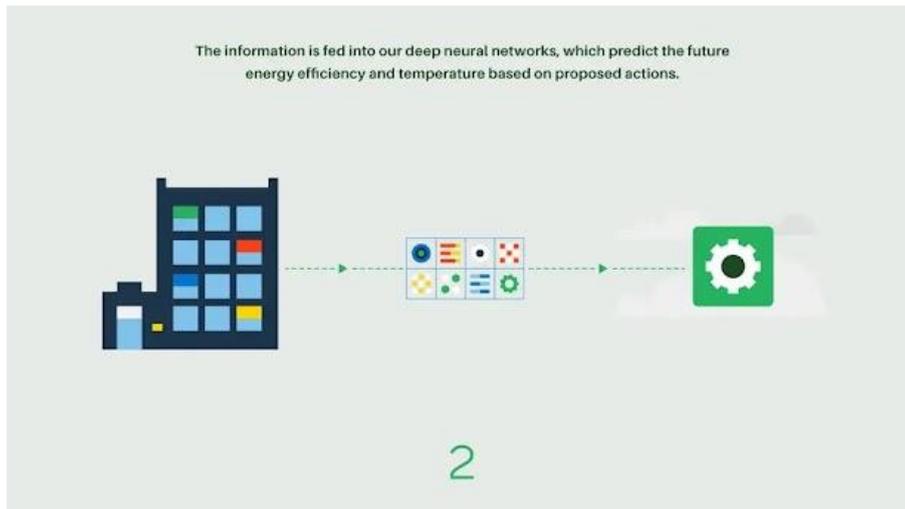


Figure 14: How Google’s DeepMind AI works- Step 2

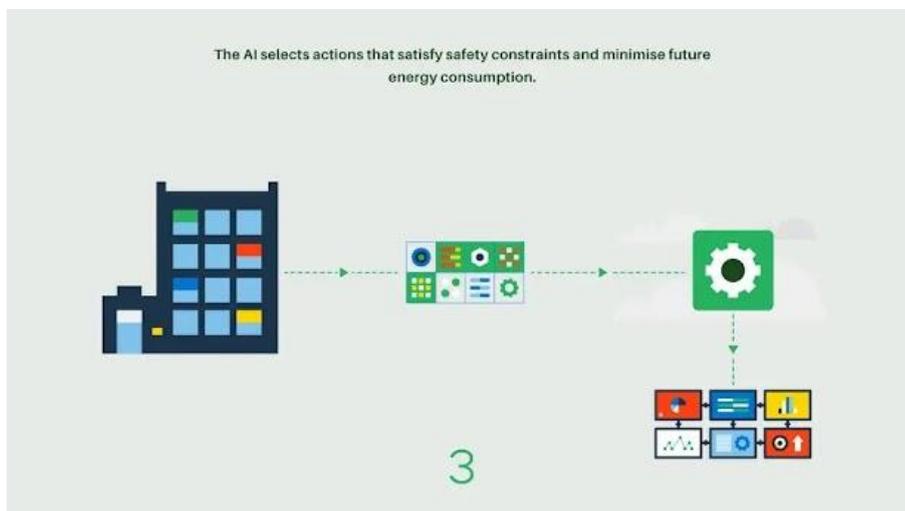


Figure 15: How Google’s DeepMind AI works- Step 3

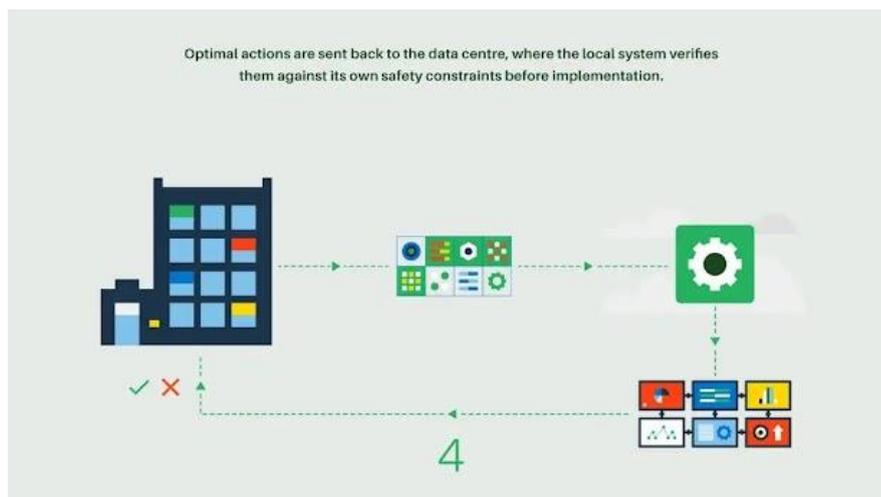


Figure 16: How Google’s DeepMind AI works- Step 4

Source: Google (2018)

The AI was trained using a large set of past data from the data centers, including information on temperatures, power usage, pump speed and other operating conditions. Thanks to this, it learned how to respond effectively in many different scenarios.

Safety and reliability were key priorities. For this reason, Google added eight different control mechanisms (Figure 17).

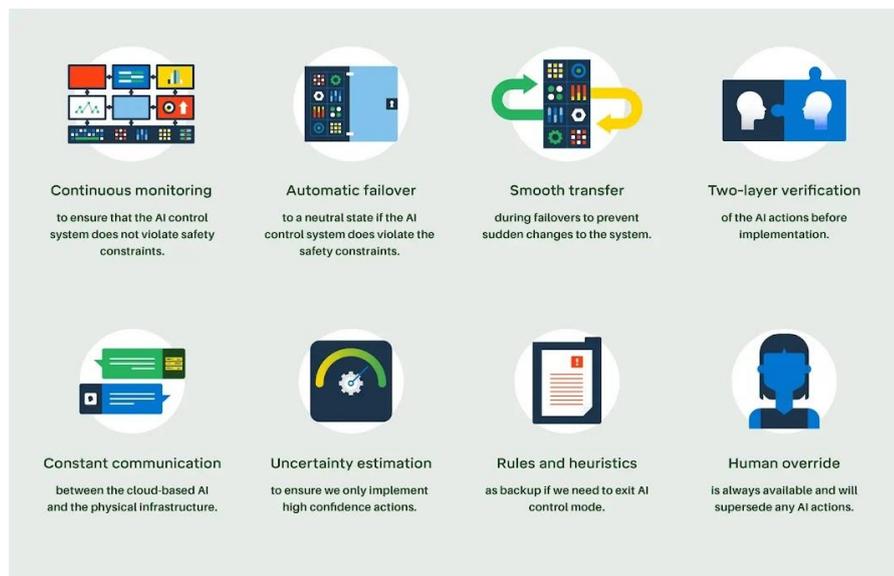


Figure 17: Safety mechanisms of Google DeepMind’s AI data center cooling system

Source: Google (2018)

One safeguard is that the AI calculates a confidence score for each possible action and automatically ignores those with low certainty. Another is a two layer checking system where the AI’s recommendations are first tested against general safety rules set by engineers and then checked again by the local control system before being applied. This guarantees that all operational limits are respected and that human operators remain in full control. They can deactivate the AI at any time and the system will revert to standard automation.

The first real world test was carried out in 2016. DeepMind’s neural networks were trained to improved Power Usage Effectiveness (PUE), which measures the ratio of total energy consumed by the data center to the energy used only by IT equipment, as explained in chapter 2. Additional models were also trained to predict short term changes in temperature and pressure, to make sure the actions recommended by the AI would remain within the operating limits.

Figure 18 illustrates a typical day of experimentation, showing when the AI’s recommendations were activated and when they were turned off

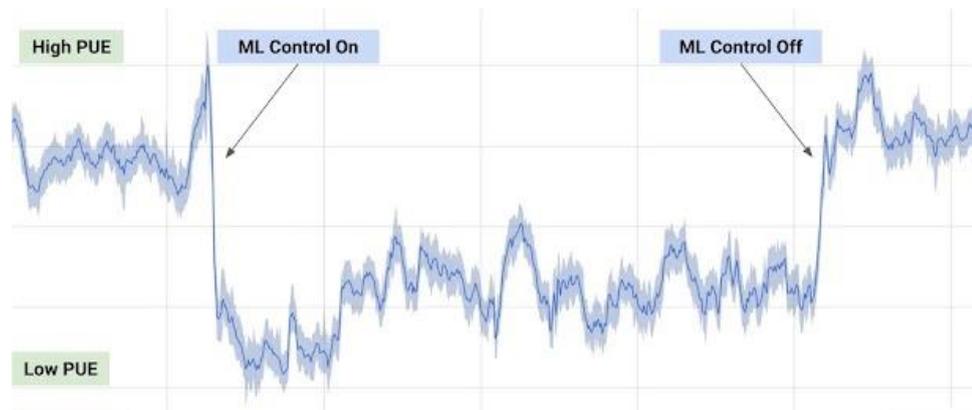


Figure 18: Google data center PUE performance with and without machine learning application

Source: Google (2016)

The deployment of AI across multiple Google data centers resulted in encouraging outcomes. Once the machine learning system was implemented, the models were able to predict Power Usage Effectiveness (PUE) with remarkable precision, showing an error margin of 0,4% and reaching the outstanding value of 1,1 PUE. Moreover, the energy consumption related to cooling dropped by around 40%, while the overall PUE of the test facility reduced by 15%. (104).

These achievements go beyond technical efficiency. They demonstrate that it is possible, through the implementation of AI solutions, for organizations running large scale data centers to cut operational expenses and, at the same time, significantly reduce their carbon footprint.

In recent years, Google established itself as the world's largest corporate purchaser of renewable energy. The company matches 100% of its annual electricity consumption with direct purchases of renewable energy (105). Yet this statement can be misleading in the interpretation because matching does not mean that every Google data center is physically always powered by renewables. Each facility remains connected to its regional electricity grid, which delivers a mixed supply of power from both renewable and fossil based sources. The reality is that renewable production is intermittent, solar panel do not generate at night and wind turbines stop when there is no wind. For this reason fossil fuels are in the grid to compensate for the gaps.

