Is Another AI Possible?
Platforms, Political Economies, and Alternatives

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About the Report

Artificial intelligence (AI) is rapidly transforming industries, economies, and societies, offering promising advances in healthcare, education, climate solutions, and beyond. Yet beneath its transformative potential lies a troubling reality: AI's development and deployment are largely controlled by a few powerful tech corporations, with very little public oversight. This concentration of power reinforces longstanding patterns of bias, inequality, labor and data exploitation, invasive surveillance, and environmental harm. This paper examines the political economy of big tech AI, critiquing its industrial and regulatory capture while exploring alternative pathways that center the public interest over corporate profit, including public utility and cooperative models, government–civil society collaborations, and Indigenous approaches to decolonial AI.

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About the Publisher

The Media, Inequality and Change Center produces engaged research and analysis while collaborating with community leaders to help support activist initiatives and policy interventions. The Center's core principles are to research, educate, connect, and engage by assessing democratic deployments of technology, contributing to policy interventions that encourage structural reform, and making material interventions around media and democracy.

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Executive Summary

Artificial intelligence (AI) is transforming industries, economies, and societies at an unprecedented pace, promising breakthroughs in healthcare, education, climate solutions, and more. Yet beneath its revolutionary potential lies a troubling reality: AI's development and deployment are dominated by a handful of powerful big tech corporations, reinforcing historical patterns of inequality, data and labor exploitations, and environmental harm. This paper examines the political economy of AI, critiquing its industrial and regulatory capture while exploring alternative pathways that center the public interest over corporate profit.

The Concentration of AI Power

The AI industry is not neutral, scientific endeavor, but a product of concentrated capital and corporate power. Firms like Apple, Amazon, Microsoft, Google (Alphabet), Meta, and Nvidia, collectively dubbed the *Magnificent Seven*, control most of the AI stack, from advanced chips (GPUs) to cloud infrastructures and data monopolies. Their dominance is enabled by economies of scale, lobbying power, and growing government support, allowing them to shape industrial AI research, models, markets, and policies to their advantage.

U.S. universities once led nonprofit AI innovation, but over the past decade, industry has taken over, accounting for 90.2% of notable AI models. In 2024, private companies invested $109.1 billion in AI, vastly outpacing public spending of $5.3 billion. Meanwhile, universities produced almost no major AI models as they lack the financial and infrastructural resources needed to build large AI models.

The Costs of Industrial AI

In addition to billions of dollars in investments, the dominant AI paradigm extracts immense human, environmental, and ethical tolls:

Data Exploitation: Large-scale AI models are trained on vast datasets scraped without consent, from copyrighted media to personal images, sparking lawsuits and ethical crises.

Bias and Discrimination: Big tech AI systems perpetuate racial, gendered, and class biases, from facial recognition misidentifying people of color to generative AI reinforcing harmful stereotypes.

Environmental Harm: Training and running large-scale AI models demand colossal energy and water resources, with data centers consuming more electricity than entire nations. For example, Google, Microsoft, and Meta used 60 terawatt-hours in 2022–23, exceeding the combined consumption of Jordan, Iceland, and Ghana. Rare earth mining for AI hardware devastates ecosystems and Indigenous communities.

Labor Exploitation: Behind "autonomous" or "self-learning" AI lies an invisible workforce, including data annotators, content moderators, and gig workers who are often in the Global South, face precarious conditions under what critics term "AI colonialism." This concern grows as AI deployment leads to widespread job loss and displacement.

Weaponizing AI Surveillance: Concerns are mounting over the use of AI for pulling sensitive public data by companies like Palantir, with the potential for political misuse.

Alternative Possibilities

Despite these challenges, grassroots and institutional efforts are forging public alternatives:

- **Public Utility Regulation**: Demands are growing for regulating digital infrastructures such as broadband and cloud computing as public utilities to provide equitable access and accountability.

- **Public Internet and AI Infrastructure**: Success stories like the municipal broadband network in Chattanooga, Tennessee, which provides affordable, high-speed internet, show that public AI infrastructure is possible through incremental growth, even if it does not span the entire AI stack.

- **Cooperatives**: Worker-owned platforms (e.g., Commons Cloud) and data cooperatives empower users to control their data and share its benefits.

- **Decolonial AI**: Indigenous-led initiatives such as Te Hiku Media's Māori language NLP tools recenter marginalized knowledge systems and resist extractive AI practices.

- **Policy Interventions**: Reversing deregulation (e.g., reinstating net neutrality) and enforcing horizontal regulations (like the EU AI Act) could curb corporate power.

Key Takeaways

In addition to billions of dollars in investments, the dominant AI paradigm extracts immense human, environmental, and ethical tolls:

- **AI is not inevitable**: Its trajectory is shaped by capitalist logics, but alternatives—public, cooperative, decolonial—are already emerging.

- **Scale is not destiny**: Small-scale, community-led models such as tribal internet networks show that equitable AI is possible without corporate monopolies.

- **Structural change is urgent**: Addressing AI's harm requires dismantling its industrial capture through antitrust measures, public investment, and ethical regulation.

- **Solidarity is critical**: The fight for equitable AI must connect with broader movements for labor rights, climate justice, and Indigenous sovereignty.

In sum, this paper argues that AI's future needs not to replicate the models and inequalities of its present. By centering public interest, democratic governance, and ecological sustainability, we can reclaim AI as a tool for collective liberation rather than corporate control. The path forward demands not just technical fixes but systemic transformation, one that connects critique with actionable alternatives.

Introduction

Artificial Intelligence (AI) technologies are rapidly transforming industries and public and private service sectors, from healthcare to genetics research, telecommunications, education, and media production. In doing so, AI technologies are constantly mushrooming, changing, evolving, and promising further massive changes, including generating unprecedented market value, increasing profits, boosting productivity and efficiency, fostering prosperity, and creating new economies and services—while also aiming to solve serious social and material problems such as climate change, pandemics, and the energy crisis. The AI industry, however, still has a long and bumpy road ahead in delivering on these promises. Whether desirable or not, most of the innovation in AI at present is spearheaded by private, for-profit enterprises, although it began with publicly funded research projects.

As critical AI scholar Meredith Whittaker puts it, industrial AI is owned, developed, and deployed by a handful of extremely powerful and wealthy big tech firms—with computational infrastructure, existing access to vast amounts of data and systems to process and store it, talent resources, research grants for elite university laboratories, deep market reach, surplus capital, incremental government support, lax regulations, and more (Whittaker, 2021). Therefore, the advances in AI products, framed as a scientific breakthrough, are actually the result of an intense concentration of capital, corporate power, and industrial capture. These companies not only control the tools, languages, and conditions of AI development, they also "make the water in which AI research swims" (p. 53). Such power, according to Whittaker, is comparable only to the way the U.S. military has captured research. In a stronger criticism, Dyer-Witheford et al. (2019) argue that AI has emerged as the ultimate instrument of capital, which will eventually render humanity obsolete. While some tech insiders are apparently worried about containing risks stemming from the "inevitable waves" (Suleyman, 2023), of AI and artificial organs, others have called out the "AI hype" created by self-interested tech executives (Bender & Hanna, 2025).

This paper examines the political economy of AI, asking how corporate power, market concentration, and neoliberal policy frameworks shape the development and deployment of AI technologies. It argues that today's AI ecosystem, dominated by a handful of big tech firms, reflects broader capitalist logics of extraction, labor exploitation, and environmental harm, while pushing public interest alternatives to the margins. By tracing the architecture of the global AI stack, from rare earth mining to cloud infrastructures and data monopolies, the paper shows how AI's material and ideological foundations entrench inequality and raise urgent ethical and structural questions.

The paper is organized into three interconnected sections. First, it maps the industrial and geopolitical dimensions of AI, examining market dominance, supply chain dependencies, and the role of public investment. Second, it critiques the socio-technical harms of AI, including data theft, algorithmic bias, environmental costs, and labor exploitation. Finally, it explores alternative possibilities of AI. By "alternative possibilities," the report envisions nonprofit, collaborative, cooperative, and publicly funded initiatives that are shaping, or have the potential to shape, AI and related infrastructures, including those still emerging or yet to be realized. These possibilities could help democratize AI development and align it with collective needs. Throughout, the analysis draws on empirical data, policy case studies, and theoretical frameworks from critical political economy and decolonial studies.

> ***Therefore, the advances in AI products... are actually the result of an intense concentration of capital, corporate power, and industrial capture.***
>
> *Merideth Whittaker*

Key research questions guide this inquiry: How does the concentration of capital and infrastructure in the AI industry reproduce historical patterns of inequality? What are the material and ecological consequences of industrial-scale AI production? And crucially, what viable pathways exist for building equitable, publicly accountable AI systems in the face of entrenched corporate and state power? By addressing these questions, the paper aims to bridge academic critique with actionable policy insights, advocating for structural interventions that recenter AI around justice, sustainability, and democratic governance.

Definition, Varieties, and Markets of AI

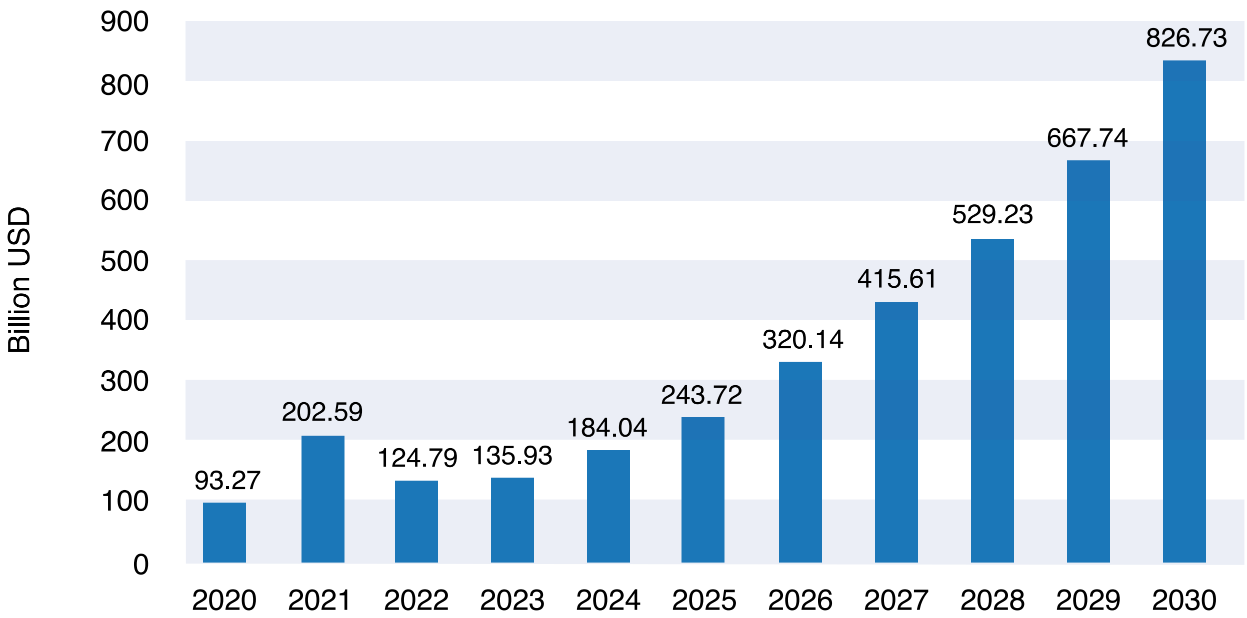
Very broadly speaking, AI is an application that allows a computer or machine to imitate how the human mind works. Digital algorithms, automation, and machine learning fall under the broad rubric of AI. Princeton University computer scientists Arvind Narayanan and Sayash Kapoor illustrate this with the metaphor of a "vehicle," pointing out how loosely the term AI can be used. Just as no vehicle is the same, no AI is the same. AI means different things to different people and AI technology can take many layers and forms (Narayanan & Kapoor, 2024). This means, depending on context, "alternative AI" may mean different things to different people.

The two most basic categories of AI are Artificial General Intelligence (AGI) and Narrow AI. AGI is still theoretical. Narrow AI has several areas, including machine learning (ML), its subset deep learning (DL), and artificial neural networks (NN). These categories further break down into subfields such as natural language processing (NLP), automation, computer vision, speech recognition, robotics, predictive analytics, content moderation, generative AI, and more. ML is widely used in chat assistants, voice commands, and apps.

Large language models (LLMs) and generative AI (Gen AI) are fundamentally built on DL using artificial neural networks. The networks assign and adjust its internal *weights* to different data inputs to figure out which features matter most. Through DL training, these models develop the ability to carry out *complex reasoning* across layers and perform *inference*, a process of generating output based on the data they've seen. Additionally, models like ChatGPT undergo fine tuning, often via *Reinforcement Learning from Human Feedback* (RLHF) to optimize their responses for coherence and relevance (Minaee et al., 2024). However, because inference relies on statistical pattern prediction rather than true understanding, these models often produce plausible but "bullshit" information, a persistent problem known as *hallucinations* (Jones, 2025).

As the Center on Privacy & Technology (2022) emphasizes, an important aspect of the "learning" part is that terms used under the umbrella of AI, including "predicting," "interpreting," "deciding," "recognizing," and "generating," do not necessarily mean that an autonomous machine is independently learning, predicting, or generating outcomes. Rather, these terms indicate that a human actor has trained the machine to perform these tasks, even if autonomous learning occurs at some point. This is why, when discussing the technological processes of AI, it is important to consider the labor, industry, market, and policy factors that shape and enable these processes.

Chart 1: *Artificial Intelligence (AI) Market Size Worldwide from 2020 to 2030*



Source: Statista, June 18, 2024.

