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Artificial Intelligence Impact on the Environment: Hidden Ecological Costs and Ethical-Legal Issues

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Abstract

Objective: to identify the hidden ecological costs associated with the elaboration, implementation and development of artificial intelligence technologies, in order to ensure its sustainable and harmonious integration with various economic sectors by identifying optimal moral-ethical and political-legal strategies.

Methods: the conducted research is based on an ecological approach to the development and implementation of artificial intelligence, as well as on an interdisciplinary and political-legal analysis of ecological problems and risks of algorithmic bias, errors in artificial intelligence algorithms and decision-making processes that may exacerbate environmental inequalities and injustice towards the environment. In addition, analysis was performed in regard to the consequences of natural ecosystems destruction caused by the development of artificial intelligence technologies due to the computing energy-intensiveness, the growing impact of data centers on energy consumption and problems with their cooling, the electronic waste formation due to the rapid improvement of equipment, etc.

Results: the analysis shows a range of environmental, ethical and political-legal issues associated with the training, use and development of artificial intelligence, which consumes a significant amount of energy (mainly from non-renewable sources). This leads to an increase in carbon emissions and creates obstacles to further sustainable ecological development. Improper disposal of artificial intelligence equipment exacerbates the problem of e-waste and pollution of the planet, further damaging the environment.

Errors in artificial intelligence algorithms and decision-making processes lead to environmental injustice and inequality. AI technologies may disrupt natural ecosystems, jeopardizing wildlife habitats and migration patterns.

Scientific novelty: the environmental consequences of the artificial intelligence use and further development, as well as the resulting environmental violations and costs of sustainable development, were studied. This leads to the scientific search for optimal strategies to minimize environmental damage, in which legal scholars and lawyers will have to determine ethical-legal and political-legal solutions at the national and supranational levels.

Practical significance: understanding the environmental impact of AI is crucial for policy makers, lawyers, researchers, and industry experts in developing strategies to minimize environmental harm. The findings emphasize the importance of implementing energy efficient algorithms, switching to renewable energy sources, adopting responsible e-waste management practices, ensuring fairness in AI decision-making and taking into account ethical considerations and rules of its implementation.

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Contents

Introduction

Artificial intelligence (AI) has emerged as a powerful and transformative force, revolutionising various aspects of human lives, from healthcare to transportation, and from customer service to financial systems. With its ability to process vast amounts of data and learn from patterns, AI has opened up new frontiers of innovation and efficiency. However, as society marvels at the advancements brought by AI, it becomes crucial to recognise and examine the hidden ecological cost associated with this technological revolution.

As the demand for AI applications grows, the energy consumption required to power the computational infrastructure also increases. According to a study conducted by Strubell et al. (2019), training a single state-of-the-art AI model can emit as much carbon dioxide as the lifetime emissions of five cars. Data centres, which are responsible for housing and running AI systems, contribute significantly to this energy consumption, often relying on non-renewable energy sources. The exponential growth of AI technology raises concerns about the long-term environmental impact, as the environmental cost associated with the AI revolution remains largely unnoticed and unaccounted for.

Moreover, the rapid evolution of AI hardware leads to shorter device lifecycles, resulting in a surge of electronic waste (e-waste). The Global E-waste Monitor 2020 report indicates that e-waste generation reached a record 53.6 million metric tonnes, with only 17.4 % being officially collected and recycled[1]. Improper management of outdated AI hardware components poses significant environmental risks, contributing to pollution and resource depletion.

Whilst AI presents immense potential for environmental monitoring and conservation efforts, its deployment can also disrupt natural ecosystems. Environmental monitoring drones and autonomous vehicles used for resource exploration, for example, have the potential to disturb wildlife habitats, interfere with migration patterns, and exacerbate ecosystem imbalances. The unintended consequences of AI on biodiversity and ecosystems necessitate careful consideration to ensure responsible and sustainable deployment.

In light of these concerns, it becomes essential to delve deeper into the environmental footprint of AI and explore strategies for mitigating its negative ecological impacts. This article will examine various aspects of the ecological cost associated with AI, highlighting the need for energy-efficient algorithms, responsible e-waste management practices, sustainable data centre infrastructure, and ethical considerations in AI

[1] Forti, V., Baldé, C. P., Kuehr, R., & Bel, G. (2020). The global e-waste monitor 2020: Quantities, flows and the circular economy potential. United Nations University (UNU), International Telecommunication Union (ITU) & International Solid Waste Association (ISWA). Bonn; Geneva; Rotterdam.

decision-making. By shedding light on these issues, it aims to foster discussions and actions that lead to a more environmentally conscious approach to AI development and deployment.