This mechanism does not guarantee that Google's own operations are always running on clean power, but it ensures that, overall, the grid contains more renewable energy than before.

In other words, Google is compensating for the fossil fuels it still indirectly relies on by paying

for an equivalent amount of renewable energy. The result is that Google's demand stimulates new investment in clean energy projects and helps reduce dependence on carbon intensive sources, even if the physical electricity mix at a given moment is not entirely renewable.

Beyond data center efficiency, Google and DeepMind have also shown how machine learning can play a crucial role in strengthening renewable energy itself, especially referring to wind power. Wind has become one of the most important sources of carbon free electricity, thanks to falling turbine costs and rapid global adoption. However, its main weakness is the variability; because wind cannot be controlled and it is unpredictable, it is less valuable to the grid compared to sources that can reliably deliver power at scheduled times. In practice, when there is uncertainty about the wind output, the grid will rely more on fossil fuels to ensure stability.

To address this challenge, Google and DeepMind extended their use of machine learning to the renewable energy sector by applying it to 700 megawatts of wind power capacity located in the central United States; an amount comparable to the electricity needs of a mid sized city.

The project involved training a neural network with two main types of data that are, publicly available weather forecasts and historical records from wind turbines. With this information, the system could anticipate the amount of energy the turbines were likely to produce up to 36 hour in advance.

Without accurate forecasts, wind power is often treated as less reliable in electricity markets, since operators cannot be sure of how much energy turbines will produce at a given hour. As a result, grid tend to rely more heavily on fossil based generation, which the availability is predictable, and ensures stability. The Google machine learning model that makes wind power more predictable (Figure 19) increases its market value, as electricity that can be committed to the grid in advance is priced higher than uncertain, variable supply, while at the same time lowering the need for fossil compensation.

The Google DeepMind machine learning outcomes were positive as at Google's wind farms, the application of machine learning has raised the value of wind power by about 20% compared to situation where no advance scheduling is possible (106).

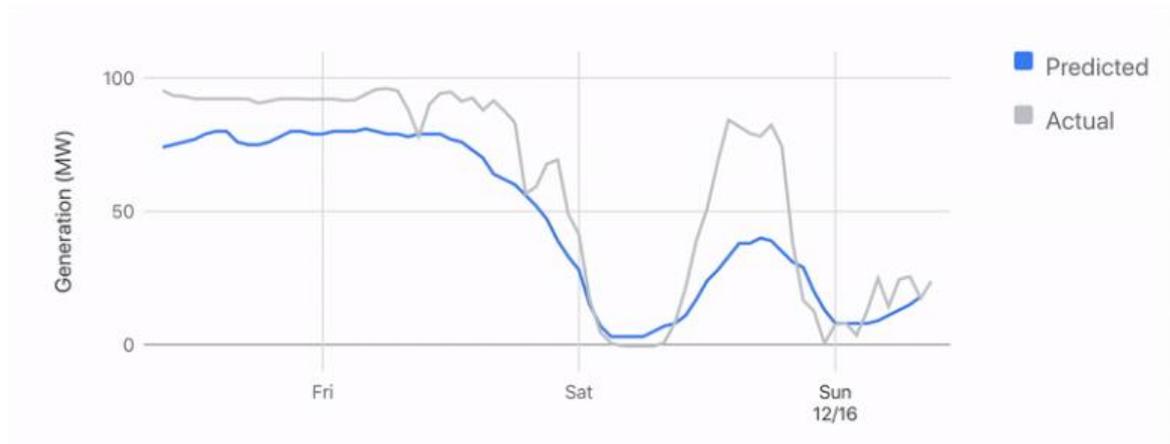


Figure 19: Graphical representation of Google Deepmind ML prediction of wind power VS the actual

Source: Google (2019)

Of course, the variability of wind cannot be eliminated entirely, but these results indicate that Artificial Intelligence can make renewable energy more stable, profitable and competitive. In addition, the approach provides operators with more data insights, enabling them to take quicker and better informed decisions on how to align energy production with demand.

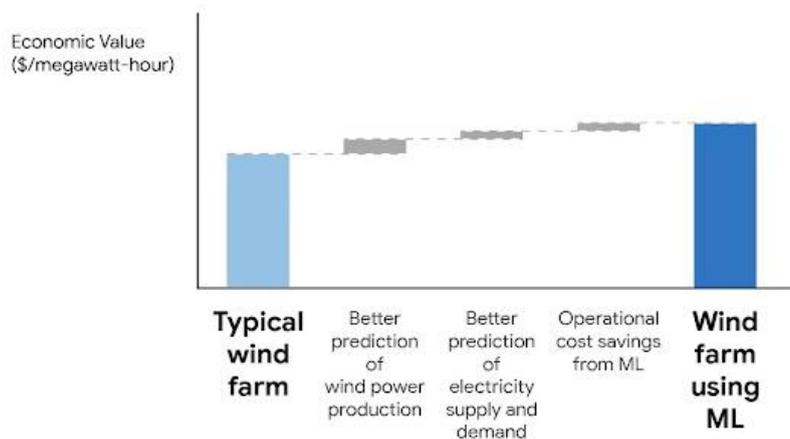


Figure 20: increase in the economic value of wind energy using ML

Source: Google (2019)

As Xiaoqin Ma, head of technology at Onyx InSight, pointed out, “Ai is already being used in renewable for tasks such as turbine blade inspection, weather forecasting and predictive maintenance. The work by DeepMind adds further confirmation that advanced data driven

methods can bring tangible benefits to the renewable energy sector” (107).

If adopted widely, such technologies, upon explained, could become a cornerstone of the energy and digital transition.

4.2 Microsoft AI for Earth

Microsoft, one of the world's leading technology companies, has increasingly taken an active role in addressing sustainability challenges. Rather than limiting its contribution to reducing its own environmental footprint, the company has invested in research, innovation and application of Artificial Intelligence, to accelerate the development of solutions for planetary environmental challenges. The company recognizes both the urgency of the planetary crisis and the necessity of accelerating the deployment and discovery of solutions that are not only environmentally effective, but also faster, cheaper and more scalable than traditional approaches. Within this vision, Artificial intelligence is seen as a transformative tool capable of amplifying human capabilities and enabling innovation that can speed up the achievement of sustainability goals (108),

Two dedicated groups of Microsoft, Microsoft Sustainability Science and Innovation and Microsoft Research, play a central role; their effort focus on creating innovative digital tools and extending the use of AI across different domains to advance both to Microsoft’s 2030 sustainability commitments and to contribute to wider systemic change that benefits ecosystem, industries and local communities worldwide. In practice, these initiatives are not only technological advances but also enablers of collective action, supporting faster and more effective responses to environmental challenges.

In 2023, Microsoft further formalized its strategy by publishing the Sustainability Playbook, a framework designed to connect AI innovation with measurable sustainability outcomes while ensuring that such technologies are implemented responsibly.

The playbook highlights three key “game changing abilities” of AI that can help overcome major obstacles slowing down global climate and biodiversity goal (Figure 21). These abilities are directly linked to three, more general objectives, that are, achieving net zero emissions, strengthening climate resilience and protecting and restoring natural ecosystems (109).

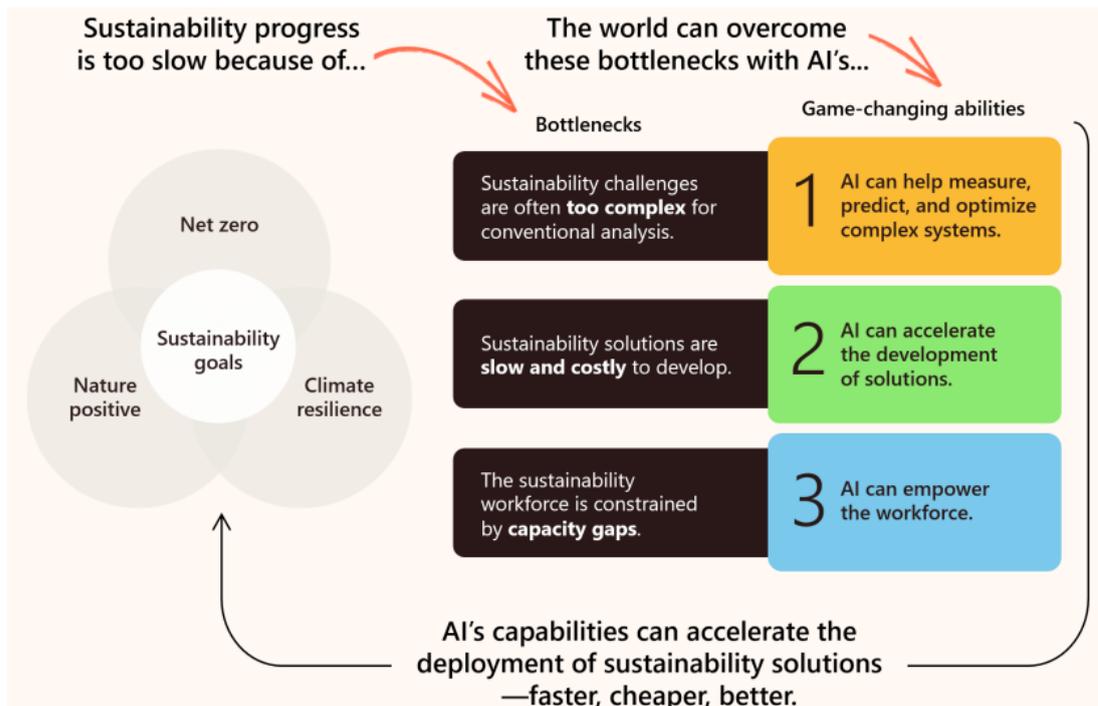


Figure 21: Overcoming sustainability bottlenecks through AI's game-changing abilities

Source: Microsoft (2023)

Regarding the first ability, it is about the potential of AI to measure, predict and optimize complex systems. Systems are highly dynamic such as supply chains, energy grids, agricultural ecosystems that often behave in ways that traditional analytical tools struggle to capture. AI, by contrast, fits perfectly with the task thanks to its capacity to process vast amounts of multimodal data, revealing patterns, anticipating changes and identifying relationships that would otherwise remain hidden. This enables more precise measurement of environmental shifts and allows for more effective optimization of system performance.

