

THE COST OF TRAINING A MACHINE: LIGHTING THE WAY FOR A
CLIMATE-AWARE POLICY FRAMEWORK THAT ADDRESSES ARTIFICIAL
INTELLIGENCE’S CARBON FOOTPRINT PROBLEM

*Patrick K. Lin**

“For a successful technology,
reality must take precedence over public relations,
for Nature cannot be fooled.”

— Richard P. Feynman¹

ABSTRACT

While artificial intelligence (AI) has been a subject of great debate in spaces such as due process, discrimination, and privacy, an area that is lacking in legal scholarship is the technology’s environmental impact. AI promises to be a silver bullet in the increasingly urgent fight against climate change, yet it comes with a considerable cost to our planet. Current industry trends involve AI models being trained on increasingly larger datasets and training methodologies that prioritize brute-force over efficiency. Thus, as AI models increase in complexity and size, so too does the computing power—and energy—required to train and deploy them. Every stage of AI research and development, from training the model, storing its data, and deploying it in the real world, consumes the Earth’s resources. The interplay between AI and climate change is further complicated by the fact that AI is often lauded as an essential component of the new clean energy economy.

If AI is meant to be a critical component of our new clean energy economy, its ever-increasing energy consumption must be addressed. By analyzing the processes and industry trends that cause AI to be a burden on the environment, this Article argues for mandating transparency around energy usage; empowering the newly

* J.D., Brooklyn Law School, 2022; B.A., New York University, 2017. All views expressed are my own.

¹ R. P. Feynman, *Personal Observations on Reliability of Shuttle*, in REPORT OF THE PRESIDENTIAL COMMISSION ON THE SPACE SHUTTLE CHALLENGER ACCIDENT 276, 280 (1986).

formed National Artificial Intelligence Initiative Office to direct sustainable AI design; and pushing data centers to adopt clean energy. The Article then proposes a policy framework that not only minimizes AI's carbon footprint but maximizes its potential to address key climate change concerns. For if we remain complacent, the very technology that could save our planet could very well be one of its greatest antagonists.

TABLE OF CONTENTS

| | |
|--|----|
| INTRODUCTION | 2 |
| I. HOW MACHINES LEARN: TRAINING AN ARTIFICIAL INTELLIGENCE | 8 |
| II. A BITTER TRUTH: THE ENVIRONMENTAL IMPACT OF ARTIFICIAL INTELLIGENCE | 11 |
| A. RED AI: BIGGER IS NOT ALWAYS BETTER..... | 12 |
| B. DATA CENTERS: REAL HOUSING FOR DIGITAL TENANTS.. | 14 |
| C. INFERENCE: THE TECH THAT KEEPS ON TAKING..... | 17 |
| III. LIGHTING THE WAY: A POLICY FRAMEWORK FOR SHRINKING ARTIFICIAL INTELLIGENCE'S CARBON FOOTPRINT | 18 |
| A. KEEPING TALLY: MEASURING EMISSIONS & REQUIRING REPORTING..... | 20 |
| B. LEAN, GREEN THINKING MACHINES: COORDINATING SUSTAINABLE DESIGN | 23 |
| C. CLEANING HOUSE: MOVING DATA CENTERS TO CLEAN ENERGY..... | 26 |
| CONCLUSION | 28 |

INTRODUCTION

Artificial intelligence (AI) regularly accomplishes remarkable feats: beating top players at complex games like Go,² protecting

² Colin Dwyer, 'Like a God,' *Google A.I. Beats Human Champ of Notoriously Complex Go Game*, NPR (May 23, 2017), <https://www.npr.org/sections/thetwo-way/2017/05/23/529673475/like-a-god-google-a-i-beats-human-champ-of-notoriously-complex-go-game>.

elephants from poachers,³ and providing healthcare professionals with diagnosis and treatment recommendations.⁴ In October 2019, researchers at OpenAI, a San Francisco-based AI research company whose founders include Elon Musk and Sam Altman, revealed an algorithm capable of learning, through trial and error, how to solve a Rubik’s Cube using a robotic hand.⁵ It was an impressive achievement, but it also required more than a thousand desktop computers and a dozen others running high-end graphics cards to make complex calculations for several months.⁶ According to one estimate, the endeavor may have consumed about 2.8 gigawatt-hours of electricity—or the output of three nuclear power plants for one hour.⁷ Relatedly, a study released in 2019 by the University of Massachusetts Amherst found that training an “off-the-shelf” AI using a single high-performance graphics card has the same carbon footprint as a one-person roundtrip flight between New York and San Francisco.⁸ However, training a more sophisticated AI produces five times more carbon dioxide than the entire lifecycle of an American car, including its manufacturing.⁹

The United Nations has called climate change “the defining crisis of our time,” and addressing it requires significant reduction of

³ Dina Temple-Raston, *Elephants Under Attacks Have an Unlikely Ally: Artificial Intelligence*, NPR (Oct. 25, 2019), <https://www.npr.org/2019/10/25/760487476/elephants-under-attack-have-an-unlikely-ally-artificial-intelligence>.

⁴ Thomas Davenport & Ravi Kalakota, *The Potential for Artificial Intelligence in Healthcare*, FUTURE HEALTHCARE 6 JOURNAL 94 (2019), <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6616181/>.

⁵ Will Knight, *Why Solving a Rubik’s Cube Does Not Signal Robot Supremacy*, WIRED (Oct. 16, 2019), <https://www.wired.com/story/why-solving-rubiks-cube-not-signal-robot-supremacy/>.

⁶ Will Knight, *AI Can Do Great Things—If It Doesn’t Burn the Planet*, WIRED (Jan. 21, 2020), <https://www.wired.com/story/ai-great-things-burn-planet/>.

⁷ *Id.* This was an estimate by Evan Sparks, CEO of Determined AI, a startup that produces software to manage AI projects. *Id.* While OpenAI “questioned the calculation, noting that it makes several assumptions,” it declined to offer an estimate of their own or disclose additional details about their project. *Id.*

⁸ Emma Strubell et al., *Energy and Policy Considerations for Deep Learning in NLP*, ARXIV:1906.02243 (2019), <https://arxiv.org/abs/1906.02243>. Here, the “off-the-shelf” AI language-processing system was Google’s BERT (Bidirectional Encoder Representations from Transformers). *Id.* Training this AI model produced over 1,400 pounds of carbon emissions. *Id.*

⁹ *Id.* Training an AI model that uses neural architecture search (NAS), a technique for automating the design of neural networks, produced 616,155 pounds of carbon emissions. *Id.*

carbon emissions.¹⁰ The scientific community generally agrees that human activity is responsible for increases in global temperature.¹¹ In fact, between 1980 and 2020, the amount of carbon dioxide in the atmosphere increased more than 20 percent, reaching levels 50 percent higher than when humanity began large-scale burning of fossil fuels during the industrial revolution.¹² The global warming that is changing the Earth's climate is already having alarming consequences: extreme weather events are more intense and occurring more frequently;¹³ the average wildfire season is three and a half months longer than it was a few decades ago;¹⁴ coral reefs are experiencing more severe bleaching

¹⁰ *The Climate Crisis – A Race We Can Win*, UNITED NATIONS, <https://www.un.org/en/un75/climate-crisis-race-we-can-win> (last visited Dec. 27, 2021).

¹¹ SPECIAL REPORT: GLOBAL WARMING OF 1.5°C, INTERGOV'TAL PANEL ON CLIMATE CHANGE (IPCC) 53 (2018), <https://www.ipcc.ch/sr15/>. According to the Climate Reality Project, 97 percent of climate scientists around the world agree that human influence is causing climate change. *The Climate Crisis in 2021*, CLIMATE REALITY PROJECT (July 16, 2021), <https://www.climateRealityProject.org/blog/climate-crisis-2021-5-key-facts-know>.

¹² Charles David Keeling started the “systematic long-term measurements of atmospheric [carbon dioxide]” in 1958 at the Mauna Loa Observatory in Hawaii. Richard Betts, *Met Office: Atmospheric CO2 Now Hitting 50% Higher than Pre-industrial Levels*, CARBON BRIEF (Mar. 16, 2021), <https://www.carbonbrief.org/met-office-atmospheric-co2-now-hitting-50-higher-than-pre-industrial-levels>; see also *Mauna Loa Carbon Dioxide Forecast for 2021*, MET OFFICE, <https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/long-range/forecasts/co2-forecast-for-2021> (last visited Dec. 28, 2021) (describing carbon dioxide concentration forecasts, noting the uncertainty following the reduction in global greenhouse gas emissions due to the COVID-19 pandemic).

¹³ Roz Pidcock & Robert McSweeney, *Mapped: How Climate Change Affects Extreme Weather Around the World*, CARBON BRIEF (Feb. 25, 2021), <https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world> (explaining the effects of climate change on extreme weather, such as floods, heatwaves, droughts, and storms); see also *Extreme Weather and Climate Change*, CTR. FOR CLIMATE AND ENERGY SOLUTIONS, <https://www.c2es.org/content/extreme-weather-and-climate-change/> (last visited Dec. 28, 2021) (measuring the economic impact of extreme weather, specifically “billion-dollar disasters”).

