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The Environmental Cost of Intelligence: Corporate Obligations and a Governance Framework for Sustainable AI

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Abstract: The field of artificial intelligence has advanced incredibly fast in recent years with an increasing focus on larger language models, generative technologies, and infrastructure of deep learning. Such development has resulted in a substantial environmental cost that has been relatively ignored – the energy, water, and carbon emissions related to training, fine-tuning, and industrial-scale operation of AI. Training one single large language model is estimated to generate as many carbon dioxide emissions as several cars throughout their entire lifetime. Data centers used for AI operations are predicted to double their energy consumption by 2026, and the amount of water required to cool down AI-related equipment is becoming a limitation in places that are already facing water shortages. Research concerning these environmental impacts of AI has flourished, while corporate disclosure of its environmental footprint is extremely rare and highly inconsistent. In this paper, the Sustainable AI Governance Framework (SAGF) is developed as a conceptual model which defines environmental obligations for corporations during the whole AI lifecycle, from the development and training stage, through its deployment, maintenance, and decommissioning stages, and introduces governance approaches on three different levels – the firm level, industry level, and regulatory level. The SAGF uses principles of corporate environmental responsibility theory (Bansal & Roth, 2000; Schaltegger & Burritt, 2018), polluter pays principle, and recent developments regarding the environmental impact of AI (Patterson et al., 2022; Lottick et al., 2019; Strubell et al., 2019) to prove that the developers and users of AI technology have environmental obligations that are not able to be shifted elsewhere.

Keywords: Green AI, Sustainable AI, AI Environmental Footprint, Carbon Emissions, Corporate Environmental Responsibility, AI Governance

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1. Introduction

Intelligence has become the core of the business world, with AI affecting all sectors ranging from health care, finance, logistics, to creative industries. Discussions concerning the impact of artificial intelligence in businesses have been primarily on its economic and competitive potentialities: automating the process, decision-making, personalization of goods and services, and creation of value in a different form. However, there is another side that remains overlooked in both academia and practice — environmental implications of AI in businesses.

There are several aspects of how large AI models impact the environment. According to Strubell et al. (2019), training one large natural language processing model using neural architecture search produces about 284 tonnes of carbon dioxide equivalent. In this regard, the process produces about five times more emissions than an average car owned by an American in its entire lifetime. Patterson et al. (2022) looked into the energy consumption for AI systems developed at Google and found out that the energy expenditure for AI training increased by about 300,000 times from 2012 to 2022 due to exponential model size growth and the transition to accelerators. The International Energy Agency (IEA, 2024) estimated that the global demand for electricity in data centers, including increasingly more AI-related computing tasks, could double from 2022 to 2026 and reach the amount of electricity consumed by Japan altogether. Another environmental challenge stems from the need to have water to cool down data centers. According to Li et al. (2023), it takes 500 milliliters of water to cool down AI computations for a single chat session with ChatGPT.

This is occurring against a background of increased global determination to fight climate change and improve corporate sustainability. Meeting the 1.5-degree Paris Agreement objective will call for rapid and radical decarbonization within all economic sectors. The Corporate Sustainability Reporting Directive (CSRD) of the EU now obligates big companies to report their environmental impact, and pressure from investors for credible net zero pledges is changing corporate strategy. Existing frameworks and standards for corporate ESG do not address the environmental impact of AI sufficiently. Standards for greenhouse gas accounting (GHG Protocol, 2015) do not include a way to quantify the training and inference emissions from AI, there is no need for models' energy or water use to be reported in the integrated reporting framework, and the existing voluntary ethical AI framework, as well as that included in the EU AI Act, consider environmental sustainability less important than safety and fairness.

The purpose of this paper is to fill this governance gap by introducing the Sustainable AI Governance Framework (SAGF), which is a conceptual framework of corporate environmental obligations through the entire AI lifecycle. It makes three contributions. First, it provides the basis for a theoretical approach towards corporate environmental obligations in respect of AI technology, based on corporate environmental responsibility theory and the polluter pays principle. Second, it outlines corporate environmental obligations throughout the lifecycle of AI, from training to deployment, maintenance, and decommissioning. Third, it suggests various governance measures at the firm, industry, and regulatory levels which would make up an integrated governance framework for sustainable AI. This paper is organized as follows. In section 2, a review of literature is presented. In section 3, the SAGF is presented. Implications of the SAGF are discussed in section 4.