In 2017 Microsoft launched Microsoft AI for Earth program (110). This program is not just a single IT product but a full ecosystem combining grants, technical assistance and open access to the Planetary Computer (111), a large scale digital platform hosting petabytes of environmental data.

To be more specific, the Planetary Computer is composed of three main components: a Data Catalog that provides free access to environmental databases hosted on Azure; APIs that allow different software applications to communicate and exchange data with each other and enable researchers to search and analyze data across space and time; a growing collection of applications developed in partnership with external organizations to address real world sustainability problems.

It is important to specify that the system is built on open source standards, making it transparent, interoperable and scalable.

Through this infrastructure, Microsoft enables NGOs, researchers but also private corporations to analyze ecosystems, model environmental scenarios and design solutions based on robust data. Indeed, AI for Earth is both a funding mechanism and an harmonized digital base for integrate the use of AI in sustainability efforts worldwide. The projects involved in AI for Earth, focus on four domains that are central for the future of the planet and these are agriculture, water, biodiversity and climate change (110)

A prominent example within AI for Earth is FarmBeats (112), an AI powered IoT platform created to make data driven precision agriculture accessible to a large number of farmers. This system puts together data collected from soil sensors, drones and cameras, which are then processed through machine learning models to provide predictive insights that support farm management. The idea behind FarmBeats was born from a pressing global challenge regarding doubling food production by 2050, considering water becoming increasingly scarce, cultivable land is shrinking and the impacts of climate change are intensifying.

In this case, precision agriculture, which applies digital tools to fine tune irrigation, fertilization and seeding is a promising way to increase efficiency farming. However the widespread adoption of traditional mechanism has been limited, mainly because collecting data directly in the field is expensive and because rural areas often lack stable internet connections.

FarmBeats addresses these challenges by integrating a small number of ground based sensors with images collected by drones, producing detailed and intelligent “precision maps” that thanks to machine learning show soil conditions such as moistures levels, health status and pH (figure 22). In this way the system lowers the overall costs of implementation without compromising the quality of the information provided. Moreover by relying on renewable power and affordable connectivity, FarmBeats is designed to remain resilient for functioning in more complicated zones, while having lower operational expenses.

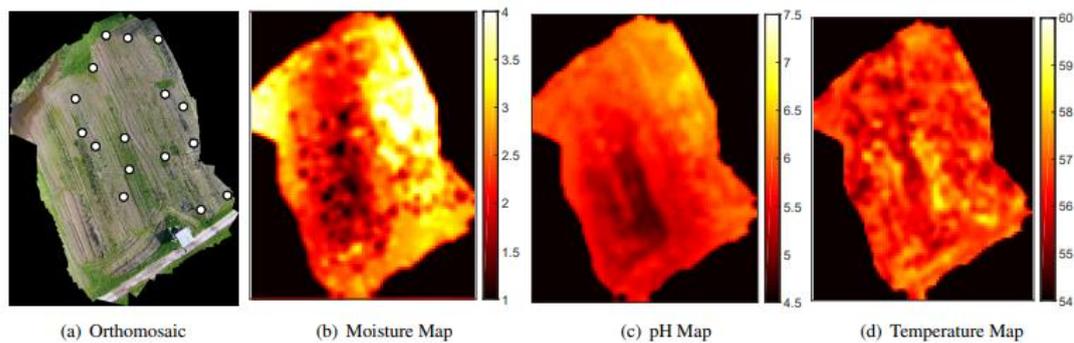


Figure 22: Precision maps generated by FarmBeats ML system

Source: Microsoft (2017)

Early trials in the United States demonstrated that FarmBeats could improve operational efficiency, maintain stable performance and significantly cut costs even if from the research, exact measurements of water or fertilizer savings were not available (113).

Its real environmental strength lies in helping farmers use input more selectively, thereby reducing agricultural output waste and boosting productivity. In Chile's Maipo Basin, for example, Microsoft collaborated with the agri-tech company Kilimo to implement AI based precision irrigation over 440 hectares of farmland. In the Maipo region, agriculture accounts for around 68% of total water consumption, so this sector plays a decisive role in improving water efficiency (114).

Whitin three years, the initiative saved about 1.5 million cubic meters of water, equivalent to 600 Olympic swimming pools and achieved at least a 13% reduction in water use compared to conventional irrigation practices, benefitting 11 farmers (115). The benefits went beyond water savings, contributing to lower agricultural runoff, reduced carbon emissions, higher crop yields and improved pesticide control.

Microsoft x Kilimo's platform integrates sensor measurement, soil analysis, satellite data and local weather forecasts to provide timely and precise irrigation recommendations. To make the adoption of this technology more attractive, Microsoft covered part of the subscription costs and offered farmers financial incentives so that they could directly benefit from the water savings achieved (116).

Today Kilimo manages precisions irrigation systems across more than 220.000 hectares in seven countries, and its collaboration with Microsoft is expanding to new regions such as Queretaro in Mexico and California's San Joaquin Valley.

The second transformative ability highlighted in Microsoft's Sustainability Playbook is linked to accelerating the pace of sustainable innovation. A major obstacle in this area is that the

development of new solutions often requires long timelines and high research costs.

One example of possible new more sustainable solution can be the once of industrial materials such as steel, cement and plastic which together generate nearly 20% of global CO₂ emissions (117, 118); so discovering less carbon intensive alternatives or improving existing process could be very useful for environment conservation, but conventional research methods move slowly . AI can shorten these processes by analyzing large datasets of materials properties and identifying promising alternatives much faster than traditional laboratory work would require (119).

In the energy sector, Microsoft's AI and Azure Quantum are being applied in partnership with Johnson Matthey to accelerate the search for more affordable catalysts to produce green hydrogen (109). Catalysts, that are substances that speed up chemical reactions without being consumed, play a crucial role in hydrogen fuel cells, which convert hydrogen into electricity. Hydrogen is a cleaner alternative to fossil fuels, since the process generates no carbon dioxide and air pollutants.

At present, platinum is the most effective electrocatalyst for these reactions, and its use has enabled fuel cells to become a feasible technology for decarbonizing heavy transport such as buses and trucks. However, platinum is both rare and extremely costly, and its extraction also carries a significant environmental footprint; so large scale dependence on platinum would undermine the economic feasibility of hydrogen solution and so the overall sustainability of the system.

To address this challenge, Microsoft's advanced AI models and high performance computing resources are being used to simulate atomic reaction and test alternative combinations that require less platinum or eliminate it. This digital approach has already sped up chemistry simulation by 50%, significantly lowering both research costs and development times (120).

For what concerns the third ability identified in the Playbook is about strengthening the sustainability workforce. AI is not seen as a substitute for human expertise but as a tool that amplifies its impact, providing more advanced analytics and insights, helpful for decision-making processes. A clear example of this is the Microsoft Cloud for sustainability (121), a cloud based platform that integrates AI to centralize and manage environmental data. Through this tool organizations can track emissions, monitor progress, comply with regulations and identify opportunities to replace high carbon practices with greener alternatives. In addition, it helps improve supply chain transparency, supports the creation of more sustainable products and optimizes logistics and material use.

4.3 Building X by Siemens

Another sector where Artificial Intelligence can bring substantial progress in terms of sustainability and energy efficiency is the building industry. Globally, buildings are estimated to account for around 40% of all energy consumption, and a considerable share of energy consumed, close to a third, is simply wasted (122). This makes the building sector a crucial area of intervention, both for reducing costs and for cutting greenhouse gas emissions on a large scale.

Over the course of their lifecycle, from planning and construction to everyday use and maintenance, buildings generate huge quantities of data. This information rarely is used effectively, for the difficulty of integration. With the spread of IoT technologies and constant connectivity, however, this data can now be collected, centralized and analyzed to generate valuable insights. Artificial Intelligence plays a decisive role in this process because it can help minimize energy waste and emissions. Smart systems, for instance, can automatically adjust heating, cooling, ventilation or lighting according to real time weather conditions and occupancy levels.

Despite the digital transformation of the building industry can be a promising approach to energy management, it has been slowed by some persistent barriers. The most significant are related to the challenge of organizing highly fragmented data, the time and resources needed to digitalize older infrastructure and the difficulty of extracting useful insights without depending heavily on human specialist (123).

To address these challenges, Siemens has introduced Building X, a cloud-based platform that brings together building data into a single platform and enables more intelligent, autonomous management of buildings. The platform is designed to be open, scalable and modular, so that it can adapt to different types of buildings and user needs. It allows users to oversee energy use, maintenance, safety and security from one central hub (124).

So, building X turns raw data into valuable insights, supporting better decision making and helps organizations optimize performance, reduce costs and move towards sustainability goals. Siemens offers these digital services on a subscription basis, with solutions covering areas such as energy management, sustainability tracking, security monitoring (e.g. fire alarms and access control) and predictive maintenance (125).

A particularly relevant area of interest for the present work, is energy and sustainability optimization, especially considering that about 75% of the European buildings is inefficient in terms of energy usage, resulting in significant energy waste (126). This represents a loss not

only for the environment but also for building users and owner's budgets.

One of the Siemens BuildingX applications for reducing energy use and improving sustainability is the Energy Management application (127). This tool gives operators the ability to monitor consumption in real time, track emissions and identify opportunities to cut costs also to stay in line with decarbonization targets. This aligns with the broader global context in which governments are starting to impose carbon emission monitoring and reduction on companies and large buildings. For example, New York City's Local Law 97 obliges buildings over 25,000 square feet to comply with GHG emission limits starting in 2024, with the ultimate goal of achieving net zero emissions by 2050 (128).