1. Energy consumption

As society continues to harness the power of AI, it becomes imperative to acknowledge and tackle the substantial energy consumption that accompanies this technological revolution. This section explores the energy-intensive nature of AI computations, the significant energy demands of data centers, and the concerning reliance on non-renewable energy sources. By shedding light on the hidden ecological costs of the AI revolution, we can gain a deeper understanding of the environmental implications associated with AI's remarkable impact on various domains of human life.

AI computations are known for their substantial energy requirements due to the processing of vast amounts of data and the execution of complex algorithms. Training state-of-the-art AI models, in particular, consumes a significant amount of energy, with large-scale models consuming as much energy as hundreds of megawatt-hours, equivalent to the energy required to power thousands of homes for several months (Strubell et al., 2019). The computational demands and iterative processes involved in training AI models contribute to their high energy consumption. These energy requirements are driven by the need to process large datasets, perform complex matrix operations, and optimise model parameters through multiple iterations. Understanding the energy footprint of AI computations is essential for comprehending the environmental impact associated with their widespread adoption.

Data centers play a vital role in supporting AI systems by housing and running the computational infrastructure. However, they contribute significantly to the overall energy consumption of AI. These facilities require substantial electricity to power servers, cooling systems, and networking equipment. The high-performance computing capabilities necessary for AI computations result in increased energy demands for data centers. Hanus et al. (2023) underscore the energy-intensive nature of data centers and the challenges they face in achieving energy efficiency. The growth of AI technology has led to an increase in the number and size of data centers, amplifying their environmental impact. The inefficient utilisation of computing resources and cooling systems in data centers further exacerbates their energy consumption and environmental footprint.

A pressing concern regarding AI's energy consumption is the reliance on non-renewable energy sources. Conventional power grids, often fueled by fossil fuels, are the primary sources of electricity for AI computations. This reliance on non-renewable energy exacerbates greenhouse gas emissions and environmental challenges. Şerban et al. (2020) stress the importance of transitioning to renewable energy sources for sustainable AI infrastructure. Incorporating renewable energy solutions, such as solar or wind power, in data centers can reduce the carbon footprint of AI systems and mitigate their environmental impact. The adoption of renewable energy technologies not only reduces greenhouse gas emissions but also promotes the development of a more sustainable energy infrastructure to support the growing demands of AI computations.

1.1. The energy-intensive nature of AI computations

The energy-intensive nature of AI computations has become a growing concern due to the significant energy requirements associated with training and running sophisticated AI models (Henderson et al., 2018). As AI applications continue to advance and become more complex, the demand for computational power has skyrocketed, leading to increased energy consumption.

One primary contributor to the energy consumption of AI computations is the training phase. Training a deep learning model involves feeding vast amounts of data into neural networks, which then adjust their internal parameters through iterative processes to optimise performance. This training process often requires multiple iterations over large datasets, utilising powerful hardware infrastructure such as graphics processing units (GPUs) or specialised tensor processing units (TPUs) (Strubell et al., 2019).

These hardware components are highly energy-intensive, consuming significant amounts of electricity to perform the complex calculations necessary for training AI models. The energy consumption during training can range from several hundred kilowatt-hours (kWh) to several thousand kWh, depending on the size and complexity of the model, the size of the dataset, and the hardware infrastructure used (Schwartz et al., 2020).

For example, a study by Schwartz et al. (2020) estimated that training a single state-of-the-art language model can emit as much carbon dioxide as the lifetime emissions of five cars. This highlights the substantial environmental impact associated with the energy consumption of AI computations.

In addition to the training phase, the deployment and inference of AI models also contribute to energy consumption. Once a model is trained, it needs to be deployed and run on various devices or cloud servers to make predictions or perform specific tasks in real-time. This inference phase also requires computational resources, although typically less intensive compared to training. However, when AI models are deployed at scale, the cumulative energy consumption can still be substantial (Strubell et al., 2019).

The energy-intensive nature of AI computations raises concerns about the environmental impact and sustainability of AI technologies. As AI applications continue to proliferate across industries and sectors, the demand for computational resources will only increase, leading to even higher energy consumption. It becomes crucial to explore energy-efficient computing architectures, develop algorithms that minimise computational requirements, and adopt renewable energy sources to power AI infrastructure (Ding et al., 2021).

