What is in Red AI? Scoping the Energy and Environmental Impacts of Artificial Intelligence

BY REID LIFSET AND ALAN PORTER

The energy consumed in training generative and other computationally-intensive forms of artificial intelligence (AI) is attracting increasing attention from computer scientists, energy modelers, policy makers, and the public. However, the development and use of AI has other potential energy and environmental impacts. Building on bibliometric analysis, this article describes impacts that are the focus of current research—energy use in training AI—those starting to be characterized in the research literature—energy use in inference—and those impacts that exist or are hypothesized to exist but have drawn little attention from researchers—including indirect impacts from the use of AI, rebound effects, and misleading inferences in environmental management and policy relying on the use of AI.

Artificial intelligence (AI) has the potential to enable increases in energy efficiency and other improvements in the energy system (Donti and Kolter, 2021; Rolnick *et al.*, 2022). Researchers and AI developers are keen to propose ways to use digital technology for environmental improvement. Scans of the literature on AI and the environment suggest that research on environmentally beneficial applications are legion (Mosavi *et al.*, 2019; Haupt *et al.*, 2022; He *et al.*, 2022).

In 2020, Schwartz et al. published "Green AI" in the *Proceedings of the Association for Computing Machinery* arguing that the AI research community "needed to make efficiency an evaluation criterion for research alongside accuracy and related measures in the development of AI". They dubbed AI research that is more environmentally friendly and inclusive as "Green AI" and that which is not as "Red AI." That paper along with seminal work in the same period, such as that by Strubell et al. (2019), prompted attention and efforts by computer scientists to address energy consumption in AI.

The potential negative energy and environmental impacts, however, are not limited to the direct energy consumed and the resulting greenhouse gas (GHG) emissions from the development of AI. Those impacts can include indirect impacts arising from the use of AI, impacts other than energy consumption and attendant emissions, and environmentally harmful changes in production and consumption. This short piece draws on an ongoing bibliometric analysis to develop search algorithms to identify research on Red AI (Porter, Lifset and Lee, 2024). For brevity, we adopt and stretch the term "Red AI," using it as shorthand for diverse potential energy and environmental impacts of AI.

Here, we describe the scope of potential environmental impacts—some of which are the focus of current research and others which have not drawn much or any attention. This is not a literature review, a synthesis of current quantitative findings, nor a bibliometric analysis, but an effort to draw attention to the range of potential impacts that can benefit from the attention of energy and environmental researchers. The references provided are not comprehensive but rather are intended as an entrée to literature.

Reid Lifset is a Research Scholar at the Yale School of the Environment and a co-leader of the Network for the Digital Economy & the Environment (NetworkDEE.org). He can be reached at reid.lifset@yale.edu. **Alan Porter** is Director, R&D, Search Technology, Inc., and Emeritus Professor, Georgia Tech

There are many different types of AI, but here we focus primarily on generative AI, the approach that underlies the now familiar chatbots. Generative AI can create new data—such as text, images, video, code, and audio—rather than, as with other types of AI, making a prediction about a specific dataset. Development of generative AI requires training, a process where the AI model is fed very large amounts of data, asked to make decisions based on the information, and then adjusted based on the AI output's accuracy. Because it is computationally intensive, generative AI models are typically energy intensive.

Direct Energy and Environmental Impacts

In response to calls for Green AI, computer scientists are increasingly looking for ways to reduce energy and GHG impacts of AI compute, that is, the development and use of software and hardware used in AI (OECD, 2022). This includes proposing ways to make training more computationally efficient (e.g., Treviso *et al.*, 2023); devising tools to measure energy consumption or emissions from AI models (e.g., Bannour *et al.*, 2021; Lannelongue and Inouye, 2023); and, debating likely trajectories of energy in AI development (Bender *et al.*, 2021; Patterson *et al.*, 2022; Luccioni, Jernite and Strubell, 2023; Castro, 2024). Much of the growing computer science literature focuses on methods to reduce the computational intensity of AI (Verdecchia, Sallou and Cruz, 2023).

Less common are analyses of energy consumed in the use of AI, known in computer science as "inference" (Luccioni, Jernite and Strubell, 2023). In part, this is because, while training typically occurs in data centers, inference may be disbursed among sites, equipment, and devices. While individual instances of inference typically consume little energy, inference has the potential to be a much greater consumer of energy because of the scale of usage (Kaack *et al.*, 2022; Vries, 2023). Research on energy consumed in specific uses of AI is limited. Some research on the carbon footprint of medical uses of AI is emerging (e.g., Yu *et al.*, 2022; Doo *et al.*, 2024) Energy consumed by AIs in the serving of digital advertising, a ubiquitous phenomenon, has attracted little research (Pärssinen *et al.*, 2018; Wu *et al.*, 2022; Pesari, Lagioia and Paiano, 2023).