Energy Manager application takes data from building automation systems and submeters, providing a detailed picture of how energy is being used and where inefficiencies occur; it is supported by BuildingX AI based platform and machine learning to not just report information but, learning from historical performance, weather patterns and usage trends to provide even more accurate recommendations. This makes the program adaptive and more effective over time.

To be more specific on the functionalities, the application offers the possibility to monitor not just individual facilities but the entire building portfolio in a single integrated view. The platform presents a customizable dashboard that shows the combination of both real time data and historical records in this way, for example companies that want to monitor and compare the utilities consumption of their buildings have an overview of how they perform over time and under varying conditions.

The dashboard makes possible to review, in detail, the main dimensions of resources use and their financial implications (Figure 23); this includes monitoring energy consumption and costs related to heating, cooling, electricity, steam and water among other utilities. Such different utility integration helps organizations gain a much clearer understanding of where resources are consumed and how spending is distributed across the portfolio.

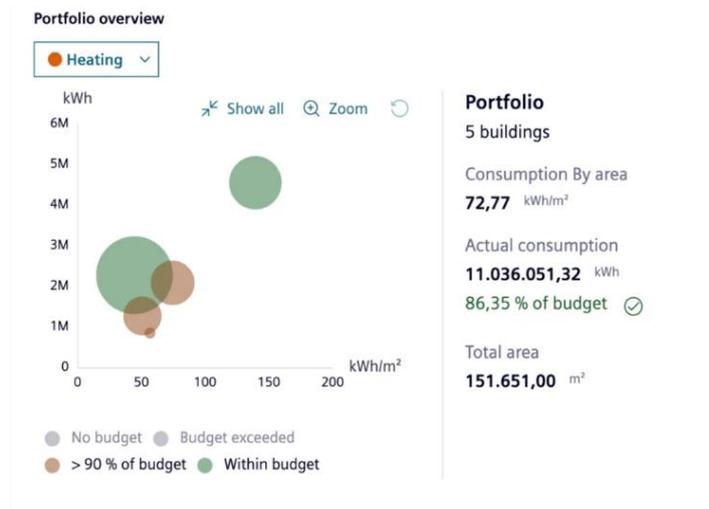


Figure 23: Illustrative Dashboard of Portfolio Performance within Siemens Building X Platform Energy Manager service

Source: Siemens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>

Another important added value of the platform application is its ability to apply weather normalization, which means that the data is corrected to take into consideration variations in external climate conditions.

This is essential because energy consumption is heavily influenced by weather and without normalization it would be difficult to evaluate whether efficiency gains are due to genuine improvements or simply related to seasonal variation.

Moreover, the application has a benchmarking function for which different buildings can be compared with other within the portfolio. So companies that have more than one operating building can understand which facilities are performing well and which is behind in terms of efficiency. Through this capability managers can identify best practices, replicate them across portfolio and direct investment or corrective measures toward the buildings that need it most.

Another area in which the application demonstrates particular strength is in the monitoring and management of greenhouse gas emissions. The platform provides a high level of visibility by allowing organizations to track emissions in real time across all three Scope 1 (direct emission generated by on site activities, and companies owns directly), Scope 2 (indirect emissions linked to purchased energy), and Scope 3 (a broader indirect emissions within the value chain, such as those produced by suppliers).⁴

⁴ Scopes definition retrieved from <https://www.nationalgrid.com/stories/energy-explained/what-are-scope-1-2-3-carbon-emissions>

This overview offered by BuildingX Energy Manager application simplifies the process of sustainability reporting, helping companies not only to meet regulatory requirements but also demonstrate greater transparency and accountability to stakeholders (Figure 24).

Emission will be showed by site and it is another insight that shows buildings that perform well or underperform in terms of emissions. Historical data analysis adds another dimension because user can examine the contribution of each building to total portfolio emissions over time through year over year trends displayed in a structured way. The historical perspective helps identify recurring patterns and also disclose long term improvements.

Site	Building type	Area [m ²]	Emissions share Total share per building	Year-on-year trend	Emissions [tCO ₂ e]
Building 2 Milano ITA/Lombardia	Office	-	56,64%	-0,49% ▼	12.312,2
Zug CHE/Europe	Office	-	12,35%	-6,61% ▼	2.684,38
Vienna AUT/Wien	Office	-	11,66%	-3,13% ▼	2.534,59
Erlangen DEU/Erlangen	Office	-	7,46%	-2,2% ▼	1.622,12
Chicago USA/Buffalo Grove	Office	-	7,05%	-3,49% ▼	1.531,51

6 of 10 sites

Figure 24: Illustrative Dashboard of GHG emissions reporting within Siemens Building X Platform Energy Manager service

Source: Simens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>

Artificial intelligence functionalities are integrated into the platform and the application uses machine learning for anomaly detection (figure 25). These technologies make the service more intelligent than a simple monitoring tool suggesting possible proactive actions. The AI algorithms are trained to recognize normal patterns of energy use within a building or across an entire portfolio; once the baseline of expected behavior has been recognized, the system is able to identify deviations, such as peaks in energy use, heating or cooling demands or unusual water consumption.

This precise monitoring ensures that inefficiencies or malfunctions, such as in air condition units, are identified quickly, often before they become visible to staff or occupants.

The platform does not merely detect these irregularities but also acts in real time with early warnings and automated alerts that are sent to facility managers or responsible teams, allowing them to intervene without delay. This approach prevents unnecessary energy waste and additional costs contributing to make buildings more efficient in terms of resources used.



Figure 25: Illustrative Dashboard of machine learning-based anomaly detection within Siemens Building X Platform Energy Manager service

Source: Simens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>

The platform provides also a more detailed level of analysis on resource consumption across different buildings, floors and rooms, enabling organizations to monitor their resources efficiency over time (Figure 26). This granular view supports a clearer understanding of consumption patterns and helps drive targeted efficiency improvements.

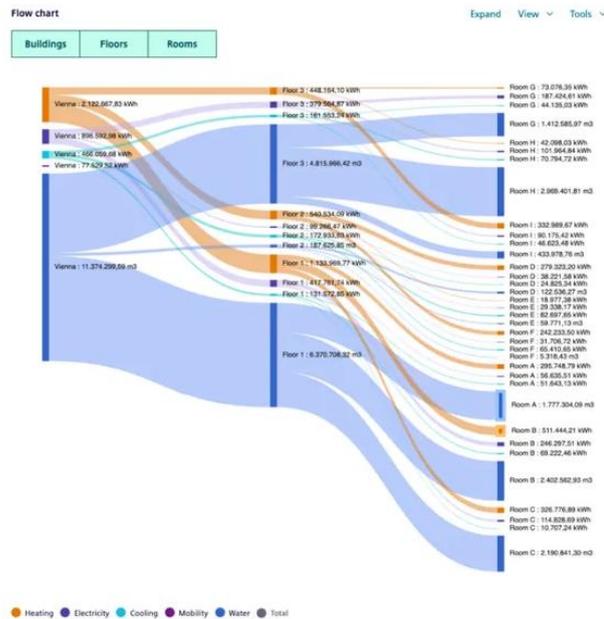


Figure 26: Illustrative Dashboard of insights into energy flows within Siemens Building X Platform Energy Manager service

Source: Siemens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>

Moreover, the Energy Manager emphasizes visualization through intuitive heat maps, which make inefficiencies easy to spot and allow users to quickly identify problem areas

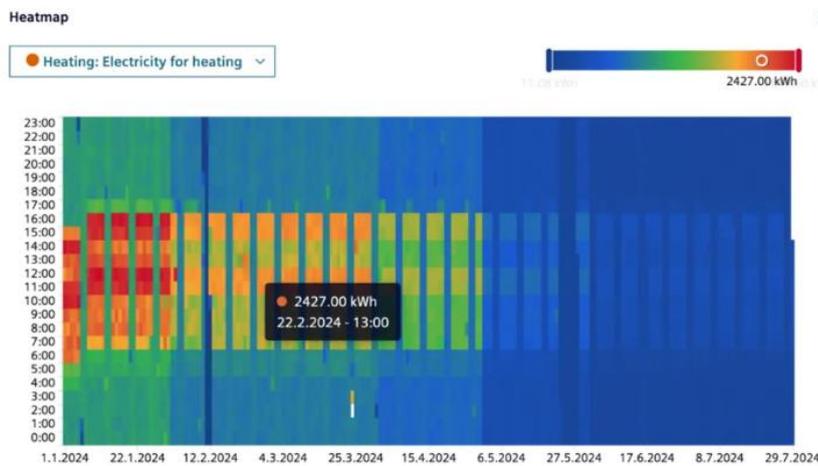


Figure 27: Illustrative Dashboard of heat maps within Siemens Building X Platform Energy Manager service

Source: Siemens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>

By visualizing a building’s energy mix in this way, organizations can have clearer insight into potential inefficiencies and possible budget overspent.

In addition to Energy Manager, Siemens’ Building X platform also gives the possibility to users to integrate another important application called Sustainability Manager (129). While both tools contribute to the optimization of building performance, the Sustainability Manager operates at a more strategic and managerial level. Unlike the energy manager, which relies on real time submeter and BAS (Building Automation System) data, the Sustainability Manager uses information from monthly utility bills. One of its most valuable functions is its ability to convert energy consumption data into equivalent greenhouse gas emissions, thus providing organizations with a clearer understanding of the environmental impact of their operations (Figure28). Consequently, it also supports the planning and monitoring of large scale energy efficiency projects, offering insights into where investments could yield the highest environmental and financial returns.