¹⁴ “[T]he number of annual large fires in the [American] West has tripled—burning twice as many acres.” *Here's How Climate Change Affects Wildfires*, ENVIRONMENTAL DEFENSE FUND, <https://www.edf.org/climate/heres-how-climate-change-affects-wildfires> (last visited Dec. 28, 2021); see Philip E. Dennison et al., *Large Wildfire Trends in the Western United States, 1984–2011*, 41 *GEOPHYS. RES. LETT.* 2928, 2929 (2014), <https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2014GL059576> (tracking the number of large fires in each ecoregion of the Western United States); see also

events, losing their color;¹⁵ and mosquitos are expanding their territory, causing disease to spread.¹⁶ Limiting global warming to 1.5°C and bringing greenhouse gas emissions to zero by the middle of the twenty-first century are necessary steps for mitigating the harmful effects of climate change on ecosystems and humanity's wellbeing.¹⁷

Faced with this dire reality, the promise of emerging technologies, like AI, to save our planet is a welcome albeit scarce source of optimism. A 2018 survey conducted by Intel and the research firm Concentrix found that 74 percent of business-decision makers working in environmental sustainability agree that AI will help solve long-standing environmental challenges.¹⁸ AI applications and their promising climate change solutions are already bearing fruit: conservationists are using AI-enabled systems to track animal movements and save the Earth's biodiversity;¹⁹ smart grids are

Daisy Dunne, *Explainer: How Climate Change is Affecting Wildfires Around the World*, CARBON BRIEF (July 14, 2020), <https://www.carbonbrief.org/explainer-how-climate-change-is-affecting-wildfires-around-the-world> (providing an overview of climate change's effect on wildfires).

¹⁵ NOAA, *How Does Climate Change Affect Coral Reefs?*, U.S. DEPARTMENT OF COMMERCE, NAT'L OCEANIC AND ATMOSPHERIC ADMIN., <https://oceanservice.noaa.gov/facts/coralreef-climate.html> (last visited Dec. 28, 2021). According to the Australian Research Council Centre of Excellence for Coral Reef Studies, more than half of the Great Barrier Reef, the world's largest coral reef system, was affected by bleaching. *See Coral Bleaching and the Great Barrier Reef*, ARC CENTRE OF EXCELLENCE FOR CORAL REEF STUDIES, <https://www.coralcoe.org.au/for-managers/coral-bleaching-and-the-great-barrier-reef> (last visited Dec. 28, 2021).

¹⁶ Rob Jordan, *How Does Climate Change Affect Disease?*, STANFORD EARTH MATTERS MAGAZINE (Mar. 15, 2019), <https://earth.stanford.edu/news/how-does-climate-change-affect-disease>; *see* Kristen Pope, *Climate Change Could Speed Mosquito Evolution*, YALE CLIMATE CONNECTIONS (Apr. 10, 2019), <https://yaleclimateconnections.org/2019/04/climate-change-could-foster-rapid-mosquito-evolution/>.

¹⁷ *See generally* SPECIAL REPORT: GLOBAL WARMING OF 1.5 °C, INTERGOV'TAL PANEL ON CLIMATE CHANGE 53 (2018), <https://www.ipcc.ch/sr15/> (detailing the impacts of global warming as well as related global greenhouse gas emission pathways).

¹⁸ Todd Brady, *Intel Study: Applying Emerging Technology to Solve Environmental Challenges*, INTEL (Dec. 13, 2018), <https://newsroom.intel.com/editorials/intel-study-applying-emerging-technology-solve-environmental-challenges/>.

¹⁹ Roberta Kwok, *AI Empowers Conservation Biology*, NATURE (Mar. 4, 2019), <https://www.nature.com/articles/d41586-019-00746-1>; *see also* Roger Brown, *Artificial Intelligence in Biodiversity: How AI Can Help in Animal Conservation*, BECOMING HUMAN: ARTIFICIAL INTELLIGENCE MAGAZINE (Dec. 16, 2020), <https://becominghuman.ai/artificial-intelligence-in-biodiversity-how-ai-can-help->

meeting local electricity demand through intelligent demand-supply matching algorithms;²⁰ and researchers are finding ways to use AI to source locally grown foods and reduce food waste.²¹ AI has become humanity's big bet.

Yet, for all its potential to reduce humanity's carbon footprint and optimize efficiencies across various sectors, a bitter truth remains: the cost of training and maintaining AI models is shockingly high. The training process requires a great deal of computer processing power, thus consuming a lot of electricity.²² Furthermore, the industry's current training trends prioritize accuracy over efficiency, resulting in massive amounts of data being fed into training models as well as trial-and-error training tactics, all of which expand the carbon footprint of AI and place an increasing burden on the environment.²³

In a cruel twist of fate, AI appears to be “destined to play a dual role” in climate change.²⁴ Nonetheless, this complicated reality does not mean that actions cannot be taken to mitigate or reduce AI's carbon footprint. In order for AI technology to live up to its promise of optimization and efficiency, the tech industry and lawmakers alike

[in-animal-conservation-1c191179def6](#) (listing the different ways AI is applied in the biodiversity context).

²⁰ Melike Erol-Kantarci, *Smart Grid? Yes, AI Says: Bring It On!*, IEEE COMMUNICATIONS SOCIETY TECH. NEWS (Apr. 21, 2021), <https://www.comsoc.org/publications/ctn/smart-grid-yes-ai-says-bring-it>; see also *Smart Grids: Electricity Networks and the Grid in Evolution*, I-SCOOP, <https://www.i-scoop.eu/industry-4-0/smart-grids-electrical-grid/> (last visited Dec. 27, 2021) (“A smart grid is an electricity network enabling a two-way flow of electricity and data with digital communications technology enabling to detect, react and pro-act to changes in usage and multiple issues.”).

²¹ ARTIFICIAL INTELLIGENCE AND THE CIRCULAR ECONOMY, ELLEN MACARTHUR FOUNDATION & GOOGLE 19 (2020), <https://ellenmacarthurfoundation.org/artificial-intelligence-and-the-circular-economy> (“AI can generate an estimated economic opportunity of up to USD 127 billion a year in 2030 . . . realised through opportunities at every step of the value chain, from farming, processing, logistics, and consumption.”).

²² *There's Greater Cost of Deploying AI and ML Models in Production—the AI Carbon Footprint*, HYPERIGHT, <https://hyperight.com/theres-greater-cost-of-deploying-ai-and-ml-models-in-production-the-ai-carbon-footprint/> (last visited Dec. 24, 2021) [hereinafter *AI and ML Models in Production*].

²³ *Id.* See generally Lance Eliot, *Brute Force Algorithms and AI: Use Case of Autonomous Cars*, AI TRENDS (June 20, 2019), <https://www.aitrends.com/ai-insider/brute-force-algorithms-and-ai-use-case-of-autonomous-cars/>.

²⁴ See Payal Dhar, *The Carbon Impact of Artificial Intelligence*, 2 NATURE MACHINE INTELLIGENCE 423, 423 (2020), <https://www.nature.com/articles/s42256-020-0219-9>.

must grapple with how power-hungry the AI training and development process is. While the largest tech companies have made bold commitments to address climate change concerns, they continue to be some of the largest consumers of electricity in the United States.²⁵ Furthermore, the absence of regulations or policies to address AI's carbon footprint suggests that this issue is not a priority for the federal government, resulting in a lack of direction and a reliance on tech companies to voluntarily cut emissions. Understanding the environmental costs and limits of AI is crucial for developing future environmental and technology regulation. Without readily available data and information or guidance from the federal government, the current industry trend of developing data- and power-hungry AI may go on until it is too late. As more and more sectors rely on AI to solve increasingly complex problems, more must be done to scrutinize and address the environmental cost of AI.

This Article argues that the current AI research and development paradigm imposes too great of an environmental cost for AI to fulfill its promise of being a planet-saving technology. AI's carbon footprint problem is further compounded by the lack of rulemaking and guidance from policymakers and federal agencies. A federal climate-aware AI policy framework should be developed to not only limit the greenhouse gas emissions of AI development but maximize AI's potential to usher in a clean economy. As a first step, a federal rule should require AI developers and companies to accurately measure the carbon emissions of their AI throughout its lifecycle and disclose those measurements to the public via periodic reporting. The federal government should rely on the newly formed National Artificial Intelligence Initiative Office (NAIIO) to coordinate and incentivize greener, more efficient AI design decisions. The NAIIO is uniquely positioned to pivot AI development and design away from its current data-intensive and trial-and-error approaches to training

²⁵ See Laura Paddison, *Big Tech's Pro-climate Rhetoric Is Not Matched by Policy Action, Report Finds*, GUARDIAN (Sept. 20, 2021), <https://www.theguardian.com/environment/2021/sep/20/big-tech-climate-change>; see also Shira Ovide, *Big Tech Versus Climate Change*, NEW YORK TIMES (July 23, 2020), <https://www.nytimes.com/2020/07/23/technology/big-tech-climate-change.html>. In 2020, Apple, Amazon, Alphabet, Facebook, and Microsoft spent roughly \$65 million on lobbying, but an average of only six percent of their lobbying activity between July 2020 and June 2021 was related to climate policy. See BIG TECH AND CLIMATE POLICY, INFLUENCEMAP (2021), <https://influencemap.org/report/Big-Tech-and-Climate-Policy-afb476c56f217ea0ab351d79096df04a>.

machine learning models. A comprehensive AI policy framework should also account for the energy consumption of the data centers that store and maintain data for AI training and development, requiring data centers to adopt clean energy.