Analysis of other instances of direct energy use by AI raises conceptual issues of causality, responsibility, and boundaries. The issue of causality can be illustrated through the examples of robots and autonomous vehicles. If use of a robot results in environmental damage and the robot employs AI in its functions, it is not clear whether the damage should be deemed an impact of the AI—no more than the material of which the robot is composed would be viewed as causing the damage.[1] Autonomous vehicles (AVs) present another conundrum in defining Red AI. The environmental impact of AVs may arise primarily from the increases in transportation and emissions that they engender, but AVs, unlike some other technologies, conspicuously would not exist at all without AI. A substantial literature exists on energy use by AVs, focusing efforts to estimate likely types and extent of use (Taiebat *et al.*, 2018). A literature on the footprint of data processing and transmission including AI in autonomous vehicles is emerging (Sudhakar, Sze and Karaman, 2023).

Other Direct Environmental Impacts of AI

Data centers where much AI compute occurs face issues in addition to energy use. Water use is drawing increased public concern, especially in places where data centers are concentrated or water supplies are constrained (Doorn, 2021; Mytton, 2021; Lei *et al.*, 2024). In a review of research needs on the environmental impacts of AI, the Organisation for Economic Cooperation and Development has called for more attention to non-energy impacts of AI including biodiversity (OECD, 2022).

Embodied Energy and Carbon

As operational energy use in computation improves, the relative importance of the impacts of producing the equipment used in AI grows. Embodied energy and carbon are attracting increasing attention (Gupta *et al.*, 2022; Wu *et al.*, 2022).

Generation of e-waste arising from AI

In some domains of the digital economy, changes in technology cause digital equipment to become obsolete. For example, in the mining of cryptocurrency, competition pressure has led to the rapid evolution of mining rigs with resulting turnover of equipment and generation of e-waste (de Vries and Stoll, 2021). Changes in the hardware used for AI could also increase the generation of e-waste.

Indirect Energy and Environmental Impacts of AI

Indirect energy and environmental impacts of AI are diverse and potentially legion with little systematic treatment. A modest but growing research literature on the indirect environmental impacts of digitization (Horner, Shehabi and Azevedo, 2016; Bieser and Hilty, 2018; Vaddadi *et al.*, 2020) does not address AI specifically. Such impacts include both shifts in consumer and producer behavior in response to changes in capabilities and costs, and broader structural changes in the economy and society. Among the indirect impacts are increases in energy consumption arising from functionality, availability, or costs of digital platforms enabled by AI and internet search (Wu *et al.*, 2022).

An important, but understated, indirect impact is increased production or consumption arising from efficiencies generated by AI. Such rebound effects are well known to and studied by energy economists (e.g., Herring and Sorrell, 2009), but, to our knowledge, only a small number of analyses of rebound effects from digitization have been conducted (e.g., Coroama and Pargman 2020; Gossart 2015). Very few papers have been published examining rebound arising from AI (Ertel, 2019; Adha and Hong, 2021; Willenbacher, 2021; Willenbacher, Hornauer and Wohlgemuth, 2022).

Other Research on Red AI

Incorrect or misleading algorithms

Algorithms developed for environmental research or management could produce misleading guidance or damaging outcomes (Rillig *et al.*, 2023). AI models can also incorporate racial or social bias or hallucinate, i.e., create false information, including nonexistent scientific references (Zhu *et al.*, 2023).

Infrastructure risk, security risk, and cascading failures

Reliance on artificial intelligence could lead to risk to infrastructure if algorithms are faulty (Nishant, Kennedy and Corbett, 2020; Galaz *et al.*, 2021; Robbins and van Wynsberghe, 2022). While this risk appears to be little different than risk arising from other forms of digitally-based management systems, AI could lead to greater autonomy of digital management or the problem of the inability to understand the basis for decisions produced through AI (Vinuesa and Sirmacek, 2021; Islam *et al.*, 2022). Similarly, increased reliance on digital management, because of the capabilities of AI, could lead to security risks if the AI applications are vulnerable.

