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The Geoeconomic and Geopolitical Implications of Artificial Intelligence

An Analysis of the Transformation of National Sovereignty in the 21st
Century

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Abstract

This thesis examines the geopolitical and geoeconomic implications of the contemporary artificial intelligence transition by situating it within a comparative historical framework that traces structural continuities between the nineteenth-century Industrial Revolution and the computational order of the 2020s. The central thesis posits that the change to AI does not represent a radical rupture in the way global power is structured. Instead, it speeds up and enhances a set of repeated patterns where general-purpose technologies change the way sovereignty is distributed, the geography of strategic resources is changed, and the terms of great-power competition are transformed. Three chapters spanning three temporal registers follow the analysis. The first examines the means, through different historical epochs, through by which control over energy resources, infrastructure networks, and the tools of manufacturing became tools of imperial power projection, technology denial, and social transformation. It then — notes their echoes in the contemporary battles over semiconductors, rare earth supply chains, and hyperscale data center infrastructure. The second investigates, in the present day, the hypothetical financial dynamics of the AI investment cycle in clear comparison with the dot-com episode, the layered vulnerabilities of the AI supply chain from energy inputs to frontier model development, the geopolitical weaponization of export controls and vital mineral dependencies, the institutional architecture of algorithmic surveillance as shown by Palantir, and the structural position of the European Union as a normative power whose regulatory goals coexist with material dependence on both American platforms and Chinese mineral supply chains. The third chapter, which deals specifically with the alignment problem, the crisis of international AI governance, and the transforming potential of AI applications in healthcare, scientific research, and climate adaption, builds forward-looking possible future scenarios for the years 2027–2035 and evaluates the financial, geopolitical, and governance pathways the AI transition may follow — from managed repricing to disorganized correction to what the thesis terms the acceleration trap. The thesis maintains throughout that the fight for AI dominance and the fight for

energy and mineral control are not separate battles but rather a single, repeatedly intertwined geopolitical process whose outcome—whether it generates generally distributed riches or destabilizing concentration of power—will be determined not by the technology itself but by the political decisions, institutional innovations, and acts of collective governance that the societies facing it demonstrate capable of producing.

Keywords: artificial intelligence; geopolitics; geoeconomics; computational sovereignty; semiconductor supply chains; critical minerals; great-power competition; dual-use technology; General-purpose technologies (GPT); AI alignment; European strategic autonomy.

Introduction

There is wide consensus among policymakers and scholars by now that artificial intelligence has grown to be a concern of geopolitical significance. This thesis examines the geopolitical and geoeconomic dimensions of Artificial Intelligence (AI) while addressing broader sociocultural and technical implications. By analyzing how the evolution of AI reshapes contemporary daily life, the study investigates the intersection of social dynamics and technological advancement. Ultimately, this comprehensive approach seeks to provide a nuanced understanding of the multifaceted impact of AI within the current global landscape. Governments across the industrialized world have published national AI strategies (The White House, 2025) (UK Government, 2021) (State Council of the People's Republic of China, 2017); the semiconductor export controls imposed by the United States on China since October 2022 constitute the most extensive technology-denial regime since the Cold War (Allen G. , 2022) (Bown, 2020); the European Union has adopted the world's first comprehensive legislative framework for the governance of AI systems (European Parliament and Council of the European Union, 2024); and military establishments on every continent are investing in autonomous weapons platforms, algorithmic targeting systems, and AI-augmented cyber capabilities at a pace that has outstripped the capacity of existing arms control frameworks to accommodate them. Most of the literature that talks about whether artificial intelligence "matters" geopolitically doesn't have a very detailed analysis of how, exactly, it matters—through what material channels, structural dependencies, and historical logics the technology changes the distribution of power among states, businesses, and people. Particularly in stories on policies and in newspapers, the most common form of interaction swings between two disappointing poles: A strategic voluntarism that sees the technology as an instrument whose effects are entirely dependent on the intentions of the actors who use it contrasts with a technological determinism that considers artificial intelligence as an autonomous force whose course will mechanically influence geopolitical outcomes. What is missing, and what this dissertation seeks to offer, is an

analytical framework that treats the AI transformation as a political-economic event—one whose dynamics are molded concurrently by the materiality of the supply chain, the structure of the financial system, the logics of great-power competition, and the institutional capacity (or incapacity) of governance frameworks to handle the effects (Acemoglu & Johnson, 2023).

Choosing to base this study on historical parallel is not only a matter of method but also of substance. According to the thesis, the geopolitical and geoeconomic trends produced by the AI transformation are not new; they instead reflect the reappearance of structural patterns that have followed every significant general-purpose technology revolution since the start of industrialization (David, 1990) (Mokyr, 1990). The same set of questions emerges with amazing regularity throughout historical periods whenever a technology surfaces able to rearrange the productive base of an economy: who is in charge of the key inputs? Who owns the infrastructure through which the technology is deployed? How do states that find themselves at a disadvantage in the emerging technological order respond—and what forms of competition, cooperation, or coercion does this response generate? The nineteenth-century transition from organic to mineral energy regimes—the shift from wood, wind, and water to coal, steam, and iron—produced answers to these questions that shaped the geopolitical order for over a century (Wrigley, 2010) (Smil, 2017): British hegemony was built on the conjunction of accessible coal seams and a global network of logistical infrastructure (Pomeranz, 2000) (Allen, R. C. (b), 2009); continental rivals pursued strategies of technological appropriation, infrastructure diplomacy, and state-led industrial policy to close the gap; late-industrialising states deployed protectionist instruments that their own liberal rhetoric simultaneously condemned; and the social costs of the transition—displacement, de-skilling, urbanisation, and the exploitation of peripheral labor—were borne disproportionately by those with the least political power to resist them. The thesis maintains that understanding the parallel is not a nostalgic trip down memory lane but rather a need for proper present analysis since each of these factors has a clear modern counterpart in the Artificial Intelligence economy of the 2020s.

Only when the artificial intelligence economy is viewed as a physical system rooted in rather complex and fragile physical supply chains, rather than as a disembodied digital

phenomenon, is the link between artificial intelligence and the seemingly far-off theatres of Greenland, Venezuela, and Iran clearly apparent. Training a frontier AI model requires tens of thousands of specialized processors — graphics processing units, or GPUs — operating continuously for weeks or months, consuming electricity at a scale that has made data centers one of the fastest-growing sources of energy demand in the industrialized world. The processors themselves are manufactured through a fabrication process of extraordinary precision, dependent on lithographic equipment produced by a single Dutch company, from semiconductor designs originating overwhelmingly in the United States, using rare earth elements whose extraction and processing is dominated by China to a degree that gives Beijing structural leverage over the entire downstream supply chain. In the American case, natural gas supplies the largest share — approximately 42% — of the electricity powering the country's compute infrastructure, with coal, nuclear, and renewables accounting for the balance (U.S. Energy Information Administration, 2025). Commercially relevant deposits of the critical raw materials required for AI hardware are concentrated in the Democratic Republic of the Congo, which dominates global cobalt and coltan supply; in Australia, the United States, and Myanmar, which together account for most non-Chinese rare-earth production; and—as the receding Greenlandic ice sheet progressively reveals—in the rare-earth-bearing carbonatite complexes of the Arctic subsurface (U.S. Geological Survey (a), 2025). The strategic justification connecting these far-flung locations is the supply chain itself: To ensure the physical basis of artificial intelligence supremacy, a nation has to provide access to the resources, the energy, and the manufacturing capacity needed for the technology to run. Within this framework, the American attitude toward Greenland makes sense as a resource sovereignty plan meant to lower reliance on Chinese rare earth imports. As pieces of a plan to surround energy, the actions in Venezuela and Iran make sense: Washington hopes to raise Beijing's energy expenses and therefore limit the fiscal ability accessible for the semiconductor infrastructure and artificial intelligence development initiatives American export restrictions were meant to damage by interfering with China's access to cheap hydrocarbons. What appears, from the vantage point of conventional foreign policy analysis, as a set of discrete regional interventions reveals itself, from the

vantage point of AI supply chain analysis, as a single, layered architecture of technological containment.

This thesis contributes to the growing interdisciplinary literature on AI and geopolitics by offering an analysis that is simultaneously historical, empirical, and forward-looking — and that insists, throughout, on the inseparability of the technological, the financial, and the political dimensions of the transition (Zuboff, 2019) (Crawford, 2021) (Miller, 2022). While most of the current literature considers the AI economy as a phenomenon inside the tech industry—a topic of compute scaling, model architecture, and benchmark performance—this study places it inside the larger political economy of resource competition, speculative finance, and great-power competition that has influenced every previous instance of technological acceleration. While policy-oriented studies usually handle particular aspects of the AI problem separately—semiconductor export restrictions in one report, energy infrastructure in another, military applications in a third, governance systems in a fourth—this thesis examines their structural links and shows that the weaknesses of the AI supply chain stack across levels in ways that sectoral analysis alone cannot properly grasp. And where much of the forward-looking literature on AI futures oscillates between utopian projection and existential alarm, this thesis attempts to construct scenarios that are grounded in the structural dynamics documented empirically in the preceding chapters, using historical precedent as a disciplining heuristic rather than as a deterministic template.

The findings that emerge from this analysis may be summarized along six axes. First, the thesis demonstrates that the spatial and material logics of the AI transition reproduce, with considerable structural fidelity, the dynamics of the nineteenth-century industrial order: the struggle for control over critical resources (from coal seams to rare earth deposits), the construction of geographically distributed infrastructure as the material foundation of power projection (from coaling stations to hyperscale data centers), the use of technology-denial regimes to freeze the development of rivals (from the British prohibition on the export of textile machinery to the “American CHIPS Act” and semiconductor export controls), and the social costs borne by peripheral populations whose labor and resources sustain the system without granting them proportional access to its benefits (from the cotton workers of Lancashire to the ghost workers of Kenya and

the Philippines) (Gray & Suri, 2019). Second, the paper makes the case that the financial structure of the AI boom has very similar speculative features as past technology cycles, especially the dot-com boom of the late 1990s. However, it is different from them in the material intensity of the infrastructure involved, the amount of money that has been spent (with projected hyperscaler expenditure exceeding six hundred billion dollars in 2026 (Brady, 2026)), and the emergence of circular capital flows among hardware manufacturers, cloud providers, and model developers that create systematic dependencies that have never been seen before in the tech industry. Third, the analysis reveals that the AI supply chain is structured as a layered system of vertical dependencies — from energy and raw materials at the base, through semiconductor fabrication and cloud infrastructure, to model development and applications at the apex — in which vulnerabilities at each level compound rather than cancel one another, and whose exploitation has become an explicit instrument of great-power competition. Fourth, the thesis documents the emergence of what it terms “algorithmic governance” as a structural feature of the contemporary security landscape, examining through the case of Palantir Technologies the institutional mechanisms through which a private corporation has acquired a position of informational centrality within the defence, intelligence, and border management architectures of the United States and several European NATO member states — a position that concentrates the preconditions of sovereign decision-making in a platform whose classification criteria, risk-assessment algorithms, and operational logic are not subject to democratic oversight. The analysis of Palantir’s role is situated within a broader examination of the asymmetry of surveillance discourse, demonstrating that the Western narrative of Chinese “social credit” surveillance has functioned (or not), in significant part, as a discursive screen that obscures the structurally comparable — and in some respects more advanced — surveillance architectures being constructed within Western democracies themselves. Fifth, the thesis assesses the structural position of the European Union as a normative power whose regulatory ambitions — embodied most visibly in the EU Artificial Intelligence Act of 2024 — coexist with a material dependency on American platforms across five interlocking pillars (cloud infrastructure, collaboration software, payment systems, AI models, and defence platforms), and on Chinese supply chains for the critical minerals upon which its hardware ambitions

depend. The thesis contends that the tension between normative leadership and technical reliance is the main axis of Europe's present strategic situation and that the language of strategic autonomy has so far not generated the institutional innovations needed to address it. Sixth, and most significantly, the thesis posits that the AI transition not only occurs in a worsening geopolitical scene but also speeds up that deterioration, therefore increasing the stakes of technological dominance to a point at which cooperative outcomes become essentially more challenging to maintain.