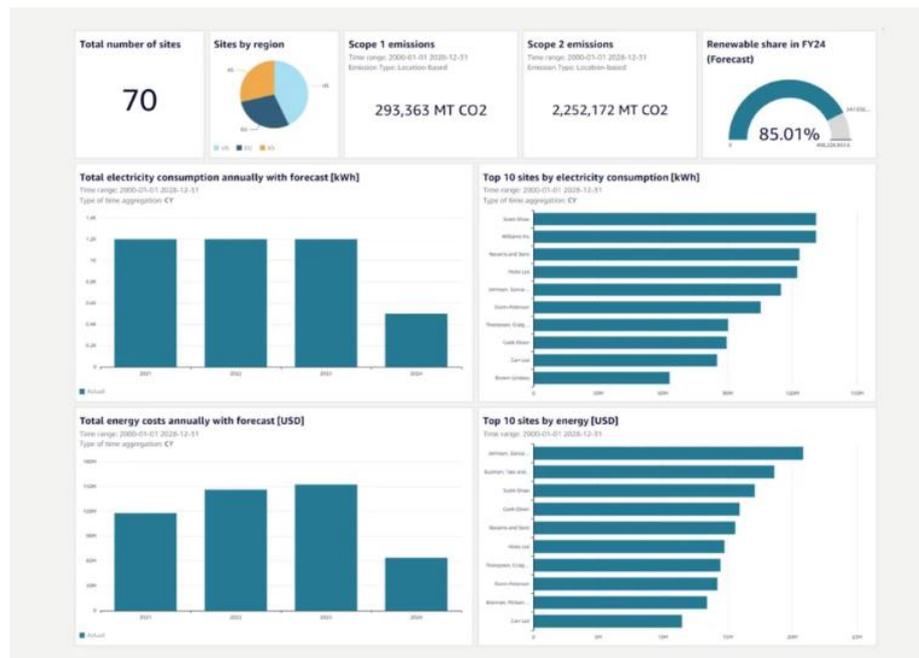


Figure 28: Illustrative Dashboard of Sustainability Manager service

Source: Simens <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/sustainability-manager.html>

In practice, the Sustainability Manager works as an oversight tool. It enables managers and executives to measure the overall effectiveness of sustainability initiatives, ensuring that emissions reduction and resource efficiency goals remain on track.

By contrast, the Energy Manager is more operational, providing immediate insights from live data to correct inefficiencies as they occur, anticipate anomalies, and manage costs more dynamically (130).

Overall, Siemens' Building X can be seen as a powerful tool for organizations, helping them to reduce energy and resource waste, keep emissions under control and lower operating costs. It demonstrates how AI can address the challenges of operational efficiency in the building sector, supporting more effective management and environmental sustainability performance achievements.

4.4 Green Horizon Project by IBM

Climate change represents one of the most pressing challenges of our time, with visible consequences already affecting populations worldwide. Climate change implies rising average temperatures, increasingly unpredictable weather patterns, the melting of polar ice caps, and the growing frequency of extreme events (131).

Traditional strategies have not succeeded in stopping or even slowing significantly the upon mentioned trends, which explain the importance of new and more technological advanced approaches.

Artificial Intelligence and Machine Learning technologies, as we have seen in the previous case studies, can analyze data on an unprecedented scale and speed, thereby opening the door to more effective and innovative solutions.

Predicting climate patterns at both global and local levels is one of the most promising applications of Artificial Intelligence in the fight against climate change; while large scale climate models aim to simulate the long term climate evolution, AI can also be applied to the important challenge of forecasting air quality in urban areas.

Thanks to its ability to process large volumes of historical and real time data with speed, AI can uncover patterns that otherwise remain hidden, and its rapid forecasting capabilities make it a valuable tool to support timely conservation policies. This functionality is closely related to the climate forecasting activity because the same meteorological data and climate dynamics that shape global climate trends also determine how pollutants spread, concentrate or disperse in cities.

A concrete example of this approach is IBM's Green Horizons initiative, which applies deep learning models to historical weather and pollution data with the goal of predicting air quality

developing a decision support system. By delivering more precise forecasts, the projects gives city administrations, utility providers and industrial actors tools to better manage factors related to climate and consequently make informed decisions about pressing topics related to energy use and pollution control (132).

A very interesting example in the Green Horizon project is the collaboration of IBM's research lab with the Beijing Municipal Ecology and Environment Bureau to develop one of the most advanced air quality forecasting system in the world. The system resulted to be able to generate high resolution forecasts, at the scale of one square kilometer, for up to 72 hours in advance, as well as trend predictions extending ten days into the future (133). These forecasts are particularly effective because they not only simulate the dispersal of pollutants in the atmosphere but also highlights the chemical interactions between pollutants and weather conditions.

Thanks to this technology, the Beijing government was able, in the first nine months of application, to reduce the presence of ultra fine particulate matter by 20%, bringing it closer to its target of a 25% reduction by 2017. Ultrafine particles, generally defined as particles smaller than $0,1\ \mu\text{m}$, are largely produced by vehicle traffic in urban areas and pose a serious threat to human health penetrating deeply into the lungs, spread through the body and cause inflammation, worsening asthma and other respiratory diseases. They are also linked to cardiovascular problems, diabetes, cancer and neurological dysfunction (134).

The potential of AI in the fight against climate change, however, is not limited to improving air quality. IBM's program also plays an important role in the integration of renewable energy into electricity grids. As already developed in the Google DeepMind case, renewable sources such as wind and solar are essential for reducing greenhouse gas emissions, but they are also variable and difficult to predict, which makes challenging for grid operators to balance supply and demand. In fact, unlike conventional carbon based energy sources, which can be easily balanced on demand, renewables depend on weather and daily conditions and are therefore less programmable. This intermittency highlights the need for complementary solutions.

IBM's forecasting technologies, part of the green horizon program, make renewable generation more predictable and reliable (Figure 28), helping to stabilize grids and enabling wider adoption of clean energy sources (133).

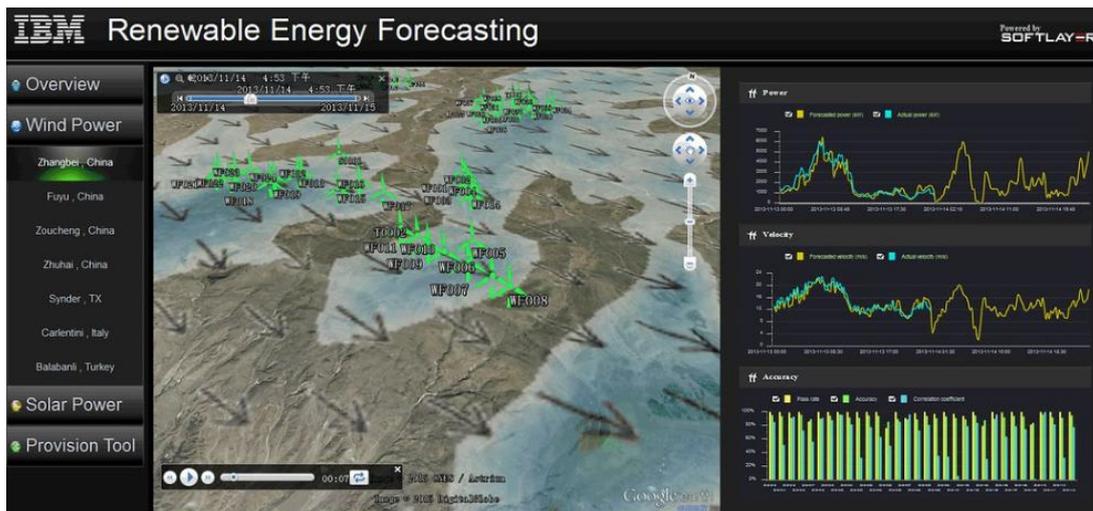


Figure 29: illustrative dashboard of IBM’s renewable energy forecasting tool

Source: IBM (2015)

This work has already been applied in different projects around the world (135).

In the United Kingdom, for example, IBM technology has been tested by SSE, a multinational company operating in the energy sector, to forecast the output of wind farms, with the ability to predict production for individual turbines several days in advance.

In Japan IBM has collaborated with the Japanese plant engineering firm Toyo Engineering Corporation and the special purpose company Setouchi Future Creation LLC to develop and operate the Setouchi Kirei Mega Solar Power Plant to optimize energy flows from one of the largest solar power plants in the country, which is made up for nearly 890.000 panels.

In the United States, IBM has extended the capabilities of its Green Horizons initiative through its involvement in the department of Energy’s SunShot Initiative, within the program concerning improving accuracy of Solar Forecasting (136).

A central outcome of this effort is the Watt Sun project, which adapts and refines Green Horizons’ predictive technologies to the specific challenge of solar energy forecasting. The project supports utilities, grid operators and solar developers in better predicting when and how much solar power their systems will generate. This is particularly important given that solar production is highly sensitive to weather variability, with cloud coverage and unexpected changes in atmospheric conditions often disrupting daily generation levels. Since utilities must ensure a reliable supply for consumers, accurate solar forecasts are essential to manage reserves efficiently and maintain grid stability.

On the foundations of Green Horizon, IBM developed, supported by funding from the U.S. Department of Energy’s program on improving the accuracy of solar forecasting, created the

Self learning weather Model and renewable forecasting technologies (SMT). This advanced machine learning system works integrating vast amounts of data from multiple sources, historical climate records, satellite imagery, real time sensors and local weather stations, while leveraging the department of energy's high performance computing resources.

Thanks to this approach, the Watt-Sun project has demonstrated the ability to improve solar forecasting accuracy by up to 30%, a result that significantly enhances the reliability of renewable integration into the grid (137). For utilities and system operators, such progress translates into a greater ability to anticipate solar generation levels, align production with demand, reduce inefficiencies and strengthen the economic competitiveness of solar energy (138).

Meanwhile, in China, the pilot projects demonstrating the potential of IBM's Green Horizons technologies is the Zhangbei Demonstration project, managed by the State Grid Jibei Electricity Power company in Hebei Province. This initiative represents the largest renewable energy project in the country and served as a testing ground to improve the efficiency of intermittent renewable power into the national grid.