Efforts are underway to address these challenges. Researchers and industry experts are actively working on developing more energy-efficient algorithms and hardware architectures, exploring techniques such as model compression, quantisation, and distributed training. These approaches aim to reduce the computational requirements of AI models without significantly compromising performance (Ding et al., 2021). Furthermore, there is an increasing focus on optimising data centre operations and adopting renewable energy sources to power AI infrastructure, reducing the carbon footprint associated with AI computations (Strubell et al., 2019).

1.2. Data centers: Energy hogs of the AI infrastructure

Data centers play a critical role in supporting the AI infrastructure, serving as the backbone for storing and processing vast amounts of data. However, these data centers are also significant energy consumers, raising concerns about their environmental impact (Dhar, 2020).

Data centers house the servers, networking equipment, and storage systems required to handle the computational demands of AI workloads. These facilities operate around the clock, consuming substantial amounts of electricity for powering and cooling the equipment, as well as providing uninterruptible power supply systems (UPSS) for backup (Shah et al., 2010).

The energy consumption of data centers is driven by various factors, including the number and efficiency of servers, the cooling systems, and the overall infrastructure design. Server racks and cooling equipment consume a significant portion of the energy, with cooling alone accounting for up to 40% of the total energy consumption (Masanet et al., 2020). A study estimated that data centers globally consumed approximately 196 to 400 terawatt-hours (TWh) of electricity in 2020, accounting for about 1 % of the global electricity consumption[2]. The energy efficiency of data centers has become a major focus in reducing their environmental footprint. Efforts are underway to improve server efficiency, optimize cooling systems, and design data centers with energy-efficient principles in mind. Techniques such as server virtualization, advanced cooling technologies, and power management strategies are being implemented to enhance energy efficiency (Shah et al., 2010).

Furthermore, there is a growing interest in adopting renewable energy sources to power data centers. Many companies are investing in renewable energy projects and purchasing renewable energy certificates (RECs) to offset their electricity consumption (Dhar, 2020). For example, Google announced in 2017 that it had achieved a milestone of purchasing

2 Garcia, C. (2022). The Real Amount of Energy A Data Center Uses. https://clck.ru/36kxEN

enough renewable energy to match 100 % of its global electricity consumption for its data centers and offices[3].

To address the energy challenges posed by data centers, industry collaborations, government regulations, and research initiatives are being established. These efforts aim to develop standards, promote best practices, and encourage the adoption of energy-efficient technologies in data center operations (Shah et al., 2010). In the UK, the Data Centre Alliance is actively working to drive energy efficiency improvements and sustainability in the data center industry[4].

1.3. Non-renewable energy sources and carbon emissions

The reliance of AI infrastructure on non-renewable energy sources has significant implications for carbon emissions and the overall environmental impact. The generation of electricity from fossil fuels, such as coal and natural gas, contributes to greenhouse gas emissions and exacerbates climate change (Ram et al., 2018). In fact, the carbon emissions from data centers alone are estimated to rival those of the aviation industry[5].

Data centers, which house the computational infrastructure for AI, are known to be energy-intensive facilities. They require substantial amounts of electricity to power the servers, cooling systems, and other supporting infrastructure. In many regions, the grid electricity used to power data centers predominantly comes from non-renewable sources. For example, in the United Kingdom, a significant portion of the electricity generation still relies on fossil fuels[6].

The carbon emissions associated with non-renewable energy sources directly contribute to the carbon footprint of AI systems. A study by Rolnick et al. (2022) estimated that training a large AI model can emit as much carbon as an average American car over its entire lifetime.

To address these concerns, there is a growing movement within the AI community to transition towards renewable energy sources and reduce carbon emissions. Several major technology companies, including Microsoft and Amazon, have made commitments to achieve carbon neutrality and rely on renewable energy for their data centers[7].

Moreover, governments and organizations are taking steps to promote the adoption of renewable energy in the AI sector. The European Union, for instance, has set targets

3 Google. (2021). Google reaches 100% renewable energy goal. https://clck.ru/36kxG4

4 Data Centre Alliance. (n.d.). About the DCA. https://clck.ru/36kxHA

5 Lim, S. (2022, July 14). Media industry's pollution equivalent to aviation, study finds. Campaign. https://clck.ru/36kxHu

6 Department for Business, Energy & Industrial Strategy. (2020). BEIS Electricity Generation Costs. https://clck.ru/36kxKS

7 Microsoft. (2022). Microsoft announces plan to be carbon negative by 2030. https://clck.ru/36kxLJ ; See also Amazon. (n.d.). Amazon and Global Optimism announce The Climate Pledge. https://clck.ru/36kxMP

to increase the share of renewable energy and reduce greenhouse gas emissions in its member states[8].

