Towards a systemic framework for assessing the environmental rebound effects of Artificial Intelligence

Anonymous

Why Assess the carbon footprint of Artificial Intelligence?

With the rapid expansion of deployment of digital services in diverse domains, the environmental implications of Information and Communication Technologies (ICTs) have become an important concern. A recent meta-analysis of ICT-related greenhouse gas (GHG) emissions estimates that after correcting for methodological biases, the sector's carbon footprint rises to 1.2 – 2.2 GtCO2e, corresponding to 2 – 4% of global GHG emissions (Freitag et al., 2021).

Although efficiency improvements have been achieved in ICT sector (Masanet et al., 2020), there is a strong warning that the associated gains in energy consumption could be offset by increasing demand for computational services, illustrating the so-called *rebound effect*, or Jevons' paradox. Empirical studies confirm this trend, showing that overall energy use in ICT has never declined despite successive technological optimizations (Freitag et al., 2021).

Artificial Intelligence (AI) is a particularly significant driver of this computational demand. In this text, I use the term "AI" in a broad sense, to refer to complex learning systems, most often based on deep learning. However, the concept of what constitutes an AI system remains ambiguous, since there is no consensus on a precise boundary that would clearly separate AI from other computational approaches. The rapid progress of machine learning and especially deep learning has resulted in models whose training and inference require massive amounts of resources (Ligozat et al., 2022; Strubell et al., 2020). For instance, training a single large language model such as GPT-3 has been estimated to emit roughly 500 tCO2e (Luccioni et al., 2023).

Despite growing concern, quantifying the environmental footprint of ICT and AI remains challenging. According to Roussilhe and Berthoud, 2021, three major obstacles restrict systematic assessment:

1. ICT systems are ubiquitous, making it difficult to define what should or should not be included in the system boundaries.
2. Critical information is often proprietary and not shared by companies, leading to inconsistent or controversial estimates (e.g. between Malmodin and Lundén, 2018 and Andrae and Edler, 2015 on ICT footprint projections).
3. ICT is strongly associated with innovation, progress and economic growth narratives, reinforcing technosolutionism imaginary.

I argue that these obstacles, although originally described for ICT in general, are equally relevant to AI. However, AI introduces additional challenges: among others, its pervasive integration into economic systems, social behaviours, and policy frameworks generates system-level dynamics that make rebound effects particularly significant, yet difficult to capture.

Existing approaches to measuring AI's environmental impacts

The scientific community has begun addressing this challenge through two main approaches. First, micro-level studies focus measuring or estimating the energy consumption and GHG emissions of specific AI models, either in training or use phase (Patterson et al., 2021; Strubell et al., 2020; Thompson et al., 2020), as well as developing practical tools to support those measures (Gay et al., 2024) and estimations (García-Martín et al., 2019). Second, broader appraoches adapt Life Cycle Assessment (LCA) methodology from industrial ecology to AI systems (Berthelot et al., 2024; Ligozat et al., 2022; Wu et al., 2022). LCA offers a standardized international framework to evaluate environmental impacts across the full life cycle of technologies, from hardware manufacturing to end-of-life disposal, thus going beyond operational and direct energy use alone.

While these approaches provide valuable insights, they offer only a partial view of AI's environmental impacts, leaving important gaps unaddressed. For instance, most existing studies rely on *attributional* LCA, which captures impacts per functional unit. However, such approach struggles to account for rebound effects, macroeconomic dynamics, and systemic behavioural changes, since it generally assumes fixed demand and does not account for the indirect or systemic changes that general AI adoption may trigger.

In parallel, social science perspectives emphasise that understanding AI's environmental footprint requires analysing its materiality as well as interactions with society at multiple scales (Crawford, 2021; Tamburrini, 2022), and calls to integrate rebound effects more explicitly in assessments of AI and ICT systems are recurrent (Galvin & Gubernat, 2016; Seebauer, 2018). As emphasised by Rudolf, 2017, "A study bounded by disciplinary frontiers of a scientific or technical innovation cannot be accepted insofar as it underestimates the potential dynamics generated by the circulation of novel products and unprecedented services."[1]. Building on this perspective, Luccioni et al., 2025 recently argued in the specific context of AI rebound effect measurement that, "understanding rebound effects requires drawing on both qualitative and quantitative methods, drawn from computer science, economics and the social sciences, as they hinge not on algorithmic design but human adaptation and use patterns.".