The three chapters of the thesis are arranged with a deliberate methodological commitment: the belief that the present can be fully understood only in light of the past, and that the future can be properly assessed only on the basis of patterns whose structural recurrence has been empirically demonstrated.

Chapter 1, titled "**The Past: Similarities with the Present Day**", examines the political economy of the steam-and-coal era and traces the ways in which control over energy sources, infrastructure networks, and the equipment of production became tools for projecting imperial power, denying technology, and transforming society during the years roughly 1800 to 1900. The chapter explores the British coal-and-steam supremacy and the worldwide coaling station network supporting it; the continental responses of Germany and the United States pursuing "carbon sovereignty" and infrastructure diplomacy to undermine British power; the "machine wars" whereby nations sought to control the diffusion of industrial technology; the social disruptions brought about by the factory system, from the Enclosure Acts to the Luddite Rebellion; the North–South imbalance where the benefits of industrialisation were disproportionately concentrated in the metropolitan center while the costs were pushed onto the colonial periphery; and the governance difficulties raised by dual-use technologies, illustrated using the Biological Weapons Convention as a precedent. Throughout, the chapter identifies structural patterns — the reorganization of resource sovereignty, the concentration of productive capacity, the weaponization of supply chains, the social costs of displacement — whose recurrence in the contemporary AI economy the subsequent chapters demonstrate.

Chapter 2, titled "**The Present, 2020–2026: The Era of Computational Sovereignty**", turns to the empirical analysis of the contemporary AI transition. The chapter starts with a careful analysis of the present investment cycle against the dot-com

period, then moves on to look at the structural parallels and contrasts in financial architecture, valuation markers, and capital flows. It then investigates the layered vulnerabilities of the artificial intelligence supply chain, exposing how these deficiencies interact throughout levels to magnify systemic risk from energy shortages and rare earth dependencies at the foundation to the semiconductor chokepoints controlled by NVIDIA, TSMC, and ASML, to the circular capital flows and GPU-backed lending techniques characterizing the infrastructure layer. The chapter investigates the geopolitical weaponization of this supply chain reliance using the cases of Greenland, Venezuela, and Iran, claiming that these seemingly unrelated events reflect interwoven steps in a unified American geoeconomic campaign meant to attack also the physical basis of Chinese artificial intelligence development. It examines the financialization of computers using GPU collateral and the deliberate control of AI standards, exposing how the informational framework of the AI economy promotes incentives for market distortion reminiscent of past speculative bubbles. Tracing its institutional origins, product design, growing integration into Western military and intelligence systems, and the governance issues this poses for democratic accountability, it presents an extensive case study of Palantir Technologies as the exemplary instance of algorithmic governance. It evaluates Europe's standing in the world AI race by looking at the EU AI Act, the structural gap with China and the United States, and the conflict between legal aspiration and actual reliance. And it subsequently analyses the security dimensions of the AI transition, from the XZ Utils supply chain attack to the proliferation of lethal autonomous weapons systems and the emerging institutional conflict between frontier AI developers and the American national security apparatus.

Chapter 3, titled “**The Future, 2027–2035: Scenarios for the Intelligence Transition**”, constructs forward-looking scenarios grounded in the structural dynamics documented in the preceding chapters. It starts with an evaluation of the capability horizon, which is the range of possible technological paths, drawing on Daniel Kokotajlo's scenario-forecasting work, Sam Altman's public statements about OpenAI's trajectory — in which intelligence is framed as an abundant, utility-like commodity converging toward the cost of electricity (Altman, S. (b), 2025) — and the existential-risk arguments in the book made by Eliezer Yudkowsky and Nate Soares (Yudkowsky &

Soares, 2025). Then, each evaluated against the historical precedent of the dot-com correction and the external risk presented by the Japanese carry trade mechanism, three financial scenarios for the AI capacity bubble are produced: orderly repricing, disruptive correction, and sustained growth. The geopolitical scenarios below look at how the US and China's tech war is getting worse, how the energy-AI nexus is changing because of the Iran crisis, how critical minerals are being used as weapons, and how tech-based alliance blocks are emerging. At the level of digital infrastructure, these blocks copy the strategic alignment dynamics of the Cold War. Before providing a thorough analysis of the transforming case for AI, the next chapter focuses on Europe's structural reliance, looked at across five pillars—cloud, defence, payments, space, and platforms—and explores the fields of healthcare, scientific research, crime prevention, education, and climate adaptation together with the shadow supply chain of hardware obsolescence and electronic waste. The chapter concludes with an analysis of the alignment problem and the governance vacuum, followed by three integrated macro-scenarios — a **managed transition**, a **disordered correction**, and what the thesis terms the “**acceleration trap**” — whose relative plausibility depends on the interaction of variables whose values are genuinely uncertain but whose structural relationships the preceding analysis has sought to clarify.

The importance of examining artificial intelligence through the lens of geopolitics and geoeconomics — rather than through the narrower frameworks of computer science, innovation economics, or technology ethics that dominate much of the existing literature — derives from a structural feature of the technology itself. Unlike earlier digital technologies, whose material requirements were comparatively modest and whose diffusion was largely unconstrained by physical geography, artificial intelligence at the frontier level is an extraordinarily resource-intensive enterprise. Its production depends on minerals extracted in politically unstable regions, fabricated into components through manufacturing processes of unparalleled precision concentrated in a single geopolitically exposed territory, powered by electricity generated from fuels whose supply is subject to the full range of great-power coercion, and deployed through cloud infrastructure controlled by a small number of American corporations whose market position confers structural leverage over every downstream actor in the ecosystem. To study artificial

intelligence without considering the political environment under which its physical supply chain runs is to conflate the surface of the technology with its substance — to mistake the model for the mine, the algorithm for the electricity, the benchmark for the barrel of oil. From a geoeconomic and geopolitical standpoint, this thesis contends, this lens is not one among many equally legitimate options; rather, it is a need for grasping the true course of the technology and its effects on power distribution in the twenty-first century.

The investigation has quite high stakes. If, as the data gathered in this study shows, the structural similarities with earlier technological shifts hold, then the AI economy is prone to the same dynamics of speculative excess, geopolitical competition, and governance failure that have defined every previous period of technical acceleration, and the communities dealing with the change have at their disposal the same limited set of institutional responses: controlled adaption, chaotic correction, or the failure to govern at all. The nineteenth-century railway mania bankrupted its promoters but left behind an infrastructure that carried the freight of the Victorian economy for six decades; the dot-com crash repriced expectations while preserving the fiber optic networks that became the backbone of the broadband internet. Whether the AI transition follows this pattern — a costly but ultimately productive overbuild whose infrastructure survives the financial correction that accompanies it — or whether the severity of the geopolitical environment, the depth of the leverage in current investment structures, the pace of capability development, and the inadequacy of the governance architecture produce consequences that are qualitatively more severe, is the question on which the geopolitical and geoeconomic architecture of the next decade depends. This thesis does not claim to answer that question definitively; it claims, rather, to have assembled — across the full arc of two centuries of technological history and three chapters of sustained analysis — the structural conditions under which it must be asked, and to have demonstrated that asking it with the analytical seriousness it deserves requires precisely the kind of integrated, historically grounded, and materially attentive framework that the following pages attempt to provide.

1. The past: 1800 - 1900 — Similarities with the present day.

Introduction of Chapter 1

In order to read the present through the lens of the past is not to flatten historical difference, but to recover a method: to treat technological change as a force that reorganizes space, power, and social life. This thesis adopts that method by placing the contemporary AI boom alongside the nineteenth-century Industrial Revolution, not as a rhetorical analogy, but as a comparative framework. The question is simple: when a general-purpose technology emerges, what kinds of geopolitical and geoeconomic patterns tend to manifest in the present—even when the “machine” has changed from steam engines to neural networks?

Between 1800 and 1900, the shift from organic energy sources (wood, wind, water) to mineral energy (coal) transformed the world's hierarchy in ways that were simultaneously technical and also territorial. As Wrigley has demonstrated on his publication, the transition to a mineral-based energy economy was not only a quantitative increase in available power but also a qualitative transformation of the relationship between territory and productive capacity — a point developed further by Pomeranz's comparative analysis of the divergence between European and Chinese development trajectories, and by Allen's account of the specific factor endowments that made British industrialization possible where other regions with comparable market institutions did not industrialize (Wrigley, 2010) (Pomeranz, 2000) (Allen, R. C. (b), 2009). Coal not only boosted business but also changed the geography of sovereignty. More than the surface area of arable land, wealth and strategic advantage become more connected to underground carbon reserves. Great Britain's ascent to hegemonic dominance was made possible by a unique combination of deep-water ports, navigable rivers, coal seams adjacent to iron, and Imperial strategies evolved as the Royal Navy moved from sail to steam. Renewed importance came for isolated "barren" sites such Gibraltar, Malta, Aden, and Singapore not for their resources but for their role as logistical nodes, coaling stations without which a steam-powered fleet remained tethered to home ports. Headrick's analysis of the technological instruments of

imperial expansion documents in detail how innovations in transport and communications infrastructure — steamships, submarine cables, and the logistics of coal supply — provided the material basis for the global reach of European power, a thesis extended by Kennedy's broader account of the relationship between economic resources and military overstretch across five centuries of great-power competition (Headrick, 1981) (Kennedy P. , 1987). Even the opening of the Suez Canal in 1869 may be regarded as a structural event with systemic ramifications: it shortened distance, hastened troop movement, and lowered trade "latency" in a manner that foretold the strategic rationale of modern connectivity corridors.

The continental reaction to British rule shows a repeating pattern: technological rivalry soon turns into a politics of autonomy. Germany's industrial goals, including the search for what might be called "carbon sovereignty", were entwined with its unification in 1871. The Ruhr's coal, combined with the iron resources of Alsace-Lorraine, enabled industrial acceleration, while overland railway projects — most ambitiously the Berlin-to-Baghdad railway, analysed by McMeekin as a deliberate strategy to construct an overland alternative to British-controlled maritime routes — sought to bypass British naval chokepoints, constituting an early form of infrastructure diplomacy aimed at securing supply chains (McMeekin, 2010). Henderson's account of German industrial ascent situates this drive within the broader institutional framework of the Zollverein and state-led industrial policy, while Landes traces the wider pattern through which Western European late-industrializers leveraged technological borrowing and institutional adaptation to close the gap with Britain (Henderson, 1975) (Landes, 1969). The United States, for its part, converted geographic scale into industrial power by integrating coal fields, manufacturing centers, and markets through the Transcontinental Railroad, constructing an internal economic space less vulnerable to European maritime leverage. As White has documented, the transcontinental railways were not merely commercial ventures but political instruments whose construction reshaped the spatial organisation of American capitalism, a process whose corporate and managerial dimensions are analysed in Chandler's foundational account of the rise of the modern industrial enterprise (White, 2011) (Chandler, 1977). In every instance, the new technical order produced a new

strategic grammar: control the energy source, control the machinery of production, and secure the pathways by which both move.