Part I of this Article provides an overview of the mechanics of training an AI model and previews how the current AI research paradigm is causing the environmental cost of AI development and machine learning to rise. Part II examines the carbon footprint at different stages of an AI model's lifecycle, specifically model training, data centers, and inference. Part III discusses guiding principles for limiting the energy demands of AI research and development, and proposes a policy framework for a more efficient training methodology that also accounts for the energy consumption of data centers.

I. HOW MACHINES LEARN: TRAINING AN ARTIFICIAL INTELLIGENCE

Broadly speaking, AI refers to “machines that can learn, reason, and act for themselves.”²⁶ AI systems are capable of making their own decisions when faced with new information, behaving “intelligently” like a human or animal.²⁷ But when journalists, policymakers, and technologists say “AI,” they generally mean machine learning, a more sophisticated application of AI that uses statistics to identify patterns in troves of data and enables algorithms to automatically improve as it takes in more data and information.²⁸ The purpose of this Part is not to provide a complete account of how AI is developed. Instead, it is intended to provide an approachable overview of the mechanics of training AI systems and preview the energy consumption problems that accompany this process.

In December 2020, Google fired prominent AI ethics researcher Timnit Gebru after making her withdraw a research paper that pointed out the risks of language-processing AI, the same type

²⁶ Karen Hao, *What is AI?*, MIT TECH. REV. (Nov. 10, 2018), <https://www.technologyreview.com/2018/11/10/139137/is-this-ai-we-drew-you-a-flowchart-to-work-it-out/>.

²⁷ *Id.* Arthur L. Samuel coined the term “machine learning” in his seminal article about teaching a computer to play checkers. See Arthur L. Samuel, *Some Studies in Machine Learning Using the Game of Checkers*, 3 IBM J. RES. & DEV. 535 (1959), <https://ieeexplore.ieee.org/document/5392560>.

²⁸ Karen Hao, *What is Machine Learning?*, MIT TECH. REV. (Nov. 17, 2018), <https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/>.

used in Google's own search engine.²⁹ Among the risks discussed in Gebru's paper is the large carbon footprint of developing this kind of AI technology.³⁰ Most AI systems require exposure to massive amounts of data to, and given enough time, hone the ability to perform tasks, like spotting patterns or making more accurate predictions.³¹ These data are known as "training data," and it is the most essential aspect of machine learning because the quality and size of this initial dataset are the main determinants of an AI system's predictive power.³² Training data is run through a neural network (e.g. a picture of a cat), which assigns parameters and weights to produce an output.³³ The final output is a decision about the data (e.g. was the original input a picture of a cat?).³⁴ AI is as computationally intensive as it is because it needs to read through significant amounts of data until it has been trained to understand it.³⁵ In fact, machine learning requires running

²⁹ See Tim Simonite, *What Really Happened When Google Ousted Timnit Gebru*, WIRED (June 8, 2021), <https://www.wired.com/story/google-timnit-gebru-ai-what-really-happened/> (providing a primer on Google's firing of Timnit Gebru and the tension between Big Tech and employee research that may conflict with business interests).

³⁰ See Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell, *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?*, PROCEEDINGS ON THE 2021 ACM CONFERENCE ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY (2021), <https://dl.acm.org/doi/10.1145/3442188.3445922> (highlighting the four main risks of large language models discussed in Gebru's research paper: (1) environmental and financial costs; (2) use of racist, sexist, and abusive language in training data; (3) research opportunity costs; and (4) misinformation).

³¹ See Arthur L. Samuel, *Some Studies in Machine Learning Using the Game of Checkers*, 3 IBM J. RES. & DEV. 535, 535–37 (1959), <https://ieeexplore.ieee.org/document/5392560>.

³² See Amal Joby, *What Is Training Data? How It's Used in Machine Learning*, G2 (July 30, 2021), <https://learn.g2.com/training-data#what-is-training-data>; see also David Martens & Foster Provost, *Pseudo-Social Network Targeting from Consumer Transaction Data* (NYU Stern Center for Dig. Econ. Research Paper No. 11-05, 2011), <https://archive.nyu.edu/handle/2451/31253> (demonstrating that massive amounts of data can lead to lower estimation variance and thus better predictive performance).

³³ Larry Hardesty, *Explained: Neural Networks*, MIT NEWS (Apr. 14, 2017), <https://news.mit.edu/2017/explained-neural-networks-deep-learning-0414>. "Neural networks are a means of doing machine learning, in which a computer learns to perform some task by analyzing training examples." *Id.*

³⁴ *Id.*

³⁵ Kate Saenko, *It Takes a Lot of Energy for Machines to Learn – Here's Why AI is So Power-Hungry*, THE CONVERSATION (Dec. 14, 2020), <https://theconversation.com/it-takes-a-lot-of-energy-for-machines-to-learn-heres-why-ai-is-so-power-hungry-151825>.

“millions of statistical experiments around the clock,” gradually tuning and refining their models to perform tasks.³⁶ Those training sessions have gone from lasting weeks to now months, making the training process even more power-hungry.³⁷

But an AI model is not trained just once.³⁸ It is trained over and over again until the parameters and weights are optimized, which means getting the model output correct as often as possible.³⁹ The more accurate a model is with this training data, the better it will be when making decisions about new data.⁴⁰ A model trained to recognize faces, for example, should be shown a lot of faces so that it knows what features to isolate and rely on when matching faces. Similarly, a model trained to understand language should be exposed to different literary works and figures of speech so that it can better understand the contexts and intricacies of language.

The finishing touches of building an AI model tend to be the most costly.⁴¹ Many models undergo a tuning process that uses trial and error to optimize a model.⁴² This additional training and tweaking has a tremendous cost but little overall gain.⁴³ However, by removing this final step, even the most costly neuro-linguistic programming model, BERT,⁴⁴ had a much more modest carbon footprint of about

³⁶ Edmund L. Andrews, *AI's Carbon Footprint Problem*, STANFORD UNIVERSITY HUMAN-CENTERED ARTIFICIAL INTELLIGENCE (July 2, 2020), <https://hai.stanford.edu/news/ais-carbon-footprint-problem>.

³⁷ *Id.*

³⁸ Danny Bradbury, *AI Caramba, Those Neural Networks are Power-Hungry: Counting the Environmental Costs of Artificial Intelligence*, THE REGISTER (Sept. 13, 2021), https://www.theregister.com/2021/09/13/ai_environmental_cost/.

³⁹ *Id.*

⁴⁰ *Id.*

⁴¹ Jessica Miley, *Training AI is Shockingly Costly to the Environment*, INTERESTING ENGINEERING (June 11, 2019), <https://interestingengineering.com/training-ai-is-shockingly-costly-to-the-environment>.

⁴² *Id.*

⁴³ See discussion *supra* Part I.

⁴⁴ BERT, or Bidirectional Encoder Representations from Transformers, is Google's pre-training model for natural language processing. See Jacob Devlin & Ming-Wei Chang, *Open Sourcing BERT: State-of-the-Art Pre-training for Natural Language Processing*, GOOGLE AI BLOG (Nov. 2, 2018), <https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html>.

1,400 pounds of carbon dioxide, roughly the same as a round-trip trans-America flight for one person.⁴⁵

According to a 2018 analysis by OpenAI, the computing power required for various large AI training models had been doubling every 3.4 months since 2012—a significant deviation from Moore’s Law, which projected this increase to occur every 18 months—accounting for a 300,000-fold increase.⁴⁶ AI models require more power to train because researchers and developers are feeding them more data than ever so that the models can produce more accurate results.⁴⁷ Today’s industry practice prioritizes more experiments, more data, and more power, demonstrating a shortsightedness that fails to account for improvements in AI training grounded in efficiency and optimization.

II. *A BITTER TRUTH: THE ENVIRONMENTAL IMPACT OF ARTIFICIAL INTELLIGENCE*

In 2018, Kate Crawford and Vladan Joler’s visual map and essay, *Anatomy of an AI System*, depicted the Amazon Echo as an “anatomical map” of human labor, data, and planetary resources.⁴⁸ From extracting resources from the Earth and the resulting environmental impacts to the sweatshops of outsourced programmers and unpaid labor of user-produced data, the authors came to an unsettling conclusion: “At every level contemporary technology is deeply rooted in and running on the exploitation of human bodies.”⁴⁹

The relationship between AI and climate change is a precarious one. AI seems fated to play two opposing roles.⁵⁰ On the one hand, AI has been hailed as one of the key technologies necessary for reducing the impact of the climate crisis.⁵¹ For instance, AI can enable smart

⁴⁵ Miley, *supra* note 127; *see also* Strubell et al., *supra* note 8.