2. Review of Literature

2.1. AI's Environmental Footprint: Evidence from Science

Following Strubell et al.'s (2019) landmark calculation of carbon emissions related to training NLP models, academic studies have increased rapidly in scope. Other studies have corroborated and expanded on these findings, depending on the model architecture, generation of hardware used, and place of analysis. Currently, the most extensive analysis on this topic has been carried out by Patterson et al. (2022), who analyzed 88 models created at Google. The calculations carried out by them indicate that proper model architecture, hardware, and power supply from data centers can reduce training carbon emissions by 1,000 times.

In addition to these findings about carbon footprint, there have been some studies that have assessed the water footprint of artificial intelligence applications. For instance, Li et al. (2023) developed an integrated approach to measuring the water footprint of AI, which not only considers the direct use of water in the cooling process of data centers but also the indirect use related to energy production. Based on their assessment, the water footprint of large language model inference can be considered as a significant pressure on water resources in water-scarce regions. On the other hand, Lottick et al. (2019) were the pioneers in developing a standard measurement for the carbon footprint of ML experiments.

2.2. The Corporate Environmental Responsibility Theory

The theory on the obligations of companies for the environmental effects of artificial intelligence technology is based on the concept of corporate environmental responsibility (CER). Bansal and Roth (2000) say that ecological responsiveness from corporations is typically prompted by three motivations: competitiveness (activities performed by a corporation for ecological reasons that yield future gains), legitimacy (activities performed by a corporation for ecological reasons that coincide with socially approved practices), and ecological responsibility (activities performed by a corporation for purely ecological reasons). Legitimacy and ecological responsibility, rather than competitiveness alone, foster proactive environmental management.

The definition of corporate sustainability management according to Schaltegger & Burritt (2018) is that it entails the inclusion of environmental and social considerations within the activities of the company and they point out that sustainability demands an assessment of the environmental impacts of the organization throughout the entire value chain. In the case of AI, it would mean that companies need to take into consideration the environmental impact of the production chain of AI technology.

Another way to allocate corporate accountability in regard to the environmental harm caused by AI is through the polluter pays principle. It is a common environmental governance norm which suggests that the polluter should cover the costs related to pollution cleanup. According to this principle, corporations working on AI development and implementation must consider the amount of greenhouse gas emissions, water consumption, and hardware waste they produce irrespective of where these processes occur, either inside the company's operations or beyond them (Heede, 2019; OECD, 2008).

2.3. Existing AI Governance Frameworks and Limitations

The current AI regulatory frameworks lack sufficient coverage for environmental sustainability. For example, the EU AI Act, which is the first comprehensive legislative proposal addressing AI (European Parliament, 2024), introduces some standards for energy efficiency when using high risk AI systems, but does not impose any obligations on the disclosure of emissions or water usage in the process of AI development. Major tech corporations such as Google, Microsoft, IBM, and Meta have issued various voluntary codes of conduct related to AI that often include the goal of promoting sustainability but never any metrics or verifiable targets (Jobin et al., 2019). Moreover, at present there are no carbon accounting standards that would apply to emissions associated with developing and operating AI systems – the GHG Protocol Corporate Standard (GHG Protocol, 2015) is one of the most prominent examples of such standards.

3. The Framework of Sustainable AI Governance

3.1. Overview of the framework

The SAGF revolves around two perspectives; the first one being the perspective of the lifecycle stage of AI while the second perspective revolves around the level of governance. The complete matrix in table 1 reveals the major environmental impacts as well as the governance actions at each life cycle stage.