This is the grammar that returns—*mutatis mutandis*—in the AI economy of the twenty-twenties. The source material has evolved from coal seams to rare earth elements, sophisticated semiconductors, and the energy systems sustaining hyperscale calculation. Still, the basic reasoning is still obvious. Data centers increasingly resemble the coaling stations of a digital era: positional infrastructures that allow “algorithmic fleets” to operate at speed across regions, minimizing delay and maximizing control. Export restrictions on semiconductor equipment reflect earlier attempts to control industrial machinery, while modern “reshoring” and “friend-shoring” initiatives aim to restore national sovereignty over essential resources. The Jevons Paradox, which stated that increases in steam engine efficiency led to an increase rather than a reduction in coal consumption, reappears in a digital version: as models get more efficient, new applications abound, and total computation expands. In short, the AI revolution, like the industrial one before it, is not merely a story of innovation. It is a story about how power re-anchors itself in infrastructure, resources, and geography.

This chapter aims to set the historical stage for the thesis as a whole. By tracing the industrial past—its energy transitions, strategic chokepoints, protectionist “machine wars”, and social transformations—it becomes possible to make an interpretation of the present not as unprecedented chaos, but as a familiar political economy operating with important new materials. The goal is not to predict the future mechanically, the goal is to cultivate judgement: to understand how technological orders are built, defended, contested, and, at times, destabilized by the very intensity of their expansion to examine whether structural patterns from the past are recurring in present configurations.

1.1. The Era of Steam and Coal (1800–1900): Energy, Geopolitical Order, and the First Technological Revolution

Any attempt to situate the contemporary geopolitics of artificial intelligence within a coherent analytical framework must reckon, at least briefly, with the historical precedents through which the relationship between technological transformation and the distribution of global power has been constituted and reconstituted over the past two centuries. The

present chapter does not claim that the transition to AI is simply a repetition of earlier technological revolutions; the specificities of digital infrastructure, the non-rival character of data as a resource, and the speed at which algorithmic capabilities can be diffused across national boundaries introduce qualitative differences that resist straightforward historical analogy. What the historical record does offer, however, is a set of structural lessons about the mechanisms through which technological leadership translates into geopolitical advantage, about the ways in which states construct and contest the spatial and infrastructural conditions of that leadership, and about the characteristic forms of dependency and exclusion that technological revolutions tend to generate for those who arrive late or poorly positioned (Modelski & Thompson, 1996).

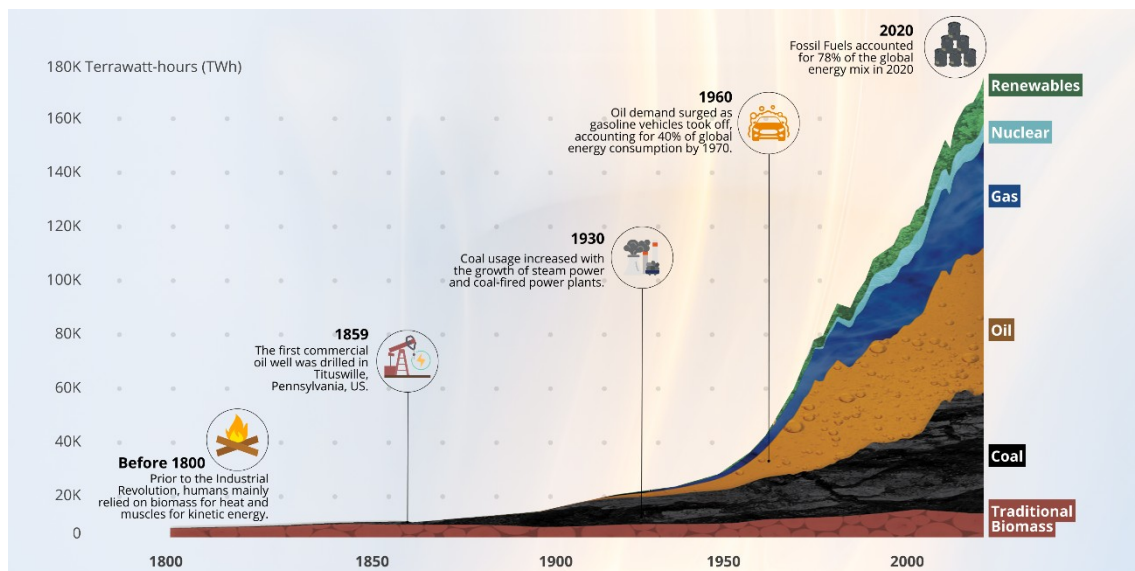


FIGURE 1: THE HISTORY OF ENERGY TRANSITION

Source: [Epconsultenergies](https://www.epconline.com/energy-trends)

With these caveats in mind, the long nineteenth century — the era defined by the transition from organic to mineral energy, by the industrialization of production and warfare, and by the emergence of a genuinely global economy organized around the infrastructural requirements of steam power — offers a historically rich and analytically productive point of departure.

1.1.1. Coal, Geology, and the Rewriting of the Global Hierarchy

The transformation that reshaped the global order between approximately 1780 and 1850 was, in its most fundamental dimension, a geological event with political consequences. The transition from the organic energy regime that had sustained all prior civilizations — in which the primary sources of mechanical power were wood, wind, water, and animal muscle, each ultimately constrained by the finite productivity of land surfaces — to a mineral energy regime based on the exploitation of coal represented a qualitative discontinuity in the relationship between human productive capacity and natural resource constraints (Smil, 2017). Where agricultural societies were bounded in their energy extraction by the photosynthetic surface of cultivated land, coal-based industrialization drew upon energy stores accumulated over geological timescales, releasing productive possibilities that no prior social order had approached. The geopolitical implications of this transition were immediate and profound: wealth was no longer determined solely by the extent of fertile surface territory, which had been the primary basis of agrarian power, but by the subterranean distribution of carbon deposits — a distribution that bore no systematic relationship to the political map inherited from the pre-industrial era, and that therefore created the conditions for a radical redistribution of relative power among states (Pomeranz, 2000).

Great Britain's emergence as the dominant power of the nineteenth century — the first instance, in modern history, of what might be described as technological hegemony in the full sense of that term — was grounded in a conjunction of geological endowment and institutional capacity that no other European state could initially replicate (Hobsbawm E., 1968). The proximity of substantial coal seams to navigable rivers, deep-water ports, and deposits of iron ore along the coalfields of South Wales, the West Midlands, and the Tyne and Wear created the material conditions for an early and self-reinforcing industrialization that continental competitors were structurally disadvantaged in matching. The British state's early development of patent law, relatively fluid capital markets, and a commercial culture oriented toward manufacturing and trade compounded these geographical advantages into a sustained competitive lead (Mokyr, 2009). The result, by the mid-nineteenth century, was a condition of technological supremacy that expressed itself simultaneously in the productive sphere — British industry accounting

for approximately 20% of global manufacturing output in 1860 and reaching its peak share of around 23% in 1880, with a still larger share of world manufactured exports and of strategic outputs such as pig iron, coal, and cotton textiles — and in the military sphere, as the Royal Navy's transition from sail to steam transformed the terms of maritime power projection in ways that systematically advantaged a state with access to abundant coal and global bunkering infrastructure (Bairoch, 1982) (Kennedy P. , 1987).

The strategic logic of British foreign policy in the high Victorian era is, from this perspective, legible as a sustained effort to construct and defend the spatial infrastructure of a coal-powered empire. The acquisition of what appeared, to observers accustomed to thinking in terms of agricultural or resource wealth, as an inexplicable collection of barren or minimally populated islands — Gibraltar (1713, consolidated as a coaling station), Malta (1800), Aden (1839), Singapore (1819), and a series of smaller Atlantic and Pacific anchorages — reflected not a lack of strategic coherence but a highly coherent strategic logic, one oriented around the operational requirements of steam-powered naval projection (Lambert, 2018). A coal-burning warship or merchant vessel was, in operational terms, an instrument of sharply limited range unless it could resupply at intermediate points; the global network of coaling stations that Britain assembled over the course of the nineteenth century was, in this sense, the infrastructural condition of possibility for its claim to universal maritime supremacy. The opening of the Suez Canal in 1869 — an event whose geopolitical significance cannot be overstated — functioned within this logic as a force multiplier of the first order, compressing the effective distance between Britain and its Indian and East Asian possessions and dramatically reducing the logistical costs of projecting naval and commercial power across the Indian Ocean (Karabell, 2003). The canal was, in effect, the critical chokepoint of a global supply chain, and Britain's 1875 acquisition of the Khedive Isma'il's 44% shareholding in the Suez Canal Company — the largest single block of stock (176,602 of 400,000 shares, purchased for £3,976,582), secured through financial rather than military means and giving Britain a decisive but minority position alongside French private holders — reflected a sophisticated understanding of the relationship between infrastructural control and geopolitical leverage that would find direct analogues in the data infrastructure competitions of the twenty-first century (Karabell, 2003) (UK Parliament, 1876).

1.1.2. The Continental Response: Germany, Carbon Sovereignty, and Infrastructure Diplomacy

The challenge that continental European states confronted in responding to British industrial and naval supremacy was not, in the first instance, a military one; it was a structural problem of resource access and spatial organisation. The Zollverein — the customs union that progressively integrated German-speaking territories between 1834 and 1866 — was, among other things, an attempt to create a sufficiently large internal market to sustain the scale economies of industrial production (Henderson, *The Zollverein*, 1959). The political unification of Germany in 1871, achieved through the wars of 1864–1871 under Bismarckian statecraft, was as much an industrial project as a nationalist one: the Prussian-led German state required not merely political consolidation but the integration of dispersed coal and iron resources into a unified productive system capable of competing with the British industrial machine. The intensive exploitation of the Ruhr Valley — whose coal deposits, combined with the coal of the Saar and the iron ore of Lorraine and Luxembourg, provided the material foundation for German heavy industry — was not possible on the necessary scale without political control of the territories in question (Pounds & Parker, 1957). The annexation of Alsace-Lorraine following the Franco-Prussian War of 1870–1871, motivated primarily by strategic-defensive considerations (the Vosges as a natural frontier and the fortress of Metz) together with nationalist ideology, acquired a major economic dimension only after the Thomas–Gilchrist basic process of 1878–1879 rendered the high-phosphorus *minette* ores of the annexed Moselle district commercially usable for steelmaking — a delayed industrial windfall that, while not the original driver of annexation, came to anchor German heavy industry and that prefigures, in modified form, the entanglement of territorial control with resource access in contemporary competition over critical minerals for the AI and clean energy transition (Wawro, 2003) (Wehler, 1985).

The more innovative dimension of German strategic response to British maritime supremacy, however, lay not in territorial acquisition but in the development of overland infrastructure as an instrument of geopolitical competition — what contemporaries and subsequent analysts have recognized as an early and instructive form of infrastructure diplomacy (McMurray, 2001). The project of the Baghdad Railway, initiated in 1903

under a German concession from the Ottoman Empire, represented an attempt to project German economic and political influence into the Middle East through the construction of a rail corridor that would provide an overland route to the Persian Gulf, bypassing the maritime chokepoints — the Suez Canal, Gibraltar, the Red Sea — that constituted the nervous system of British imperial power. The strategic logic was explicit: a direct rail connection from the German heartland to the Gulf would reduce German dependence on sea lanes controlled by the Royal Navy, create German spheres of economic influence along the route, and potentially provide access to the petroleum deposits of Mesopotamia whose strategic significance was becoming apparent as naval planners began to contemplate the transition from coal to oil (Yergin, 1991). The Baghdad Railway was never completed in its intended form, and its strategic ambitions were overtaken by the catastrophe of 1914–1918; but as an analytical precedent, it illuminates with considerable clarity the structural logic through which states that are disadvantaged in an existing infrastructural order attempt to construct alternative spatial configurations — a logic that finds contemporary expression in the Belt and Road Initiative and in the competition over submarine cable routes and data center locations that defines the infrastructural politics of the AI era.