At the heart of the project there is the IBM Hybrid Renewable Energy forecasting (HyRef) system, which combines advanced weather modeling with Big Data analytics to predict availability of renewables energy sources, such as wind, solar and hydro, that as said before are highly variable. The system relies on different tools to track cloud movements, and sensors that monitor wind speed, temperature and direction. By processing these inputs, HyRef can estimate the expected performance of individual renewable plants several days in advance, allowing grid operators to anticipate how much power can be fed into the system or diverted into storage. This predictive capacity helps minimize waste and ensures that renewable energy is used as efficiently as possible.

At Zhangbei, the forecasting system resulted in the integration of 10% more renewable power into the grid, which is enough to supply electricity to more than 14000 households.

These four case studies demonstrate that Artificial Intelligence, when applied across diverse domains and areas of intervention, can act as a powerful tool to make some processes more environmental sustainable.

From reducing the energy footprint of data centers and making renewable energy more predictable, to enabling precision agriculture and improving the efficiency of buildings, AI solutions show tangible benefits both in terms of natural and economic resource savings and emission reduction. In this sense, the projects of Google, Microsoft, Siemens and IBM are not

isolated experiments but concrete demonstrations that digital innovation can accelerate the sustainable transition.

Conclusion

The purpose of this work was to analyze the complex relationship between Artificial Intelligence and environmental sustainability. In fact, as previously discussed, AI model training and deployment consume large amounts of energy and water and generate electronic waste, but, when used with the right purpose and designed in a “green way”, AI can become an important tool to help companies and governments to reach their climate sustainability goals. This duality of AI, as both part of the problem and part of the solution, is the central topic of this thesis.

An accurate analysis of AI’s environmental impacts has shown that the development and use of this technology create a disproportionate level of energy and water consumption. Training advanced models requires enormous computational power, and data centers, the backbone of AI, need a constant availability of electricity and water for operations. These processes directly translate into greenhouse gas emissions, water stress and waste creation that put pressure on the global ecosystems.

Without specific binding mechanisms, the rapid expansion of AI may be difficult to sustain from an environmental perspective.

The regulatory framework is still far from addressing adequately the environmental challenges of this new technological phenomenon. In Europe, the AI Act and the GDPR create a strong framework in terms of ethics, transparency and data protection, but as previously discussed, they do not provide answers to the environmental consequences of AI. Environmental regulatory instruments for emission reduction like the Green Deal, the European Climate Law and the European Emissions Trading System as well as the Water Framework Directive, do not address specifically the environmental sustainability concerns related to AI. For this reason, this thesis delves into proposals about the integration of AI infrastructure regulation into these policies.

Despite this, some progress has been made, such as the Energy Efficiency Directive and the Commission Delegated Regulation introducing reporting obligations for data centers, but these are only initial steps.

Looking beyond Europe, the United States, where most of the global data centers are concentrated, provides another example: here, a recent executive order has prioritized competitiveness and rapid expansion of AI infrastructure, weakening safeguards for environmental sustainability. While effective in the short term from an economic point of view, this model raises doubts about its long term sustainability, as it risks locking in energy intensive

infrastructure and delaying the possibility of a transition to a low carbon economy.

The analysis of a not complete regulatory framework both in Europe and in the United States example highlighted the important role of companies in driving innovation in a greener way. In fact, the case studies examined in the IT sector, represent the core of the thesis, as they provide concrete evidence that Artificial Intelligence, when strategically directed to the right purpose, can be applied successfully for the achievement of environmental targets. AI can improve efficiency of its own infrastructure, as shown by Google's work on reducing the energy footprint of data centers. It can also be applied to broader environmental sustainability challenges, such as precision agriculture renewable energy integration, smarter buildings and air quality management, as demonstrated by the cases of Microsoft, Siemens and IBM. These successful use case in the IT sector show that AI is not only a technology with significant environmental costs, but also a concrete instrument that, if designed and used responsibly, can support the transition towards more sustainable models and contribute to global environmental sustainability goals.

Bibliography

- (1) McCarthy, J., Minsky, M., Shannon, C. E., Rochester, N., & Dartmouth College. (1955). *A proposal for the Dartmouth summer research project on artificial intelligence*.
<https://doi.org/10.1609/aimag.v27i4.1904>
- (2) IBM (2024). *What is Artificial Intelligence?*. Retrieved from
<https://www.ibm.com/think/topics/artificial-intelligence>
- (3) Dick, S (2019). *Artificial Intelligence*. <https://doi.org/10.1162/99608f92.92fe150c>
- (4) IBM (2024). *Che cos'è l'AI generativa?*. Retrieved from <https://www.ibm.com/it-it/think/topics/generative-ai>
- (5) McKinsey&Company (2023). *The economic potential of generative AI: The next production frontier*. Retrieved from <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier>
- (6) Kufel, J., Bargieł-Łączek, K., Kocot, S., Koźlik, M., Bartnikowska, W., Janik, M., Czogalik, Ł., Dudek, P., Magiera, M., Lis, A., Paszkiewicz, I., Nawrat, Z., Cebula, M., & Gruszczyńska, K. (2023). *What Is Machine Learning, Artificial Neural Networks and Deep Learning? Examples of Practical Applications in Medicine*.
<https://doi.org/10.3390/diagnostics13152582>
- (7) *Ibidem*
- (8) IBM (2024). *What is deep learning?*. Retrieved from
<https://www.ibm.com/think/topics/deep-learning>
- (9) IBM (2024). *What is agentic AI?*. Retrieved from
<https://www.ibm.com/think/topics/agentic-ai>
- (10) Accenture (2025). *Accenture Technology Vision 2025. AI: A Declaration of Autonomy. Is trust the limit of AI's limitless possibilities*. Retrieved from
<https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Tech-Vision-2025.pdf>
- (11) Choi, T., & Leigh, N. G. (2024). *Artificial Intelligence's creation and displacement of labor demand. Technological Forecasting and Social Change*.
<https://doi.org/10.1016/j.techfore.2024.123824>
- (12) IBM (2024). *What is responsible AI?*. Retrieved from
<https://www.ibm.com/think/topics/responsible-ai>
- (13) International Organization for Standardization (2023). *Responsible AI & ethics, general requirements*. Retrieved from

- <https://msblogs.thesourcemediaassets.com/sites/5/2022/06/Microsoft-Responsible-AI-Standard-v2-General-Requirements-3.pdf>
- (14) Microsoft (2022). *Microsoft Responsible AI Standard*. Retrieved from <https://msblogs.thesourcemediaassets.com/sites/5/2022/06/Microsoft-Responsible-AI-Standard-v2-General-Requirements-3.pdf>
- (15) Irwin, K. (2024). *LinkedIn is quietly training AI on your Data-here's how to stop it*. Retrieved from <https://www.pcmag.com/news/linkedin-is-quietly-training-ai-on-your-data-heres-how-to-stop-it>
- (16) IBM (2024). *Exploring privacy issues in the age of AI*. Retrieved from <https://www.ibm.com/think/insights/ai-privacy>
- (17) King, J. & Meinhardt C. (2024). *Rethinking privacy in the AI Era*
- (18) Euroactiv (2023). *Italian data protection authority bans ChatGPT citing privacy violation*. Retrieved from <https://www.euractiv.com/section/tech/news/italian-data-protection-authority-bans-chatgpt-citing-privacy-violations/>
- (19) Italian Data Protection Authority (2023). *Artificial Intelligence: stop to ChatGPT by the Italian SA, Personal data is collected unlawfully, no age verification system is in place for children*. Retrieved from <https://www.garanteprivacy.it/web/guest/home/docweb/-/docweb-display/docweb/9870847#english>
- (20) European Union Agency for Fundamental Rights (2022). *Bias in algorithms- Artificial Intelligence and discrimination*. Retrieved from https://fra.europa.eu/sites/default/files/fra_uploads/fra-2022-bias-in-algorithms_en.pdf
- (21) Miltenburg E. (2016). *Stereotyping and Bias in the Flickr30k Dataset*. Retrieved from <https://pure.uvt.nl/ws/files/27962110/stereotyping.pdf>
- (22) Dastin J. (2018). *Amazon scraps secret AI recruiting tool that showed bias against women*. Reuters. Retrieved from <https://www.reuters.com/article/world/insight-amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK0AG/>
- (23) European Commission (2020). *Assessment List for Trustworthy Artificial Intelligence (ALTAI) for self-assessment*. Retrieved from <https://digital-strategy.ec.europa.eu/en/library/assessment-list-trustworthy-artificial-intelligence-altai-self-assessment>
- (24) Deckker D. & Sumanasekara S. (2025). *Dreams and data: ghibli-style art, copyright, and the rise of viral ai imagery*. International Journal of Global Economic Light. <https://doi.org/10.36713/epra22071>

- (25) European Innovation Council and SMEs Executive Agency (2025). *Studio Ghibli vs AI: tribute or copyright infringement?* Retrieved from https://intellectual-property-helpdesk.ec.europa.eu/news-events/news/studio-ghibli-vs-ai-tribute-or-copyright-infringement-2025-04-15_en
- (26) *Ibidem*
- (27) George S. (2024). *Artificial Intelligence and the Future of Work: Job Shifting Not Job Loss*. Partners Universal Innovative Research Publication (PUIRP)
<https://puirp.com/index.php/research/article/view/46/40>
- (28) Aghion P., Antonin C., Bunel S. (2020). *The power of creative destruction*.
- (29) International Labor Organization (2023). *Generative AI and Jobs: Policies to manage the Transition*. Retrieved from
https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@dgreports/@inst/document/s/publication/wcms_898026.pdf
- (30) *Ibidem*
- (31) OECD (2022). *Measuring the environmental impacts of artificial intelligence compute and application. The AI footprint*. Retrieved from
https://www.oecd.org/content/dam/oecd/en/publications/reports/2022/11/measuring-the-environmental-impacts-of-artificial-intelligence-compute-and-applications_3ddddd5/7babf571-en.pdf
- (32) Crawford K., Joler V. (2018). *Anatomy of an AI system*. Retrieved from
<https://anatomyof.ai/>
- (33) *Ibidem*
- (34) Malmodin J., Lundén D. (2018). *The Energy and Carbon Footprint of the Global ICT and E&M Sectors 2010-2015*. <https://doi.org/10.3390/su10093027>
- (35) Wu C. et al. (2022). *Sustainable AI: Environmental Implications, Challenges and Opportunities*. <https://arxiv.org/pdf/2111.00364>
- (36) Hao K. (2019). *Training a single AI model can emit as much carbon as five cars in their lifetimes*. MIT Technology Review. Retrieved from [Training a single AI model can emit as much carbon as five cars in their lifetimes | MIT Technology Review](https://www.technologyreview.com/2019/07/25/400000/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/)
- (37) International Energy Agency (2024). *Electricity 2024. Analysis and forecast to 2026*. Retrieved from <https://iea.blob.core.windows.net/assets/6b2fd954-2017-408e-bf08-952fdd62118a/Electricity2024-Analysisandforecastto2026.pdf>