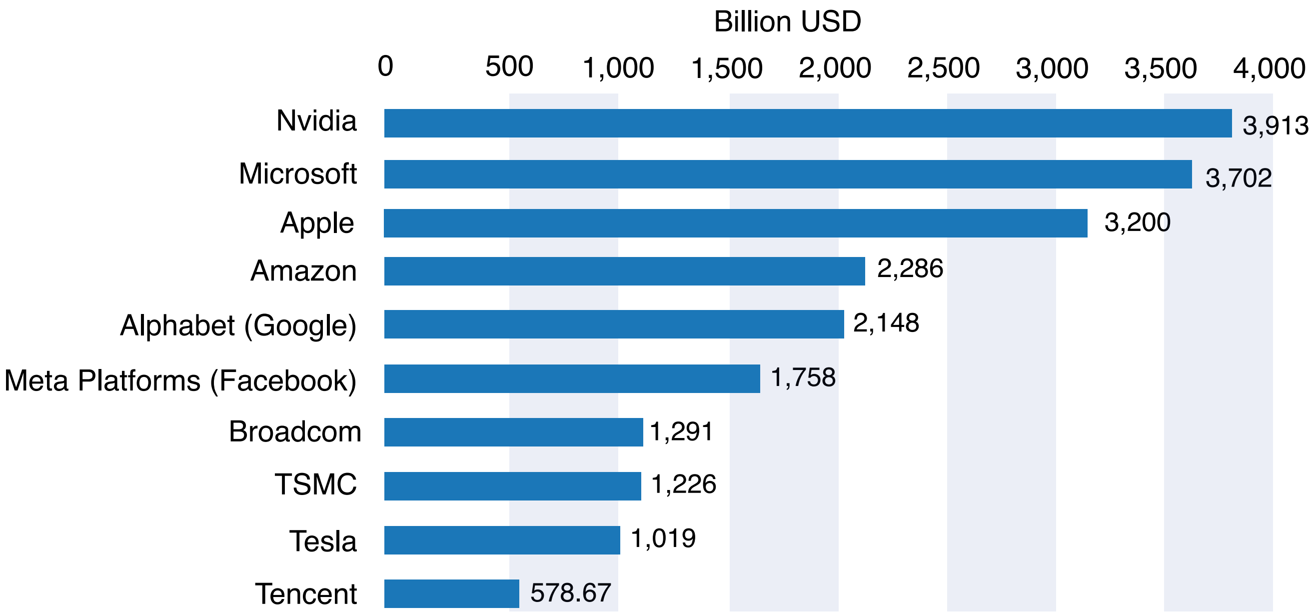
Global AI Markets

The AI industry, along with all the hype surrounding it, is changing not by the year but by the day. As **Chart 1** shows, the global consumer market for AI technologies is vast and growing rapidly. In 2023, the AI market was valued at 50 billion U.S. dollars. By 2024, it grew beyond 184 billion, and it is reported to reach around 244 billion U.S. dollars in 2025. By 2030, it is expected to surpass 800 billion U.S. dollars (Statista, 2024, June 18; **Chart 1**).

Some categorize AI industries into two types based on how central AI is to their core business: AI core industries (such as OpenAI, which produces AI tools like ChatGPT) and AI-driven industries (for example, the self-driving auto industry that relies on AI). Others classify AI companies more broadly based on their relationship to other technologies (Hamilton, 2023). For instance, big tech research companies that develop and train AI language models include Alphabet, Microsoft, Meta, OpenAI, Amazon, Salesforce, Baidu, and more recently, Apple.

Then there are application companies that repackage and resell AI language models as premium products, such as Jasper AI, GitHub Copilot, Eleven Labs, and Kingsoft. There are also high-potential AI startups with substantial equity funding, known as *AI unicorns*, a term referring to privately owned startups valued at one billion USD or more. However, once a company goes public through an IPO or is acquired, it loses its unicorn status. Notable unicorns include JUUL, Databricks, xAI, Waymo, SpaceX, Anthropic, Cruise, Stripe, Epic Games, and Fanatics—all valued above 5 billion U.S. dollars as of February 2025.

Chart 2: *Leading Tech Companies Worldwide as of March 3, 2025, by Market Capitalization*



Source: CompaniesMarketCap.com, July 3, 2025.

Big Tech Dominates

It is perhaps no surprise that the most traditional big tech companies (see **Chart 2**) are also the leading investors in AI research, development, application, and marketing industries. Some scholars use the term "Big AI" and "AI as platforms" to describe the deep interconnection between AI and Big Tech, emphasizing how AI relies on cloud computing platforms to rapidly scale infrastructures, known as *hyper-scalability* (Mahnke & Bagger, 2024; van der Vlist et al., 2024). For instance, Google Cloud Platform provides the backbone for its AI development.

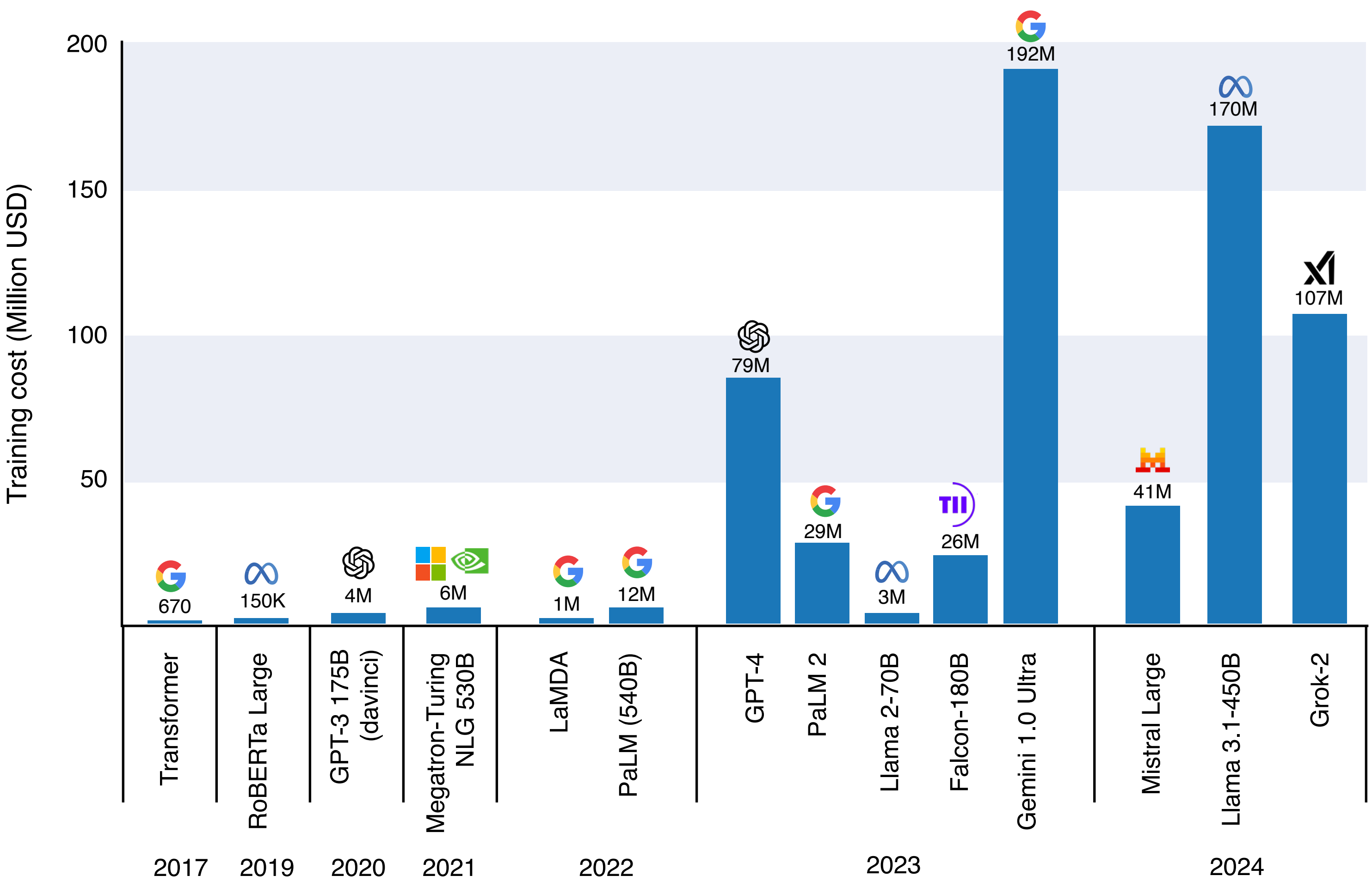
In addition, venture capital firms like Sequoia Capital (investor in Google and Apple), Accel (investor in Meta and Spotify), and Japan's SoftBank play a pivotal role in financing Silicon Valley's global expansion in digital platforms and AI (Qiu & Chan, 2025). This concentration of market power is underpinned not only by financial muscle but also by the ability to sustain large-scale investments and absorb risks that smaller players cannot. The U.S. big techs or big AI companies, often dubbed the *Magnificent Seven* (Apple, Microsoft, Amazon, Alphabet, Meta, Nvidia, and Tesla), hold first-mover advantage, economies of scale, network effects, and vendor lock-in mechanisms that secure their grip on the rapidly expanding AI markets and scalable commodities.

As of July 3, 2025, Nvidia and Microsoft have both surpassed Apple as the world's top tech companies by market capitalization USD (see **Chart 2**, CompaniesMarketCap.com, July 3, 2025; also see **Appendix Table 1** for a list of top 20 tech companies by

Market Capitalization). Despite a dip in valuation in January 2025 after the release of DeepSeek's AI model, Nvidia is now valued at 3.89 trillion USD. Microsoft has a market capitalization of 3.7 trillion USD and Apple is now valued at 3.2 trillion USD. Numerous other large- and mid-market-cap AI and related companies also compete in this space, including IBM, DeepSeek, TSMC, Adobe Inc., Oracle, and Palantir.

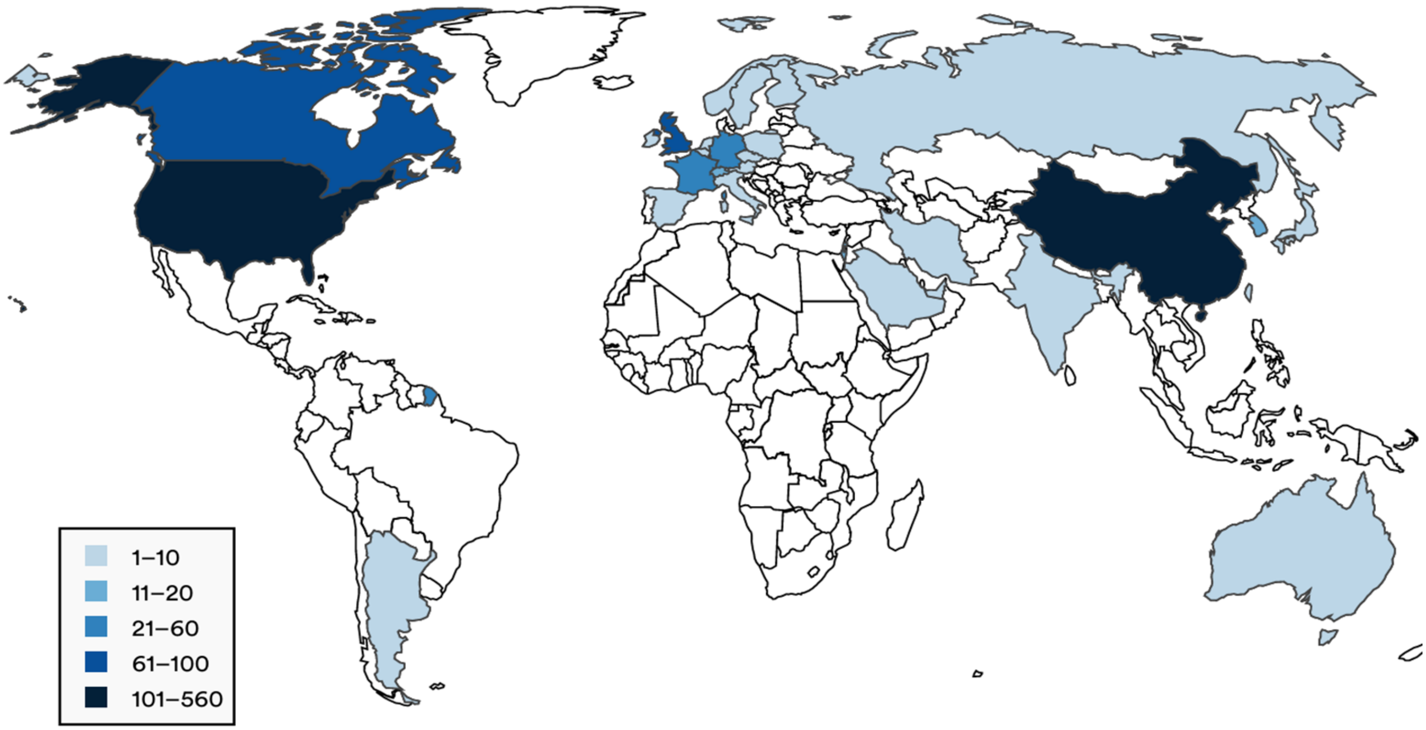
In developing and deploying industrial-scale AI systems, these major firms are uniquely positioned to take significant risks, rapidly acquire or shed talent, buy out emerging competitors, sustain ongoing investments, absorb substantial losses when necessary, and shoulder the enormous costs of training and maintaining advanced AI models. For example, the estimated training costs for OpenAI's GPT-4 and Meta's Llama 3.1-405B were $79 million and $170 million respectively (Stanford HAI, 2025, p. 66, see **Chart 3**).