Additionally, research efforts are focused on developing energy-efficient algorithms and hardware designs to minimise energy consumption and carbon emissions during AI computations. Techniques like model compression, quantisation, and specialised hardware architectures are being explored to optimise the energy efficiency of AI systems (Strubell et al., 2019).

1.4. Exploring the need for energy-efficient AI algorithms and hardware

As the demand for AI continues to grow, there is a pressing need to develop energy-efficient algorithms and hardware to mitigate the environmental impact of AI computations. The energy consumption of AI systems is a significant concern, considering the carbon emissions associated with non-renewable energy sources (Rolnick et al., 2022).

Researchers are actively exploring techniques to improve the energy efficiency of AI algorithms. Model compression, for instance, aims to reduce the computational requirements of deep neural networks by pruning unnecessary connections or reducing the precision of weights and activations (Han et al., 2015). This approach can significantly decrease the energy consumption and inference time without sacrificing model performance.

Another approach is quantisation, which involves representing numerical values with fewer bits. By reducing the precision of parameters and activations, quantisation reduces memory usage and computational complexity, leading to energy savings during both training and inference (Hubara et al., 2016). Efforts are also being made to improve the energy efficiency of training algorithms. Gradient compression techniques, such as sparsification and quantisation, aim to reduce the communication overhead between distributed devices during distributed training, thus decreasing the energy consumption (Alistarh et al., 2017). Additionally, advancements in optimisation algorithms and learning rate schedules can minimise the number of training iterations required, resulting in energy savings (You et al., 2017).

The development of energy-efficient AI hardware is also a crucial aspect of mitigating energy consumption. Traditional computing architectures are often not optimised for AI workloads, leading to inefficient energy usage. To address this, researchers are exploring new hardware designs, including neuromorphic computing and memristive devices, which mimic the structure and functioning of the human brain, offering potential energy efficiency improvements (Merolla et al., 2014; Prezioso et al., 2015).

8 European Commission. (n.d.). EU Climate Action. https://clck.ru/36kxSS

2. Electronic Waste Generation

In addition to the energy-intensive nature of AI computations, the hardware used in AI systems also contributes to another significant environmental challenge: electronic waste generation. The rapid pace of technological advancement and the constant need for more powerful hardware result in a high turnover rate, leading to a growing accumulation of electronic waste (Ferro et al., 2021).

AI hardware, including GPUs, application-specific integrated circuits (ASICs), and other specialised components, have relatively short lifespans due to the relentless progress in technology. As newer generations of hardware are developed, older ones quickly become obsolete and are often discarded, exacerbating the issue of electronic waste[9].

The disposal of AI hardware contributes to the release of hazardous substances and materials into the environment when not properly managed. These substances can contaminate soil, water, and air, posing risks to human health and ecosystems. The improper disposal of electronic waste not only leads to environmental degradation but also wastes valuable resources embedded in the hardware. Moreover, the disposal of hardware that contains toxic materials such as lead, mercury, and flame retardants can further contribute to pollution if not handled properly[10].

To tackle the issue of electronic waste generation in the AI industry, it is crucial to implement sustainable practices. One approach is to promote the reuse and recycling of AI hardware. By refurbishing and remanufacturing older hardware, its lifespan can be extended, reducing the need for constant production of new devices (Ferro et al., 2021). Additionally, implementing take-back programs and establishing recycling facilities ensure that discarded hardware is properly managed and valuable materials are recovered for reuse[11].

In the design and manufacturing of AI hardware, eco-friendly principles should be embraced. Using materials with lower environmental impacts, designing for recyclability, and reducing the presence of hazardous substances can contribute to a more sustainable hardware lifecycle. Adopting modular designs that allow for component replacement and upgrading can also help prolong the usefulness of AI hardware, reducing the frequency of complete device replacement (Ferro et al., 2021).

9 Baldé, C. P., Forti, V., Gray, V., Kuehr, R., & Stegmann, P. (2017). The global e-waste monitor 2017: Quantities, flows and resources. United Nations University, International Telecommunication Union, and International Solid Waste Association.

10 Ibid.

11 Ibid.

2.1. The rapid pace of AI hardware advancements

The hardware technologies in the field of AI are undergoing rapid advancements, fueled by continuous innovation that leads to the creation of increasingly powerful and efficient AI systems (Amodei et al., 2016). A notable development in AI hardware is the evolution of GPUs into a key component for AI computations. Originally designed for graphics rendering, GPUs have found extensive adoption in AI due to their ability to handle parallel processing tasks effectively (Amodei et al., 2016). Their high throughput and computational power make them well-suited for training and running AI models.