1.1.3. The American Case: Continental Integration, Protected Markets, and the Geography of Industrial Power

The trajectory of American industrial development in the nineteenth century represents a third and analytically distinct model of the relationship between technology, geography, and geopolitical ambition — one in which the primary strategic challenge was not the projection of power across contested maritime space, as in the British case, nor the construction of overland alternatives to a hostile maritime order, as in the German case, but the spatial integration of a continental territory of extraordinary resource richness into a coherent national economy capable of generating and sustaining industrial scale (Chandler, 1977). The Appalachian coalfields of Pennsylvania and West Virginia provided the energetic foundation for the industrialization of the American Northeast, and their exploitation from the mid-nineteenth century onwards transformed the United States from a predominantly agrarian exporter of primary commodities into the world's largest

industrial economy within a single generation — a transition whose speed and scale were enabled by the distinctive combination of resource abundance, continental market size, and institutional frameworks for private capital formation that characterized the American political economy (Gordon, 2016).

The role of railway infrastructure in this transformation was not merely logistical but fundamentally geopolitical. The Transcontinental Railroad, completed in 1869 and enabled by massive federal land grants to private railroad corporations, was a state-building project in the most direct sense: it stitched together the Pacific and Atlantic seaboards of a territory whose vast interior had previously constituted a barrier to the coherent exercise of national power, created the conditions for the settlement and agricultural exploitation of the Great Plains, and established the protected internal market that the American System of tariff policy was designed to construct and defend (White, 2011). The strategic significance of this internal integration was that it made the United States, in economic terms, substantially independent of the European-dominated maritime trading system: American industrial output could circulate within a continental market sufficiently large to sustain modern-scale production without requiring access to sea lanes that a European naval power could interdict. This continental self-sufficiency — which was, at one level, a product of geography, but at another level the result of deliberate infrastructural and policy choices — provided the United States with a degree of strategic autonomy that neither Germany nor any other continental European power possessed, and that would prove decisive in the two world conflicts of the twentieth century (Kennedy P. , 1987).

The later extension of American strategic attention toward the Caribbean and the isthmus of Central America, culminating in the construction of the Panama Canal (opened 1914) and the consolidation of what historians have termed an American informal empire in the Caribbean basin, reproduced at the hemispheric level the same spatial logic that had governed British coaling station strategy at the global level (McCullough, 1977). The canal was not, in the first instance, a commercial infrastructure project, however significant its commercial effects; it was a strategic asset that resolved the fundamental problem of projecting naval power simultaneously across two oceans, and that thereby transformed the United States from a regional into a genuine global naval power. The

protection of transit routes for American industrial output and raw material imports — the security of the supply chain, in contemporary terminology — was the organising principle of American strategic behaviour in the Western Hemisphere throughout the late nineteenth and early twentieth centuries, and it established the precedent of technological and infrastructural primacy as the foundation of American geopolitical leadership that would be reproduced, in successive technological registers, through the oil era, the nuclear era, and, as the subsequent chapters of this thesis argue, into the era of artificial intelligence (Gilpin, 1981) (Modelske & Thompson, 1996).

1.1.4. Historical Lessons for the AI Transition: Continuity and Discontinuity

The foregoing analysis of the first technological order — the era of steam, coal, and industrial capitalism — is offered not as an exhaustive account of nineteenth-century geopolitics but as a preliminary cartography of structural patterns whose recurrence in the contemporary AI competition is, the remainder of this thesis argues, neither accidental nor superficial. Four such patterns merit particular emphasis as points of analytical continuity. The first is the decisive importance of the spatial distribution of the critical resource — coal in the nineteenth century, semiconductor manufacturing capacity and rare earth minerals in the twenty-first — in determining which states are structurally advantaged in the transition to a new technological order, independently of their prior political or military standing (Smil, 2017). Second is the function of infrastructure, which includes railways, canals, coaling stations, and subsequently submarine cables and power grids, as both the physical basis of technological power projection and the main battleground on which geopolitical rivalry for the conditions of the new order is fought (McMurray, 2001). The third is the characteristic reaction of late-developing countries— Germany in the 1870s, China in the 2010s—to structural disadvantage in an existing technological order: the endeavour to create alternative spatial configurations, using infrastructure diplomacy and state-guided industrial policy, that either bypass or circumvent the chokepoints of the current order (Gerschenkron, 1962). The fourth, and perhaps most consequential for the analysis developed in the chapters that follow, is the tendency for technological revolutions to reproduce and amplify existing patterns of international inequality even as they create new opportunities for competitive challenge:

the states that led the coal and steam transition extracted disproportionate geopolitical benefits from it, and those that were incorporated into the new order primarily as suppliers of raw materials or markets for manufactured goods found their relative positions entrenched rather than improved — a structural dynamic whose implications for the distribution of AI's benefits and costs between the Global North and Global South remains a question of the first political importance (Perez, 2002).

1.2. Comparison and Continuities: The Silicon–Carbon Parallel

The structural parallels between the coal-and-steam order of the nineteenth century and the silicon-and-data order of the twenty-first are sufficiently striking, and sufficiently specific, to warrant treatment as more than superficial historical analogy. The preceding chapter traced the ways in which the Industrial Revolution reorganized the global distribution of power along the axes of resource access, infrastructural reach, and the capacity to translate technological leadership into geopolitical leverage. What the present chapter argues is that the AI transition is following a recognizably similar logic — not because technological revolutions are governed by iron historical laws, but because the structural conditions of competition among states, the role of geography in mediating access to critical inputs, and the tendency of powerful actors to encode their advantages into the architecture of the systems they build, generate recurrent patterns that transcend the specificities of any particular technological paradigm (Gilpin, 1981). The shift from carbon to silicon as the decisive substrate of power does not dissolve these patterns; it reproduces them in new material and spatial forms, while introducing qualitative discontinuities that the analysis must simultaneously acknowledge.

1.2.1. Hyperscale Data Centers as the New Coaling Stations: Infrastructure, Latency, and Digital Power Projection

The most immediately legible parallel between the two technological orders concerns the role of geographically distributed infrastructure as the material foundation of power projection. Just as the steam-powered empire required a global network of coaling stations — intermediate points at which vessels could resupply, and without which the operational range of a coal-burning fleet was radically constrained — the contemporary

AI economy requires a globally distributed network of hyperscale data centers whose location, ownership, and connectivity architecture determine the spatial reach of the algorithmic systems they support (Hu T. , 2015). A large language model or a real-time intelligence platform operating from a data center thousands of miles from its point of deployment confronts latency constraints that are, in their operational consequences, directly analogous to the fuel constraints faced by a steam warship operating beyond the range of its nearest coaling station: both represent a degradation of capability that is not merely technical but strategically decisive (Goldsmith & Wu, 2006). The deployment of data center infrastructure in strategically significant regions — the Gulf states, Southeast Asia, sub-Saharan Africa — is accordingly not simply a commercial decision driven by proximity to emerging markets, but an exercise in what might be termed latency diplomacy: the deliberate inscription of informational advantage into the spatial organisation of digital infrastructure, such that the states and corporations that control the nearest node in the network also control the speed, reliability, and terms of access through which AI capabilities are delivered to client governments and populations (Couldry & Mejias, 2019).

Yet what distinguishes the present infrastructural order from its nineteenth-century antecedent is not merely the substitution of silicon for coal, but a qualitative shift in how control is exercised through the architecture itself. The internet was initially designed around an imaginary of radical equality: an end-to-end principle that promised all connected nodes equivalent standing, a generative common in which any participant could deploy new protocols without seeking permission from any authority in the middle of the network (Zittrain, 2008). That imaginary, and its attendant freedoms, did not survive contact with commercial privatization. Network operators, enabled by equipment vendors, inscribed hierarchy into the infrastructure through middleboxes, firewalls, and traffic differentiation, shifting the locus of control progressively from the edges — the users and their devices — toward the network's center (ten Oever, 2021). The hyperscale data center is, in this sense, not simply a new coaling station. It is the terminal point of a longer transformation in which the open architecture of the early internet was progressively reconfigured to serve the interests of the few corporations large enough to own its pipes and populate its clouds. When a state discovers today that its digital

sovereignty rests on infrastructure it neither owns nor governs, it is not confronting an accident of innovation; it is encountering the accumulated sediment of three decades of deliberate architectural politics, whose geopolitical consequences are only now becoming fully legible to the states most directly affected (Pohle & Thiel, 2020).

1.2.2. Resource Sovereignty from the Ruhr to the Rare Earth Frontier: Chips, Minerals, and the New Technology Nationalism

The second axis of continuity between the two technological orders concerns the geopolitics of critical inputs: the struggle, in the nineteenth century, for access to coal and iron, and, in the twenty-first, for access to the rare earth elements, advanced semiconductors, and specialized manufacturing capabilities upon which the AI supply chain depends. The parallel is at this level of abstraction simple: In both cases, the decisive military and economic technologies of the age demand material inputs whose geographic distribution does not match the distribution of political power, therefore creating structural incentives for countries to look for control—through territorial annexation, contractual agreement, or market power—over the resources they cannot produce domestically (Klare, 2012). No industrial empire without coal; no border artificial intelligence system without expensive graphics processing components. The functional equivalence is real, even if the specific material properties, the geographies of extraction, and the political economies of production differ substantially between the two cases.

The more precise and analytically productive parallel, however, concerns not the raw material inputs themselves but the mechanisms through which leading powers have attempted to freeze the technological development of rivals by controlling access to the machinery of production. The British prohibition on the export of textile machinery and the emigration of skilled mechanics — maintained with varying degrees of effectiveness through the late eighteenth and early nineteenth centuries, partially relaxed by the 1824 repeal of the artisan-emigration prohibition and the 1825 introduction of Board of Trade licensing for machinery exports, and only fully dismantled by the Exportation of Machinery Act 1843 — reflected the same strategic logic that animates the contemporary American export control regime for advanced semiconductors (Jeremy, 1977). The

restrictions imposed by the United States government, from 2019 onwards, on the export to China of advanced chips produced using American technology, and the subsequent pressure on the Netherlands to restrict ASML — the sole manufacturer of the extreme ultraviolet lithography machines without which the most advanced semiconductor fabrication is impossible — from supplying its equipment to Chinese foundries, represent the most consequential technology-denial strategy since the Cold War's COCOM regime (Introl Blog, 2026). In both historical cases, the objective is structurally identical: to maintain the technological distance between the leading power and its principal rival by restricting access not merely to the end product but to the productive infrastructure through which that product is manufactured, on the theory that such restrictions, if maintained long enough, will prevent the rival from achieving the self-sufficient manufacturing capability that would render the controls irrelevant (Mastanduno, 1992). The degree to which this strategy will succeed in the semiconductor case — given China's declared ambition of technological self-reliance and its substantial, if still lagging, domestic semiconductor industry — is one of the central unresolved questions of contemporary geoeconomics.

The geography of the new resource competition adds a further dimension of spatial complexity that the coal-era analogy illuminates only partially. Rare earth elements — whose extraction and processing is currently dominated by China to a degree that gives Beijing substantial leverage over the supply chains of both Western AI hardware and clean energy infrastructure — are distributed across the planet in a pattern that bears no relationship to the existing order of technological and political power (Grasso, 2011). Greenland has emerged, in this context, as a site of intensified geopolitical attention precisely because its subsoil is believed to contain substantial deposits of the rare earth elements that current and projected AI hardware requires, much as the Pennsylvania coalfields acquired strategic significance in the mid-nineteenth century not because of Pennsylvania's existing political importance but because of what lay beneath it (Nuttall, 2021). The geological and political obstacles to large-scale extraction in Greenland — permafrost conditions, indigenous land rights, Danish constitutional authority, and the environmental regulatory framework of the Kingdom of Denmark — are such that the timeline for any significant Greenlandic contribution to global rare earth

supply remains highly uncertain. What is analytically significant, however, is the structure of the strategic attention itself: states and corporations are once again mapping resource geographies onto political maps, identifying territories whose importance derives not from their current political or economic weight but from what lies beneath their surface, and constructing diplomatic and commercial strategies designed to secure preferential access (Le Billon, 2012). The renewed American strategic interest in Greenland — including the Trump administration’s publicly stated aspiration to acquire the island, an aspiration that provoked significant diplomatic friction with Denmark and the EU — is legible, within this framework, as an instance of the same territorial-resource logic that drove nineteenth-century competition for coal-bearing regions, transposed into the mineral geography of the AI era.