Chart 3: *Estimated Training Cost of Select AI Models, 2017–24*



Source: Stanford University HAI AI Index Report 2025, p. 66.

Chart 4: *Number of notable AI models by geographic area, 2003–24*



Source: Stanford University HAI AI Index Report 2025, p. 47.

Their dominance extends beyond finances and talent to a complex infrastructure that supports every stage of AI development and deployment. These companies also benefit from an extensive, established network spanning the AI stack, including layers of networks, data mining, application programming interfaces (APIs), third-party app developers, software development kits (SDKs), supply chains, value chains, and data brokers (Verdegem, 2023). Their lobbying networks reach the highest political levels, enabling them to delay or neutralize legal challenges, such as those related to monopoly, antitrust, and copyright, for as long as necessary.

This industrial concentration has led to a geographic concentration of innovation in advanced and foundational models within the Gen AI industry (Korinek & Vipra, 2024). As shown in **Chart 4**, the creation, ownership, and production of the most significant AI models in recent years remain limited to a handful of countries, including the United States, China, the United Kingdom, Canada, and France, with few other minor players. This geographic concentration underscores the global power imbalance in AI innovation, raising concerns about equitable access and control.

Public Investment in AI

While major tech companies dominate AI development through vast resources and networks, public investment tells a different story. According to Stanford University's HAI *AI Index Report 2025*, U.S. private sector investment in AI soared from $72.4 billion in 2023 to $109.1 billion in 2024 (p. 293). That's nearly 12 times more than China's $9.3 billion and 24 times the U.K.'s $4.5 billion, both for 2024. In stark contrast, public spending in the U.S. remained during 2023 relatively limited, despite years of steady increases, with just $830.98 million in AI-related public tenders and $4.5 billion in grants (Stanford HAI, 2025, p. 352). In other words, in 2023, private tech companies spent nearly 14 times more on AI investments than public institutions.

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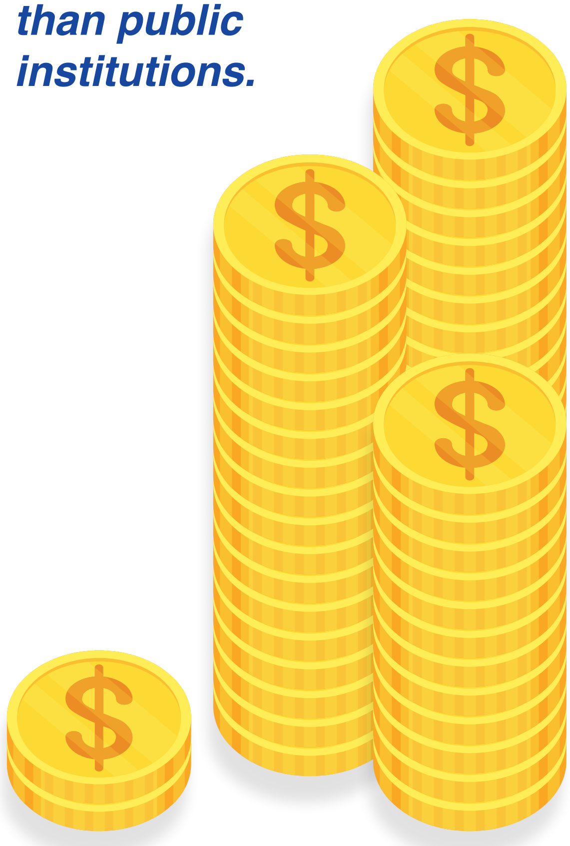
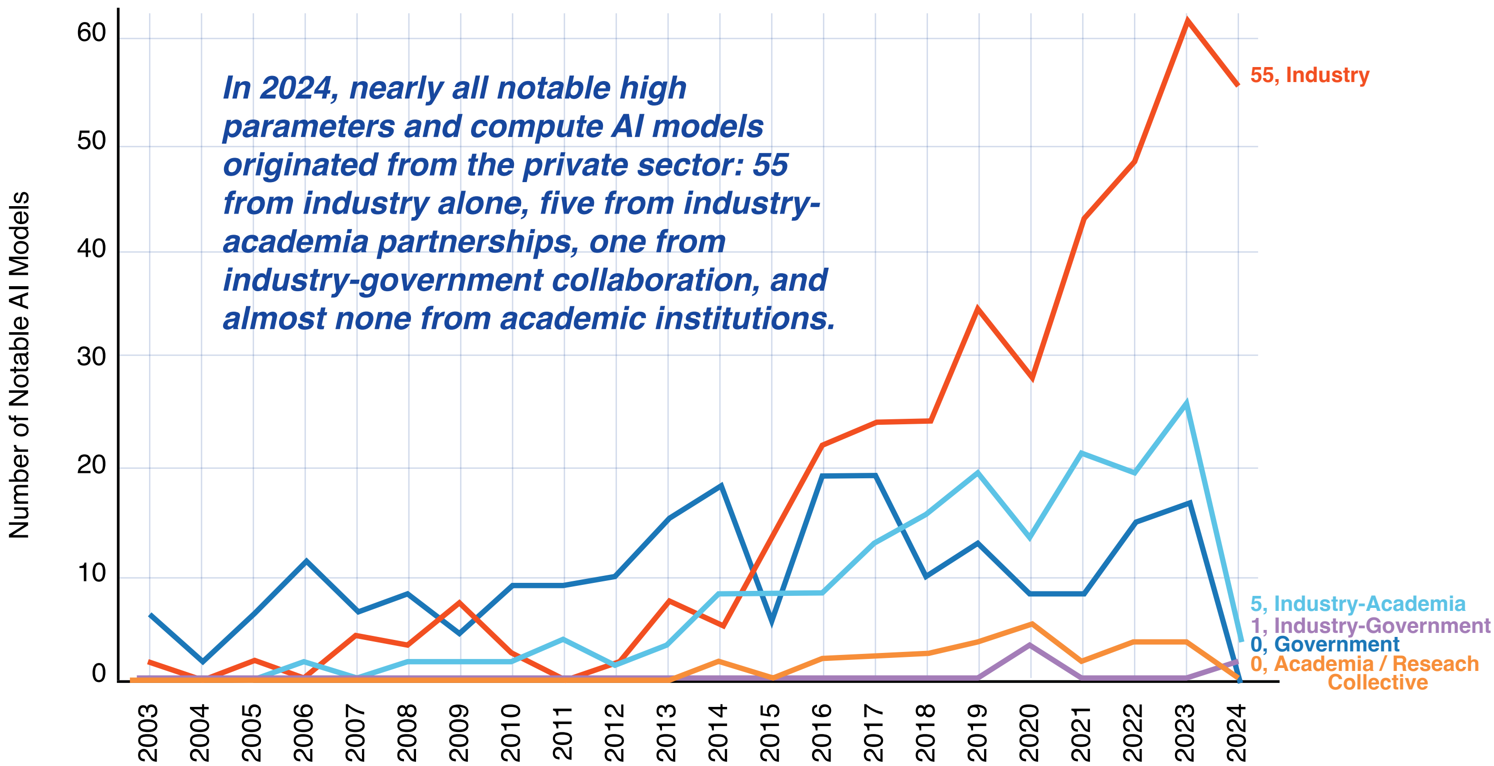


Until 2014, universities were the primary source of AI models, but since then, a significant shift has taken place. In 2024, nearly all notable high parameters and compute AI models originated from the private sector: 55 from industry alone, five from industry-academia partnerships, one from industry-government collaboration, and almost none from academic institutions (Stanford HAI, 2025, p. 47; see **Charts 5 and 6**). This stark disparity highlights the widening gulf between public research and private enterprise in shaping the future of AI.

The widening gap between academia and industry in AI innovation reflects not only differences in resources but also divergent capacities to absorb the high costs of development. One key reason academia has fallen behind while industry players lead is that today's cutting-edge AI models demand enormous amounts of data, computing power, and financial resources—assets most academic institutions lack. In contrast, big

Chart 5: *Number of notable AI models by sector, 2003–24*



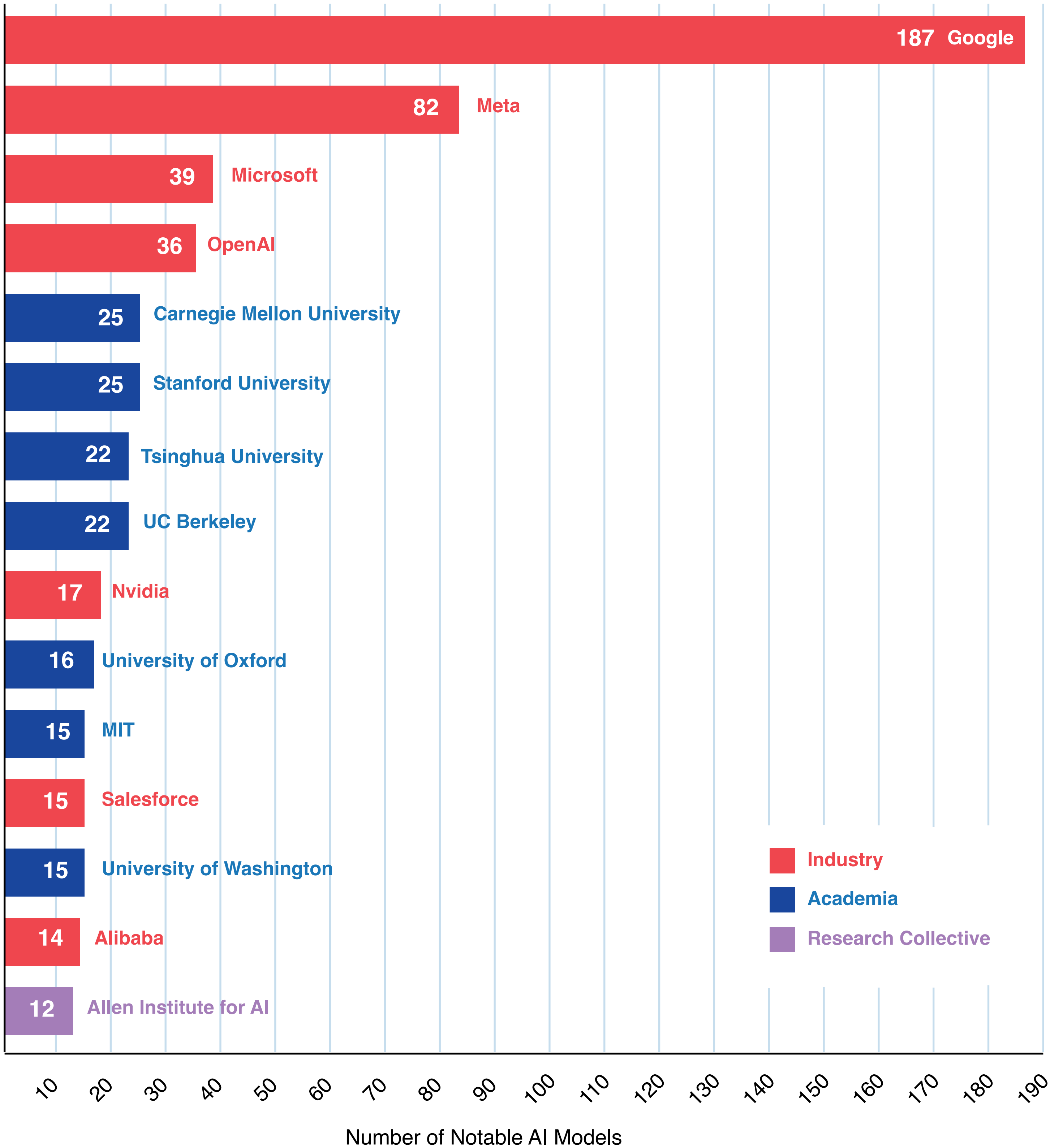
Source: Stanford University HAI AI Index Report 2025, p. 48.

tech firms can afford to take risks, absorb significant losses, and sustain the massive costs involved in AI development (Stanford HAI, 2025, p. 66).

However, keeping in mind that drawing an "academia versus industry" opposing binary could be confusing, as many elite universities have become active enablers of industrial AI power by supplying knowledge, experiments, and a talented workforce. That said, some well-funded universities do produce AI models using collaborative research, innovative techniques, and open-source models. **Chart 6** shows the number of notable AI model contributions by both private and public universities in the U.S., U.K., and China, although limited in number.

Another factor is public spending in AI fluctuates with governmental priorities and abilities. Although public investment rarely matches the scale of private spending, several governments have pledged substantial funding for AI infrastructure and research. Notable examples include Canada's $2.4 billion AI infrastructure package, China's $47.5 billion semiconductor fund, France's €109 billion investment, India's $1.25 billion commitment, and Saudi Arabia's $100 billion Project Transcendence initiative (Stanford HAI, 2025).

Chart 6: *Sum of the number of notable AI models by organization, 2014–24*



Source: Stanford University HAI AI Index Report 2025, p. 49.

The Architecture of the Global AI Stack

To understand where AI's power and wealth concentration comes from, now we turn to the global AI ecosystem's layered architecture, which is a dynamic ecosystem of machines, software, protocols, and industries. Van der Vlist et al. (2024) defines the AI "stack" as the layered structure of AI technology, encompassing infrastructure, models, and applications. While AI models are largely controlled by a few firms, the ecosystem itself is not monolithic. Like the Internet, the AI supply chain spans various technologies, labor systems, and services. This layered structure is often called the "AI stack" (Wagener, 2025).