⁴⁶ Dario Amodei & Danny Hernandez, *AI and Compute*, OPENAI (May 16, 2018), <https://openai.com/blog/ai-and-compute/>.

⁴⁷ Bradbury, *supra* note 38.

⁴⁸ Kate Crawford and Vladan Joler, *Anatomy of an AI System*, AI NOW INSTITUTE and SHARE LAB (Sept. 7, 2018), <https://anatomyof.ai>.

⁴⁹ *Id.*

⁵⁰ Ricardo Vinuesa et al., *The Role of Artificial Intelligence in Achieving the Sustainable Development Goals*, 11 NAT. COMMUN. (Jan. 13, 2020), <https://www.nature.com/articles/s41467-019-14108-y> (indicating that for each Sustainable Development Goal AI enables, it also undermines that goal with its high-energy needs, particularly with respect to environmental goals).

⁵¹ Amy L. Stein, *Artificial Intelligence and Climate Change*, 37 YALE J. ON REG. 890, 895 (2020).

grids to better match a community's electricity demands, model the potential effects of climate change, and monitor deforestation and desertification trends with satellite images.⁵² On the other hand, AI systems are a significant emitter of carbon.⁵³ Researchers at the University of Massachusetts Amherst analyzed different natural language processing training models to estimate the carbon emissions and electricity costs required to train them.⁵⁴ The authors estimated that the carbon footprint of training a single large language model is equal to around 300,000 kilograms of carbon dioxide emissions.⁵⁵ To put this value into perspective, this level of energy consumption is equivalent to that of 125 round-trip flights between New York and Beijing.⁵⁶

For all its potential to reduce energy consumption and optimize efficiencies, AI can also be a large consumer of electricity. The computing power used to train the average AI model increases by a factor of 10 each year.⁵⁷ Although this trend is partially driven by improvements to hardware, namely GPUs and TPUs,⁵⁸ that allow more operations and experiments to be performed, it has primarily been propelled by AI researchers and developers "repeatedly finding ways to use more chips in parallel and being willing to pay the economic cost of doing so."⁵⁹

A. Red AI: Bigger Is Not Always Better

Today's AI research agenda prioritizes achieving advances in AI through sheer scale: more data, more complex models, more computing power.⁶⁰ When OpenAI debuted its GPT-3 language model in 2020, it was composed of 175 billion parameters.⁶¹ Its predecessor

⁵² Vinuesa et al., *supra* note 50.

⁵³ *Id.*

⁵⁴ See Strubell et al., *supra* note 8.

⁵⁵ *Id.*

⁵⁶ See Dhar, *supra* note 23.

⁵⁷ Amodei & Hernandez, *supra* note 46.

⁵⁸ "GPU" refers to a graphics processing unit, which is the graphics chip found in graphics cards. "TPU" refers to a tensor processing unit, which is an AI accelerator application-specific integrated circuit (ASIC) that Google specifically designed for neural networking machine learning.

⁵⁹ Amodei & Hernandez, *supra* note 46.

⁶⁰ See discussion *supra* Part I.

⁶¹ Khari Johnson, *OpenAI Debuts Gigantic GPT-3 Language Model with 175 Billion Parameters*, VENTUREBEAT (May 29, 2020), <https://venturebeat.com/2020/05/29/openai-debuts-gigantic-gpt-3-language-model->

model GPT-2—which was considered state-of-the-art when it was released in 2019—had just 1.5 billion parameters.⁶²

AI models that follow the trend of using massive compute power to achieve better results are known as “Red AI,” a term first introduced in a 2019 paper co-authored by Roy Schwartz, a postdoctoral researcher at the Allen Institute for AI.⁶³ Schwartz and his colleagues consider three factors that capture much of the computation cost of Red AI:

the cost of executing the model on a single example (either during training or at inference time); the size of the training dataset, which controls the number of times the model is executed during training, and the number of hyperparameter experiments, which controls how many times the model is trained during model development.⁶⁴

The cost of producing an AI result increases linearly with each of these dimensions, but Schwartz found diminishing returns of throwing more data at a neural network.⁶⁵ In other words, for a linear gain in an AI model’s performance, an exponentially larger model is required.⁶⁶ To that end, either the size of the training dataset must increase or the number of experiments must increase.⁶⁷ In both cases, computational costs rise, and therefore carbon emissions rise.⁶⁸ Worse yet, the vast majority of AI research tends to target accuracy rather

with-175-billion-parameters/; see also Tom B. Brown et al., *Language Models are Few-Shot Learners*, ARXIV:2005.14165 (2020), <https://arxiv.org/abs/2005.14165> (describing the capabilities of GPT-3, including natural language processing tasks that range from language translation to generating news articles to answering SAT questions).

⁶² Rob Toews, *Deep Learning’s Carbon Emissions Problem*, FORBES (June 17, 2020), <https://www.forbes.com/sites/robtoews/2020/06/17/deep-learnings-climate-change-problem/>.

⁶³ See Roy Schwartz et al., *Green AI*, 63 COMM’N OF THE ACM 54 (2020), <https://cacm.acm.org/magazines/2020/12/248800-green-ai/fulltext>.

⁶⁴ *Id.* at 57.

⁶⁵ *Id.* at 56–57.

⁶⁶ *Id.* (demonstrating the diminishing returns of training on more data: “object detection accuracy increases linearly as the number of training examples increases exponentially”).

⁶⁷ *Id.* at 56.

⁶⁸ *Id.*

than efficiency, hence most AI models are considered Red AI.⁶⁹ By relying on ever-larger models to drive progress in AI, the energy expenditure, and thus carbon emissions, will also grow larger with each new iteration or advancement.⁷⁰

As Schwartz and his colleagues note, a significant factor driving AI's massive energy draw is the fact that machine learning today remains largely an exercise in trial and error.⁷¹ During the training stage, researchers and developers often build multiple versions of a model, then experiment with different neural architectures and hyperparameters before identifying an optimal design.⁷² In the short term, AI's carbon footprint can be reduced by adopting more efficient hyperparameter search methods and reducing the number of unnecessary experiments during model training.⁷³

B. Data Centers: Real Housing for Digital Tenants

Although the carbon cost of training large machine learning models is hefty, it is only part of the problem. For a more complete picture, closer attention must be paid to the carbon footprint of the infrastructure around the deployment of AI. More specifically, the physical structures involved in the creation and maintenance of these digital assets. The energy consumed to store data alone is staggering.

As AI becomes more complex, some models are expected to use even more data. This data is stored in data centers, buildings dedicated to housing information technology and networked computer systems, including servers and storage systems.⁷⁴ The U.S. Department of Energy estimates that data centers account for about

⁶⁹ *Id.* Schwartz et al. advocate for “green AI” as an alternative to the current trend of “red AI.” *Id.* at 59. “Green AI” is defined as “AI research that yields novel results without increasing computational cost, and ideally reducing it.” *Id.*

⁷⁰ Toews, *supra* note 62.

⁷¹ Schwartz et al., *supra* note 63, at 57.

⁷² See Strubell et al., *supra* note 8.

⁷³ See generally Alexandre Lacoste, *Quantifying the Carbon Emissions of Machine Learning*, ARXIV: 1910.09700 (2019), <https://arxiv.org/abs/1910.09700> (recommending best practices for the overall machine learning research community to reduce the carbon footprint of training models).

⁷⁴ See Fred Pearce, *Energy Hogs: Can World's Huge Data Centers Be Made More Efficient*, *YALE ENVIRONMENT* 360 (Apr. 3, 2018), <https://e360.yale.edu/features/energy-hogs-can-huge-data-centers-be-made-more-efficient>.

two percent of total U.S. electricity usage.⁷⁵ Worldwide, data centers consume roughly 200 terawatt hours of power per year—more than some countries⁷⁶—and by 2025, that computing and communications technology will consume “somewhere between 8 percent (best case) and 21 percent (expected),” with data centers accounting for one-third of that.⁷⁷

The largest data centers require more than 100 megawatts of power capacity, which is enough to power roughly 80,000 U.S. households, according to energy and climate think tank Energy Innovation.⁷⁸ IBM’s The Weather Company processes around 400 terabytes of data per day—or as IBM boasts, “enough to fill 75 million 400-page novels in printed form”—to enable its models to predict the weather in advance around the globe.⁷⁹ Facebook generates about 4 petabytes (or 4,000 terabytes, using The Weather Company for comparison) of data per day and its data warehouse, known as Hive, contains 300 petabytes of data.⁸⁰

All of this data processing requires servers and storage. The electricity used by servers and network devices is converted into heat, which must be removed from the data center by cooling equipment,

⁷⁵ *Data Centers and Servers*, DEPARTMENT OF ENERGY, OFFICE OF ENERGY EFFICIENCY & RENEWABLE ENERGY, <https://www.energy.gov/eere/buildings/data-centers-and-servers> (last visited Dec. 24, 2021).