Other Environmental Concerns

There are other environmentally related concerns voiced in the research literature that have varying degrees of connection to energy issues. These include ethical critiques (e.g., Dauvergne, 2021), discussions of potential negative impacts of smart cities (e.g., Colding and Barthel, 2017), and the likely impact of AI on the sustainable development goals (SDGs) (Vinuesa *et al.*, 2020).

Much is unknown about Red AI. As noted above, the likely magnitude of the impacts arising from the growth of AI such as training AI models—currently a focus of study—is contested. The character and significance of other potential impacts such as misleading algorithms or increases in e-waste remain largely unexplored.

References

Adha, R. and Hong, C.-Y. (2021) 'How Large the Direct Rebound Effect for Residential Electricity Consumption When the Artificial Neural Network Takes on the Role? A Taiwan Case Study of Household Electricity Consumption', *International Journal of Energy Economics and Policy*, 11(3), pp. 354–364.

Bannour, N. *et al.* (2021) 'Evaluating the carbon footprint of NLP methods: a survey and analysis of existing tools', *SUSTAINLP* [Preprint]. Available at: https://doi.org/10.18653/v1/2021.sustainlp-1.2.

Bender, E.M. *et al.* (2021) 'On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?' in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. New York, NY, USA: Association for Computing Machinery (FAccT '21), pp. 610–623. Available at: https://doi.org/10.1145/3442188.3445922.

Bieser, J.C.T. and Hilty, L.M. (2018) 'Indirect Effects of the Digital Transformation on Environmental Sustainability: Methodological Challenges in Assessing the Greenhouse Gas Abatement Potential of ICT', in. *ICT4S2018. 5th International Conference on Information and Communication Technology for Sustainability*, pp. 68–53. Available at: https://doi.org/10.29007/lx7q.

Castro, D. (2024) *Rethinking Concerns About AI's Energy Use*. Center for Data Innovation, Information Technology and Innovation Foundation (ITIF). Available at: https://itif.org/publications/2024/01/29/rethinking-concerns-about-ai-energy-use/ (Accessed: 29 February 2024).

Colding, J. and Barthel, S. (2017) 'An urban ecology critique on the "Smart City" model', *Journal of Cleaner Production*, 164, pp. 95–101. Available at: https://doi.org/10.1016/j.jclepro.2017.06.191.

Coroama, V.C. and Pargman, D. (2020) 'Skill rebound: On an unintended effect of digitalization', in *ACM International Conference Proceeding Series*, pp. 213–219. Available at: https://doi.org/10.1145/3401335.3401362.

Dauvergne, P. (2021) 'The globalization of artificial intelligence: consequences for the politics of environmentalism', *Globalizations*, 18(2), pp. 285–299. Available at: https://doi.org/10.1080/14747731.2020.1785670.

Donti, P.L. and Kolter, J.Z. (2021) 'Machine Learning for Sustainable Energy Systems', *Annual Review of Environment and Resources*, 46(1), pp. 719–747. Available at: https://doi.org/10.1146/annurev-environ-020220-061831.

Doo, F.X. *et al.* (2024) 'Economic and Environmental Costs of Cloud Technologies for Medical Imaging and Radiology Artificial Intelligence', *Journal of the American College of Radiology*, 21(2), pp. 248–256. Available at: https://doi.org/10.1016/j.jacr.2023.11.011.

Doorn, N. (2021) 'Artificial intelligence in the water domain: Opportunities for responsible use', *Science of The Total Environment*, 755, p. 142561. Available at: https://doi.org/10.1016/j.scitotenv.2020.142561.

Ertel, W. (2019) 'Artificial Intelligence, the spare time rebound effect and how the ECG would avoid it', in *International Conference: Economy for the Common Good*, Bremen, p. 4.

Galaz, V. *et al.* (2021) 'Artificial intelligence, systemic risks, and sustainability', *Technology in Society*, 67, p. 101741. Available at: https://doi.org/10.1016/j.techsoc.2021.101741.

Gossart, C. (2015) 'Rebound Effects and ICT: A Review of the Literature', in L.M. Hilty and B. Aebischer (eds) *ICT Innovations for Sustainability*. Cham: Springer International Publishing (Advances in Intelligent Systems and Computing), pp. 435–448. Available at: https://doi.org/10.1007/978-3-319-09228-7_26.

Gupta, U. *et al.* (2022) 'Chasing Carbon: The Elusive Environmental Footprint of Computing', *IEEE Micro*, 42(4), pp. 37–47. Available at: https://doi.org/10.1109/MM.2022.3163226.