Furthermore, specialised hardware known as ASICs has emerged to cater specifically to AI workloads. ASICs offer improved performance and energy efficiency by customising the hardware architecture to optimise AI algorithm execution (Amodei et al., 2016). These dedicated AI chips provide higher computational density and faster processing speeds compared to general-purpose processors.

The rapid advancements in AI hardware have been instrumental in enabling significant breakthroughs across various AI applications. In computer vision, for example, the availability of high-performance hardware has facilitated complex image recognition and object detection tasks with remarkable accuracy (Amodei et al., 2016). Similarly, in natural language processing, powerful hardware accelerates the training and inference of language models, enabling applications such as machine translation and sentiment analysis.

However, the swift progress in AI hardware also brings challenges. The rapid turnover of hardware due to newer generations becoming available leads to a significant accumulation of electronic waste. Outdated hardware components contribute to the growing e-waste problem, requiring proper disposal and recycling measures to minimise environmental impact (Ferro et al., 2021).

The continuous introduction of new AI hardware also presents a learning curve for developers and researchers. Staying up to date with the latest hardware technologies demands constant adaptation, training, and investment, posing challenges for those involved in AI development (Amodei et al., 2016). Furthermore, optimising AI algorithms and software to leverage the capabilities of different hardware architectures adds complexity to the development process.

2.2. Device lifecycles and the E-waste predicament

The rapid advancement of AI technologies has led to a proliferation of electronic devices, resulting in a concerning rise in electronic waste, or e-waste, which poses significant environmental and health risks[12]. The lifecycles of AI hardware play a crucial role in determining the extent of e-waste generated and the environmental impact associated with it.

12 Ibid.

The lifecycle of AI hardware begins with the extraction of raw materials and the manufacturing process. The production of AI devices involves the extraction of precious metals, rare earth elements, and other valuable materials, many of which are non-renewable and require substantial energy inputs (Ferro et al., 2021). The extraction and processing of these materials contribute to environmental degradation and often involve hazardous substances that can harm ecosystems and human health.

As AI hardware advances rapidly, the lifecycle of devices becomes shorter, with newer models frequently replacing older ones. This phenomenon, known as planned obsolescence, exacerbates the e-waste predicament, as outdated AI devices are discarded, leading to a significant accumulation of electronic waste[13]. E-waste contains hazardous components such as lead, mercury, and flame retardants, which can leach into the environment and contaminate soil, water sources, and air if not properly managed.

The improper disposal and inadequate recycling of e-waste further compound the problem. Many electronic devices end up in landfills or are incinerated, releasing toxic substances and contributing to air and soil pollution[14]. Inadequate recycling practices also result in the loss of valuable resources that could be recovered and reused.

Policymakers play a crucial role in establishing regulations and incentives to promote proper e-waste management. Policies such as extended producer responsibility (EPR) can hold manufacturers accountable for the environmental impact of their products throughout their lifecycle, encouraging them to adopt sustainable practices and invest in recycling infrastructure[15]. Additionally, the development of effective collection systems, recycling programmes, and refurbishment initiatives can help divert AI devices from landfills and promote their reuse.

The circular economy approach offers a promising solution to the e-waste predicament. It emphasises the reuse, refurbishment, and recycling of electronic devices, aiming to minimise resource consumption and environmental impact (Ferro et al., 2021). By adopting circular economy principles, AI hardware can be designed and managed in a way that maximises its lifespan and reduces the need for constant upgrades, thus mitigating the generation of e-waste.

2.3. Strategies for responsible e-waste management in AI

In order to address the environmental concerns associated with electronic waste generated by AI hardware, several strategies have been proposed to promote responsible e-waste

13 Baldé, C. P., Forti, V., Gray, V., Kuehr, R., & Stegmann, P. (2017). The global e-waste monitor 2017: Quantities, flows and resources. United Nations University, International Telecommunication Union, and International Solid Waste Association.

14 Ibid.

15 Ibid.

management throughout the AI lifecycle. These strategies aim to mitigate the adverse impacts of e-waste disposal and contribute to a more sustainable approach to AI technology.

1. Incorporating Design for Disassembly (DfD) and Design for Recycling (DfR) principles in the design and manufacturing of AI hardware can facilitate the efficient separation and recycling of components. By ensuring that devices are designed with ease of disassembly and recyclability in mind, the amount of e-waste generated can be reduced.