1.2.3. The Energy Paradox: Jevons’s Rebound and the Insatiable Appetite of Algorithmic Computation

A third and particularly instructive parallel concerns the relationship between technological efficiency and aggregate energy consumption — a relationship whose counterintuitive character was first systematically analysed by the Victorian economist William Stanley Jevons in his 1865 study of the British coal economy, and whose relevance to the contemporary AI transition has become increasingly apparent as the energy demands of large-scale machine learning have grown to a scale that challenges the assumptions of both climate policy and infrastructure planning (Jevons, 1865). Jevons’s central insight — subsequently theorized as the rebound effect — was that improvements in the fuel efficiency of the steam engine did not, contrary to intuitive expectation, reduce total coal consumption; they reduced the cost of each unit of mechanical work, which increased the range of applications for which steam power was economically viable, which expanded the total demand for coal, which in aggregate increased consumption rather than reducing it (Polimeni, Mayumi, Giampietro, & Alcott, 2008). The dynamic was not a market failure or a policy error; it was the predictable consequence of the interaction between falling unit costs and expanding demand in a general-purpose technology whose productive applications were, at the time of Jevons’s writing, still far from fully exploited.

The structural parallel with the contemporary AI economy is precise enough to constitute more than metaphor. Each successive generation of AI hardware — from the early GPU clusters of the mid-2010s through the specialized AI accelerators of the present decade — has delivered substantial improvements in the energy efficiency of individual computational operations, measured in floating-point operations per watt (Schwartz, Dodge, Smith, & Etzioni, 2020). These efficiency improvements have not, however, produced a reduction in the aggregate energy consumption of the AI sector. They have instead enabled the development of substantially larger models, the proliferation of AI applications across domains that were previously computationally inaccessible, and the deployment of AI inference at a scale — millions of queries per day per major model — that was not contemplated when current energy infrastructure was planned (Strubell, Ganesh, & McCallum, 2019).

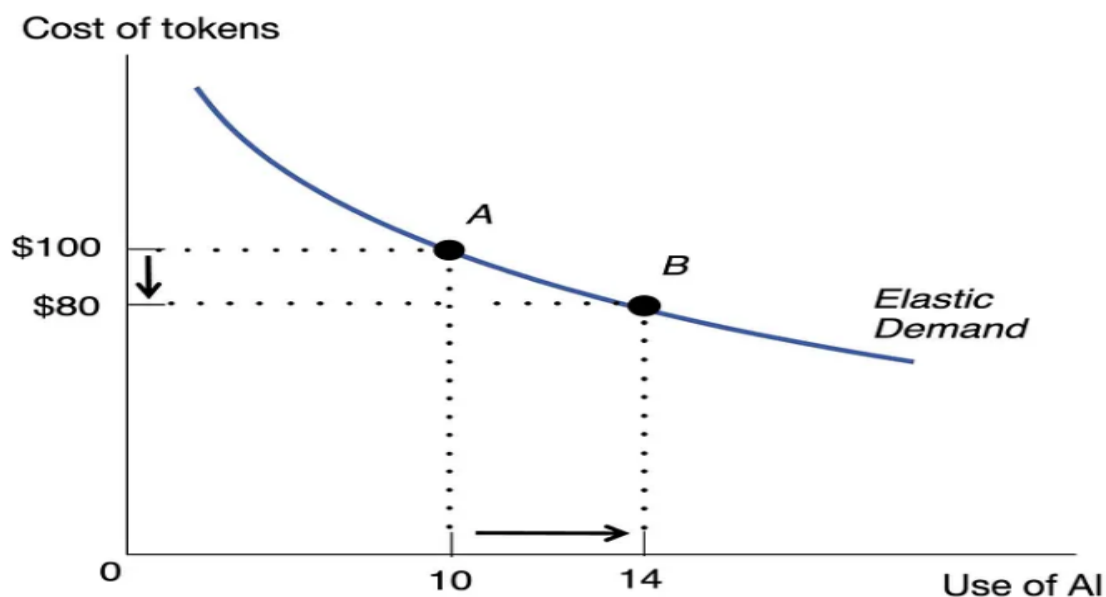


FIGURE 2: EXAMPLE OF THE JEVONS PARADOX
SOURCE: [MEDIUM](#)

The result is a condition of structural energy hunger that has significant implications for both the geography of AI infrastructure and for the geopolitics of energy supply. Data centers designed to support frontier AI training and inference require not merely reliable electricity supply but access to it at a scale — gigawatts rather than megawatts — and a cost that severely constrains their possible locations, concentrating them in regions with

access to abundant, cheap, and ideally low-carbon electricity (International Energy Agency (c), 2025). Venezuela's vast hydroelectric and fossil fuel reserves, like the Middle Eastern petroleum deposits that became strategically significant during the twentieth-century energy transition, are increasingly viewed through this lens: not primarily as inputs to conventional industrial production, but as potential substrates for the energy-intensive computational infrastructure upon which the AI economy depends — a revaluation of energy geography whose political consequences for resource-rich but technologically peripheral states remain, at the time of writing, substantially undetermined (Yergin, 2012).

1.2.4. Architectural Politics and the Limits of the Analogy

The parallels traced in this chapter are real and analytically productive, but they should not be pressed to the point at which the qualitative novelties of the AI transition are obscured by the force of historical comparison. The most significant of these novelties concerns precisely what the original text for this section identified, in embryonic form, as the architectural politics of digital infrastructure: the extent to which control over the AI economy is exercised not primarily through the ownership of physical assets — coal mines, coaling stations, railway lines — but through the design of software systems, the governance of standards, and the legal architecture of intellectual property, all of which operate across territorial borders in ways that make the spatial politics of the steam era seem, by comparison, relatively tractable (DeNardis, 2014). A state that wished to contest British coaling station supremacy in the nineteenth century needed ships, bases, and coal; a state that wishes to contest American or Chinese platform supremacy in the twenty-first century must navigate a governance landscape of technical standards bodies, export control regimes, bilateral investment treaties, and the proprietary architectures of privately owned systems whose physical infrastructure may be located on its territory while remaining entirely outside its legal control. The silicon-carbon parallel, in other words, illuminates the structural logic of great-power competition over transformative technologies, but it does not fully capture the novel forms of power and dependency that the specific properties of digital infrastructure — its non-rivalry, its network externalities,

its tendency toward platform monopoly — generate in the contemporary geopolitical environment. These novelties are the subject of the chapters that follow.

Conclusion of the section 1.2.

The frantic expansionism of the Industrial Revolution was, at its core, a violent and fundamental geographic reorganization of the planet, executed to satisfy the relentless hunger of the steam engine. The nineteenth-century transition from agrarian cycles to mineral-intensive production was not merely a triumph of human ingenuity; it was a ruthless restructuring of global space. Today, the meteoric rise of Artificial Intelligence represents a secondary, digital-physical reorganization of the world, designed to feed the insatiable computational appetites of the neural networks. Although the main players have changed from coal barons and imperial naval officers to cloud architects and chip-design titans and "silicon" has replaced the crucial component of "carbon," the fundamental geopolitical strategy is rather the same: to guarantee the supply chain, monopolize the machinery of production, and rule the energy source.

Traditionally, the nineteenth-century powers understood that the new judges of sovereignty were coal "seams"—that is, those subterranean veins of fossilized energy. Countries did not simply trade for coal; they moved politically and militarily to take control of the territory above it or the sea routes connecting to it. Strategically, "vertical integration" aimed to guarantee that the German industrial engine would never be held hostage by outside suppliers, exemplified by the consolidation of the coal-rich Ruhr within the unified German Empire in 1871 — a process whose economic logic Section 1.1.2 examined in detail (Wawro, 2003). This in the artificial intelligence industry reflects the modern "Reshoring" and "Friend-shoring" trends. The **U.S. CHIPS Act** and China's state-led push for semiconductor autonomy are the modern equivalents of seizing the Ruhr. They represent an acknowledgment that the "seams" of the twenty-first century are the silicon manufacturing facilities (fabs) and the rare earth deposits of Greenland and the DRC (Democratic Republic of the Congo). To lack domestic control over these nodes is to accept a state of permanent geopolitical vulnerability.

Moreover, the nineteenth-century coaling station—which turned distant islands like Aden or Singapore into critical hubs of empire—finds its modern resurgence in the **Hyperscale Data Center**. Modern artificial intelligence is linked to the terrestrial reality of the power

grid, just as a steamship was worthless without a physical refuelling site. Securing huge data center investments, a country like the UAE or Saudi Arabia is not just using a new software suite; they are establishing themselves as the "coaling stations" of the digital era. Much as the British used the Suez Canal to dominate the flow of coal-driven trade, they are arranging their country to be essential to the worldwide flow of intelligence.

The **Jevons Paradox** acts as the connective tissue between these two ages. The world thought in 1865 that more effective steam engines would conserve coal; Instead, efficiency caused coal use to soar as steam energy became quite widespread. Today we observe a digital version of this irony: Every advancement in hardware optimization or algorithmic performance does not lower the carbon footprint of artificial intelligence. Rather, it makes the "neural network" so essential to every facet of the global economy that it demands the construction of gargantuan infrastructures like **Colossus 2** which is the next-generation artificial intelligence supercomputer being built by xAI, Elon Musk's company, in Memphis, Tennessee. Designed as the world's first gigawatt-scale AI training data center, it is expected to host approximately 555,000 Nvidia GB200 and GB300 GPUs for an estimated capital outlay of around \$18 billion, with the December 2025 acquisition of a third adjacent building ('MACROHARDRR') in Southaven, Mississippi raising planned total site capacity to roughly 2 gigawatts and keeping xAI on a publicly stated trajectory toward 1 million GPUs at the Memphis complex (Bloomberg, 2025) (Wheatley, 2025). The hunger is not diminishing; it is scaling. Whether it is the black smoke of the Victorian factory or the silent heat of a server farm in Tennessee, the quest remains a physical one. Nations are once again moving to secure the "new coal" and the "new seams," proving that in the theater of global power, geography—and the energy extracted from it—remains the ultimate protagonist.

1.3. Industrial Secrecy and Technological Protectionism: The Machine War of the Nineteenth Century

1.3.1. The British Monopoly and the First Technology-Denial Regime

During the late eighteenth and early nineteenth centuries the British state treated its most advanced textile and mechanical technologies — the water frame, the power loom, the

steam engine — not as commercial commodities subject to the ordinary logic of market exchange, but as strategic national assets whose diffusion to foreign competitors would directly undermine Britain’s position as the preeminent industrial power (Jeremy, 1977). The legislative response was correspondingly severe: a succession of Exportation of Machinery Acts prohibited the sale of machine designs abroad, and what was arguably more consequential, the emigration of ‘skilled artificers’ — the mechanics and engineers whose embodied knowledge constituted the real bottleneck in technology transfer — was made a criminal offence (Harris, 1998). The underlying strategic logic was precise and self-conscious: Britain understood that its industrial supremacy was not grounded in any permanent national genius, but in its current control over a specific set of productive instruments whose replication elsewhere was the necessary precondition for any rival’s industrialization. Hardware, in this sense, was the chokepoint. If the machinery of production could be withheld, the machinery of production would remain British.