Table 1: The Sustainable AI Governance Framework (SAGF): Lifecycle Level Matrix

Lifecycle Stage	Firm Level Obligations	Industry Level Standards	Regulatory Requirements
Training	Measure and disclose training emissions; optimize architecture for efficiency; use renewable energy; select low carbon data center locations	Standardize training emission reporting metrics (CO_2e, energy kWh, PUE); develop model efficiency benchmarks	Mandate pre training environmental impact assessment for large models; require public disclosure of training carbon budget
Deployment	Monitor inference energy per query; disclose aggregate inference emissions; optimize serving infrastructure efficiency	Develop inference efficiency leaderboards; standardize energy per query reporting across model providers	Include AI inference emissions in Scope 2/3 GHG reporting requirements; mandate water consumption disclosure for data centers
Maintenance	Account for fine tuning and update emissions; assess whether model updates reduce or increase environmental impact per task	Develop lifecycle environmental management standards for AI systems; include maintenance impacts in model cards	Require lifecycle environmental accounting in AI product documentation for regulated sectors
Decommissioning	Account for hardware disposal impacts; implement responsible e waste management for AI hardware; publish end of life plans	Develop AI hardware circular economy standards; establish industry take back schemes for AI accelerator chips	Apply existing e waste regulation to AI hardware; require responsible disposal plans as condition of large model deployment authorization

3.2. Firm Level Obligations

As viewed from the standpoint of a business, the SAGF describes the responsibilities for the environment along four major groups. The obligation for measurement and reporting entails the responsibility on the side of firms not just to measure the environmental footprint but also to report about the environmental impact of its AI technologies at every stage of life cycle according to such metrics as carbon dioxide equivalent, electricity consumption in kilowatt hours, water consumption in liters and hardware waste in kilograms. In addition to the measurement and reporting of their own impact, companies have to account for the impact of the entire value chain related to the usage of AI technologies such as the energy consumption by third-party data centers, impact of hardware production and embedded emissions caused by cloud computing services.

A firm is advised to carry out a structured approach towards evaluating and reducing its environmental impact based on unit of AI performance because as the AI becomes more capable, then its environmental impact has to be measured against the output of AI performance. The topic has been addressed widely by authors Lottick et al. (2019). Efficiency optimization by Patterson et al. (2022) leads to reductions in training emissions without affecting performance. In case where a firm relies on outside firms for their AI infrastructure such as cloud computing firms, data centers, or specialist hardware producers, then there is need for using environmental considerations.

3.3. Industry Level Standards

Industry-level governance is crucial in terms of developing common measurements and standards, which are necessary for both the environmental management of individual firms and regulations. What is most important is standardization of measurement as the absence of a way of verifying and measuring emissions from the usage and training of AI makes it impossible to verify the information provided by companies. Among other priority tasks is the extension of current carbon emission measurement of corporations, including the GHG Protocol Corporate Standard (GHG Protocol, 2015).

Model cards are the documentation that highlights the benefits, drawbacks, and uses of an AI model and which accompanies the AI model (Mitchell et al., 2019). This is an existing practice in the industry which can easily be used to document the environmental impact of the AI models. If extended model cards become common practice in the industry, it would significantly increase transparency in the disclosure of AI's environmental impacts without any need for regulation.

3.4. Regulatory Oversight

Regulatory intervention is necessary for ensuring that the governance tools at the level of the individual firm and at the industry level deliver true environmental accountability, rather than simply being a way of speaking about sustainability. The SAGF identifies three areas in which regulatory action should be taken. There should be disclosure obligations that are akin to those of the SEC and the CSRD requirements of the EU, which should include details on AI-specific environmental impacts, as well as disclosure of the training emissions, overall inference energy consumption, and water consumption of large-scale AI providers and users. Environmental impact assessments should be mandatory prior to the deployment of very large AI models, in the same way that they are required for large infrastructure projects (European Parliament, 2024; IEA, 2024).

4. Discussion

SAGF asks for much more transparency in terms of environmental effects from the use of AI compared to existing practice. Tech giants issue annual sustainability reports, which outline their aims and activities, including the use of renewable sources of energy and improvement in data centers efficiency. What is missing in these reports is information on training emissions, inference energy, and water use in AI. It is not a question of measuring because there are already methods of measuring such effects in academic literature (Lottick et al., 2019; Patterson et al., 2022; Strubell et al., 2019).