2. The concept of Extended Producer Responsibility holds manufacturers accountable for the entire lifecycle of their products, including their proper disposal (Kahhat et al., 2008). Implementing EPR regulations specific to AI hardware can incentivize manufacturers to design products with recyclability in mind and take responsibility for their environmentally sound disposal and recycling.

3. Establishing effective take-back and recycling programs is crucial for facilitating the responsible disposal of AI hardware. Manufacturers can collaborate with specialised e-waste recyclers or set up collection points to ensure the proper recycling of AI devices and prevent them from ending up in landfills or informal recycling facilities.

Embracing the principles of a circular economy can help minimise e-waste generation by promoting resource efficiency and product reuse (Geissdoerfer et al., 2017). Strategies such as refurbishing and repurposing AI hardware, as well as creating secondary markets for used devices, can extend the lifespan of AI systems and reduce the need for new production.

Continued research and development of advanced recycling technologies are essential for improving the efficiency and effectiveness of e-waste recycling (Widmer et al., 2005). Innovations such as hydrometallurgical and biotechnological processes can extract valuable materials from AI hardware while minimising environmental impact and reducing the reliance on traditional extraction methods.

By implementing these strategies, responsible e-waste management practices can be integrated into the AI industry, leading to a more sustainable approach to AI hardware production, use, and disposal.

3. Data Centre Infrastructure

Data centres have witnessed significant growth in recent years due to the increasing demand for digital services. This expansion has resulted in a heightened environmental impact. The construction and operation of data centres require substantial land and resources, contributing to land use changes and habitat destruction (Mell & Grance, 2011). Moreover, the proliferation of data centres in urban areas has raised concerns about their impact on local communities and infrastructure.

Data centres are renowned for their high energy consumption. The constant operation of servers, networking equipment, and cooling systems demands a considerable amount of electricity. Cooling data centres poses particular challenges. The heat generated by servers and other IT equipment needs efficient dissipation to maintain optimal operating conditions. However, traditional cooling methods, such as air conditioning, are energy-intensive and inefficient. This has prompted the exploration of innovative cooling technologies, including liquid cooling and advanced airflow management systems, to enhance energy efficiency and reduce the environmental impact of data centres (Masanet et al., 2020).

Water is a vital resource used in data centres for cooling purposes. However, the substantial water consumption of data centres can strain local water resources, especially in regions already grappling with water scarcity or competing demands. Cooling towers, relying on evaporation, can consume significant volumes of water.

To address the environmental impact of data centres, industry stakeholders are actively exploring and implementing sustainable practices. These practices include:

Energy-efficient design: Data centres can adopt energy-efficient design principles, such as optimising server utilisation, improving power distribution systems, and utilising energy-efficient hardware. These measures can significantly reduce energy consumption and carbon emissions (Beloglazov et al., 2011).

Transitioning to renewable energy sources, such as solar or wind power, can assist data centres in reducing their dependence on fossil fuels and decreasing greenhouse gas emissions.

Rather than dissipating the heat generated by data centres, waste heat can be captured and utilised for other purposes, such as heating buildings or generating electricity. This approach maximises the energy efficiency of data centres and reduces their overall environmental impact.

Implementing water-efficient cooling technologies, such as closed-loop cooling systems and water-saving cooling towers, can help reduce water consumption in data centres. Additionally, recycling and reusing water within data centre operations can minimise the strain on local water resources.

By adopting these sustainable practices, data centres can strike a balance between meeting the increasing demand for digital services and minimising their environmental impact, contributing to a more sustainable and responsible digital infrastructure.

4. Understanding biases in AI training data

AI algorithms heavily rely on training data to make informed decisions. However, these datasets can often contain inherent biases, which can lead to biased outcomes in environmental decision-making. Biases in training data can arise from various sources, including historical data reflecting existing societal inequalities and systemic biases (Caliskan et al., 2017). It is crucial to recognise and address these biases to ensure fair and equitable environmental decision-making processes.

Biased AI applications in environmental decision-making can exacerbate existing environmental disparities faced by marginalised communities. For example, if AI algorithms are trained on datasets that disproportionately represent affluent areas, decisions regarding resource allocation or environmental policies may neglect the needs and concerns of marginalised communities (Benjamin, 2019). This further marginalises these communities, perpetuating environmental injustices.

Biased AI applications can perpetuate and amplify inequalities by reinforcing existing social, economic, and environmental disparities. For instance, if AI algorithms are biased against certain demographics or geographic areas, it can lead to unequal distribution of environmental benefits, such as access to clean air, water, or green spaces. Furthermore, biased algorithms can result in discriminatory outcomes, such as disproportionate pollution burdens or inadequate environmental protections in marginalised communities.