Generally speaking, the global AI stack includes:

- **User layer** – Enterprise and individual users interact with AI using interfaces
- **Model layer** – deep learning-based foundation models
- **Data layer** – generalized and unlabeled training data
- **Infrastructure layer** – includes computing and networking chips and hardware
- **Raw materials** – critical and rare earth mineral essential for the devices

The bottom two foundational layers (raw materials and infrastructure) also support non-AI digital systems, such as consumer electronics assembly lines, gaming devices, smart cars, weapons, etc.

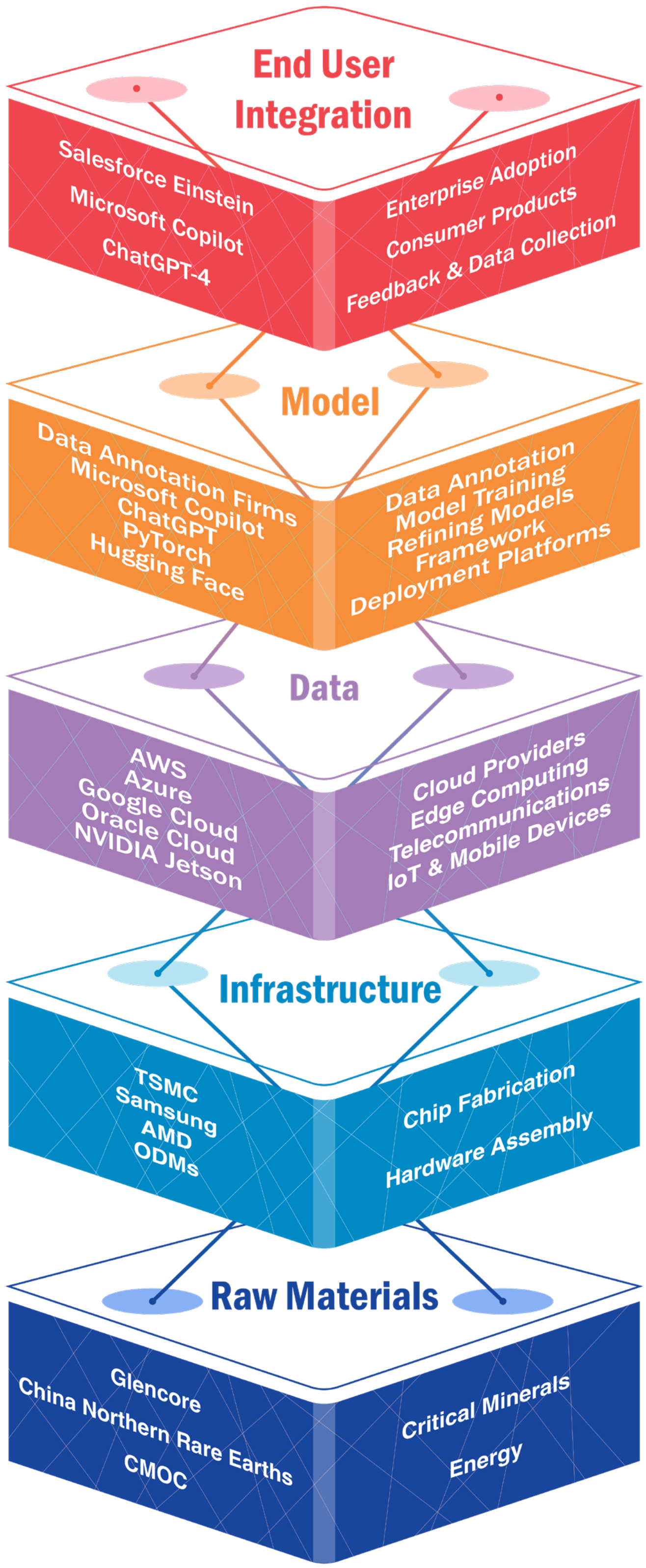
Chart 7 visualizes this global AI stack, and **Appendix Table 2** provides detailed layer functions and key industry players. The lines show dynamic interactions and overlapping between the layers.

Industrial AI production requires vast and expensive infrastructures, including graphics processing units (GPU), cloud servers, data centers, and high-bandwidth networks. These systems consume enormous amounts of electricity and require substantial water resources for cooling and heat recycling. Sustaining energy and managing e-waste both are critical for these systems, as explained here.

Rare Earth Minerals

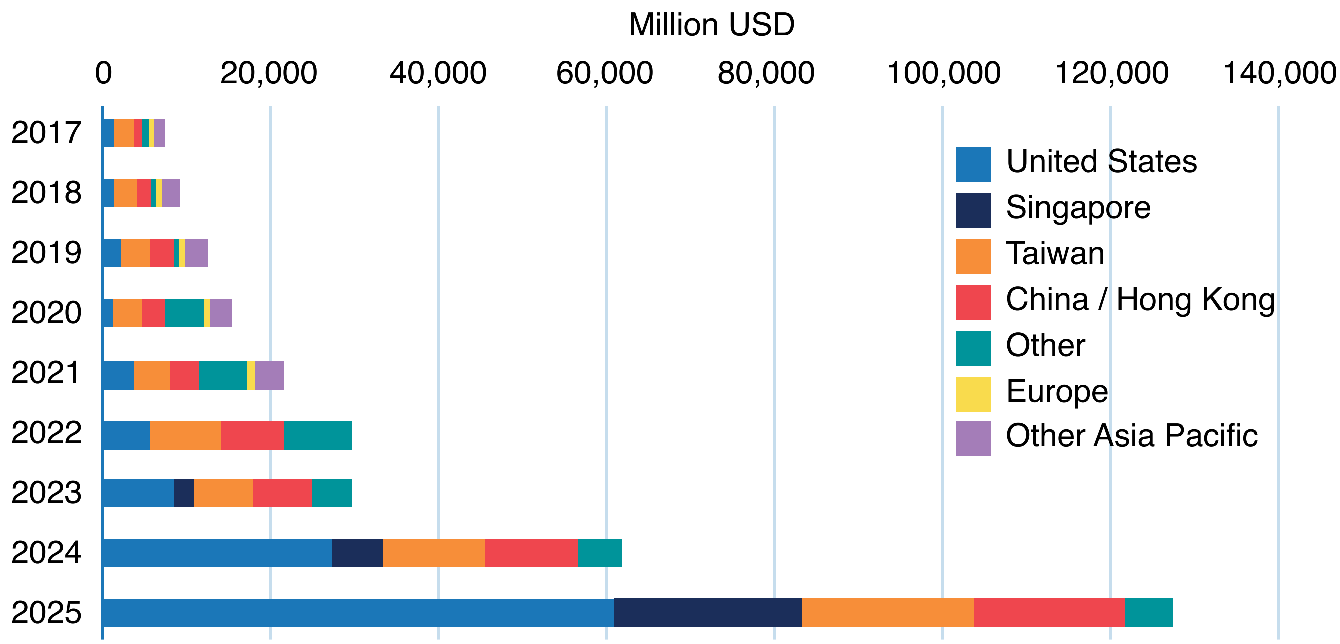
Rare earth minerals and specialized metals are foundational to AI's computing power. Elements like neodymium, gallium, germanium, silicon, and phosphorus are necessary for producing essential technologies like GPUs, ASICs, and FPGAs (Pallardy, 2025). Notably, China dominates the global rare earth supply chain, accounting for approximately 70% of global mining output and 90% of refining capacity (Agrawal, 2025). These elements are vital for manufacturing advanced techs such as wind turbines, defense systems, and electric vehicles, as well as numerous consumer goods.

Chart 7: *Vertical AI Stack of Global AI Supply Chain. Listed are the key players (left) and functions (right) of each layer.*



Source: Author. Data current as of April 27, 2025. Sources listed in Appendix Table 2.

Chart 8: *Nvidia Revenue Worldwide 2017 - 2025, by Region*



Source: Nvidia, February 26, 2025.

Graphics Processing Units

Companies like Nvidia, Intel, IBM, TSMC, and Huawei lead the GPU industry (Bastian, 2024). Nvidia and TSMC, in particular, make high-performance GPUs essential for training and running big AI models at scale. These chips handle massive computations. Most GPUs are sold to a few major firms with the means to build large AI training and data centers (Hubbard, 2024).

As Nvidia's Form 10K filing shows, in January FY2025, Nvidia's global revenue reached nearly $130.5 billion, with a whopping $97.85 billion in profit, more than double the 2024 figure (p. 52). This growth was driven by rising demand for AI model training and AI adoption largely in the U.S., but also in Singapore, Taiwan, China (see **Chart 8**).

Cloud Infrastructures

GPUs power AI, but cloud infrastructure enables it to scale. Industrialization of large AI systems is deeply tied to Big Tech's dominance over cloud infrastructure. Cloud systems offer remote computing and global connectivity that few organizations could afford on their own. Amazon, Microsoft, and Google's large cloud systems allow them to influence investments, competition, and access to AI innovation (van der Vlist et al., 2024). Consolidation in the cloud market has priced out smaller developers, locked in ecosystem dependencies, and choked off competition (Hubbard, 2014).

There are six markets in global cloud services: SaaS, IaaS, PaaS, BPaaS, DaaS, and DRaaS. Amazon Web Services (AWS), Microsoft Azure, and Google Cloud control about two-thirds of this market. Their dominance has triggered antitrust actions in the U.S., EU, and UK due to restrictive licensing, high data transfer fees, and vendor lock-in. Meanwhile, in China, Alibaba, Baidu, Huawei, and Tencent lead the AI-driven cloud market and partner with the government's Digital Silk Road projects, which are expanding across the Global South and often outcompeting U.S. firms with more affordable, efficient services (Canalys, 2024; Feakin, 2025).

Data Centers

While cloud platforms provide a virtual environment for storage and processing, data centers are the physical backbone that make cloud computing and AI development possible. A data center is a temperature-controlled facility containing computing infrastructure such as cloud servers, storage systems, and networking equipment. For example, Amazon runs over 100 data centers, each with roughly 50,000 servers powering AWS (Zewe, 2025). As of April 2025, there were 9,454 data centers in 164 countries: the U.S. hosts 3,645, about 39% of the total, illustrating a striking geographical concentration. The meteoric rise of Gen AI has fueled a surge in hyperscale data-center building, intensifying concerns over inequality and environmental impact.

Energy Requirement

All of this infrastructure depends on energy. For example, a single ChatGPT query consumes roughly 5x the electricity of a web search (Zewe, 2025). Especially, AI development has made major tech firms among the U.S.'s biggest electricity consumers. In 2022–23, Google, Microsoft, and Meta together consumed over 60 TWh of electricity, more than the annual usage of Jordan, Iceland, and Ghana combined (Visual Capitalist, 2024). Electricity comes from both traditional utility grids and renewable sources. Despite improved efficiency, energy demand keeps growing (Stanford HAI, 2025). To meet this growth, major tech firms are investing in next-generation energy infrastructure, including fission and experimental fusion-powered small modular reactors (Liou, 2023; Stover, 2024).

... AI should be treated like a public utility—similar to water or electricity—so that its benefits are shared more equally. This means making AI more transparent, more democratic, and more accountable to the public.

Critical Studies of AI

As the global AI industry grows rapidly, a wave of critical thinking is also gaining ground. These perspectives come from fields like media studies, technology studies, and political economy, and they ask important questions about who controls AI, who benefits from it, and who might be left behind. A relatively newer area of inquiry is how AI, data, algorithms, internet, platforms converge with media and journalism production at large, which I have partially addressed in an earlier work (Rahman, 2025). A natural extension of this discussion is the critical political economy of AI. In communication studies, this approach offers the critique of wealth concentration and power from production, distribution, and consumption of communication resources, and by extension, any information and digital resources (Mosco, 2009).

Critical scholar Pieter Verdegem (2023) has extended this approach to AI. He examines how ownership of AI systems, such as cloud infrastructure, supercomputers, large datasets, and app development platforms, is increasingly concentrated in the hands of a few companies. He also highlights how AI depends on things like data centers, click farms, and advanced computing tools, all of which are part of a much bigger industrial supply chain. But Verdegem doesn't just focus on who owns what—he also critiques the ideas and hype that surround AI. He argues that much of the excitement around AI serves to hide its downsides: labor exploitation, environmental harm, and growing inequality. In his view, AI has become an ideology, one that benefits the powerful while claiming to be for everyone. Instead of accepting this model, Verdegem calls for a different path. He suggests that AI should be treated like a public utility, similar to water or electricity, so that its benefits are shared more equally. This means making AI more transparent, more democratic, and more accountable to the public (Verdegem, 2023).

Contributing to this conversion, the following sections highlight areas that require greater scrutiny, particularly the role of training datasets and the resulting biases and representational harm embedded in AI systems.

Theft and Opacity of Training Data

Dominant large language models are trained on a vast corpus of data from the public internet as well as from websites behind paywalls but most often without consent or explicit permission from the original data sources, and typically without public knowledge. For instance, *The New York Times*, along with Ziff Davis, the digital publisher behind prominent tech sites such as Mashable, PCMag, and Lifehacker, and several other media organizations filed a lawsuit against OpenAI and its partner Microsoft, accusing them of stealing their content (Mullin, 2025). In another case, Clearview AI, an American start-up, amassed over 30 billion facial images by scraping platforms like Facebook, YouTube, Venmo, and millions of other websites without user consent, quickly becoming popular among federal and state law enforcement agencies (Hart, 2024). More recently, authorities removed the China-based AI chatbot DeepSeek from a South Korean app store, claiming that it had transferred user-prompted data offshore without user consent (Butts, 2025).