There are various implications of the adherence of SAGF to the polluter pays principle when it comes to the costs associated with environmental management of AI. Should the developers and users of AI be made responsible for the impacts that their technologies generate, such as greenhouse gases or water pollution, then the costs associated with assessing and mitigating these impacts will not anymore be imposed on the general public through the hidden climate costs but should appear directly in AI products pricing and investments. Thus, the polluter pays principle implies the necessity of implementing various regulatory policies such as carbon pricing, environmental impact fees, and environmental liability insurance, which will force companies to reduce the negative impacts of AI on the environment (Heede, 2019; OECD, 2008).

The adoption of the polluter pays principle would have an impact on corporate ESG strategies. Firms that develop sustainable AI based on energy sourcing, hardware improvement, and environmental reporting would be advantaged with respect to ESG regulations becoming stringent and institutions enhancing their assessment of AI risks. The reputation and regulatory risks of failing to address the environmental impact of AI are increasing rapidly, and firms that develop sustainable AI would have an edge over others in governance terms (Bansal & Roth, 2000; Schaltegger & Burritt, 2018).

5. Conclusion

This paper has outlined the Sustainable AI Governance Framework (SAGF) which represents the conceptual framework of corporate environmental duties covering the whole AI life cycle, at both firm-, industry-, and regulator-level. This framework has addressed the increasingly urgent problem of environmental concern which is still widely unrecognised – energy consumption, carbon footprint, and water usage associated with the production and utilisation of AI. Based on the theories of corporate environmental responsibility, the polluter pays principle, and the findings from the existing scientific literature on the environmental impacts of AI, this paper has outlined the actual duties of firms engaged in the production and use of AI concerning the issues of measurement and disclosure, efficiency enhancement, supply chain management, and decommissioning. While the foremost step towards the successful governance of the environmental impacts of AI is the regulation aimed at making the measurement and pre-deployment assessment of AI's environmental footprint mandatory, the development of standards for measurement of this impact would be the necessary precondition for the proper management of the companies and regulation at large.

References

Bansal, P., & Roth, K. (2000). Why companies go green: A model of ecological responsiveness. *Academy of Management Journal*, 43(4), 717 to 736. https://doi.org/10.2307/1556363

European Parliament. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council laying down harmonised rules on artificial intelligence* (Artificial Intelligence Act). Official Journal of the European Union.

GHG Protocol. (2015). *Corporate accounting and reporting standard* (Revised ed.). World Resources Institute & World Business Council for Sustainable Development.

Heede, R. (2019). *Carbon majors: Updating activity and emissions data for the world's largest oil and gas companies*. Climate Accountability Institute.

IEA. (2024). *Electricity 2024: Analysis and forecast to 2026*. International Energy Agency.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389 to 399. https://doi.org/10.1038/s42256-019-0088-2

Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). *Making AI less 'thirsty': Uncovering and addressing the secret water footprint of AI models*. arXiv preprint arXiv:2304.03271.

Lottick, K., Susai, S., Friedler, S. A., & Wilson, J. P. (2019). *Energy usage reports: Environmental awareness as part of algorithmic accountability*. *NeurIPS Workshop on Tackling Climate Change with Machine Learning*. arXiv preprint arXiv:1911.08354. https://doi.org/10.48550/arXiv.1911.08354

Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). *Model cards for model reporting*. Proceedings of the Conference on Fairness, Accountability, and Transparency, 220 to 229. https://doi.org/10.1145/3287560.3287596

OECD. (2008). *The polluter pays principle: Definition, analysis, implementation*. OECD Publishing. https://doi.org/10.1787/9789264044845-en

Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L.-M., Rothchild, D., So, D. R., Texier, M., & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. *Computer,* 55(7), 18 to 28. https://doi.org/10.1109/MC.2022.3148714

Schaltegger, S., & Burritt, R. (2018). Business cases and corporate engagement with sustainability: Differentiating ethical motivations. *Journal of Business Ethics*, 147(2), 241 to 259. https://doi.org/10.1007/s10551-015-2938-0

Strubell, E., Ganesh, A., & McCallum, A. (2019). *Energy and policy considerations for deep learning in NLP*. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 3645 to 3650. https://doi.org/10.18653/v1/P19-1355