To mitigate the biases and promote fairness in AI environmental decision-making, several measures need to be taken:

It is essential to ensure that AI training datasets encompass diverse perspectives and accurately represent the affected communities. This requires careful curation of data to address underrepresentation and avoid reinforcing existing biases (Sweeney, 2013).

Developing AI algorithms that are transparent and explainable allows for scrutiny and identification of biases. This helps stakeholders, including affected communities, to understand how decisions are made and challenge potential biases (Burrell, 2016).

Continual monitoring and evaluation of AI systems are crucial to identify and rectify biases that may emerge over time. This involves ongoing assessment of AI applications' impacts on different populations and their alignment with equity and fairness goals (Crawford & Calo, 2016).

Involving affected communities in the design, implementation, and evaluation of AI environmental decision-making processes can help ensure fairness and equity.

By addressing biases in AI training data, acknowledging environmental disparities faced by marginalised communities, and implementing measures to promote fairness and equity, it is possible to mitigate the risks of AI amplifying environmental injustices. Responsible and inclusive AI applications can support informed and equitable decision-making processes that contribute to a more just and sustainable environment for all.

5. Disruption of Natural Ecosystems

The expansion of AI technologies and their integration into various sectors has raised concerns about their potential impact on natural ecosystems. One area of concern is the disruption of wildlife habitats and migration patterns. AI-driven infrastructure, such as the construction of data centers and communication networks, often requires significant land use, leading to habitat fragmentation and loss. This disruption can have adverse effects on wildlife populations by limiting their access to resources and disrupting crucial migration routes, ultimately posing a threat to biodiversity and ecological resilience.

The use of AI for environmental monitoring and conservation presents both opportunities and challenges. On one hand, AI enables efficient data collection, analysis, and interpretation, thereby enhancing our understanding of biodiversity, climate change, and ecosystem health. It enables us to detect patterns, make predictions, and inform conservation strategies. On the other hand, an overreliance on AI may result in a reduction in field-based research and human involvement, potentially overlooking the nuanced ecological processes that can only be observed through direct observation (Koh & Wich, 2012).

To mitigate the ecological disruption caused by AI, it is crucial to adopt responsible deployment practices. This includes conducting comprehensive environmental impact assessments before implementing AI technologies, evaluating potential risks to ecosystems, and identifying appropriate mitigation strategies. Moreover, it is important to integrate AI into existing conservation strategies and involve local communities in decision-making processes. This participatory approach fosters a holistic understanding of ecological systems and facilitates the co-design of AI applications that benefit both biodiversity and human well-being.

6. Existing Regulations Related to AI's Environmental Impact in the European Union

The growth of artificial intelligence has prompted governments and regulatory bodies to address its potential environmental impact. Some countries and regions have already taken steps to regulate the ecological cost of AI.

In the European Union, the EcoDesign Directive (2009/125/EC) has been extended to cover servers and data storage products since March 2020. This regulation sets minimum energy efficiency requirements for these products, including those used in AI hardware. It aims to reduce energy consumption and curb the environmental impact of data centers and other AI infrastructure components[16].

[16] Directive 2009/125/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for the setting of ecodesign requirements for energy-related products (recast) (Text with EEA relevance). (2009). Official Journal of the European Union, L 285, 10–35. https://clck.ru/36kxU5

Along with the EcoDesign Directive, the Waste Electrical and Electronic Equipment (WEEE) Directive plays a crucial role in the sustainable management of electronic waste, including AI hardware components. The WEEE Directive outlines rules for the proper handling and disposal of electronic waste, ensuring that discarded AI hardware is managed in an environmentally responsible manner. The responsibility for the collection and recycling of e-waste is placed on manufacturers and users, promoting the circular economy and minimizing the environmental impact of AI hardware disposal[17].

As part of the WEEE Directive's evaluation process, a public consultation on the EU Directive on waste electrical and electronic equipment was scheduled for June 2023. This consultation allows stakeholders and the public to provide feedback and input on the effectiveness and future improvements of the WEEE Directive.

The European Union has also implemented the Regulation (EU) 2019/424 on the eco-design requirements for servers and data storage products. This regulation, which entered into force in March 2020, aims to set minimum energy efficiency requirements for these products, including those used in AI hardware, with the purpose of reducing energy consumption and curbing the environmental impact of data centers and other AI infrastructure components[18].

These regulations within the European Union demonstrate the commitment to address the environmental impact of artificial intelligence and promote sustainable practices in the technology sector. By setting energy efficiency standards and promoting responsible e-waste management, the EU aims to foster a greener and more environmentally friendly approach to AI development and deployment.