The structural logic of this position finds its direct twenty-first-century analogue in the American Foreign Direct Product Rule and the associated semiconductor export control architecture, which the preceding chapter examined in the context of ASML and advanced lithography. Both regimes rest on the same analytical premise: that while the “knowledge” underlying a technology — its scientific principles, its design logic — may in principle be reproduced by a sufficiently determined rival, the specialized physical equipment required to manufacture it at commercially and militarily relevant scale constitutes a point of leverage that can be defended for a strategically significant period (Allen G. , 2022). The advanced GPU and the extreme ultraviolet lithography machine occupy, in the contemporary AI competition, precisely the position that the power loom and the precision lathe occupied in the industrial competition of the early nineteenth century: they are, in the language of that era, the tools that make the tools, and their control is therefore a precondition for the control of everything that follows.

1.3.2. Espionage as State-Building: The American and German Response

The emergence of the United States and Germany as industrial powers capable of challenging British supremacy was not, in its early phases, primarily a story of original innovation; it was, rather, a story of systematic technological appropriation whose

methods ranged from the individually audacious to the institutionally organized (Headrick, 1988). Samuel Slater's arrival in New York on 18 November 1789 — followed by his move to Pawtucket, Rhode Island in January 1790, where he reconstructed Arkwright's water-frame spinning machinery from memory in violation of British law — is the paradigmatic case of the former: a single actor, subsequently celebrated in America as the “Father of the American Industrial Revolution” and condemned in his native Belper as 'Slater the Traitor,' initiating a national industrial trajectory through an act that contemporary legal frameworks would classify unambiguously as intellectual property theft (Tucker B. M., 1984). The German case, unfolding across the middle decades of the nineteenth century, was more systematic and arguably more instructive: state-sponsored ‘industrial tourists’ visited British manufacturing facilities to sketch machinery and recruit skilled workers, while the competitive dynamic was so asymmetric that the British attempt to stigmatize inferior German imitations by mandating the ‘Made in Germany’ label on exported goods ultimately backfired — Germany used the protected period of technological apprenticeship to master precision engineering and industrial chemistry to a standard that would, by the 1890s, surpass British capability in several key sectors (Mokyr, 1990).

The contemporary parallel is not merely structural but operational. China’s current drive for technological self-reliance — articulated through the “Made in China 2025” industrial policy and the more recent emphasis on indigenous innovation across semiconductor design and fabrication — reproduces, in its broad strategic logic, the position of early American and German industrialization: a state prevented from acquiring the machinery of production through normal market channels, investing massively in the domestic replication of capabilities it has been denied (Kennedy S. , 2015). The accusations of intellectual property appropriation, forced technology transfer, and industrial espionage that have characterized the US–China technology conflict since at least 2018 echo, with considerable precision, the complaints that British factory owners lodged against the mechanics who emigrated to America and the ‘industrial tourists’ who visited Lancashire. What the nineteenth-century precedent suggests, and what the present analysis must hold in view, is that technology-denial strategies of this kind are capable of delaying but not permanently preventing the diffusion of productive capabilities to

determined and resource-sufficient rivals — and that the period of delay, however significant in the short term, typically ends with the ‘imitator’ becoming an ‘innovator’ whose competitive position the original leader is no longer able to constrain (Perez, 2002).

1.3.3. The Return of Industrial Policy: Infant Industries, Techno-Blocs, and the Chips Acts

The intellectual framework through which nineteenth-century late-industrialising states justified their departure from the free-trade orthodoxy that British interests promoted was provided, in its most influential form, by Alexander Hamilton’s 1791 Report on Manufactures and the ‘infant industry’ argument that Friedrich List systematised in *The National System of Political Economy* (1841): the proposition that domestic industries competing against established foreign producers require a period of state-supported protection before they can achieve the scale economies and learning-curve advantages necessary for international competitiveness (List, 1841). The argument was explicitly nationalist in orientation and explicitly hostile to the universalist claims of Ricardian comparative advantage, which List recognized as a doctrine whose practical effect — whatever its theoretical elegance — was to recommend to industrialising nations a specialization in agricultural and primary commodity production that would permanently subordinate them to the manufactured-goods exports of the already-industrialized (Chang, 2002).

The structural return of this logic in the contemporary semiconductor and AI policy landscape is sufficiently direct to constitute not merely an analogy but a historical recurrence. The American CHIPS and Science Act (2022) and its European counterpart, the European Chips Act (2023), are not, in any meaningful sense, free-market policies; they are aggressive programs of state-funded industrial subsidy designed to ‘re-shore’ semiconductor manufacturing capacity that decades of globalization had distributed across the supply chains of geopolitical rivals (European Commission, 2023). The political economy of this shift — the recognition that deep interdependence with China in the production of strategically critical hardware constitutes a vulnerability rather than an efficiency gain — represents an explicit rejection of the globalization consensus that governed trade policy for much of the post-Cold War period, and a return to the

Hamiltonian-Listian framework that the United States itself abandoned as its own industrial supremacy made protectionism unnecessary (Farrell & Newman, 2023). The consolidation of ‘techno-blocs’ — regions defined less by formal trade agreements than by shared technology standards, interoperable AI infrastructure, and aligned semiconductor supply chains — is the twenty-first-century equivalent of the protected internal markets through which the United States and Germany built their industrial bases in the nineteenth, and it carries comparable implications for those states that find themselves excluded from, or dependent upon, the bloc whose infrastructure defines the terms of participation.

Conclusion of Section 1.3.

The technology-denial strategies of the nineteenth century demonstrate, with a clarity that the passage of time only sharpens, both the potential and the limits of attempting to defend technological supremacy through the control of productive hardware. Britain succeeded in delaying American and German industrialization by a period that was strategically significant; it did not succeed in preventing it. The geopolitical pressure of competition — the structural incentive facing any state that aspires to industrial or military parity with a leading power — proved sufficient to drive the sustained investment in domestic capability that eventually rendered the original controls irrelevant. Whether the considerably more complex and capital-intensive barriers to semiconductor self-sufficiency that China currently confronts will prove more durable than the machine-export prohibitions of the 1800s is, at the time of writing, genuinely uncertain; what the historical record makes difficult to sustain is the optimism that they will prove permanent (Mastanduno, 1992).

1.4. Social and Urban Transformations: Labor, Alienation, and the Human Cost of General-Purpose Technologies

1.4.1. Industrial Urbanisation and Its Digital Counterpart

The social geography of the nineteenth-century industrial transition was defined, at its most visible, by the violent reorganization of human settlement around the spatial

requirements of machine production. The Enclosure Acts, which progressively dispossessed the English rural poor of common land rights across the eighteenth and early nineteenth centuries, functioned as the ‘push’ mechanism that drove surplus agricultural labor into the newly forming industrial cities, while the concentration of steam-powered machinery in factory complexes provided the ‘pull’ (Thompson, 1963). The industrial city — Manchester, Leeds, Sheffield, Birmingham — was not a city in any pre-industrial sense; it was, rather, an urban factory whose spatial logic was entirely dictated by proximity to coal supplies and navigable waterways, and whose living conditions — documented with corrosive precision in the investigations of Friedrich Engels, Edwin Chadwick, and, later, Charles Booth — reflected the subordination of the human environment to the requirements of productive machinery (Engels, 1845).

The modern artificial intelligence transformation results in a structurally similar but spatially inverted rearrangement of economic and urban geography. The hyperscale data center, the twenty-first-century mill, demands proximity not to labor but to energy and cooling infrastructure, thereby creating a geography of digital production frequently strikingly distant from the populations it ostensibly serves (Crawford, 2021). The reconfiguration of local electricity grids, water supply systems, and land-use planning around the requirements of large-scale AI infrastructure in areas like Northern Virginia, Silicon Valley, London, Dublin, Beijing (Chinese AI Capital) or Shenzhen (Hardware & Deep Tech), in modern form, the subordination of the urban environment to productive machinery that characterized the Victorian industrial city — with the significant difference that the employment generated is a small fraction of that which the nineteenth-century mill provided, compounding rather than alleviating the social dislocation associated with technological transition (Ceschi, 2026) (Mosco, 2014).

1.4.2. Alienation, Cognitive De-Skilling, and the Ghost Workers of the Global South

The social theory of industrial labor was worked out, with an analytical sharpness that subsequent decades have done little to supersede, by two thinkers writing some seventy years apart: Adam Smith, who observed in *The Wealth of Nations* (1776) that the division of labor, however productive in aggregate, tended to render the individual worker "as stupid and ignorant as it is possible for a human creature to become", and Karl Marx,

whose concept of *Entfremdung* — alienation — identified the structural condition of the factory worker as one in which the product of labor appeared as an alien power confronting its producer, and the worker was reduced from an autonomous agent exercising craft and judgment to a subordinate operator of machinery whose pace and logic he no longer controlled (Smith A. , 1776) (Marx, 1844). What both analyses identified, beneath their different theoretical frameworks, was the same social phenomenon: the systematic degradation of the skilled artisan’s relationship to their own work as a consequence of the reorganization of production around the requirements of machinery rather than the capacities of persons.

The contemporary resonances of this analysis are sufficiently close to constitute more than metaphor. The ‘cognitive de-skilling’ associated with the proliferation of generative AI tools — the reduction of writers, programmers, designers, and analysts to ‘verifiers’ of algorithmically generated output rather than originators of substantive work — reproduces, at the level of intellectual labor, the dynamic that nineteenth-century mechanization imposed on manual craft (Brynjolfsson & McAfee, 2014). More starkly, the condition of the ‘ghost workers’ employed in content moderation and data labelling operations across the Global South — the workers in Kenya, the Philippines, and Venezuela whose repetitive, often psychologically traumatic task it is to produce the annotated training data upon which frontier AI systems depend — maps with uncomfortable precision onto the position of the Victorian factory operative: performing essential but devalued labor in conditions determined by the requirements of a productive system they do not own or control, and from whose outputs they are structurally separated (Gray & Suri, 2019).

1.4.3. Neo-Luddism as Political Economy: Agency, Compensation, and the Limits of Technological Progress

The Luddite movement of 1811–1816 has been subjected, across two centuries of retrospective commentary, to a persistent misrepresentation as a technophobic reaction against machinery as such. The historical record is considerably more specific. The Luddites were skilled textile workers — framework knitters and hand-loom weavers — whose objection was not to the existence of power looms but to their deployment as

instruments of wage depression and the circumvention of apprenticeship regulations that had historically protected skilled labor (Thompson, 1963). Their frame-breaking was, as subsequent labor historians have argued, a form of collective bargaining by other means: an attempt to impose costs on employers who were using machinery to bypass legal and customary constraints on labor exploitation, in circumstances where conventional industrial action was ineffective and the relevant legal protections were either absent or unenforced (Hobsbawm E. , 1952).

The structural parallel with contemporary resistance to generative AI in creative and professional labor markets is sufficiently specific to sustain extended analysis. The Hollywood writers' and actors' strikes of 2023, the lawsuits filed by visual artists and authors against generative AI companies, for the unauthorised use of creative work in training datasets, and the broader unionisation efforts in the technology sector, share with the Luddite movement the same fundamental grievance: not an opposition to AI as a technology, but a resistance to its deployment as a mechanism for reducing the compensation and institutional leverage of skilled workers by substituting algorithmically generated outputs for human creative labor (Acemoglu, 2021). A pertinent illustration of this tension occurred in June 2025, when **The Walt Disney Company** and **NBCUniversal** initiated joint litigation against the generative artificial intelligence firm **Midjourney**. The plaintiffs alleged that the defendant's image synthesis model constitutes a "bottomless pit of plagiarism," contending that the platform's underlying architecture relies upon the unauthorized ingestion of copyrighted intellectual property to facilitate the derivation of infringing visual content (BBC News, 2025). The question that these conflicts are, in effect, litigating — whether the productivity gains of general-purpose AI technologies should be captured primarily by the owners of productive capital or distributed more broadly across the workers whose labor generates the training data and whose creative outputs constitute the benchmark against which AI systems are evaluated — is structurally identical to the question that the Luddite movement, and the broader labor movement of the nineteenth century, ultimately forced onto the political agenda (Polanyi, 1944).