Haupt, S.E. *et al.* (2022) 'The History and Practice of AI in the Environmental Sciences', *Bulletin of the American Meteorological Society*, 103(5), pp. E1351–E1370. Available at: https://doi.org/10.1175/BAMS-D-20-0234.1.

He, P. *et al.* (2022) 'Towards green smart cities using Internet of Things and optimization algorithms: A systematic and bibliometric review', *Sustainable Computing: Informatics and Systems*, 36, p. 100822. Available at: https://doi.org/10.1016/j.suscom.2022.100822.

Herring, H. and Sorrell, S. (eds) (2009) *Energy efficiency and sustainable consumption :, the rebound effect /*. Basingstoke [England] ; Palgrave Macmillan, (Energy, climate and the environment series), pp. xiv, 266 p.

Horner, N.C., Shehabi, A. and Azevedo, I.L. (2016) 'Known unknowns: Indirect energy effects of information and communication technology', *Environmental Research Letters*, 11(10). Available at: https://doi.org/10.1088/1748-9326/11/10/103001.

Islam, M. *et al.* (2022) 'A Systematic Review of Explainable Artificial Intelligence in Terms of Different Application Domains and Tasks', *Applied Sciences-Basel*, 12(3). Available at: https://doi.org/10.3390/app12031353.

Kaack, L.H. *et al.* (2022) 'Aligning artificial intelligence with climate change mitigation', *Nature Climate Change*, 12(6), pp. 518–527. Available at: https://doi.org/10.1038/s41558-022-01377-7.

Lannelongue, L. and Inouye, M. (2023) 'Carbon footprint estimation for computational research', *Nature Reviews Methods Primers*, 3(1), p. 9. Available at: https://doi.org/10.1038/s43586-023-00202-5.

Lei, N. *et al.* (2024) 'The Water Footprint of Data Center Workloads: A Review of Key Determinants'. Research Square [Preprint]. Available at: https://doi.org/10.21203/rs.3.rs-4159702/v1.

Luccioni, A.S., Jernite, Y. and Strubell, E. (2023) 'Power Hungry Processing: Watts Driving the Cost of AI Deployment?' arXiv. Available at: https://doi.org/10.48550/arXiv.2311.16863.

Mosavi, A. *et al.* (2019) 'State of the Art of Machine Learning Models in Energy Systems, a Systematic Review', *Energies*, 12(7), p. 1301. Available at: https://doi.org/10.3390/en12071301.

Mytton, D. (2021) 'Data centre water consumption', *npj Clean Water*, 4(1), p. 11. Available at: https://doi.org/10.1038/s41545-021-00101-w.

Nishant, R., Kennedy, M. and Corbett, J. (2020) 'Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda', *International Journal of Information Management*, 53, p. 102104. Available at: https://doi.org/10.1016/j.ijinfomgt.2020.102104.

OECD (2022) *Measuring the environmental impacts of artificial intelligence compute and applications: The AI footprint*. 341. Paris: Organisation for Economic Co-operation and Development. Available at: https://doi.org/10.1787/7babf571-en.

Pärssinen, M. *et al.* (2018) 'Environmental impact assessment of online advertising', *Environmental Impact Assessment Review*, 73, pp. 177–200. Available at: https://doi.org/10.1016/j.eiar.2018.08.004.

Patterson, D. *et al.* (2022) 'The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink', *Computer*, 55(7), pp. 18–28. Available at: https://doi.org/10.1109/MC.2022.3148714.

Pesari, F., Lagioia, G. and Paiano, A. (2023) 'Client-side energy and GHGs assessment of advertising and tracking in the news websites', *Journal of Industrial Ecology*, 27(n/a), pp. 548–561. Available at: https://doi.org/10.1111/jiec.13376.

Porter, A.L., Lifset, R. and Lee, T. (2024) 'The Challenging Search for Research on the Environmental Impacts of Artificial Intelligence'. [In review].

Rillig, M.C. *et al.* (2023) 'Risks and Benefits of Large Language Models for the Environment', *Environmental Science & Technology*. Available at: https://doi.org/10.1021/acs.est.3c01106.

Robbins, S. and van Wynsberghe, A. (2022) 'Our New Artificial Intelligence Infrastructure: Becoming Locked into an Unsustainable Future', *Sustainability*, 14(8), p. 4829. Available at: https://doi.org/10.3390/su14084829.