⁷⁶ Nicola Jones, *How to Stop Data Centres from Gobbling Up the World’s Electricity*, NATURE (Sept. 12, 2018), <https://www.nature.com/articles/d41586-018-06610-y>.

⁷⁷ Stein, *supra* note 51, at 917. See Anders S. G. Andrae & Tomas Edler, *On Global Electricity Usage of Communication Technology: Trends to 2030*, 6 CHALLENGES 117, 138 (2015); see also Martin Giles, *Is AI the Next Big Climate-Change Threat? We Haven’t a Clue*, MIT TECH. REV. (July 29, 2019), <https://www.technologyreview.com/2019/07/29/663/ai-computing-cloud-computing-microchips> (“[I]n the absence of significant innovation in materials, chip manufacturing and design, data centers’ AI workloads could account for a tenth of the world’s electricity usage by 2025.”).

⁷⁸ Eric Masanet & Nuo Lei, *How Much Energy Do Data Centers Really Use?*, ENERGY INNOVATION (Mar. 17, 2020), <https://energyinnovation.org/2020/03/17/how-much-energy-do-data-centers-really-use/>.

⁷⁹ Kristin Johnson, *Keeping People Safer in Extreme Weather*, IBM (Oct. 1, 2015), <https://www.ibm.com/case-studies/the-weather-company-ibm-cloud/>.

⁸⁰ Nathan Bronson & Janet Wiener, *Facebook’s Top Open Data Problems*, META RESEARCH (Oct. 22, 2014), <https://research.facebook.com/blog/2014/10/facebook-s-top-open-data-problems/>.

which also runs on electricity.⁸¹ On average, servers and cooling systems account for the greatest shares of direct electricity use in data centers.⁸² Data centers also use tremendous amounts of water as a form of evaporative cooling. This cooling method reduces electricity use but uses about three to five million gallons of water per day per hyperscale data center.⁸³ The water used for cooling purposes can also become polluted in the process.⁸⁴

Although data centers have generally become more electrically efficient over the past decade,⁸⁵ some experts estimate that electricity only accounts for about 10 percent of a data center's carbon emissions.⁸⁶ A data center's infrastructure, including the building's cooling systems and servers, also have a carbon impact.⁸⁷ In fact, in a conventional data center, standard air conditioning costs eat up 40 percent of the energy bill.⁸⁸

The reliance on data centers is only expected to grow not only as new AI models are trained but even as society demands and produces more data through seemingly mundane activities such as

⁸¹ Masanet & Lei, *supra* note 78.

⁸² ARMAN SHEHABI ET AL., LAWRENCE BERKELEY NATIONAL LABORATORY, UNITED STATES DATA CENTER ENERGY USAGE REPORT 24–25 (2016), <https://eta.lbl.gov/publications/united-states-data-center-energy> (estimating historical data center electricity consumption since 2000 and forecasting consumption to 2020).

⁸³ Olivia Solon, *Drought-stricken Communities Push Back Against Data Centers*, NBC NEWS (June 19, 2021), <https://www.nbcnews.com/tech/internet/drought-stricken-communities-push-back-against-data-centers-n1271344>. Hyperscale data centers are “super-efficient information factories that use an organized, uniform computing architecture that easily scales up to hundreds of thousands of servers.” Jones, *supra* note 76.

⁸⁴ Mark Labbe, *Energy Consumption of AI Poses Environmental Problems*, TECHTARGET (Aug. 26, 2021), <https://www.techtargget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems>.

⁸⁵ See generally Eric Masanet et al., *Recalibrating Global data Center Energy-use Estimates*, 367 SCIENCE 984 (Feb. 28, 2020) (finding that while the amount of computing done in data centers increased by about 550 percent between 2010 and 2018, the amount of energy consumed by data centers only grew by six percent during the same time period).

⁸⁶ Masanet & Lei, *supra* note 78.

⁸⁷ Masanet & Lei, *supra* note 78. See generally SHEHABI ET AL., *supra* note 83.

⁸⁸ Jones, *supra* note 76.

watching Netflix⁸⁹ or saving photos on a cloud storage service.⁹⁰ There is a significant risk that the rapidly growing demand for products and services that rely on AI will outpace the efficiency gains that have historically offset the energy usage of data centers.⁹¹

C. Inference: The Tech That Keeps on Taking

The discussion so far has focused on training machine learning models, but training is only the starting point of the AI lifecycle. After a model is trained, it is deployed in the real world. Inference is the process of taking an AI model and deploying it onto a device, which will then process incoming data to look for and identify whatever it has been trained to recognize.⁹² An AI model deployed in the real world relies on inference to act and make decisions, and this process calls for even more energy than training.⁹³ In fact, NVIDIA estimates that 80 to 90 percent of the cost of a neural network is in inference processing rather than training.⁹⁴

⁸⁹ Netflix accounts for about 40 percent of total Internet bandwidth at peak times, ahead of YouTube, which accounts for 15 percent, and Facebook, which accounts for 2.7 percent. Todd Spangler, *Netflix Bandwidth Usage Climbs to nearly 37% of Internet Traffic at Peak Hours*, VARIETY (May 28, 2015), <https://variety.com/2015/digital/news/netflix-bandwidth-usage-internet-traffic-1201507187/>. Netflix uses Amazon Web Services (AWS) for virtually all its computing and storage needs, including recommending and streaming movies and shows to users, using more than 100,000 server instances. *Netflix & Amazon Kinesis Data Streams Case Study*, AWS (2017), <https://aws.amazon.com/solutions/case-studies/netflix-kinesis-data-streams/>.

⁹⁰ The Institution of Engineering and Technology (IET) estimates that the average adult in the United Kingdom takes almost 900 photos a year, and when left in cloud storage, accumulate 10.6 kilograms of carbon emissions per person annually. *Dirty Data*, INST. OF ENG'G AND TECH (Oct. 26, 2021), <https://www.theiet.org/media/press-releases/press-releases-2021/press-releases-2021-october-december/26-october-2021-dirty-data/>. The total carbon emissions generated in the UK alone from this stored data is the equivalent of 112,500 roundtrip flights between London and Australia. *Id.*

⁹¹ Masanet & Lei, *supra* note 78.

⁹² Alejandro Lince & Steven Ross, *Efficient Machine Learning Inference*, O'REILLY (May 18, 2021), <https://www.oreilly.com/content/efficient-machine-learning-inference/>.

⁹³ Radosvet Desislavov et al., *Compute and Energy Consumption Trends in Deep Learning Inference*, ARXIV:2109.05472 at 1, <https://arxiv.org/abs/2109.05472> (“[F]or deployed systems, inference costs exceed training costs, because of the multiplicative factor of using the system many times.”).

⁹⁴ Karl Freund, *Google Cloud Doubles Down on NVIDIA CPUs For Inference*, FORBES (May 9, 2019),

AI models consume power when they are trained, but model inference is a bigger source of energy consumption because of its repetitious and continuous nature.⁹⁵ Once deployed, the model performs inference on a continuous basis in order to perform its tasks.⁹⁶ In contrast, even though training typically involves repetition, it is only done once while inference is done repeatedly.⁹⁷ Model inference is performed every single day, nonstop, for as long as the AI system or device is in use.⁹⁸ Thus, the more parameters the model has, the greater the energy costs are for this ongoing inference.⁹⁹ Still, due to the “multiplicative factors” of model inference, energy consumption can rise just by means of increased penetration, “in the same way that cars have become more efficient in the past two decades but there are many more cars in the world today.”¹⁰⁰

III. *LIGHTING THE WAY: A POLICY FRAMEWORK FOR SHRINKING ARTIFICIAL INTELLIGENCE’S CARBON FOOTPRINT*

In 1983, Iowa’s Republican state legislature voted to adopt the first renewable energy standard in the United States.¹⁰¹ Today, 30 states—red and blue alike—passed laws requiring electric utilities to use more renewable or clean energy.¹⁰² Currently, 23 states are committed to 100 percent clean energy goals, with targets ranging from 2030 to 2070.¹⁰³ More than 200 cities and counties have policies

<https://www.forbes.com/sites/moorinsights/2019/05/09/google-cloud-doubles-down-on-nvidia-gpus-for-inference/>.

⁹⁵ Desislavov et al., *supra* note 93, at 2.

⁹⁶ *Id.*

⁹⁷ *Id.*

⁹⁸ *Id.*

⁹⁹ Toews, *supra* note 62.

¹⁰⁰ Desislavov et al., *supra* note 93, at 12.