Unless alternatives are found, we may continue to see more lawsuits and complaints like these, as AI companies are likely to run out of scrapable and new public human text data in the next few years (Jones, 2024). They are increasingly interested in harvesting data from untapped and unconventional sources, including AI-generated or synthetic data, which carries the risk of "model collapse," a term referring to the outputs of models worsening in quality (Milmo, 2025).

The coercive power of big tech turns ironic when one AI company illegally obtains data from another AI company's websites, violating terms of use, but faces no retaliation because the practice is widespread. For example, Google scraped data from YouTube to train its AI model Veo. After DeepSeek challenged American AI hegemony, OpenAI issued a statement claiming DeepSeek violated its user agreement by using ChatGPT to train DeepSeek's model through a process called 'distillation.' A 404Media article gained momentum on BlueSky with the headline: "OpenAI furious DeepSeek might have stolen all the data OpenAI stole from us (the users)" (Koebler, 2025).

Interestingly, while AI companies have the capacity to scrape and accumulate vast data from the internet, they often lack clear knowledge of what kind of data is used in training their models. Journalist Karen Hao (2025) reports that once public datasets became inaccessible, reproducibility broke down, and OpenAI began relying on vast, unvetted training data, often without knowing what was inside. This shift was driven primarily by profit, moving away from the initial promise of "human" and "transparent" AI systems.

AI Biases

A major consequence of rolling out AI models without sufficient scrutiny of the training datasets and product testing is the low quality and inaccurate results produced by AI chatbots and snippets. For example, Google's "AI Overview" feature once suggested using glue to stick cheese on a pizza (Eckstein, 2024). While the training datasets remain opaque and inaccessible, the design principles and coding practices reveal familiar patterns of racial, gender, and class biases already identified by critical algorithm scholars (Costanza-Chock, 2020; Eubanks, 2018).

Many of these tools, especially those that claim to predict future outcomes but influence present decision-making, such as predicting crime or loan repayment likelihood, are considered AI snake oil, or "AI that does not and cannot work as advertised" (Narayanan & Kapoor, 2024, p. 2). Beyond this, sexualized stereotypes and gender misrepresentation appear in Google search results (Noble, 2018), and racial misidentification occurs in facial recognition technologies (Buolamwini, 2024). AI image generators like Stable Diffusion and DALL-E often portray slim, white women as the standard of beauty and depict Muslims as bearded figures resembling Osama Bin Laden or his relatives (Tiku et al., 2023). These examples highlight the systemic and harmful biases embedded in AI systems, which contribute to broader inequities. These biases largely stem from unrepresentative training datasets and annotations, model architecture, and research methodologies (Bender et al., 2021; Benjamin, 2020).

A large data center can consume more than a million gallons of water daily, and some data centers are being built in areas where water is already scarce. Just a few ChatGPT queries can use as much water as a standard 12oz bottle, which multiplies dramatically with hundreds of millions of queries every day.

Environmental Toll

The expansion of industrial AI production and consumption calls for a closer look at the connections between AI, energy use, and climate change, especially whether AI's rapid growth is accelerating the climate crisis. Between 2020 and 2023, carbon emissions by major firms grew sharply rising by 182% at Amazon, 155% at Microsoft, 145% at Meta, and 138% at Google (ITU & WBA, 2025). Benedetta Brevini (2021) warned about this in her 'eco-political economy' framework that maps AI's environmental harm across various segments: resource extraction, energy consumption and carbon emissions, and digital waste. Cloud infrastructures, servers, and data centers all require extensive cooling systems that rely on chilled air or water and heat recycling systems. A large data center can consume more than a million gallons of water daily, and some data centers are being built in areas where water is already scarce. Just a few ChatGPT queries can use as much water as a standard 12oz bottle , which multiplies dramatically with hundreds of millions of queries every day.

Brevini (2024a) also highlights AI's heavy dependence on rare minerals like lithium and cobalt, often mined under exploitative conditions in the Global South, causing serious ecological damage and health risks. For instance, lithium mining in Chile's Atacama Desert diverts critical freshwater from Indigenous communities. At the same time, AI hardware generates toxic e-waste that is frequently dumped in the Global South. Global e-waste reached 62 million tons in 2022, an 82% increase since 2010, with projections reaching 82 million tons by 2030. Yet only 1% of rare earth elements are recycled. Generative AI worsens this trend by speeding up server and chip replacement cycles, especially for Nvidia's energy-intensive GPUs, pushing e-waste to record levels (Brevini, 2024b).

Brevini argues that global AI policies, such as the EU AI Act, must impose strict environmental regulations on AI providers and deployers. Some media researchers, collaborating with environmental experts, have even proposed creating a new international body to monitor or regulate AI research, potentially modeled on organizations like the International Atomic Energy Agency or the Intergovernmental Panel on Climate Change (Bak-Coleman, 2023).

Laboring AI

While the environmental impacts of AI are increasingly clear, it is equally important to examine the manual labor rooted in the AI production chain, which often remains overlooked. A key component of the AI stack is the human workforce. Despite the perception of AI as fully autonomous, human labor remains central to its development. This labor includes both visible and invisible components. The visible workforce—such as software engineers, prompt engineers, and users—is often traceable to the countries where company headquarters are located.

Lilly Irani (2019) argues that automation and advancements in AI don't necessarily replace human labor but displace it, creating new jobs and roles for human workers, who might be visible at first sight. The hidden workforce, such as data annotation laborers, content moderators, infrastructure maintenance workers, and service sector employees, is dispersed globally and largely concentrated in the Global South (Casilli, 2025; Karanja, 2025). These undervalued "data janitors", in Lilly Irani's word, perform essential tasks like collecting, annotating, labeling, curating, and verifying datasets used to train machine learning algorithms (Irani, 2019). They often face labor exploitation, job insecurity, and exposure to harmful content (Muldoon et al., 2025; Crawford, 2021).

The adoption of Western corporate AI in the global South creates new forms of exploitation and power imbalances through *colonial supply chain of AI*, echoing historical colonial practices, and deepening international division of digital labor (Muldoon & Wu, 2023). Karen Hao (2025) term this condition as *AI colonialism* highlights the disproportionate burden placed on workers in the Global South by AI development.

As much as the AI industry deepens global labor inequality, it raises another alarming concern: it may eliminate far more jobs than it creates. Goldman Sachs estimates that AI could result in loss of 300 million full-time jobs, representing 9.1% of all jobs worldwide (Howarth, 2025). This fear is further amplified by the most recent hype around agentic AI, which are designed to perform multiple complex tasks autonomously and simultaneously. Anthropic's CEO and others have warned of a looming "whitecollar bloodbath," where AI could wipe out up to half of all entry-level white-collar jobs and push unemployment to 10–20% within the next one to five years. Most Americans, and many members of Congress, seem unaware of this looming "blood booth," despite clear early warning signs in the wave of layoffs sweeping through tech and corporate sectors (VandeHei & Allen, 2025).

AI-powered Surveillance

Similar to most social media and digital marketing platforms, common generative and predictive AI models are powerful data extraction machines, collecting enormous amounts of personal data, including every keystroke entered a chat box, from users across all possible devices (Ramezan, 2025). While most users are unaware of the extent of data collected by AI tools, even when they opt out, the real danger lies in how that data can move from a trusted company to an untrustworthy entity for unknown purposes and without consent, accountability, or regulatory oversight.

As Edward Snowden revealed, the dominant big tech companies and their platforms serve as tools for cyber surveillance warfare on behalf of the Five Eyes alliance (Foster & McChesney, 2014). The AI-driven data grab by big tech, including Google, Microsoft, Amazon, and Palantir, thus injects more pervasive and panoptic power into the military-industrial complex, making these companies more lucrative to co-opt and even perpetually indispensable for covert surveillance, autonomous weapons, and high-tech cyber warfare at home and abroad (for notable examples, see Davies & Abraham, 2025; Hooker & Vallance, 2025; Knight, 2023; Loewenstein, 2025; Mitchell, 2025).

For instance, on the one hand, the collaboration between the Department of Government Efficiency (DOGE) and data analytics firm Palantir for extracting sensitive information from across federal agencies grants Palantir a dangerous level of AI-powered surveillance authority on behalf of the administration, a hybrid power that could be politically weaponized when needed (Bogost & Warzel, 2025; Frenkel, 2025). On the other hand, Palantir's Maven Smart System AI/ML capabilities for targeting threats made it a profitable partner of DoD and NATO (Mitchell, 2025). Such collaborations are not necessarily evidence of a healthy public–private partnership; rather, they signal the rise of an AI plutocracy, where fierce competition for data grab is playing out both domestically and globally, aiding U.S. geopolitical supremacy.

Not so surprisingly, the Trump administration is aggressively pursuing private-sector partnerships, notably courting $500 billion for 'Stargate' data centers in Texas and Abu Dhabi. The UAE facility, to be built by G42, operated by OpenAI and Oracle, and funded by Nvidia, Cisco, and SoftBank, would consolidate U.S. control over data exports and surveillance under the CLOUD Act 2018 (Wiggins, 2025). Such large-scale transnational governmental-industrial partnerships will further enable American AI operations to dominate global data governance.

... critics envision digital platforms that are decommodified, deprivatized, and de-commercialized, starting with a truly public internet.

Alternative Possibilities of AI

In the wake of multiple structural crises affecting hyper-capitalist and profit-driven information and communication systems, calls for public alternatives have grown louder. Moving beyond band-aid fixes to these planetary-scale structural problems, critics envision digital platforms that are decommodified, deprivatized, and de-commercialized, starting with a truly public internet (Pickard & Berman, 2023).

> *"In this view, there is a structural antagonism between the owners of the internet and its users, between the profit interests of digital monopolists and the public's interest in an open, empowering internet. In other words: we can have an internet that works for Silicon Valley and telecom companies, or we can have an internet that works for the people. But we cannot have both."*
>
> *(Pickard & Berman, 2023)*

Following this logic, is it possible to have a fully decommodified, deprivatized, and de-commercialized AI system as an alternative to commercial industrial AI? Is it even feasible to build a fully public AI stack without depending on any for-profit infrastructure or product?

Phillip Agre (1998), a notable AI critic trained as a computer engineer who later moved into social science, pointed out that AI is not only a technical schema but also a discursive practice. He observed that "AI people" or practitioners have little tolerance for criticism of their work unless an alternative AI system demonstrates practical utility. Agre further suggested that the idea of an *alternative AI* can be misleading because making a clean break from existing methods is nearly impossible. The language and technical practices of AI, like those of any discipline, are deeply embedded, often in ways we don't fully recognize. From this perspective, a purely public AI is unrealistic and unattainable. The systemic roots of AI's languages, practices, and infrastructures, like any sociotechnical system, run deeper than what any single country or society can fully control. According to Agre, a more productive goal is to engage critically and reflexively with the existing system rather than seeking a clean break.

While Agre may be correct about the impossibility of an entirely separate AI stack running parallel to the dominant industrial one, there is still room for considering the incremental and modular development of micro-techno AI systems. Consider the case of S1, an experimental, non-profit reasoning model developed by AI researchers at Stanford and the University of Washington, which achieved performance benchmarks comparable to advanced models like OpenAI's o1 and DeepSeek's R1 (Muennighoff et al., 2025). This was made possible through a process called **distillation**, a method for training a smaller or more efficient model to replicate the capabilities of a more complex one. The S1 team trained small datasets using a free model from Alibaba-owned **Qwen**, running it on 16 **Nvidia** H100 GPUs for a short time. They then replicated the "thinking process" of Google's **Gemini 2.0** Flash Thinking Experimental model using **supervised fine-tuning**. While Google may have spent hundreds of millions of dollars developing large-scale frontier models in the Gemini series, the S1 team spent just $50 on cloud compute credits and $20 to rent the necessary compute resources (Zeff, 2025).

Cases like this raise important questions about what we mean by alternative possibilities for AI and its future. S1, as an academic project, was able to reverse engineer big AI using big tech, although not vastly better. The researchers did not need massive datasets, and they are not competing with industrial LLMs like Gemini or ChatGPT at the *application layer* of the AI stack. However, they did rent or depend on, at least temporarily, big tech cloud and processing power at the *infrastructure layer*. This suggests that slower and less efficient alternatives to large industrial models are possible, but not entirely independent of them. The transition will need to be gradual, strategic, and long term. Such incremental development of alternative digital systems is evident in the broadband, data, and cloud platform sectors, supported by the public utility and public interest approaches, which we discuss next and expand on with practical examples.

Public Utility Approach to Media and Tech Regulation

Building on the public interest rationale for a more equitable internet, a growing movement argues for treating digital communications infrastructure—including the internet itself—as a public utility (Fuchs, 2021; Rahman, 2018; Schiller, 2020; Tarnoff, 2016; Verdegem, 2023). Although these demands have gained traction in the digital age, their roots trace back to pre-internet debates. In the 1980s and 1990s, political economy scholars including William Melody (1997) and Harry Trebing (1984) advocated reforming telecommunications as public utilities, insisting that such essential infrastructures should operate in public interest.

The principle of public utility regulation centers on the idea that certain private businesses, because of their widespread societal impact, should be held to higher standards of accountability and service. For over a century, public utilities have included telephone, electricity, gas, and water services. In some contexts, public transportation has also been regulated under this model (Melody, 1997). Dan Schiller (2020) notes that the public utility model was never a fixed formula but emerged from democratic struggles over infrastructure. While it sometimes replaced more radical goals like full public ownership or nationalization, Schiller still sees potential in the tradition and calls for a broad utility-based framework to support open and democratic systems, including at the levels of public internet and algorithms.