Rolnick, D. *et al.* (2022) 'Tackling Climate Change with Machine Learning', *ACM Computing Surveys*, 55(2), p. 42:1-42:96. Available at: https://doi.org/10.1145/3485128.

Strubell, E., Ganesh, A. and McCallum, A. (2019) 'Energy and Policy Considerations for Deep Learning in NLP', in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. *ACL 2019*, Florence, Italy: Association for Computational Linguistics, pp. 3645–3650. Available at: https://doi.org/10.18653/v1/P19-1355.

Sudhakar, S., Sze, V. and Karaman, S. (2023) 'Data Centers on Wheels: Emissions From Computing Onboard Autonomous Vehicles', *IEEE Micro*, 43(1), pp. 29–39. Available at: https://doi.org/10.1109/MM.2022.3219803.

Taiebat, M. *et al.* (2018) 'A review on energy, environmental, and sustainability implications of connected and automated vehicles', *Environmental Science and Technology*, 52(20), pp. 11449–11465. Available at: https://doi.org/10.1021/acs.est.8b00127.

Treviso, M. *et al.* (2023) 'Efficient Methods for Natural Language Processing: A Survey', *Transactions of the Association for Computational Linguistics*, 11, pp. 826–860. Available at: https://doi.org/10.1162/tacl_a_00577.

Vaddadi, B. *et al.* (2020) 'Towards a conceptual framework of direct and indirect environmental effects of co-working', in. *ACM International Conference Proceeding Series*, pp. 27–35. Available at: https://doi.org/10.1145/3401335.3401619.

Verdecchia, R., Sallou, J. and Cruz, L. (2023) 'A systematic review of Green AI', *WIREs Data Mining and Knowledge Discovery*, 13(4), p. e1507. Available at: https://doi.org/10.1002/widm.1507.

Vinuesa, R. *et al.* (2020) 'The role of artificial intelligence in achieving the Sustainable Development Goals', *Nature Communications*, 11(1), p. 233. Available at: https://doi.org/10.1038/s41467-019-14108-y.

Vinuesa, R. and Sirmacek, B. (2021) 'Interpretable deep-learning models to help achieve the Sustainable Development Goals', *Nature Machine Intelligence*, 3(11), pp. 926–926. Available at: https://doi.org/10.1038/s42256-021-00414-y.

Vries, A. de (2023) 'The growing energy footprint of artificial intelligence', *Joule,* 7(10), pp. 2191-2194. Available at: https://doi.org/10.1016/j.joule.2023.09.004.

de Vries, A. and Stoll, C. (2021) 'Bitcoin's growing e-waste problem', *Resources, Conservation and Recycling*, 175, p. 105901. Available at: https://doi.org/10.1016/j.resconrec.2021.105901.

Willenbacher, M. (2021) 'A Short Overview of Rebound Effects in Methods of Artificial Intelligence', *International Journal of Environmental Sciences & Natural Resources*, 28(4), pp. 1–7. Available at: https://doi.org/10.19080/IJESNR.2021.28.556246.

Willenbacher, M., Hornauer, T. and Wohlgemuth, V. (2022) 'Rebound Effects in Methods of Artificial Intelligence', in V. Wohlgemuth et al. (eds) *Advances and New Trends in Environmental Informatics*. Cham: Springer International Publishing (Progress in IS), pp. 73–85. Available at: https://doi.org/10.1007/978-3-030-88063-7_5.

Wu, C.-J. *et al.* (2022) 'Sustainable AI: Environmental Implications, Challenges and Opportunities', in D. Marculescu, Y. Chi, and C. Wu (eds) *Proceedings of Machine Learning and Systems*. *MLSys Conference, Santa Clara, CA, USA, 2022*, pp. 795–813. Available at: https://proceedings.mlsys.org/paper/2022/file/ed3d2c21991e3bef5e069713af9fa6ca-Paper.pdf.

Yu, J.-R. *et al.* (2022) 'Energy Efficiency of Inference Algorithms for Clinical Laboratory Data Sets: Green Artificial Intelligence Study', *Journal of Medical Internet Research*, p. e28036. Available at: http://dx.doi.org/10.2196/28036.

Zhu, J.-J. *et al.* (2023) 'ChatGPT and Environmental Research', *Environmental Science & Technology*. Available at: https://doi.org/10.1021/acs.est.3c01818.

Footnotes

[1] Note, however, that embodied carbon in the robot, that is, the GHG emissions generated in the production of the materials used in the robot could be considered as arising from the use of the robot when taking a life cycle perspective.