Conclusion of Section 1.4.

The Industrial Revolution established that the emergence of a general-purpose technology capable of reorganising the entire structure of economic production does not automatically produce broad social improvement; it produces, instead, a period of intense social conflict whose resolution — through labor legislation, collective bargaining, and eventually the welfare state — required sustained political struggle and took several generations to achieve (Hobsbawm E. , 1968). The historical record terms this prolonged interval the "Engels' pause" — the period from approximately 1790 to 1840 during which British industrial productivity rose substantially while real wages stagnated, encompassing Peterloo (1819), the early Chartist movement, and the formative phase of the Victorian social crisis (Allen, R. C. (a), 2009). The relevance of this concept to the contemporary labor displacement dynamics examined in Chapter 3 is direct: every prior general-purpose technology transition has imposed a transitional interval whose duration the optimistic literature on technological compensation has consistently underestimated. The AI transition is currently in what might be described as the ‘pre-regulatory’ phase of this cycle: the productive potential of the technology is clearly established, its capacity to generate social disruption is empirically documented, and the political institutions whose task it would be to manage the transition are operating considerably behind the pace of technological change. Whether the eventual resolution of this tension will produce outcomes as relatively favorable to labor as those of the Victorian transition is, at this stage, genuinely uncertain.

1.5. The North–South Asymmetry: Technological Colonialism and the New Great Divergence

1.5.1. The Great Divergence and the Colonial Factory Model

The “Great Divergence” — the process through which the gap in living standards, productive capacity, and geopolitical power between the industrialising core and the agrarian periphery widened from relatively modest proportions in the early eighteenth century to the dramatic asymmetry of the late Victorian era — was not, as Pomeranz’s foundational study established, primarily a product of any inherent cultural or institutional

superiority in the West (Pomeranz, 2000). It was, rather, the consequence of a specific combination of resource endowments, including coal proximity and access to colonial markets and raw materials, whose effects were then amplified and extended through deliberate political and economic strategies designed to prevent industrialization from occurring outside the core (Acemoglu, Johnson, & Robinson, 2001). Colonial powers, led by Britain, enforced what amounted to a ‘primary product mandate’ on their colonial territories: India, which had been a leading global exporter of finished textiles at the beginning of the eighteenth century, was systematically de-industrialized over the course of British rule, its domestic manufacturing destroyed by the combination of tariff policy and cheap Lancashire imports, and reduced to a supplier of raw cotton for the mills whose products it was then obliged to purchase (Davis M. , 2001). The consequence was not merely economic underdevelopment but the encoding of dependency into the productive infrastructure of colonial territories in ways that proved extraordinarily durable long after formal colonial rule ended.

1.5.2. Data Colonialism and the Computational Divergence

The structural parallel with the contemporary AI economy is, if anything, more analytically compelling than the infrastructure and resource parallels traced in the preceding chapters, because it operates at the level of the productive logic of the technology itself rather than merely its material preconditions (Couldry & Mejias, 2019). The extraction of ‘behavioural surplus’ — the data generated by the digital activity of users in the Global South, harvested by platform companies headquartered in the North, processed through computational infrastructure located primarily in North America and Western Europe, and returned to the populations from which it was extracted in the form of proprietary AI services — reproduces, with considerable structural fidelity, the colonial commodity circuit of the nineteenth century: raw material extracted from the periphery, processed in the metropolitan core, and sold back as a value-added product whose ownership and governance remain firmly in the hands of the extracting power (Zuboff, 2019).

What distinguishes this dynamic from its nineteenth-century predecessor, and in some respects renders it more intractable, is the extent to which the asymmetry is

reproduced not merely through market mechanisms and corporate strategy but through the governance architecture of the digital infrastructure itself. Research into the institutions that produce internet standards — the Internet Engineering Task Force, the Internet Corporation for Assigned Names and Numbers, and the broader ecosystem of multi-stakeholder governance bodies through which the technical rules of global connectivity are established — has documented how civil society actors from the Global South have struggled, with only partial success, to inscribe human rights commitments and non-commercial interests into the protocols that govern the networks they depend upon (Milan & ten Oever, 2017). The self-regulatory architecture of internet governance, which was designed in part to embody the open, participatory ideal of the early network, has in practice been substantially shaped by the affiliated employees of a small number of transnational corporations whose business models depend on the extraction and monetisation of user data (ten Oever, 2021). The Global South is accordingly not merely excluded from the high-margin layer of the AI economy; it is structurally underrepresented in the forums where the rules of that economy are written, and the protocols through which its populations access digital services encode this underrepresentation as a technical condition rather than a political choice (Milan & ten Oever, 2017).

The struggle for mineral sovereignty in the Democratic Republic of Congo — whose cobalt and tantalum deposits dominate global production — and in Argentina, Bolivia, and Chile, the three countries of the South American 'Lithium Triangle' that together hold approximately 56% of the world's known lithium reserves, together with the parallel competition over the rare earth elements concentrated in China, Australia, and a handful of other producers, is a direct echo of the nineteenth-century scramble for rubber, tin, and cotton, and carries similarly asymmetric implications for the territories from which the materials are extracted (U.S. Geological Survey (b), 2025) (Klare, 2012) (International Energy Agency (a), 2025). The geopolitical question is not only whether the Global South will have 'access' to AI systems developed elsewhere, but whether it will participate in the governance and ownership of the productive infrastructure through which those systems are built. History suggests that without such participation, the promise of technological leapfrogging is liable to function, as it did for colonial

commodity producers in the nineteenth century, as a faster route to structural dependency than to developmental autonomy (Chang, 2002).

Conclusion of Section 1.5.

The North–South asymmetry of the Industrial Revolution was not dissolved by the mere diffusion of industrial technology to the periphery; it was reproduced in new forms as the terms of productive participation were set by those who controlled the machinery and the markets. The AI transition is generating a structurally analogous dynamic in which the central geopolitical question is not access to AI outputs — which is likely to be extensive — but ownership of, and governance over, the productive infrastructure through which those outputs are generated. As the preceding chapters have argued, it is precisely in the domain of that infrastructure — the data centers, the semiconductor supply chains, the internet governance forums — that power in the AI era will be most consequentially exercised.

1.6. Governing Dual-Use Technologies: The Biological Weapons Convention as Historical Analogy

1.6.1 The BWC as Precedent: Dual-Use, Verification, and the Limits of International Law

The Biological Weapons Convention of 1972 occupies a distinctive position in the history of arms control, both for what it achieved and for the structural problem it identified but could not resolve (Wheelis, Rózsa, & Dando, 2006). It was the first multilateral treaty to prohibit an entire category of weapons of mass destruction, and it did so in circumstances where the technology in question — molecular biology and the manipulation of pathogenic organisms — was advancing at a pace that made any static technical definition of prohibited activities rapidly obsolete. The governance challenges the BWC confronted was not primarily a problem of state willingness, however significant the defection of the Soviet biological weapons programme from its own treaty obligations subsequently proved to be; it was a structural problem generated by the dual-use character of the underlying science (Rappert & Dando, 2009). The same laboratory equipment, the same

biological agents, the same experimental techniques that enable the development of vaccines and the study of infectious disease also enable, with minimal modification, the production of weaponised pathogens. Unlike the nuclear case, where the industrial infrastructure required for weapons-grade enrichment is both enormous and distinguishable from civilian applications with some degree of confidence, biological weapons development is, in principle, possible in facilities indistinguishable from legitimate research or pharmaceutical production (Nixdorff, 2013).

The consequence of this dual-use indistinguishability was the verification trap that has undermined the BWC's effectiveness since its entry into force: any inspection regime intrusive enough to provide meaningful assurance that a state party is not conducting prohibited activities would necessarily require the disclosure of commercially sensitive research data and proprietary manufacturing processes, creating a conflict between national security imperatives and scientific freedom — or, more precisely, between the legitimate interests of states in protecting sovereign research activities and the international community's interest in verification — that the treaty's signatories have never been able to resolve (Tucker J. , 2001). The collapse of the negotiations over a BWC verification protocol in 2001, in which the United States withdrew its support for a draft protocol that had been in negotiation for seven years, illustrated the limits of arms control in a domain where the productive infrastructure of the prohibited activity is indistinguishable from that of legitimate science.

1.6.2. AI as a Dual-Use Technology: The Pre-Treaty Phase

The governance landscape of artificial intelligence at the present moment bears a structural resemblance to the pre-BWC phase of biological weapons governance: a period in which the dual-use potential of the technology is clearly understood, in which the geopolitical incentives for developing its military applications are substantial, and in which the international community is aware of the need for governance frameworks but has not yet achieved the degree of consensus necessary to produce binding constraints (Scharre, 2018). The analogy is not exact; artificial intelligence does not possess the same direct catastrophic mass-casualty potential as biology; yet, the structural logic of the governance issue is quite similar. Architecturally, a large language model able to write

administrative code for a hospital is identical to one able to spot weaknesses in vital national infrastructure; From external observation, a data centre running a climate modelling simulation is operationally identical to one training an autonomous targeting system (Brundage, 2018).

The verification challenge for any putative AI governance framework is, if anything, more severe than that which undermined the BWC protocol negotiations. Biological weapons development, however difficult to verify, at least involves the production of physical agents that exist in the world and are subject in principle to detection; the ‘weaponization’ of an AI system — its fine-tuning for malicious applications, its deployment in offensive cyber operations, or its integration into autonomous weapons systems — may involve no physical change in the underlying infrastructure whatsoever, leaving no trace that any inspection regime currently conceived could reliably identify (Horowitz, 2018). The history of Cold War arms control also suggests a further risk that the BWC precedent illustrates: that formal treaty commitments may function, in the absence of credible verification, as diplomatic cover for continued prohibited activities, as the Sverdlovsk anthrax leak of 1979 subsequently demonstrated with respect to the Soviet biological weapons programme (Leitenberg M. & Zilinskas, 2012). The concern that 'existential risk' framings of AI danger, however sincerely held by some of their advocates, function in practice to concentrate regulatory attention on speculative future scenarios rather than the documented present harms of algorithmic systems — labor displacement, discriminatory automated decision-making, the enablement of mass surveillance — is, in this context, analytically significant: it reproduces, in the AI domain, the dynamic through which Cold War biological weapons discourse sometimes focused verification efforts on dramatic scenarios while overlooking the incremental accumulation of prohibited capabilities (Bender, Gebru, McMillan-Major, & Shmitchell, 2021) (Birhane, et al., 2022).

Conclusion of Section 1.6.

The Biological Weapons Convention demonstrates, as a historical precedent whose lessons remain directly relevant to the governance of artificial intelligence, that the international community is capable of stigmatising the weaponization of a dual-use

technology and of establishing legal norms against it, but that the translation of such norms into effective verification and enforcement mechanisms founders on the structural problem of dual-use indistinguishability and the unwillingness of states to accept inspection regimes that would expose commercially and militarily sensitive activities. Any governance framework for AI weapons applications — whether addressing autonomous lethal systems, offensive cyber capabilities, or the militarisation of surveillance infrastructure — will confront this same structural problem in a form that the specific properties of AI, particularly its software character and its dependence on infrastructure that is inherently dual-use, render considerably more difficult to resolve than the biological case (Scharre, 2018). The institutional innovations — mandatory compute thresholds, algorithmic auditing regimes, international AI safety standards with independent verification capacity — that have been proposed in recent policy literature represent attempts to escape the verification trap, but their adequacy to the challenge remains to be demonstrated in the conditions of great-power competition that the preceding chapters have described (Anderljung, et al., 2023).