Towards a systemic and interdisciplinary analytical framework

To capture the indirect and systemic effects of AI systems, among them the rebound effect, I argue that it is necessary to move beyond disciplinary silos and to adopt approaches capable of analysing complex socio-technical systems. This implies conducting a systemic analysis, both quantitatively and qualitatively, of the environmental pressures of AI systems, considering not only direct emissions but also indirect effects such as rebound dynamics, supply chain interdependencies, and behavioural change. Ultimately, disseminating insights and supporting policy processes requires situating results and proposed alternatives in a normative and context-specific framework, in other words one that considers local environmental concerns such as land use change, water resource management, and ecosystem preservation, in addition to carbon oriented measurements.

To achieve this, I propose a unified framework of analysis that integrates insights from ecological economics, computer science, and science and technology studies (STS) in order to:

- Capture indirect effects such as rebound dynamics within ICT and in particular AI systems.
- Map systemic interdependencies across economic, technical, and social dimensions.
- Situate environmental impacts in normative local contexts to empower policy-makers to devise novel action strategies.

In this proposal, each perspective contributes to distinct but complementary insights, and together they enable a systemic analysis of AI's environmental footprint.

From ecological economics, I suggest to adopt *Structural Path Analysis* (SPA) (Defourny & Thorbecke, 1984) as a means to trace environmental pressures across supply chains. SPA is a decomposition technique in input–output analysis (Leontief, 1936) that traces the chains of dependencies behind final demand, therefore revealing indirect and higher-order effects. It is useful for studying rebound effects as it transparently maps how efficiency gains or behavioural shifts propagate through socio-technical systems, highlighting unintended systemic feedbacks (Freire-González et al., 2025; Wang et al., 2025).

I propose to enrich this perspective with network science, which offers tools to represent supply chains as networks of processes, producers, and consumers. Centrality metrics, such as PageRank (Page et al., 1999) or betweenness (Freeman, 1977), then allow us to emphasise the most influential nodes in the network, as well as dominant pathways in the system. This complements SPA by revealing how rebound effects propagate through the structure of interdependencies and by identifying crucial sectors or actors for intervention within a policy-guiding oriented perspective

[1] Author translation.

Finally, insights from STS are essential to situate these quantitative analyses within the broader socio-technical context. AI systems are not only technical infrastructures but also cultural and organizational artifacts shaped by human practices and economic incentives. Qualitative analyses in the form of semi-structured interviews for instance, for examining how data is produced, or how professional practices adapt to AI, would shed light on the human and institutional dynamics that drive rebound effects. Additionally, modelling interactions between human and non-human actors (Latour, 1987) is essential for capturing the feedback loops and systemic dynamics underlying rebound effect.

By combining these three perspectives, our framework moves beyond isolated technical or economic models to deliver a comprehensive analysis of AI's environmental impacts, with a specific focus on rebound effect. In practice, integrating SPA, network science, and STS is challenging because it involves combining distinct epistemologies and data types. Quantitative frameworks like SPA were developed for material or economic flows, making it difficult to represent complex, adaptive human behaviours and the feedback loops between social and technical systems. Existing studies have mainly avoided this integration by focusing either on physical flows or on human practices, rarely combining both into a comprehensive analysis.

The environmental impacts of AI arise from complex interactions between technical systems and human behaviours. While AI is often framed primarily as a driver of economic growth, the study and quantification of its environmental consequences, particularly through rebound effect, remains largely undone. Addressing this gap requires a systemic and interdisciplinary approach that captures material pressures and systemic interdependencies. Our proposal meets this need by integrating SPA, network analysis, and STS, providing a framework that simultaneously accounts for physical flows and interdependencies between humans and non-humans.

References

Andrae, A. S. G., & Edler, T. (2015). On Global Electricity Usage of Communication Technology: Trends to 2030. *Challenges*, *6*(1), 117–157.

Berthelot, A., Caron, E., Jay, M., & Lefèvre, L. (2024). Estimating the environmental impact of generative-AI services using an LCA-based methodology. *Procedia CIRP*, *122*, 707–712.