Victor Pickard (2023) picks up on Schiller's cue. Aiming to rescue American journalism from the flawed commercial media system, including market failures, big tech capture, and growing news deserts, Pickard puts forward a radical proposal for an entirely new public stack: public media centers (PMCs). These would cover both "platforms and pipes" and be supported by a policy framework designed to "enhance positive externalities while minimizing social harms" (p. 293). Modeled after long-standing public infrastructures like libraries, post offices, and public schools, PMCs would operate in every community across the country. In essence, "PMCs must look like and address the needs of the diverse community members they serve" (Pickard, 2023, p. 292). Their mandate is to provide universal access to reliable and diverse news across digital, broadcast, print, and community broadband services.

The public media centers, as envisioned by Pickard, would enable media democracy from the ground up, owned by journalists and representative members of the public, protected by labor unions, cooperatively and transparently governed, independent yet highly accountable to public oversight boards at both federal and state levels. The PMC model will have six overlapping layers: funding, governance, ascertainment, infrastructure, algorithm, and engagement (see **Table 1**). While centralized and top-down governance may be necessary to initiate the structure of these layers, each layer will pursue its own democratization process.

***... public communication infrastructures can be built through regulatory and structural reforms, either by converting dominant platforms into public utilities or by subjecting them to utility-style oversight*.**

Pickard's PMC model is reflected in initiatives like the BBC's **Local Democracy Reporting Service** and the **Local Journalism Initiative** proposed by Robert McChesney and John Nichols (2021). It also reflects a culmination of various scholarly efforts to build on the public utility approach in imagining what democratizing digital platforms might look like. For instance, political scientist James Muldoon advocates for "platform socialism," which he describes as grassroots efforts by communities, tech workers, and users to take ownership and control of the platforms they use, organized as cooperatives (Muldoon, 2022).

Extending this logic, others argue that breaking up corporate monopolies like GAFAM (acronym that stands for Google, Apple, Facebook, Amazon, and Microsoft) should be pursued through a mix of antitrust litigation and grassroots organizing (T. Wu, 2018). Similarly, legal scholars Rahman and Teachout (2020) suggest that public communication infrastructures can be built through regulatory and structural reforms, either by converting dominant platforms into public utilities or by subjecting them to utility-style oversight.

Table 1

Six-Layers Model of a Public Media Center

Layer	Function
Funding	Determines how PMCs are financially sustained by a large trust fund supported by various mechanisms including taxing platform monopolies, public subsidies and congressional funding.
Governance	Guarantees collective decision-making around resource allocation and key operations.
Ascertainment	Discovers and determines critical information needs of a community.
Infrastructure	Addresses material and technological needs (e.g., universal broadband) for access.
Algorithmic	Prioritizes public media content in search engines and news feeds.
Engagement	Involves local communities in producing news and sharing their own stories as well as building trust providing grassroot support.

Source: Based on Pickard, 2023, p. 291.

Their case rests not only on the platforms' centrality to everyday life but also on the enormous, often unaccountable power they wield over public discourse. While reclassifying tech giants as public utilities may sound radical or infeasible, precedent exists. In the U.S., governments have historically used utility regulation to impose obligations such as common carriage, nondiscrimination, interoperability, and fair pricing (Rahman & Teachout, 2020).

Table 2
Public Utility Approach to AI Development and Regulation

Core Principal	Application in AI Context
Public Funding	Fund AI research centers, datasets, and compute infrastructure as public resources
Public Ownership	Develop open-source AI models maintained by public institutions
Democratic Governance	Regulated at federal and state levels in consultation with municipal boards with civil society representatives, experts, and impacted groups
Transparency	Require algorithmic audits, model explainability, and public reporting
Equity-First Mandates	Prioritize AI tools that address social needs (e.g. accessibility, environmental justice)
Interoperability Standards	Ensure public models and tools can connect with existing systems to reduce vendor lock-in
Tax and Redistribution	Tax platform and cloud giants to fund public utility and public-interest AI development
Local Adaptation	Allow regional and municipal control over AI deployment based on community needs
Sustainability Focus	Incentivize energy-efficient training methods and resource-aware AI system design

Source: Author

What a Public Utility Approach to AI May Look Like

As a complement to antitrust and breakup strategies, the public utility framework outlined in Pickard's PMC model offers a promising pathway for imagining an alternative AI stack. A public utility approach would treat AI as essential public infrastructure, not merely as a private innovation driven by corporate interests. This approach would center equity, community engagement, public accountability, and democratic governance, pushing back against the concentration of AI development and deployment in the hands of a few powerful tech firms.

If the ideology of industrial LLMs and machine learning is built on profiting from large capital investments, hyperscaled data extraction, and exploitation systems within a concentrated market entangled with the military-industrial complex, then a public utility AI alternative will require a counter-ideology rooted in public funding, decommodification, decentralization, decolonization, and cooperative governance at the community level.

Table 2 outlines what a public utility approach to AI may look like. AI applications, especially those embedded in ***public services*** such as healthcare, education, law enforcement and criminal justice, social services, water, electricity, telecommunication, and transportation, should be treated as ***public utilities***. AI in public utility approach would be considered as critical infrastructures that require public oversight, equitable access, and democratic governance.

Similar to the PMC funding model, a large trust fund can be established through taxes on big tech, public subsidies, and congressional allocations to support both existing publicly funded AI research labs and data centers, as well as the creation of new ones at state and county levels. AI initiatives under this approach would be governed and regulated by multi-stakeholder models at federal and state levels, in consultation with municipal boards made up of civil society representatives, technical experts, and members of marginalized communities. To ensure transparency and accountability, these boards would require algorithmic audits, explainability standards, and public documentation of AI models used in critical sectors. With an *equity-first* approach, the boards would also prioritize racial justice, employment security, labor rights, environmental protection, the reduction of carbon emissions, and a decrease in the AI industry's reliance on public water, land, and electricity resources.

Like the PMC model, the public utility approach to AI is also vulnerable to political will, requires large and sustained funding that is not reliant on voluntarism, and can be dismantled with changes in government. There are also risks of U.S.-centric legal frameworks, technocratic capture, greenwashing, whitewashing, and tokenism. For this reason, a public approach must be grounded in broader sociopolitical structural reforms. In its early stages, lawmakers, research institutions, and advocacy groups can collaborate to establish pilot public AI centers, develop regulatory frameworks rooted in the public interest, and legislate safeguards to protect public AI initiatives from corporate lobbying and legal backlash.

By drawing from public-centered strategies in telecommunications and internet practices, we can envision how an alternative to "capitalist realism" may look like in the AI platform economy. To assess whether a public utility model of AI can be meaningfully developed at any level of the global AI stack, we must present evidence of alternative industrial practices and paradigms relevant to that stack. The next sections explore the structure of the non-profit AI supply chain, beginning with public internet and platform cooperatives, cloud computing and data cooperatives, collaborative projects between government entities and civil society, as well as public media and public interest AI initiatives. It also considers decolonial movements, all of which suggest that an alternative approach to AI is not only possible, it is already underway.

Public Internet and Platform Cooperatives

While a fully public AI stack may seem out of reach, the evolution of alternative internet infrastructures offers important lessons for building more democratic and decentralized digital systems. The failure of tech giants to uphold democratic values has spurred efforts to create a more equitable internet. Pickard and Berman (2019, 2023) document several of these initiatives, highlighting how over 900 U.S. communities now operate public broadband networks—often faster, cheaper, and more democratically managed than corporate providers like Comcast or Verizon. One standout case is Chattanooga, Tennessee, whose municipal network delivers gigabit-speed service while reinvesting its surplus to provide free internet to low-income residents. “This [Chattanooga] is a prime example of what a focus on the public interest (rather than profits) can achieve,” write Narayanan and Kapoor (2024, pp. 259–260). “It shows that a radically different way is possible.”

In contrast to very large online platforms (VLOPs) like Facebook, another vision for digital infrastructure lies in *digital public infrastructure*: a constellation of very small online platforms (VSOPs), community-developed software, public policies, and civic norms that support non-corporate, non-extractive digital spaces governed by their users (Zuckerman, 2020). Alongside these developments, grassroots communities, tech workers, and users are experimenting with platform cooperatives, meaning platforms which are collectively owned and governed by their users, as alternatives to venture-backed models (Brophy & Grayer, 2019; Muldoon, 2022; Scholz & Schneider, 2017).

These advances show that the public internet is not only imaginable, but also already being built:

> *“Public broadband thus prefigures what an alternative communications system—one committed to maximizing the public good rather than corporate profits—might look like. It gives lie to the conceit that the internet can only be provided by for-profit telecom giants that perpetuate digital inequities based on exclusion and extraction…. Another internet is therefore not only possible—its germinations are already here… Although municipal broadband and alternative social media platforms may currently be relatively small in scale, they gesture toward a much more expansive political program for democratizing the internet.”*
>
> *Pickard & Berman, 2023*

Such public communication and information infrastructures are a prerequisite for a revitalized and functional public media system, as well as for addressing the digital divide (Pickard, 2020, 2022).

Cloud Computing and Data Cooperatives

Generally, cooperative models refer to businesses owned and operated by their workers, who collectively control capital ownership and distribution. These models prioritize community or public-oriented goals and typically offer a more equitable approach to business than investor-owned private companies (Hubbard, 2024). Well-known examples include REI, Ocean Spray, Dairy Farmers of America, and the Associated Press. In the digital sector, two promising examples of cooperative infrastructure are **Commons Cloud** (https://www.commonscloud.coop/community/) and **Co-op Cloud** (https://coopcloud.tech/) , which aim to build decentralized, collectively governed cloud services that support democratic control and community stewardship.

> *"Co-op cloud community project. Co-op Cloud is a software stack that aims to make hosting libre software applications simple for small service providers such as tech co-operatives who are looking to standardize around an open, transparent and scalable infrastructure. It uses the latest container technologies and configurations are shared into the commons for the benefit of all."*
>
> *Retrieved March 19, 2025, https://coopcloud.tech/*

This collaborative ecosystem relies on grassroots, user-based, decentralized server hosting that is also scalable. It enables app packagers and developers to directly connect, share app "recipes," and benefit from mutual cooperation. Although these projects do not yet provide the scale of computing power needed for large-scale AI training, they signal a growing public demand for alternative infrastructure. Recent appeals for a "public AI" option underscore the urgency of developing non-corporate alternatives to today's dominant cloud providers (Hubbard, 2024).

In response to extractive data practices, data cooperatives present a people-centered alternative. They allow individuals to pool their data, retain control over how it is used, and share in the value it produces. These cooperatives draw on the legacy of credit unions and labor unions, institutions built to protect individuals through collective ownership and bargaining. **Superset**, for example, is a data trust that compensates its members and negotiates terms of data use with commercial partners, including **Delphia**. **Cohere's Aya** project gathered multilingual data from global contributors to train an open-source language model. The **Driver's Seat Cooperative** supports gig workers by helping them aggregate and analyze their mobility data to increase earnings.

While much of the industry prioritized scale, some researchers pursued a different path: smaller, carefully curated datasets with transparent sources. Projects like Mozilla's **DeepSpeech** and Hugging Face's **BLOOM** have shown that technical performance can be achieved alongside rigor and responsibility. These efforts highlight the potential of data cooperatives to reshape digital infrastructure around public interest goals and provide a more equitable foundation for AI development (Hubbard, 2024).

Government and Civil Society Collaboration

Cooperative efforts to develop non-profit investment partnerships in AI are emerging as alternatives to the philanthropic initiatives led by tech billionaires. One such example is Mozilla's collaboration with the German Ministry for Economic Cooperation and Development (BMZ) to support the Rwandan start-up **Digital Umuganda**. This initiative benefited from Mozilla's **Common Voice** and **DeepSpeech** projects, which focus on voice recognition technologies for African languages (Mbayo, 2020). Building on this approach, in September 2024, the Mozilla Foundation launched the **Public AI project**, an open-source initiative designed to promote inclusive, community-driven AI applications that serve public needs in areas such as social services, education, and environmental justice (Marda, Sun, & Surman, 2024).

Public Media AI

Modern journalistic production relies on a range of digital platforms, devices, and software that integrate narrow AI components such as ML and NLP to support specialized tasks. In the United States, well-established media organizations are increasingly using commercially available AI tools to manage both major and minor newsroom operations at various stages of content production. However, only a small number of news outlets have financial and technical capacity to develop large, complex AI systems internally.

As per the 2021 UNESCO Recommendation on the Ethics of Artificial Intelligence, the use of AI and its multiple components including their algorithm and data must be auditable and traceable (Berger, 2023). In contrast, most commercial data-tracking algorithmic services used by public media enterprises characterize an internal contradiction between the demands for "digital commons", and "universal" nature of Public Service Media (PSM) content on the one hand, and data extractive, exploitative, proprietary and black-box nature of commercial AI systems and algorithms. This reflects both ideological and structural contradictions between PSM mission and needs for content gatekeeping, production and delivery infrastructures.