¹⁰¹ *Iowa – State Energy Profile Analysis*, U.S. ENERGY INFO. ADMIN. (June 17, 2021), <https://www.eia.gov/state/analysis.php?sid=IA>; see also Susan Cosier, *A Federal Clean Energy Standard Would Build on Decades of State Experience*, AUDUBON MAGAZINE (Sept. 23, 2021), <https://www.audubon.org/news/a-federal-clean-energy-standard-would-build-decades-state-experience>.

¹⁰² *State Renewable Portfolio Standards and Goals*, NAT’L CONFERENCE OF STATE LEGISLATURES (Aug. 13, 2021), <https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx>. Washington, D.C. and two territories also have active renewable or clean energy requirements. *Id.* Three states and one territory have voluntary renewable energy goals. *Id.*

¹⁰³ Warren Leon, *100% Clean Energy Collaborative*, CLEAN ENERGY STATES ALLIANCE, <https://www.cesa.org/projects/100-clean-energy-collaborative/guide/table-of-100-clean-energy-states/> (last visited Dec. 29, 2021). Included in this number are states that have committed to 100 percent clean or

aiming for 100 percent clean energy.¹⁰⁴ In fact, more than one in three Americans already live in a city or state that committed to, or even achieved, 100 percent clean electricity.¹⁰⁵ Unsurprisingly, more than two-thirds of voters support the federal government moving the country to a 100 percent clean energy electricity grid by 2035.¹⁰⁶ Even Google, one of the largest electricity consumers in the US, is targeting “24/7 carbon-free energy” in all its facilities, including data centers and campuses, by 2030.¹⁰⁷

There is a proven openness to—even a hunger for—clean energy. The missing ingredient is federal policy. Considering the urgency to bring greenhouse gas emissions to zero by the middle of the twenty-first century, a unifying federal policy could ensure that every state and utility is adopting clean sources at the necessary pace.¹⁰⁸ A federal policy or national clean energy standard should also account for AI and limit its burden on the environment. While AI researchers and developers in academia and the tech industry alike should operationalize environmental sustainability with respect to AI development, the federal government should develop a policy framework that mandates accurate measuring and reporting of AI’s carbon emissions, incentivizes greener and more efficient AI design,

renewable energy as well as those that have only committed to 100 percent carbon-free electricity. *Id.*

¹⁰⁴ *Progress Toward 100% Clean Energy in Cities & States Across the U.S.*, UCLA LUSKIN CTR. FOR INNOVATION (Nov. 2019), <https://innovation.luskin.ucla.edu/wp-content/uploads/2019/11/100-Clean-Energy-Progress-Report-UCLA-2.pdf>.

¹⁰⁵ *Progress Toward 100% Clean Energy in Cities & States Across the U.S.*, UCLA LUSKIN CTR. FOR INNOVATION (Nov. 2019), <https://innovation.luskin.ucla.edu/wp-content/uploads/2019/11/100-Clean-Energy-Progress-Report-UCLA-2.pdf>.

¹⁰⁶ Danielle Deiseroth et al., *Voters Support 100% Clean Electricity by 2035*, DATA FOR PROGRESS (Feb 2021), <https://www.filesforprogress.org/memos/voters-support-a-clean-electricity-standard.pdf>; see also *POLL: Voters Support Transition to 100% Clean Economy*, CLIMATE NEXUS (Oct. 27, 2020), <https://climatenexus.org/wp-content/uploads/2015/09/Public-Gas-Poll-Press-Release.pdf>.

¹⁰⁷ Sundar Pichai, *Our Third Decade of Climate Action: Realizing a Carbon-Free Future*, GOOGLE (Sept. 14, 2020), <https://blog.google/outreach-initiatives/sustainability/our-third-decade-climate-action-realizing-carbon-free-future/>.

¹⁰⁸ See JOHN ROMANKIEWICS ET AL., *THE DIRTY TRUTH: ABOUT UTILITY CLIMATE PLEDGES*, SIERRA CLUB (Jan. 2021), <https://coal.sierraclub.org/the-problem/dirty-truth-greenwashing-utilities> (showing that utilities will not adopt clean energy fast enough without a national clean energy standard).

and require data centers to adopt clean energy not unlike requirements utilities are subject to.

A. Keeping Tally: Measuring Emissions & Requiring Reporting

The first step for producing less power-hungry AI models is for AI developers and companies to know how much carbon dioxide their machine learning experiments are producing and how much those emissions could be reduced.¹⁰⁹ After all, a problem cannot be solved if it cannot be measured. However, measuring the power consumption of an AI model can be challenging because a single machine can typically train multiple models simultaneously, so each training session must be untangled from the others.¹¹⁰ Translating this power consumption into carbon emissions can be another endeavor depending on the allocation of renewable and fossil fuels that produced the electricity.¹¹¹ This mix can vary based by location as well as time of day.¹¹² California, for example, draws much of its renewable energy from solar plants, causing experiments run during the day to use approximately two-thirds of the energy of night-time experiments.¹¹³

Today, very little data or information on tech companies' energy use is available to the public.¹¹⁴ As a result, researchers and policymakers are left to rely on either the few public sources of data available or voluntary company disclosures, and tech companies have no incentives to release it.¹¹⁵ The scarcity of readily accessible

¹⁰⁹ See generally Peter Henderson et al., *Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning*, ARXIV:2002.05651, <https://arxiv.org/abs/2002.05651> (sharing a new tool for measuring both how much electricity a machine learning project will use and its carbon emissions, developed by a team of researchers from Stanford, Facebook AI Research, and McGill University).

¹¹⁰ *Id.* at 7.

¹¹¹ *Id.* at 8.

¹¹² *Id.*

¹¹³ *Id.* The researchers also estimated that training an AI model in Estonia, which primarily relies on oil shale, will produce 30 times the volume of carbon dioxide as the same model trained in Quebec, which is mostly powered by hydroelectricity. *Id.* at 11–12.

¹¹⁴ Roel Dobbe & Meredith Whittaker, *AI and Climate Change: How They're Connected, and What We Can Do about It*, AI NOW INSTITUTE (Oct. 17, 2019), <https://medium.com/@AINowInstitute/ai-and-climate-change-how-theyre-connected-and-what-we-can-do-about-it-6aa8d0f5b32c>.

¹¹⁵ *Id.*

information hampers research and regulation efforts.¹¹⁶ To address this lack of transparency, policymakers should direct key players in the tech and energy sectors to energy consumption and carbon emissions data available to the public.

When a team of researchers from Stanford University, Facebook, and McGill University searched for accurate reporting of energy and carbon usage, they turned to the California Independent System Operator, more commonly known as CAISO, which tracks real-time emissions data and manages the flow of electricity over most of the state's grids.¹¹⁷ ISOs came about as a response to the Federal Energy Regulatory Commission's (FERC) Order No. 888, which was issued on April 24, 1996 to "remedy undue discrimination in access to the monopoly owned transmission wires that control whether and to whom electricity can be transported in interstate commerce."¹¹⁸ Order No. 889, issued the same day, required public utility, including ISOs, to provide information "about available transmission capacity, prices, and other information that will enable [customers] to obtain open access non-discriminatory transmission service."¹¹⁹

Given FERC's precedent of directing ISOs to provide open access information, FERC should now require ISOs to provide real-time carbon emissions data to the public. CAISO currently provides data on electricity demand, forecasted peaks, electricity load served by renewable energy, carbon dioxide emission levels, and other key

¹¹⁶ See Lotfi Belkhir & Ahmed Elmeligi, *Assessing ICT Global Emissions Footprint: Trends to 2040 & Recommendations*, 117 J. OF CLEANER PROD. 448 (2018) (exemplifying the research consequences stemming from lack of access and information, where researchers resorted to estimating 2018 data center energy consumption using data from 2008).

¹¹⁷ *Id.* at 8, 23. See also *Understanding the ISO*, CALIFORNIA ISO, <http://www.caiso.com/about/Pages/OurBusiness/Default.aspx> (last visited Dec. 28, 2021).

¹¹⁸ See Order No. 888, FED. ENERGY REGUL. COMM'N (Apr. 24, 1996), <https://www.ferc.gov/industries-data/electric/industry-activities/open-access-transmission-tariff-oatt-reform/history-oatt-reform/order-no-888>; see also 18 C.F.R. § 35 (1996). Because interstate transmission lines fall under the jurisdiction of federal commerce laws, the Federal Energy Regulatory Commission (FERC) regulates CAISO. See *Regulatory*, CALIFORNIA ISO, <http://www.caiso.com/rules/Pages/Regulatory/Default.aspx> (last visited Dec. 28, 2021).

¹¹⁹ See Order No. 889, FED. ENERGY REGUL. COMM'N (Apr. 24, 1996), <https://www.ferc.gov/industries-data/electric/industry-activities/open-access-transmission-tariff-oatt-reform/history-of-oatt-reform/order-no-889-1>; see also 18 C.F.R. § 37 (1996).

datapoints that enable researchers to measure the environmental impact of AI.¹²⁰ Taking CAISO's approach to transparent and real-time data access as a blueprint, FERC can create a template for other ISOs to provide similar data to the public.