Crawford, K. (2021). *The atlas of ai: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

Defourny, J., & Thorbecke, E. (1984). Structural path analysis and multiplier decomposition within a social accounting matrix framework. *The Economic Journal*, *94*(373), 111–136.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 35–41.

Freire-González, J., Chen, Q., & Bordón-Lesme, M. (2025). Worldwide rebound effects: A multiregional input–output analysis.

Freitag, C., Berners-Lee, M., Widdicks, K., Knowles, B., Blair, G. S., & Friday, A. (2021). The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations. *Patterns*, *2*(9).

Galvin, R., & Gubernat, A. (2016). The rebound effect and schatzki's social theory: Reassessing the socio-materiality of energy consumption via a german case study. *Energy Research & Social Science*, *22*, 183–193.

García-Martín, E., Rodrigues, C. F., Riley, G., & Grahn, H. (2019). Estimation of energy consumption in machine learning. *Journal of Parallel and Distributed Computing*, *134*, 75–88.

Gay, P., Bilinski, É., & Ligozat, A.-L. (2024). Coca4ai: Checking energy behaviors on AI data centers.

Latour, B. (1987). *Science in action: How to follow scientists and engineers through society*. Harvard university press.

Leontief, W. W. (1936). Quantitative input and output relations in the economic systems of the united states. *The review of economic statistics*, 105–125.

Ligozat, A.-L., Lefèvre, J., Bugeau, A., & Combaz, J. (2022). Unraveling the hidden environmental impacts of AI solutions for environment life cycle assessment of AI solutions. *Sustainability*, *14*(9), 5172.

Luccioni, A. S., Strubell, E., & Crawford, K. (2025). From efficiency gains to rebound effects: The problem of jevons' paradox in AI's polarized environmental debate. *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency*, 76–88.

Luccioni, A. S., Viguier, S., & Ligozat, A.-L. (2023). Estimating the carbon footprint of bloom, a 176b parameter language model. *Journal of machine learning research*, *24*(253), 1–15.

Malmodin, J., & Lundén, D. (2018). The energy and carbon footprint of the global ICT and E&M sectors 2010–2015. *Sustainability*, *10*(9).

Masanet, E., Shehabi, A., Lei, N., Smith, S., & Koomey, J. (2020). Recalibrating global data center energy-use estimates. *Science*, *367*(6481), 984–986.

Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). *The pagerank citation ranking: Bringing order to the web.* (tech. rep.). Stanford infolab.

Patterson, D., Gonzalez, J., Le, Q., Liang, C., Munguia, L.-M., Rothchild, D., So, D., Texier, M., & Dean, J. (2021). Carbon emissions and large neural network training. *arXiv preprint arXiv:2104.10350*.

Roussilhe, G., & Berthoud, F. (2021). Le numérique face à la crise environnementale. *Alternatives Non-Violentes*, *199*(2), 11–13.

Rudolf, F. (2017). La sociologie de l'environnement ou le naturalisme revisité. *Socio-logos. Revue de l'association française de sociologie*, (12).

Seebauer, S. (2018). The psychology of rebound effects: Explaining energy efficiency rebound behaviours with electric vehicles and building insulation in austria. *Energy research & social science*, *46*, 311–320.

Strubell, E., Ganesh, A., & McCallum, A. (2020). Energy and policy considerations for modern deep learning research. *Proceedings of the AAAI conference on artificial intelligence*, *34*(09), 13693–13696.

Tamburrini, G. (2022). The AI carbon footprint and responsibilities of AI scientists. *Philosophies*, *7*(1), 4.

Thompson, N. C., Greenewald, K., Lee, K., & Manso, G. F. (2020). The computational limits of deep learning. *arXiv preprint arXiv:2007.05558*.

Wang, W., Cai, Z., Zhu, Y., Yu, D., Zhan, J., Li, X., & Wang, X. (2025). Mitigating CO2 emissions associated with digital economy sectors through whole supply chain management. *PLoS One*, *20*(5), e0323350.

Wu, C.-J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., Chang, G., Aga, F., Huang, J., Bai, C., et al. (2022). Sustainable AI: Environmental implications, challenges and opportunities. *Proceedings of machine learning and systems*, *4*, 795–813.