- (38) U.S. Energy Information Administration (2023). *Nuclear explained. U.S. nuclear industry*. Retrieved from <https://www.eia.gov/energyexplained/nuclear/us-nuclear-industry.php>
- (39) @AIatMeta (April 2025). *We announced Llama’s first 1 billion downloads last month, and we’re updating that number to 1.2 billion downloads today*. X (previously Twitter). <https://x.com/AIatMeta/status/1917353528580006071>
- (40) O’Donnell J., Crownhart C. (2025). *We did the math on AI’s energy footprint. Here’s the story you haven’t heard*. MIT Technology Review. Retrieved from <https://www.technologyreview.com/2025/05/20/1116327/ai-energy-usage-climate-footprint-big-tech/#content>
- (41) Google (2024). *2024 Environmental Report*. Retrieved from <https://sustainability.google/reports/>
- (42) Philadelphia Water Department (n.d.). *Gallons Used Per Person Per Day*. Retrieved from <https://water.phila.gov/wp-content/uploads/files/home-water-use-ig5.pdf>
- (43) Shehabi, A., et al. (2024). *United States data center energy usage report*. <https://doi.org/10.71468/PIWC7Q>
- (44) Strubell, E., et al. (2019). *Energy and policy considerations for deep learning in NLP*. <https://doi.org/10.48550/arXiv.1906.02243>
- (45) Li P., et al. (2025). *Making AI Less “Thirsty”: Uncovering and Addressing the Secret Water Footprint of Ai Models*. <https://doi.org/10.48550/arXiv.2304.03271>
- (46) Federal Reserve Bank of Richmond (2023). *Virginia’s Data Centers and Economic Development*. Retrieved from https://www.richmondfed.org/publications/research/econ_focus/2023/q2_feature2
- (47) International Labour Organization (2014). *Tackling informality in e-waste management: The potential of cooperative enterprises*. Retrieved from <https://www.ilo.org/publications/tackling-informality-e-waste-management-potential-cooperative-enterprises>
- (48) Adám B., et al. (2021). *From inequitable to sustainable e-waste processing for reduction of impact on human health and the environment*. <https://doi.org/10.1016/j.envres.2021.110728>
- (49) ibidem
- (50) University of Toronto (2022). *More developed countries dumping toxic e-waste in Global South, U of T researchers find*. Retrieved from

<https://www.utoronto.ca/news/more-developed-countries-dumping-toxic-e-waste-global-south-u-t-researchers-find>

- (51) World Health Organization (2024). *Electronic waste (e-waste)*. Retrieved from [https://www.who.int/news-room/fact-sheets/detail/electronic-waste-\(e-waste\)](https://www.who.int/news-room/fact-sheets/detail/electronic-waste-(e-waste))
- (52) European Parliament (2025). *EU AI Act: first regulation on artificial intelligence*. Retrieved from <https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence>
- (53) Ben-Shahar, O., Schneider, C. E. (2011). *The Failure of Mandated Disclosure*. [10.2139/ssrn.1567284](https://ssrn.com/abstract=10.2139/ssrn.1567284)
- (54) Regulation (EU) 2016/679
- (55) Hacker P. (2023). *Sustainable AI Regulation*. Retrieved from <https://arxiv.org/pdf/2306.00292>
- (56) Amsterdam Court of Appeals (2023). *Case 200.295.806/01*
- (57) Pessach D., Shmueli E., (2022). *A Review on Fairness in Machine Learning*. <https://doi.org/10.1145/3494672>
- (58) Henzinger, T. A., Karimi, M., Kueffner, K., & Mallik, K. (2023). *Monitoring algorithmic fairness*. <https://doi.org/10.48550/arXiv.2305.15979>
- (59) COM(2019) 640 final
- (60) COM(2023) 62 final
- (61) Regulation (EU) 2021/1119
- (62) United Nations (2015). *The 2030 agenda for sustainable development*. Retrieved from <https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf>
- (63) United Nations (2015). *Paris Agreement*. Retrieved from https://unfccc.int/sites/default/files/english_paris_agreement.pdf
- (64) European Commission (n.d). *The European Green Deal*. Retrieved from https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en
- (65) Directive 2003/87/EC
- (66) European Commission (n.d.). *About the EU ETS*. Retrieved from https://climate.ec.europa.eu/eu-action/carbon-markets/eu-emissions-trading-system-eu-ets/about-eu-ets_en

- (67) European Commission (2010). *Guidance on Interpretation of Annex I of the EU ETS Directive*. Retrieved from https://climate.ec.europa.eu/system/files/2016-11/guidance_interpretation_en.pdf
- (68) IBM (2025). *What is data processing?* Retrieved from <https://www.ibm.com/think/topics/data-processing>
- (69) Directive (EU) 2023/1791
- (70) Regulation (EU) 2024/1364
- (71) Ebert K., Alder N., Herbrich R., Hacker P. (2024). *AI, Climate, and Regulation: From Data Centers to the AI Act*. Retrieved from <https://arxiv.org/html/2410.06681v1#bib.bib10>
- (72) German Parliament (2023). *Energy Efficiency Act*
- (73) *ibidem*
- (74) Li P., et al. (2025). *Making AI Less “Thirsty”: Uncovering and Addressing the Secret Water Footprint of Ai Models*. <https://doi.org/10.48550/arXiv.2304.03271>
- (75) Directive 2000/60/EC
- (76) Court of Justice of the European Union (2015). *Bund für Umwelt und Naturschutz Deutschland e.V. v Bundesrepublik Deutschland*. Case C-461/13. Retrieved from <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:62013CC0461>
- (77) The White House (2025). *Accelerating Federal Permitting of Data Center Infrastructure*. Retrieved from <https://www.whitehouse.gov/presidential-actions/2025/07/accelerating-federal-permitting-of-data-center-infrastructure/>
- (78) U.S. Environmental Protection Agency (n.d.). *What is the National Environmental Policy Act?*. Retrieved from <https://www.epa.gov/nepa/what-national-environmental-policy-act>
- (79) European Parliament (2021). *The role of Artificial Intelligence in the European green deal*. Retrieved from [https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662906/IPOL_STU\(2021\)662906_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662906/IPOL_STU(2021)662906_EN.pdf)
- (80) Accenture (2024). *Uniting technology and sustainability*. Retrieved from <https://www.accenture.com/content/dam/accenture/final/a-com-migration/pdf/pdf-177/accenture-tech-sustainability-uniting-sustainability-and-technology.pdf#zoom=40>
- (81) *Ibidem*
- (82) Nature portfolio (2025). *Greening cement production*. Retrieved from <https://www.nature.com/articles/d42473-021-00161-z>
- (83) Microsoft (2025). *2025 Environmental Sustainability Report*. Retrieved from <https://cdn->

[dynmedia-](#)

1.microsoft.com/is/content/microsoftcorp/microsoft/msc/documents/presentations/CSR/2025-Microsoft-Environmental-Sustainability-Report.pdf#page=01

(84) Microsoft (2020). *Microsoft will be carbon negative by 2030*. Retrieved from

<https://blogs.microsoft.com/blog/2020/01/16/microsoft-will-be-carbon-negative-by-2030/>

(85) Accenture (2023). *Supply chains key to unlocking net zero emissions*. Retrieved from

[https://www.accenture.com/us-en/services/supply-](https://www.accenture.com/us-en/services/supply-chain?c=acn_glb_unungceostudy2sprinklradvocac_13614285&n=smc_0423)

[chain?c=acn_glb_unungceostudy2sprinklradvocac_13614285&n=smc_0423](https://www.accenture.com/us-en/services/supply-chain?c=acn_glb_unungceostudy2sprinklradvocac_13614285&n=smc_0423)

(86) European Pharmaceutical Review (2025). *Sanofi accelerates towards its “factory of the future” vision*. Retrieved from

<https://www.europeanpharmaceuticalreview.com/news/264421/sanofi-digital-manufacturing-supply-accelerator-lyon/>

(87) Ayoubi, H., Tabaa, Y., El Kharrim, M. (2023). *Artificial Intelligence in Green Management and the rise of Digital Lean for Sustainable Efficiency*.

<https://doi.org/10.1051/e3sconf/202341201053>

(88) Accenture (2021). *Shaping the sustainable organization*

(89) Hao, K. (2019). *Training a single AI model can emit as much carbon as five cars in their lifetimes*. MIT Technology Review. Retrieved from

<https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/>

(90) Amodei, D., Hernandez, D. (2018). *AI and compute*. Retrieved from

<https://openai.com/index/ai-and-compute/>

(91) Podder, S., Singh, S. K. (2022). *Sustainable Data: In pursuit of net zero*. The Economist. Retrieved from <https://bit.ly/3k5r1ST>

(92) Accenture (2020). *The green behind the cloud*. Retrieved from

<https://www.accenture.com/content/dam/accenture/final/a-com-migration/pdf/pdf-142/accenture-the-green-behind-the-cloud-transcript.pdf>

(93) Evans, R., Gao J. (2016). *DeepMind AI reduces Google Data Centre Cooling Bill by 40%*. Retrieved from <https://deepmind.google/discover/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40/>

(94) Google (2020). *Our Data centers now work harder when the sun shines and wind blows*.