Conclusion

In conclusion, when reflecting on the hidden ecological cost of AI, it becomes evident that we must acknowledge and address the environmental implications that come with its development and integration. The energy-intensive nature of AI computations, the generation of electronic waste, the disruption of natural ecosystems, and the potential for biased decision-making all highlight the need for proactive measures. By recognising the importance of sustainable practices such as energy-efficient algorithms, transitioning to renewable energy sources, responsible e-waste management, and ethical considerations, we can strive towards a more harmonious and environmentally conscious integration of AI.

[17] Consolidated text: Directive 2012/19/EU of the European Parliament and of the Council of 4 July 2012 on waste electrical and electronic equipment (WEEE) (recast) (Text with EEA relevance). https://clck.ru/36kxYS

[18] Commission Regulation (EU) 2019/424 of 15 March 2019 laying down ecodesign requirements for servers and data storage products pursuant to Directive 2009/125/EC of the European Parliament and of the Council and amending Commission Regulation (EU) No 617/2013 (Text with EEA relevance). (2019). Official Journal of the European Union, L 74, 46–66. https://clck.ru/36kxbm

It is our collective responsibility to navigate the path towards a better future where AI benefits both humanity and the planet. By prioritising environmental sustainability and taking proactive steps to mitigate the ecological footprint of AI, we can create a future that harnesses its potential while preserving and protecting our natural resources. Through collaboration, research, and the development of policies and regulations, we can shape the evolution of AI towards a more sustainable and ethically sound direction.

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Воздействие искусственного интеллекта на окружающую среду: скрытые экологические издержки и этико-правовые вопросы

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Ключевые слова

алгоритмическая предвзятость,
искусственный интеллект,
потребление энергии,
право,
природные экосистемы,
устойчивое развитие,
центр обработки данных,
цифровые технологии,
экологические издержки,
электронные отходы

Аннотация

Цель: выявление скрытых экологических издержек, связанных с разработкой, внедрением и развитием технологий искусственного интеллекта, с целью его устойчивой и гармоничной интеграции с различными секторами экономики путем определения оптимальных нравственно-этических и политико-правовых стратегий.

Методы: в основе проведенного исследования лежит экологический подход к разработке и внедрению искусственного интеллекта, междисциплинарный и политико-правовой анализ экологических проблем и рисков алгоритмической предвзятости, ошибок в алгоритмах искусственного интеллекта и процессах принятия решений, которые могут усугубить экологическое неравенство и несправедливость в отношении к окружающей среде. Кроме того, подвержены анализу вызванные развитием технологий искусственного интеллекта последствия разрушений природных экосистем, обусловленные энергоемким характером связанных с ним вычислений, растущим влиянием центров обработки данных на потребление энергии и проблем с их охлаждением, образование электронных отходов из-за быстрого совершенствования оборудования и др.

Результаты: проведенный анализ показывает разнообразие экологических, этических и политико-правовых проблем, связанных с обучением, использованием и развитием искусственного интеллекта, потребляющего значительное количество энергии (в основном из невозобновляемых источников), что приводит к увеличению выбросов углерода и создает препятствия для дальнейшего устойчивого экологического развития. Неправильная утилизация оборудования искусственного интеллекта усугубляет проблему электронных отходов, загрязнения планеты, еще больше нанося ущерб окружающей среде. Ошибки в алгоритмах искусственного интеллекта и процессах

принятия решений ведут к несправедливости в отношении окружающей среды и экологическому неравенству. Технологии искусственного интеллекта могут нарушать природные экосистемы, ставя под угрозу среду обитания диких животных и модели миграции.

Научная новизна: исследование экологических последствий использования и дальнейшего развития искусственного интеллекта, вызванных в связи с этим экологических нарушений и издержек устойчивого развития позволяет определить научный поиск оптимальных стратегий минимизации вреда окружающей среде, в котором правоведам и юристам предстоит установить этико-правовые и политико-правовые решения на национальном и наднациональном уровнях.

Практическая значимость: понимание экологического воздействия искусственного интеллекта имеет решающее значение для политиков, юристов, исследователей, отраслевых специалистов при разработке стратегий минимизации вреда окружающей среде. Полученные данные подчеркивают важность реализации энергоэффективных алгоритмов, перехода на возобновляемые источники энергии, внедрения ответственной практики обращения с электронными отходами, обеспечения справедливости при принятии решений искусственным интеллектом и учета этических соображений и правил его внедрения.

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