In addition, regulators should require companies to disclose energy consumption and carbon emissions in AI development. While companies are often eager to share successes or vaguer data points,¹²¹ comprehensive and specific and occasionally unflattering data should still be disclosed to facilitate the free flow of data for AI research and development purposes. Requiring this information to be disclosed to regulatory agencies and the public not only informs future AI and environmental policies but also incentivizes researchers and developers to be more cognizant of and accountable for their AI design decisions.

The current and dominant industry trend is scaling up machine learning to solve bigger problems, using more compute power and more data.¹²² As that happens, researchers, developers, and companies alike must evaluate whether resource-intensive AI models are improving other efficiencies and whether those efficiency gains offset the initial costs and ongoing inference costs. At present, AI is being rolled out across virtually every industry as a strategic priority, generally without consideration for its environmental cost.¹²³ In 2016, the UK Energy Research Centre found that policy proposals in non-energy sectors, such as agriculture and transportation, do not account for climate impact.¹²⁴ Without access to data to make these

¹²⁰ See *Today's Outlook*, CALIFORNIA ISO, <https://www.caiso.com/TodaysOutlook/Pages/index.html> (last visited Dec. 30, 2021) (providing real-time data on electricity demand and supply as well as emissions levels).

¹²¹ See *24/7 Carbon-Free Energy by 2030*, GOOGLE DATA CENTERS, <https://www.google.com/about/datacenters/cleanenergy/> (last visited Dec. 30, 2021); see also *Green Power Partnership Top 30 Tech & Telecom*, U.S. ENV'T PROT. AGENCY, <https://www.epa.gov/greenpower/green-power-partnership-top-30-tech-telecom> (last visited Dec. 30, 2021) (listing companies and their amount of green power as a percentage of total electricity use).

¹²² Andrews, *supra* note 36.

¹²³ See generally EMILY COX ET AL., *THE IMPACTS OF NON-ENERGY POLICIES ON THE ENERGY SYSTEM*, UK ENERGY RESEARCH CENTRE (2016), <https://ukerc.ac.uk/publications/impact-of-non-energy-policies-on-energy-systems/>; see also Dobbe & Whittaker, *supra* note 109.

¹²⁴ EMILY COX ET AL., *THE IMPACTS OF NON-ENERGY POLICIES ON THE ENERGY SYSTEM*, UK ENERGY RESEARCH CENTRE 6–10 (2016),

determinations, it could become a challenge to evaluate the costs of AI—as well as its benefits.

B. Lean, Green Thinking Machines: Coordinating Sustainable Design

In September 2019, workers from 12 tech companies, including Amazon, Facebook, Google, Microsoft, and Twitter, united to form the Tech Workers Coalition and joined the global climate strike, demanding “zero carbon emissions by 2030, zero contracts with fossil fuel companies, zero funding of climate denial lobbying or other efforts, and zero harm to climate refugees and frontline communities.”¹²⁵ In order for these important demands to be met, key decisionmakers in the tech industry must not only acknowledge the industry’s contribution to climate change, but also incorporate environmental sustainability as a core principle of responsible AI development and design.¹²⁶

Having more data can certainly increase the accuracy of an AI model, but there exists a threshold where even adding infinite amounts of data cannot improve the model’s accuracy any further.¹²⁷ Large tech companies have vast financial resources that afford them the ability to “buy” accurate AI models through brute force.¹²⁸ This approach does not underscore the intelligent design AI is capable of.

On January 1, 2021, a bipartisan legislation known as the National Artificial Intelligence Initiative Act (NAIIA) established the

<https://ukerc.ac.uk/publications/impact-of-non-energy-policies-on-energy-systems/>. Policies in non-energy sectors are “policies relating to all other sectors.” *Id.* at 15. Although non-energy policies “may have an effect on energy systems, they are not explicitly designed to do so.” *Id.*

¹²⁵ Dobbe & Whittaker, *supra* note 109.

¹²⁶ See Dhar, *supra* note 24, at 425 (outlining suggestions from the Copenhagen Centre on Energy Efficiency).

¹²⁷ See Schwartz et al., *supra* note 58.

¹²⁸ *Id.* at 2. See Mike James, *ImageNet Training Record – 24 Minutes*, 1-PROGRAMMER (Sept. 21, 2017), <https://www.i-programmer.info/news/202-number-crunching/11140-imagenet-training-record-24-minutes.html> (“[O]ur hardware budget is only 1.2 million USD, which is 3.4 times lower than Facebook’s 4.1 million USD.”); see also Quoc Le & Barrett Zoph, *Using Machine Learning to Explore Neural Network Architecture*, GOOGLE AI BLOG (May 17, 2017), <https://ai.googleblog.com/2017/05/using-machine-learning-to-explore.html> (“[T]here are 800 networks being trained on 800 GPUs concurrently at anytime.”).

National Artificial Intelligence Initiative (NAII) as well as a dedicated NAIIO Office (NAIIO) tasked to:

- Provide technical and administrative support to the Select Committee on AI (the senior interagency committee that oversees the NAII) and the National AI Initiative Advisory Committee;
- Oversee interagency coordination of the NAII;
- Serve as the central point of contact for technical and programmatic information exchange on activities related to the AI Initiative across Federal departments and agencies, industry, academia, nonprofit organizations, professional societies, State and tribal governments, and others;
- Conduct regular public outreach to diverse stakeholders; and
- Promote access to technologies, innovations, best practices, and expertise derived from Initiative activities to agency missions and systems across the Federal government.¹²⁹

Here, the two specific functions of the NAII—“sustain consistent support for AI R&D” and “plan and coordinate Federal interagency AI activities”—empower it to set new standards for efficient and environmentally sustainable AI training methodologies.¹³⁰ To address the energy consumption of today’s brute force model training practices and the accompanying environmental costs, NAIIO should collaborate with FERC and the U.S. Department of Energy’s Office of Energy Efficiency & Renewable Energy (EERE) to develop climate-aware guidance for AI training and development. Considering all three government agencies were established with economic competitiveness in mind, it is unlikely for coordinated guidance to produce requirements that will hinder innovation and development in AI. From developing algorithms that are better at

¹²⁹ *About*, NATIONAL ARTIFICIAL INTELLIGENCE INITIATIVE OFFICE (NAIIO), <https://www.ai.gov/about/#NAII-NATIONAL-ARTIFICIAL-INTELLIGENCE-INITIATIVE> (last visited Dec. 25, 2021) [hereinafter NAIIO Website]; *see also* H.R. 6395, Division E – National Artificial Intelligence Initiative Act of 2020, <https://www.congress.gov/116/crpt/hrpt617/CRPT-116hrpt617.pdf#page=1210>.

¹³⁰ *See* NAIIO Website, *supra* note 124.

“cherry-picking the most relevant data”¹³¹ to minimizing model training cycles or even opting to not use deep neural networks and deep learning architectures.¹³²

While developing cross-agency guidance and requirements take time, NAIIO should take on low-hanging fruit that can start reducing the environmental burden of AI. For instance, NAIIO should encourage researchers to share weights and architectures to lower computational costs.¹³³ While AI researchers in industry may be more reluctant to share their work, researchers in academia may benefit from pooling resources and findings. Furthermore, Big Tech may be no stranger to government subsidies,¹³⁴ but state and local governments should attach conditions to subsidies and tax abatement programs to incentivize more efficient AI training and development methodologies.¹³⁵ NAIIO should direct state and local governments to consider these conditions when using taxpayer money to potentially fund AI development. These conditions can also be applied to government contracts and request for proposals (RFPs) to signal to AI

¹³¹ Kim Martineau, *Shrinking Deep Learning’s Carbon Footprint*, MIT NEWS (Aug. 7, 2020), <https://news.mit.edu/2020/shrinking-deep-learning-carbon-footprint-0807>. See Yue Meng et al., *AR-Net: Adaptive Frame Resolution for Efficient Action Recognition*, ARXIV:2007.15796 (2020), <https://arxiv.org/abs/2007.15796> (proving a training approach that leads to faster video classification at half the computational cost by designing a model that captures more-relevant images and skips less-relevant images).

¹³² North Carolina State University, *New Technique Cuts AI Training Time by More Than 60 Percent*, SCIENCEDAILY (Apr. 8, 2019), <https://www.sciencedaily.com/releases/2019/04/190408114322.htm>; see generally Andrew Ng, *AI Doesn’t Have to Be Too Complicated or Expensive for Your Business*, HARVARD BUSINESS REVIEW (July 29, 2021), <https://hbr.org/2021/07/ai-doesnt-have-to-be-too-complicated-or-expensive-for-your-business> (suggesting making judicious use of deep learning techniques and architectures).

¹³³ See generally Bryan A. Plummer et al., *Neural Parameter Allocation Search*, ARXIV:2006.10598 (2021), <https://arxiv.org/abs/2006.10598> (introducing Shapeshifter Networks, “which automatically learns where and how to share parameters between all layers in a network, even between layers of varying sizes and operations.”).