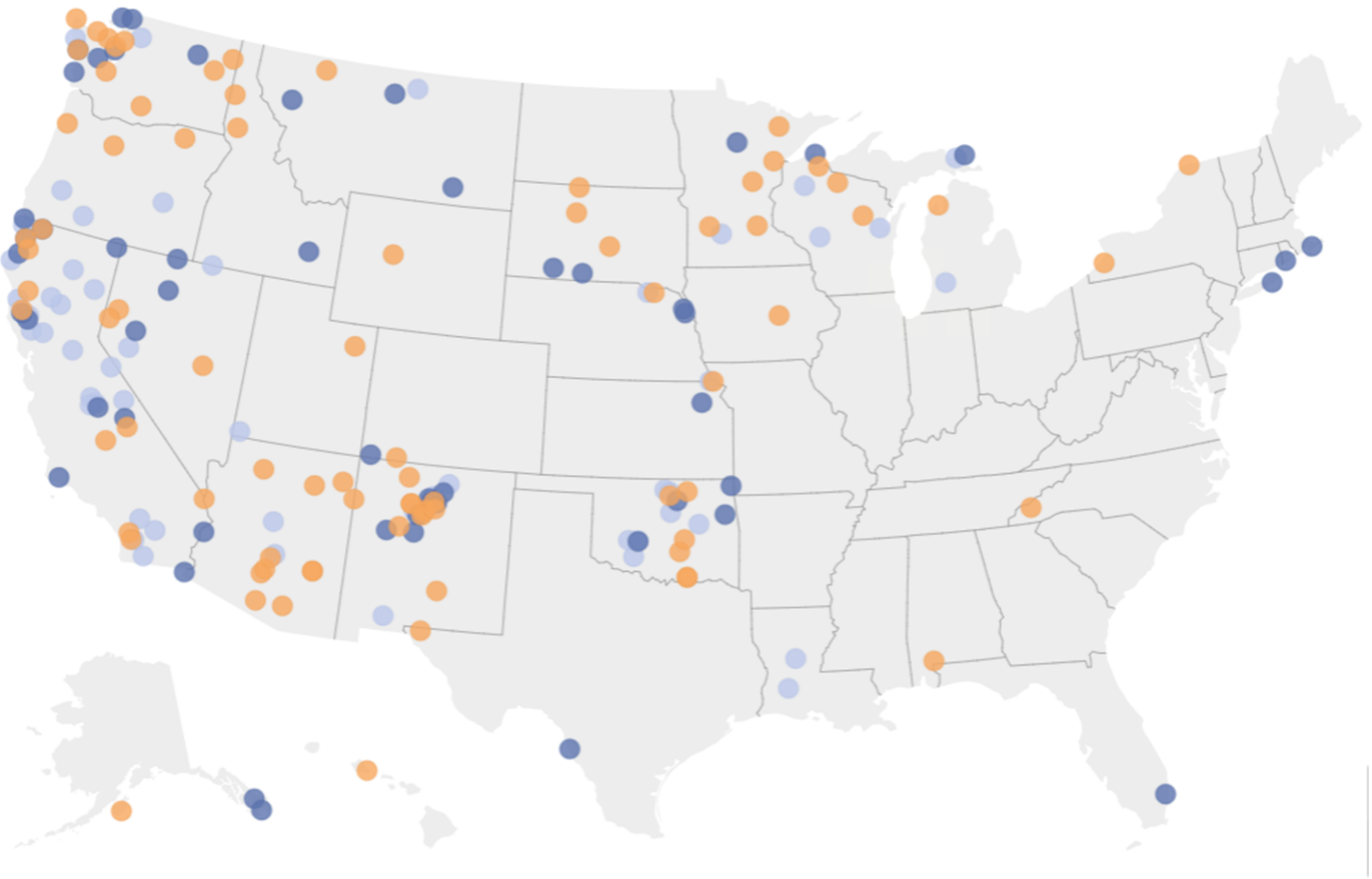
Several case studies show that inhouse AI initiatives are gaining momentum among some organizations, including VRT (Belgium), BBC News (UK), Yle (Finland), SWR (Germany), and RTVE (Spain), among others (Degraeve, 2025; Public Media Alliance, n.d., 2023; European Broadcasting Union, 2024). In sum, public media need public AI but only a few relatively well-funded public media in Europe and the USA are investing in research and development to develop in-house AI tools that are consistent with the values of PSM (Rahman, 2025). While their ability and level of advancement vary, there is a clear need for alternative models that work well with transparency, universality, accountability, and fairness obligations of public media.

Public Interest AI

Critical scholars are paying growing attention to public interest infrastructures for AI. As noted in a recent call for papers by Fenwick McKelvey, public interest AI refers to "support those outcomes best serving the long-term survival and well-being of a social collective construed as a 'public'". The Paris Charter (2025), released after the Paris AI Summit, promotes inclusive and locally grounded AI systems that can be adapted across regions. Yet the term remains contested and overlaps with phrases like "AI for Good" or "Responsible AI," which are often used as ethics washing (Bourne, 2024; Wagner, 2018). A critical scholarship is needed to ground the concept (F. Mckelvey, personal communication, June 11, 2025).

In this line, **Appendix Table 3** highlights a range of socially grounded *Public Interest AI* (n.d.) projects developed primarily by academic and nonprofit actors across health, education, environment, and information sectors. **Botometer**, developed by Indiana University, has been active since 2014 and supports social media transparency using traditional machine learning. Its work is publicly funded and research driven. **ClinicalBERT**, built with NYU grants and philanthropic support, brings deep learning into health data analysis using minimally resource-intensive methods; it was trained on a single GPU to reduce environmental impact. Its code is open source, and the project is developed by academic researchers. **Tech4Nature Mexico**, developed with international cooperation, supports biodiversity protection using deep learning techniques. While not all projects are open source, several make their methods and outcomes available and transparent through the open-source community or academic publications.

Chart 9: *Internet networks owned by Native Nations in the U.S.*



Active: Offering Retail Services or Operating Institutional Network and/or Lit Middle Mile
Expected: Currently Building Network and/or Funded for Construction
Prospective: Expressed Interest in Developing Internet Infrastructure

Source: Tribal Broadband Bootcamp. (n.d.).

Tribal broadband initiatives show that it is not necessarily the scale of the technology, but the guiding principle of building small-scale, not-for-profit, community-led communication infrastructure that can be replicated elsewhere.

Decolonial AI

In response to the rise of tech monopolies and AI dominance, a decolonial AI movement has emerged across the Global South (Medrado & Verdegem, 2024). A decolonial AI approach draws inspiration from indigenous knowledge systems to counteract neo-colonial and neoliberal structures of power, value systems, and utility of AI (Arora, 2024). Decolonial theories examine how historical power structures continue to shape modern systems. When applied to AI development, this perspective provides critical foresight to align technological innovation with ethical principles, particularly by centering communities most vulnerable to harm from unchecked technological progress (Mohamed et al., 2020). From a decolonizing perspective, Roberts and Montoya (2022) delineate the **CARE principles**—Collective benefit, Authority to control, Responsibility, and Ethics—as foundational to Indigenous data governance.

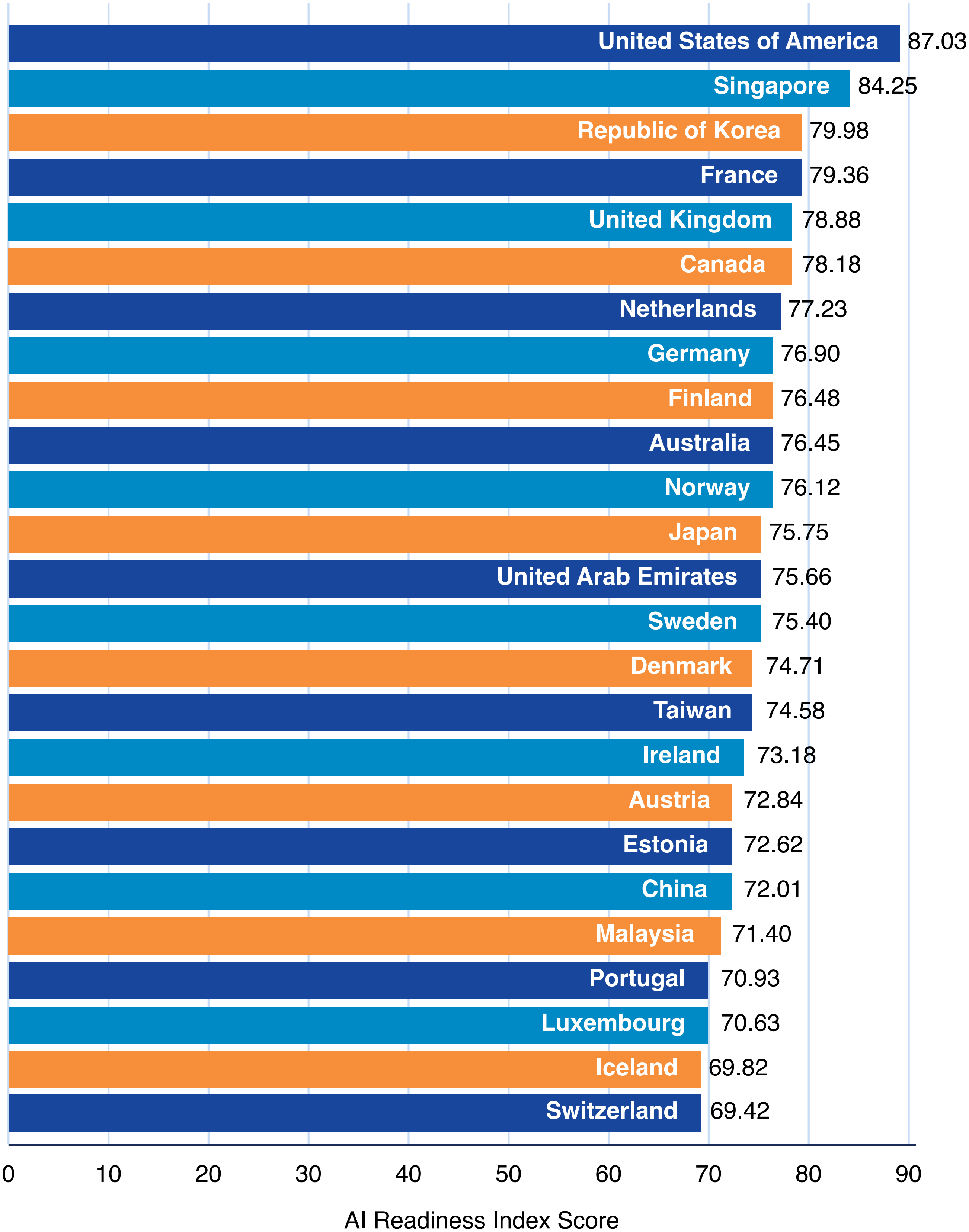
A practical example is **Te Hiku Media**, a Māori radio station led by Peter-Lucas Jones and Keoni Mahelona. They launched ***Papa Reo***, an Indigenous-led multilingual language platform, to train their own NLP tools using automatic speech recognition (ASR) and speech synthesis algorithms. Their goal is to revitalize the Māori language while maintaining control over Indigenous data (Jones et al., 2023).

Reflecting diverse cultural contexts, initiatives like Mhlambi's **Decolonial AI Manyfesto** (https://manyfesto.ai/) call for choosing dignity over dependency and empowering marginalized communities to shape their own dignified socio-technical futures (Stanford HAI, 2022). Initiatives like these contribute to the broader Indigenous data sovereignty movement, which challenges dominant models of AI and public service to empower historically marginalized communities as co-creators of their own futures (Rahman, 2025).

A notable movement in this area is the development of tribally owned internet networks in the United States (see **Chart 9**). Through efforts such as the **Tribal Broadband Bootcamp** (https://tribalbroadbandbootcamp.org/media/), Indigenous communities are building local communication infrastructures. Eighty networks are currently active, 50 more are expected, and 55 are in planning (Tribal Broadband Bootcamp, n.d.). Tribal broadband initiatives show that it is not necessarily the scale of the technology, but the guiding principle of building small-scale, not-for-profit, community-led communication infrastructure that can be replicated elsewhere.

Chart 10:

Government Artificial Intelligence (AI) Readiness Index Rankings Worldwide in 2024, by Country



Source: Oxford Insights (2024)

"Fears about technology are fears about capitalism … To address the labor impact of AI, then, we need to address the impact of capitalism."

— Narayanan & Kapoor, 2024, p. 278, citing Ted Chiang

Conclusion: Challenges for Public AI and the Way Forward

It is clear from the discussion above that, like alternative internet systems, alternative AI pathways are not only possible but already here. However, this movement remains nascent, frugal, decentralized, and scattered, largely concentrated in the Global North . There are multiple challenges for these independent and standalone public AI initiatives to become a serious and organized global movement that can be replicated worldwide to subvert the status quo. Here, I focus on the inequality of power, which manifests in multiple forms, including the digital divide and regulatory capture.

Proposals to nationalize Amazon or regulate OpenAI within a public utility framework, even if realized through a series of political miracles, will not solve AI's global needs or scale issues. Initiatives that support alternative AI stack such as public platforms, clouds, and data cooperatives are limited in scale and may not always be affordable in countries in the Global South, where digital divides are deeper (Yu et al., 2023). For much of the Global South, the AI revolution is likely to cause further erosion of journalistic autonomy in already treacherous contexts characterized by inadequate funding, low job security, high rates of self-censorship, patterns of labor exploitation, and threats of physical harm (Rahman, 2025).

It is perhaps no surprise that the public sector in wealthy economies with industrial tech hubs is at the forefront of benefiting from AI adoption. According to Oxford Insights, which assessed the readiness of 181 countries to utilize AI for public services in 2023, the United States ranked highest on the global AI readiness index with a score of 87.03. Singapore, South Korea, and France followed in second, third, and fourth places, respectively. Although China ranked 20th due to the index measuring AI readiness rather than implementation, it is more advanced in applying AI to public services, as this remains a top government priority (**Chart 10**).

In contrast, regions with the lowest scores are mainly in the Global South, including sub-Saharan Africa, Central and South Asian nations, and some countries in Latin America (Yu et al., 2023). This shows that inequality in industrial AI likely extends to inequity in public AI, as not all countries or communities are well positioned to develop or benefit from public AI initiatives.