Retrieved from <https://blog.google/inside-google/infrastructure/data-centers-work-harder-sun-shines-wind-blows/>

- (95) Arimetrics (2025). *What is Dark Data*. Retrieved from <https://www.arimetrics.com/en/digital-glossary/dark-data>
- (96) Meta (2021). *Most of computing's carbon emissions are coming from manufacturing and infrastructure*. Retrieved from <https://tech.facebook.com/engineering/2021/3/sustainable-computing/>
- (97) The Economic Times (2021). *Reuse and recycle: Google, Microsoft & Dell join forces to tackle e-waste crisis by 2030*. Retrieved from: <https://economictimes.indiatimes.com/magazines/panache/reuse-and-recycle-google-microsoft-dell-join-forces-to-tackle-e-waste-crisis-by-2030/articleshow/81585724.cms?from=mdr>

References

- (98) Google DeepMind (2023). *Using AI to fight climate change*. Retrieved from <https://deepmind.google/discover/blog/using-ai-to-fight-climate-change/>
- (99) OECD (2022). *Measuring the environmental impacts of artificial intelligence compute and application. The AI footprint*. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2022/11/measuring-the-environmental-impacts-of-artificial-intelligence-compute-and-applications_3ddddd5/7babf571-en.pdf
- (100) Koomey, J. G. (2011). *Growth in data center electricity use 2005 to 2010*. Retrieved from https://alejandrobarrros.com/wp-content/uploads/old/4363/Growth_in_Data_Center_Electricity_use_2005_to_2010.pdf
- (101) International Energy Agency (2024). *Energy demand from AI*. Retrieved from <https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai>
- (102) Google DeepMind (2016). *DeepMind AI Reduces Google Data Center Cooling Bill by 40%*. Retrieved from <https://deepmind.google/discover/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40/>
- (103) Google DeepMind (2018). *Safety-first AI for autonomous data centre cooling and industrial control*. Retrieved from <https://deepmind.google/discover/blog/safety-first-ai-for-autonomous-data-centre-cooling-and-industrial-control/>
- (104) Gao, J. (2014). *Machine Learning Application for Data Center Optimization*. Retrieved from <https://static.googleusercontent.com/media/research.google.com/it//pubs/archive/42542.pdf>
- (105) Google (2018). *Moving toward 24x7 Carbon-Free Energy at Google Data Centers*:

Progress and Insights. Retrieved from <https://storage.googleapis.com/gweb-sustainability.appspot.com/pdf/24x7-carbon-free-energy-data-centers.pdf>

(106) Google DeepMind (2019). *Machine learning can boost the value of wind energy*.

Retrieved from <https://deepmind.google/discover/blog/machine-learning-can-boost-the-value-of-wind-energy/>

(107) Forbes (2019). *DeepMind and Google Train AI To Predict Energy Output Of Wind Farms*.

Retrieved from <https://www.forbes.com/sites/samshead/2019/02/27/deepmind-and-google-train-ai-to-predict-energy-output-of-wind-farms/>

(108) Microsoft (2025). *2025 Environmental Sustainability Report*. Retrieved from

<https://cdn-dynmedia-1.microsoft.com/is/content/microsoftcorp/microsoft/msc/documents/presentations/CSR/2025-Microsoft-Environmental-Sustainability-Report.pdf#page=01>

(109) Microsoft (2023). *Accelerating Sustainability with AI: A Playbook*. Retrieved from

https://msblogs.thesourcemediaassets.com/sites/5/2023/11/Microsoft_Accelerating-Sustainability-with-AI-A-Playbook-1.pdf

(110) Microsoft (2018). *AI for Earth: Helping save the planet with data science*. Retrieved

from <https://news.microsoft.com/apac/features/ai-for-earth-helping-save-the-planet-with-data-science/>

(111) Microsoft (n.d.). *A Planetary Computer for a Sustainable Future*. Retrieved from

<https://planetarycomputer.microsoft.com/>

(112) Microsoft (2019). *FarmBeats: AI, Edge & IoT for Agriculture*. Retrieved from

<https://www.microsoft.com/en-us/research/project/farmbeats-iot-agriculture/>

(113) Vasisht, D., et al. (2017). *FarmBeats: An IoT Platform for Data-Driven Agriculture* .

Retrieved from <https://www.microsoft.com/en-us/research/wp-content/uploads/2017/03/FarmBeats-webpage-1.pdf>

(114) NRDC (2019). *A new course: managing drought and downpours in the Santiago metropolitan region* .

Retrieved from <https://www.nrdc.org/sites/default/files/new-course-managing-drought-downpours-santiago-report.pdf>

(115) Microsoft (2025). *Kilimo helps farmers save water*. Retrieved from [https://cdn-](https://cdn-dynmedia-1.microsoft.com/is/content/microsoftcorp/microsoft/msc/documents/presentations/CSR/Kilimo-Case-Study.pdf)

[dynmedia-1.microsoft.com/is/content/microsoftcorp/microsoft/msc/documents/presentations/CSR/Kilimo-Case-Study.pdf](https://cdn-dynmedia-1.microsoft.com/is/content/microsoftcorp/microsoft/msc/documents/presentations/CSR/Kilimo-Case-Study.pdf)

(116) *Ibidem*

- (117) Nature (2022). *Cement and steel- nine steps to net zero*. Retrieved from <https://www.nature.com/articles/d41586-022-00758-4>
- (118) Ritchie, H., (2023). *How much of global greenhouse gas emissions come from plastics?*. Retrieved from <https://ourworldindata.org/ghg-emissions-plastics#article-citation>
- (119) Nature (2021). *Machines learn to unearth new materials*. Retrieved from <https://www.nature.com/articles/d41586-021-01793-3>
- (120) Microsoft (2023). *Microsoft and Johnson Matthey join forces to speed up hydrogen fuel cell innovation with Azure Quantum*. Retrieved from <https://azure.microsoft.com/en-us/blog/quantum/2023/04/13/microsoft-and-johnson-matthey-join-forces-to-speed-up-hydrogen-fuel-cell-innovation-with-azure-quantum/>
- (121) Microsoft (2025). *What is Microsoft for Sustainability?*. Retrieved from <https://learn.microsoft.com/en-us/industry/sustainability/overview>
- (122) Siemens (2022). *Energy efficiency*. Retrieved from <https://www.siemens.com/global/en/products/buildings/energy-sustainability/energy-efficiency.html#Facingenergyefficiencychallenges>
- (123) Siemens (2022). *Building Meets Artificial Intelligence*. Retrieved from <file:///C:/Users/chiar/OneDrive/Desktop/Building-Meets-Artificial-Intelligence-Market-Insight-Report-US.pdf>
- (124) Dietrich, S. (2024). *Siemens To Accelerate Net-zero Transition With Building X Sustainability manager*. Retrieved from <https://control.com/news/siemens-to-accelerate-net-zero-transition-with-building-x-sustainability-manager/>
- (125) Siemens (2022). *BUILDING X Applications*. Retrieved from <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications.html>
- (126) European Commission (2020). *In focus: Energy efficiency in buildings*. Retrieved from https://commission.europa.eu/news-and-media/news/focus-energy-efficiency-buildings-2020-02-17_en
- (127) Siemens (n.d.). *BUILDING X Energy Manager*. Retrieved from <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/energy-manager.html>
- (128) City of New York (2019). *Local Laws Of The City Of New York For The Year 2019*. Retrieved from https://www.nyc.gov/assets/buildings/local_laws/l197of2019.pdf
- (129) Siemens (2024) *Building X Sustainability Manager Report*. Retrieved from

<https://assets.new.siemens.com/siemens/assets/api/uuid:fb2174a8-9904-45ed-9d34-2749d2b16d80/Building-X-Sustainability-Manager-Brochure-Siemens-Smart-Infrastructure-US.pdf>

(130) Siemens (n.d.) *BUILDINGX Sustainability Manager Web Site Page*. Retrieved from <https://xcelerator.siemens.com/global/en/products/buildings/building-x/solutions/applications/sustainability-manager.html>

(131) United Nations Development Programme (2023). *The climate dictionary: An everyday guide to climate change*. Retrieved from <https://climatepromise.undp.org/news-and-stories/climate-dictionary-everyday-guide-climate-change>

(132) European Institute of Management & Technology (2024). *AI for Climate Change: How Machine Learning Can Tackle Environmental Issues*. Retrieved from <https://www.eimt.edu.eu/ai-climate-change-how-machine-learning-addresses-environmental-issues>

(133) IBM (2015). *IBM Expands Green Horizons Initiative Globally To Address Pressing Environmental and Pollution Challenges*. Retrieved from <https://uk.newsroom.ibm.com/2015-Dec-09-IBM-Expands-Green-Horizons-Initiative-Globally-To-Address-Pressing-Environmental-and-Pollution-Challenges>

(134) Shraufnagel, D.E., (2020). *The health effects of ultrafine particles*. Retrieved from <https://www.nature.com/articles/s12276-020-0403-3#citeas>

(135) IBM (2015). *Corporate Responsibility Report*. Retrieved from https://www.responsibilityreports.com/HostedData/ResponsibilityReportArchive/i/NYSE_IBM_2015.pdf

(136) U.S. Department of Energy (2016). *EERE Success story- Solar forecasting gets a boost from Watson, accuracy improved by 30%*. Retrieved from <https://www.energy.gov/eere/success-stories/articles/eere-success-story-solar-forecasting-gets-boost-watson-accuracy>

(137) *Ibidem*

(138) IBM Research (2015). *IBM Improves Solar Forecasting Technology*. Retrieved from <https://www.youtube.com/watch?v=cj2RXjvRKOA&t=1s>