¹³⁴ See Dominic Rushe, *US Cities and States Give Big Tech \$9.3bn in Subsidies in Five Years*, GUARDIAN (July 2, 2018), <https://www.theguardian.com/cities/2018/jul/02/us-cities-and-states-give-big-tech-93bn-in-subsidies-in-five-years-tax-breaks>; see also *Subsidy Tracker*, GOOD JOBS FIRST, <https://www.goodjobsfirst.org/subsidy-tracker> (last visited Dec. 30, 2021).

¹³⁵ See also discussion *infra* Part III.C.

developers that only environmentally sustainable models should be created for government uses.

Lastly, the trend toward training larger and larger AI models underscores another growing problem in AI: the sheer intensity of resources now necessary for producing paper-worthy results has made it progressively more challenging for people working in academia to continue contributing to research.¹³⁶ The result is a privatization of AI research. Using massive amounts of data to train a complex AI model is not feasible for academic researchers due to a lack of computational resources. The equitable access gap between researchers in academia and researchers in industry grows as tech companies continue trying to one-up each other's AI capabilities. Investing in developing more efficient hardware and algorithms would also help level the playing field.

C. Cleaning House: Moving Data Centers to Clean Energy

Data centers, according to the U.S. Department of Energy, are one of the most energy-intensive building types, “consuming 10 to 50 times the energy per floor space of a typical commercial building.”¹³⁷ As the use of information technology, including cloud computing, rises, data center and server energy use is expected to rise too.¹³⁸ Before the demand for data center-reliant technologies outpaces actual and perceived energy efficiency gains from these structures, the federal government should focus data center regulation on two fronts: require data centers to adopt renewable (or at the very least low-carbon) energy sources and improve data centers' energy efficiency.

Although large tech companies tend to be the largest consumers of electricity, they have also been some of the earliest and most eager

¹³⁶ Karen Hao, *Training a Single AI Model Can Emit as Much Carbon as Five Cars in Their Lifetimes*, MIT TECH. REV. (June 6, 2019), <https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/>.

¹³⁷ *Data Centers and Servers*, U.S. DEP'T OF ENERGY, OFFICE OF EFFICIENCY & RENEWABLE ENERGY, <https://www.energy.gov/eere/buildings/data-centers-and-servers> (last visited Dec. 24, 2021).

¹³⁸ *Id.* See also CLICKING CLEAN: WHO IS WINNING THE RACE TO BUILD A GREEN INTERNET, GREENPEACE 16 (2017) (demonstrating that the global IT sector's electricity consumption in billion kilowatt-hours would make it the world's third largest energy-consuming country, behind China and the US).

adopters of renewable energy.¹³⁹ Because of the slower adoption of renewable energy in the US, Big Tech has actively built data centers or signed contracts to receive energy supplies from wind and solar farms in Europe. Google and Microsoft, for instance, recently built massive data hubs in Finland,¹⁴⁰ and Facebook did the same in Denmark and Sweden.¹⁴¹ In 2020, Google signed a deal to purchase all of the energy from the Netherland's largest solar energy power to power one of its four European data centers.¹⁴²

The energy efficiency of these European data centers is enhanced by their cooler climates.¹⁴³ Unfortunately, most of the world's largest data centers are in hot or temperate climates, consuming vast amounts of energy to prevent overheating.¹⁴⁴ Of the world's 10 largest, two are in Nevada, and others are in Georgia and Virginia.¹⁴⁵ A meaningful and impactful step toward reducing AI carbon footprint is to move model training exercises to a location supplied mainly by renewable energy sources.¹⁴⁶

Federal policy should also push data centers to adopt liquid cooling methods, which are not only more efficient than air cooling but can also handle the higher temperatures emitted by newer and more

¹³⁹ See Pearce, *supra* note 74. Large tech companies can afford these purchases and contracts, but most companies lack the resources needed to build their own hyperscale data centers and rely on conventional data centers, which are less energy efficient. See Pierre Delforge, *America's Data Centers Consuming and Wasting Growing Amounts of Energy*, NATURAL RESOURCES DEFENSE COUNCIL (Feb. 6, 2015), <https://www.nrdc.org/resources/americas-data-centers-consuming-and-wasting-growing-amounts-energy>.

¹⁴⁰ Eeva Haaramo, *Finland: The World's Next Datacentre Powerhouse?*, ZDNET (Apr. 16, 2015), <https://www.zdnet.com/article/finland-the-worlds-next-datacentre-powerhouse/>.

¹⁴¹ Nikolaj Skydsgaard, *Facebook to Build Third Foreign Data Center in Denmark*, REUTERS (Jan. 19, 2017), <https://www.reuters.com/article/us-facebook-denmark/facebook-to-build-third-foreign-data-center-in-denmark-idUSKBN15310F>.

¹⁴² Joao Lima, *Google Buys Data Centre Power From Netherlands' Largest Solar Energy Park*, BROADGROUP (June 25, 2020), <https://www.broad-group.com/data/news/documents/b1m2y626kk9cwx/google-buys-data-centre-power-netherlands-largest-solar-energy-park>.

¹⁴³ See Pearce, *supra* note 74; see also *AI and ML Models in Production*, *supra* note 22 (explaining that data centers use their local geography for natural cooling).

¹⁴⁴ *Id.*

¹⁴⁵ *Id.*

¹⁴⁶ Andrews, *supra* note 36.

powerful technologies.¹⁴⁷ Liquid cooling also lowers electricity costs by using less electricity than their air-cooling counterparts.¹⁴⁸ When constrained by geography and climate, liquid cooling may be a more energy efficient alternative. To minimize water waste, government initiatives such as the Federal Energy Management Program (FEMP),¹⁴⁹ should provide guidance to data center operators, particularly hyperscale data centers, which require millions of gallons per day to cool technology in their massive facilities.¹⁵⁰

Adopting AI as a tool for improving a data center's energy efficiency may also offset training and longer-term inference costs. AI can allow data centers to automate routine tasks such as monitoring and resource allocation.¹⁵¹ Similar to the way AI has been used to develop smart electrical grids, a similar application can help data centers anticipate peak hours and identify performance issues.

CONCLUSION

There is still a broad assumption that digital is intrinsically green. However, digital solutions still have physical infrastructures that consume the Earth's resources. From start to finish, AI is power-hungry and energy-intensive. This will continue to be the case as the demand for AI rises.

If left to its own devices, AI's energy consumption and carbon emissions could exacerbate the current climate crisis. But AI's destiny

¹⁴⁷ Thomas Griffin, *Why We Should Care About The Environmental Impact of AI*, FORBES (Apr. 17, 2020), <https://www.forbes.com/sites/forbestechcouncil/2020/08/17/why-we-should-care-about-the-environmental-impact-of-ai/>.

¹⁴⁸ *Id.*

¹⁴⁹ FEMP is a part of the Office of Energy Efficiency & Renewable Energy. *Cooling Water Efficiency Opportunities for Federal Data Centers*, DEPARTMENT OF ENERGY, OFFICE OF ENERGY EFFICIENCY & RENEWABLE ENERGY, <https://www.energy.gov/eere/femp/cooling-water-efficiency-opportunities-federal-data-centers> (last visited Dec. 30, 2021).

¹⁵⁰ Solon, *supra* note 83.

¹⁵¹ For instance, Google in 2015 used AI to reduce its data centers' excess heat production by 40 percent. Richard Evans & Jim Gao, *DeepMind AI Reduces Google Data Centre Cooling Bill by 40%*, DEEPMIND (July 20, 2016), <https://deepmind.com/blog/article/deepmind-ai-reduces-google-data-centre-cooling-bill-40>; see also Megan Russo, *How Artificial Intelligence Can Combat Climate Change*, THE REGULATORY REVIEW (Aug. 25, 2021), <https://www.theregreview.org/2021/08/25/russo-artificial-intelligence-combat-climate-change/>.

is not set in stone. Recognizing the environmental drawbacks of AI provides a unique opportunity for the tech industry, academia, and government to collaborate and identify pathways for developing sustainable AI solutions that serve the future, not just the present. A climate-aware policy response to the current state of AI research and development should enhance transparency and data access; incentivize environmental sustainability in AI design; and facilitate data center's move toward clean energy. The federal policy framework proposed in this Article offers pragmatic and achievable solutions that limit the environmental harms of AI so that the technology can realize its potential as a planet-saving technology.

AI will likely remain a controversial technology, one that requires constant scrutiny and even skepticism.¹⁵² Its potential to serve and improve humanity cannot be ignored, but unless researchers, Big Tech, and policymakers alike are willing to reassess and reform today's AI research agenda, the very technology we have counted on to save us and our planet will become an antagonist in our fight against climate change.

¹⁵² PATRICK K. LIN, MACHINE SEE, MACHINE DO: HOW TECHNOLOGY MIRRORS BIAS IN OUR CRIMINAL JUSTICE SYSTEM (2021).