Another key challenge for public AI development comes from the familiar hurdle of **public funding** via governmental mechanisms, which are often vulnerable to termination with changes in political power and priorities. For instance, the expansion of public broadcasting in the 1930s and 1940s in the United States was possible due to President Roosevelt's New Deal (Shepperd, 2023). Similarly, the creation of the early Internet, such as NSFNet, was made possible through extensive subsidies from federal and state governments and state-funded universities. These examples show how governments, in both cases, prioritized public interest communication by adopting a *social democratic* principle—that some public services are too vital to be profit-driven—over the *corporate libertarianism* principle, which holds that corporations possess individual freedom, and that government should work in the interest of corporate profit (Pickard & Berman, 2019).

With neoliberal institutional changes in regulatory bodies and the rise of authoritarian populism, we see how President Donald Trump's two terms either repealed, cancelled, or reversed a range of regulatory policies in the public interest, which were introduced first by Barack Obama and later by the Joe Biden administrations. **Appendix Table 4** shows some significant examples of reversals that negatively affected public interest and benefited for-profit entities. For example, the termination of the **Digital Equity Act 2021** and the defunding of the **Affordable Connectivity Program (ACP)** on one hand widened the digital divide for over 35 million vulnerable Americans and on the other hand contributed to broadband monopoly (Garner & Tepper, 2025). Similarly, the **AI Bill of Rights of 2023** was introduced as a guideline to curb algorithmic discrimination, but with the removal of the Biden Administration's executive order on AI, there is now an increased risk of discriminatory AI in hiring, lending, and law enforcement (APA, 2025, February 28).

In 2024, U.S. federal agencies introduced 59 AI-related regulations, more than double the number in 2023, and these were issued by twice as many agencies (Stanford HAI, 2025). Many of these regulations are *vertical regulations*, meaning that instead of creating a separate regulatory body, existing agencies like the FDA regulate AI use in specific settings such as medical care (Narayanan & Kapoor, 2024). However, the policy rifts between the Biden and Trump administrations, as well as their respective political parties, become starkly clear when, far from regulating the big tech companies dominating the AI industry, Republican lawmakers advanced President Donald Trump's "**One Big Beautiful Bill Act**," which includes a 10-year ban on U.S. states regulating AI (O'Brien, 2025).

This puts American AI tech in further conflict with the rest of the world, especially when it encounters *horizontal regulation*, where AI applications are subject to a uniform policy regardless of which company or ministry deploys them. International laws such as the European Union's **General Data Protection Regulation (GDPR)** and the **EU AI Act**, which require transparency for high-risk AI, make jurisdiction a significant obstacle. For instance, the British Information Commissioner's Office fined Clearview £7.5 million and took legal action against the company for harvesting the data of U.K. residents but lost the case in court because Clearview is a foreign entity and therefore beyond the jurisdiction of U.K. GDPR (Clarke, 2023).

Governments around the world often leave some provisions of public safety to technology companies, assuming that market competition will encourage more ethical behavior. Self-regulation works to a limited extent because companies do not want reputational damage and loss of profit caused by flawed AI products. However, when companies lack incentives to address the harm caused by their business, regulation in the public interest becomes essential (Narayanan & Kapoor, 2024, p. 269). Moreover, in the U.S., the self-regulated social media landscape disproportionately amplifies one side of the entrenched partisan divide than the other—a bias that could easily extend to AI self-regulation. To counter this, Napoli and Adi (2025) suggest a dedicated regulatory body to oversee both social media and generative AI.

Regulation is not a cure-all, though. Narayanan and Kapoor also argue that "regulation can be captured." Ruha Benjamin (2025a, 2025b) warns about the power of the "tech broligarchy," the combined interests of tech billionaires and executives who use their wealth to exert political influence, often in the form of lobbying. They shape policy and public discourse to serve their own interests and suppress alternative visions of what AI could be and who it could serve. AI companies compete for regulatory capture by promising investments and job creation, using extensive lobbying efforts behind the scenes in both domestic and international arenas. Sam Altman, the CEO of OpenAI, often appears as an advocate for global AI regulation. Yet behind the scenes, he has been lobbying to weaken key elements of the most comprehensive AI legislation in the world, the EU's AI Act (Perrigo, 2023).

In contrast to the AI models promoted by the "tech broligarchy," and their valorization of investments in commercial AI (Napoli & Adi, 2025) public utility AI must address ethical challenges such as dataset sourcing, energy use, and environmental impact. This can be achieved through small-scale AI development and gradually reducing dependency on the commercial AI supply chain. Public AI entities will also need to ensure fair labor practices. It would also have to be an alternative to data surveillance-prone AI, protecting users' data privacy rights.

This brings us back to the broader structural issues that limit the egalitarian potential of alternative imaginaries within the capitalist framework. The struggle for alternative AI and internet systems is closely linked to the struggle for alternative economic systems both within and outside capitalism. As Narayanan and Kapoor (2024) note, flawed commercial AI or “AI snake oil” appeals to broken institutions—for example, flawed predictive AI hiring tools are attractive in a hyper-competitive market with high unemployment risks. Therefore, Public AI initiatives or efforts to reform commercial AI in the public interest cannot stand alone. They need to align with collective responses against capitalist and colonial exploitation, including those coming from labor unions, community cooperatives, and Indigenous collective agreements.

Benjamin (2025, April 10) reminds us of that computational depth without social and historical depth is not deep learning but rather superficial learning. Only by taking intersectional AI approaches—combining insights from decolonization movements, struggles for racial and gender justice, and data with dignity—can we foreground ethical, equitable, diverse, open, bottom-up, and alternative AI platforms and applications in the future. A multitude of empirical research awaits this point.

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Appendix

Appendix Table 1: *Approximate Market Capitalization of Tech Companies in Billion USD*

Company	Market Capitalization (billion USD)	AI Products
NVIDIA	$3,910.00	GPUs, CUDA, AI Platforms
Microsoft	$3,702.00	Azure AI, Copilot
Apple	$3,200.00	Apple Intelligence
Amazon	$2,353.00	Alexa, AWS AI Services
Alphabet Inc. (Google)	$2,171.00	Google AI, DeepMind
Meta Platforms (Facebook)	$1,796.00	LLaMA, AI Research
Tesla	$1,011.00	Full Self-Driving (FSD) Software
Oracle	$649.83	Oracle AI
SAP	$358.94	SAP Leonardo
IBM	$269.77	Watson
Salesforce	$260.09	Einstein AI
Intuit	$217.49	Intuit AI
ServiceNow	$215.09	Now Platform AI
Adobe	$161.19	Adobe Sensei
Intel	$97.35	Intel AI
Workday	$64.70	Workday AI
Baidu	$29.47	Baidu AI Cloud, DuerOS
Splunk	$26.44	Splunk AI
UiPath	$7.06	UiPath AI
C3.ai	$3.48	C3 AI Suite

Source: CompaniesMarketCap.com, July 3, 2025.

Appendix Table 2: *Global AI Industry Stack Architecture*

Layer	Function	Key Players
Raw Materials Mining and Energy	**Critical Minerals:** Companies that extract elements like cobalt, lithium, and rare earth metals that are essential for semiconductor production	Glencore, China Northern Rare Earth Group, CMOC
	Energy is a foundational resource across all layers of the AI stack, with demand intensifying, especially in cloud data centers	
Chip Fabrication & Hardware Assembly	**Fabrication Facilities:** Companies that fabricate AI-specialized chips (e.g., NVIDIA's H100, AMD MI300X)	TSMC (Taiwan), Samsung (South Korea), NVIDIA (USA), AMD (USA), and Intel (USA)
	Manufacturing and Assembly Hubs: Companies that assemble AI hardware, including servers, GPUs, AI accelerators, and edge devices	Foxconn and Pegatron and other ODMs (Original Design Manufacturers)
	Logistics: Global distribution networks deliver the hardware to data centers, research labs, and end-users	Localized and globalized companies including shipping and transportation providers
Cloud & Compute Infrastructures	**Cloud Providers:** companies that provide data storage and servers and computing services	AWS, Microsoft Azure, Google Cloud, Oracle Cloud, NVIDIA Jetson, Alibaba Cloud, Tencent Cloud
	Edge Computing: companies that integrate AI processing at the device level	NVIDIA, Qualcomm
	Telecommunication: internet connection, services and networks that will allow real-time application of AI in IoT and mobile devices	Localized and globalized ISPs such as Verizon and Starlink

Source: Author drawing from various news articles, blogs, and academic sources including Gambacorta & Shreeti, 2025; Gonzalez-Cabello et al., 2024; Huang et al., 2023; Muldoon et al., 2025; and Wagener, 2025

Appendix Table 2: *Global AI Industry Stack Architecture*

Layer	Function	Key Players
Software Development & Application	**Model Training:** Companies equipped with specialized hardware using massive datasets train large-scale AI models on supercomputers and hyperscaler clouds	Click farms and hidden army of AI data workers who perform the behind-the-scenes work of preparing datasets
	Refining models involves refinement and fine tuning of the foundational models using feedback	OpenAI (GPT-4), Anthropic (Claude), Google DeepMind (Gemini), Meta (Llama3), DeepSeek V3
	Frameworks: Software libraries and tools that are used for model development	PyTorch, TensorFlow (Google), Cognitive Toolkit/ CNTK (Microsoft), AX
	Deployment Platforms: Specialized service providers that host and gives access to pre-trained models and framework tools	OpenAI API, Hugging Face
End-User Integration	**Enterprise Adoption:** Businesses and public entities integrate industrial AI into operations	Salesforce Einstein, Microsoft Copilot, ServiceNow AI
	Consumer products: AI features embedded in smart devices and electronic services	ChatGPT, Midjourney (image gen), TikTok recommender, Google Maps AI routing
Regulation	**Organizational level regulation** involves testing, trials, ethics audits and red teaming	IBM's AI ethics
	National and local governments that create regulatory policies and provide incentives	The CHIPS and Science Act 2022 (U.S.) Shanghai Regulations on Promoting the Development of the AI Industry (China)
	International organizations that create international regulatory policies	The EU AI Act 2024

Source: Author drawing from various news articles, blogs, and academic sources including Gambacorta & Shreeti, 2025; Gonzalez-Cabello et al., 2024; Huang et al., 2023; Muldoon et al., 2025; and Wagener, 2025

Appendix Table 3: *Examples of Non-Profit and Public AI Tools in North America*

Examples	Botometer	Clinical BERT	Equitable AI	Tech4Nature Mexico
Status	Running since April 2014	Beta/testing since August 2019	Running since December 2021	Running since April 2014
Sector	Information and communication, Professional, scientific and technical activities	Human health and social work activities	Prevent and mitigate gender bias in Early Warning Systems for school dropouts	Biodiversity protection and nature conservation
Usage of AI	Data Management and Analysis, Information Retrieval, Classification	Natural Language Processing	Data Management and Analysis	Traditional Machine Learning
Generation of AI	Traditional Machine Learning	Deep Learning	Traditional Machine Learning	Deep Learning
Model Training	Supervised Learning	Semi-supervised Learning, Unsupervised Learning	Supervised Learning	Semi-supervised Learning
Source Type	Closed Source	Open Source	Closed Source	Closed Source
Developed By	Observatory on Social Media at Indiana University	New York University, One Fact Foundation	PIT Policy Lab; Itad; Women in Digital Transformation, Athena Infonomics	C Minds and the Ministry of Sustainable Development of Yucatan
Funding Source	Public	NYU grants, philanthropy	International Cooperation [USAID]	International Organization

Source: Based on Public Interest AI, n.d. data, https://publicinterest.ai/tool/map

Appendix Table 4 : *Notable Internet and AI Policies Reversed by Trump Administration*

Policy/Law/Act/ Initiative Name	Administration	Public Interest Focus	Trump's Reversal Action	Impact of Reversal
Digital Equity Act 2021 (part of Infrastructure Investment and Jobs Act 2021)	Biden	Funded digital inclusion programs ($2.75B) for broadband access, devices, and digital literacy training	Terminated in May 2025 via executive action, branded "illegal" and "unconstitutional"	Rescinded grants for rural laptop distributions, telehealth access, and digital navigators; widened digital divide; broadband monopolies
Net Neutrality (2015 Open Internet Order)	Obama	Classified broadband as utility (Title II), preventing ISP throttling/ prioritization	FCC repealed in 2017 (Restoring Internet Freedom Order) (was restored in 2014)	Allowed ISPs to create internet "fast lanes," disadvantaging smaller services; reduced equal access; benefited ISPs
AI Bill of Rights 2023 (framework/ guideline)	Biden	Established 5 principles against algorithmic discrimination with transparency requirements	Revoked the Biden Administration's executive order on AI, and issued a new executive order	Removed mandatory bias audits; increased risk of discriminatory AI in hiring, lending, and law enforcement
Affordable Connectivity Program	Biden	Subsidized internet for 23M low-income households	Defunded in 2024	23M households lost subsidized internet; exacerbated affordability crisis
AI R&D Strategic Plan	Obama	Prioritized ethical AI research and workforce training	Replaced in 2025 with military/ economic dominance focus	Diverted $1.8B research funding from bias mitigation to defense applications. Defense contractors, AI
Executive Order 14110 (Safe AI)	Biden	Required AI safety assessments, civil rights protections, and Chief AI Officers in agencies	Revoked January 2025 (replaced with an executive order to remove barriers to "America's global AI dominance"	Eliminated mandatory safety checks; increased risks of harmful AI outcomes

Source: *Author drawing from various sources including, APA, 2025, March 12, 2025, APA, 2025, February 28; Garner & Tepper, 2025; Federal Communications Commission, 2015, 2024; Felten & Lyons, 2016.*

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