2. The Present: 2020–2026 — The Era of Computational Sovereignty

Technical Foundations: A Glossary for the Non-Specialist Reader

What's Artificial Intelligence? From a common perspective it seems that the definition of AI took life only when ChatGPT went public in 2022. Before descending into the layers of the computational stack, however, the object of analysis itself requires a more deliberate definition, for "artificial intelligence" is a term whose meaning has shifted markedly across the seven decades since it entered scientific discourse and whose persistent ambiguity continues to condition the policy and academic debates documented in this thesis. The expression was coined in the summer of 1955 by the American mathematician John McCarthy in the proposal he drafted with Marvin Minsky, Nathaniel Rochester, and Claude Shannon for what would become the Dartmouth Summer Research Project on Artificial Intelligence, held the following year, in which the founding ambition of the field was articulated as the conjecture that every aspect of learning or any other feature of intelligence could in principle be so precisely described that a machine could be made to simulate it (McCarthy, Minsky, Rochester, & Shannon, 1955). Five years earlier, Alan Turing had already proposed the operational reformulation of the question — replacing the philosophically intractable problem of whether machines can think with the empirical problem of whether a machine can sustain a textual exchange indistinguishable from that of a human interlocutor — that has structured the discipline's epistemology ever since (Turing, 1950). From these foundational interventions, the field has bifurcated repeatedly: between symbolic approaches, which sought to encode human reasoning through explicit rules and logical inference, and connectionist approaches, which sought to reproduce intelligent behaviour through learning from data in networks loosely modelled on neural architecture; between definitions oriented to the imitation of human thought and those oriented to the achievement of rational action, irrespective of cognitive verisimilitude; and between narrow conceptions of AI as the automation of specific tasks and broader conceptions of AI as the construction of systems capable of general-purpose reasoning across domains (Nilsson, 2010). The dominant working

definition in contemporary research, articulated most influentially in the standard textbook of Stuart Russell and Peter Norvig, treats artificial intelligence as the study and construction of rational agents — entities that perceive their environment through sensors and act upon it through actuators in pursuit of specified objectives — a formulation sufficiently capacious to encompass both the rule-based "expert systems" of the 1980s and the deep learning models that dominate the present decade (Russell & Norvig, 2020). Below these definitional conflicts, the operational reality of modern artificial intelligence is mathematically significantly less vague than the phrase implies. New paradigms of AI systems are statistical machines that approximate functions over high-dimensional data, calculating probability distributions over potential outputs using sequences of linear algebra operations – matrix multiplications, vector additions, and non-linear transformations – applied to numerical representations of the input. What is colloquially described as "reasoning" or "understanding" is, at the computational level, the iterative adjustment of billions of numerical parameters to minimise the discrepancy between the model's predictions and the patterns observed in training data, a process whose lineage runs more directly through the statistical tradition of regression and pattern recognition than through the symbolic logic that the field's founders had originally envisaged (Bishop, 2006). What distinguishes the contemporary moment from the cyclical "AI winters" of preceding decades, in which funding and public expectations collapsed under the weight of unmet promises, is the empirical demonstration — beginning with the AlexNet results in image recognition in 2012 and accelerating dramatically with the transformer architectures introduced by Google researchers in 2017 — that performance on a wide and previously intractable range of cognitive tasks scales reliably with computational resources and training data, a relationship that has transformed AI from an episodically promising research programme into the principal infrastructure project of the twenty-first century, and whose strategic implications constitute the subject matter that follows (Krizhevsky, Sutskever, & Hinton, 2012) (Vaswani, et al., 2017).

The geopolitical and geoeconomic analysis that follows operates across a set of technical concepts whose meaning, for readers trained in the social sciences, international relations, or political economy, may not be self-evident. This preliminary section provides the conceptual equipment necessary to engage with the argument, structured not as a

dictionary but as a guided descent through the layered architecture of the AI system — from the physical substrate at its base to the applications at its surface — because the strategic significance of each component is intelligible only in relation to the components upon which it depends. At the foundation of the entire system lies the semiconductor: a chip fabricated from silicon whose microscopic circuits perform the mathematical operations that constitute computation. The lineage of this device reaches back to the early 1970s, and to a contribution often underacknowledged in Anglophone histories of the field: the first commercial microprocessor, the Intel 4004, was designed in 1971 by a team led by the Italian physicist Federico Faggin (who also co-invented the first touchpad and touchscreen), whose earlier development of MOS silicon-gate technology at Fairchild Semiconductor had furnished the fabrication process — subsequently adopted across the industry — on which much of modern integrated-circuit manufacturing was built; it is a foundational role that Bill Gates once distilled into the observation that “before him, Silicon Valley was just the Valley” (Faggin, 2019) (Università della Svizzera italiana, 2024). The specific type of semiconductor that has become the critical hardware of the AI era is the GPU, or Graphics Processing Unit — a chip type that emerged in the 1990s and was definitively established as a distinct category by the American firm NVIDIA with the GeForce 256 in 1999, originally designed to render the complex visual calculations required by video games, but whose architecture, organized around thousands of small processors capable of performing many calculations simultaneously rather than the few powerful processors of a conventional CPU (Central Processing Unit), proved uniquely suited to the parallel mathematical operations that underpin modern artificial intelligence (Peddie, 2021) (NVIDIA(a), 2025). It is this historical contingency — a gaming chip repurposed for machine learning — that explains NVIDIA's dominance of the AI hardware market and, consequently, its centrality to the semiconductor export controls, the valuation dynamics, and the geopolitical rivalries examined throughout this chapter. Alongside the GPU, AI computation requires specialized memory: DRAM (Dynamic Random-Access Memory) provides the temporary storage that processors access during computation, and its high-bandwidth variant, HBM (High-Bandwidth Memory), stacks multiple layers of memory chips to deliver data to GPUs at the speeds that AI workloads demand — a technical requirement that has transformed the memory market into a

geopolitical contest examined in section 2.6, because the three firms that dominate HBM production (Samsung and SK Hynix of South Korea, and Micron of the United States) occupy a strategic chokepoint analogous to ASML's position in lithography equipment (Refers to Chapter 2, section 2.6). These chips are housed in data centers — physical facilities ranging from warehouse-scale buildings to campus-sized complexes that contain thousands of servers, networking equipment, cooling systems, and the electrical infrastructure required to power them. Data centers are not, as the colloquial metaphor of "the cloud" might suggest, immaterial; they are among the most energy-intensive structures in the built environment, consuming electricity at a scale that, as sections 2.2 and 2.8 document, is projected to represent a growing share of national grid demand through the late 2020s, and their geographic distribution — concentrated overwhelmingly in the United States, with significant clusters in northern Europe, East Asia, and the Gulf states — is a matter of sovereignty rather than merely of real estate, because the jurisdiction in which a data center operates determines the legal regime under which the data it processes is governed (Crawford, 2021). The largest operators of data centers are the “hyperscalers” — a term denoting the small number of technology corporations (principally Amazon Web Services, Microsoft Azure, Google Cloud Platform, and, in China, Alibaba Cloud and Tencent Cloud) whose scale of infrastructure investment permits them to offer computational resources on demand to firms, governments, and individuals who lack the capital to build their own; "cloud computing," in this sense, is not a meteorological abstraction but a business model in which computation is rented rather than owned, and in which the three American firms that dominate the global cloud market exercise, through that dominance, a form of infrastructural power whose implications for European sovereignty section 2.9 examines.

While this thesis focuses on the hyperscale data-center model that has dominated the AI economy from 2022 to the present, recent developments — Apple Intelligence, Google's Gemini Nano, Microsoft's Copilot+ PCs, and the broader distillation of frontier capabilities into smaller models capable of running on consumer hardware — suggest that a partial migration of inference workloads to user-owned devices may, over the medium term, reshape the energy and infrastructure dynamics that this thesis documents; the geopolitical implications of that migration, however, lie largely beyond the scope of the

present argument and remain analytically unsettled in the existing literature (Hanff, 2026).

Upon this physical substrate — chips, memory, data centers, cloud infrastructure — the computational architecture of artificial intelligence is constructed. Artificial intelligence, in its broadest usage, refers to any system that performs tasks typically requiring human cognitive abilities; machine learning, a subset of AI, denotes systems that improve their performance on a task through exposure to data rather than through explicit programming; and deep learning, a further subset, employs artificial neural networks — mathematical structures loosely inspired by the architecture of the human brain, composed of layers of interconnected nodes through which data is processed and patterns are extracted — to learn representations of increasing complexity from raw inputs (Goodfellow, Bengio, & Courville, 2016). The dominant architecture of the current AI era is the large language model, or LLM: a deep learning system trained on enormous quantities of text (and, increasingly, images, audio, and video) to predict the next element in a sequence — a deceptively simple objective whose pursuit at sufficient scale produces systems capable of generating coherent prose, answering questions, writing code, and reasoning through complex problems with a fluency that, while not equivalent to human understanding in any philosophically rigorous sense, is functionally indistinguishable from it for a wide range of practical purposes (Bommasani, Hudson, Adeli, Altman, & Arora, 2021). A generative language model is a system that estimates the conditional probability distribution $P(x_t | x_1, \dots, x_{t-1})$ over sequences of tokens, without such predictive ability implying semantic understanding or knowledge representation (Bengio, Ducharme, Vincent, & Jauvin, 2003) (Bender, Gebru, McMillan-Major, & Shmitchell, 2021). The word "large" in "large language model" is not a casual descriptor; it is the operative term for geopolitics, because the performance of these systems has, for most of the period since 2020, improved in rough proportion to the quantity of computational resources devoted to their training — a relationship formalised in the scaling laws that section 2.3 discusses — meaning that the capacity to build the most capable AI systems is a direct function of access to the largest quantities of the most advanced chips, the most extensive data center infrastructure, and the most abundant energy supply, which is precisely why the control of these resources has become a matter of interstate competition

(Kaplan, et al., 2020). The computational process of building these models is called training — a one-time but extraordinarily expensive operation in which the model's billions or trillions of numerical parameters (called weights, whose specific values are opaque even to the researchers who produce them) are adjusted through exposure to training data; the subsequent process of using the trained model to respond to individual queries is called inference, and it is inference — not training — that scales with every user interaction, consuming energy and computational resources in proportion to the number of people using the system and thereby producing the Jevons Paradox dynamics that section 2.1 examines: as the cost of inference declines, usage expands, and total energy consumption increases even as efficiency per query improves. The unit of measurement for both training and inference is the token — a fragment of text, typically a word or a portion of a word, that the model processes as a single computational unit — and it is in tokens that AI services are increasingly priced and sold, a development whose implications Sam Altman articulated when he stated that 'we see a future where intelligence is a utility like electricity or water and people buy it from us on a meter,' with every query, every generated paragraph, and every automated task consuming a measurable quantity of computational resources whose cost is determined by the infrastructure stack described above (Altman, 2026).

Two further concepts require definition because they recur throughout the chapter and carry specific analytical weight. The first is the AI agent — a system that does not merely generate text in response to a prompt, as a chatbot does, but that can plan, reason, use tools, and execute multi-step tasks in digital or physical environments with limited human oversight. The terminology is older than the recent prominence of AI agents might suggest: the word "agent" derives from the Latin *agens*, meaning "the doer," and its use in computer science dates to the 1950s and 1960s, when researchers began formalising the concept of a rational agent — an entity that perceives its environment and acts upon it to achieve specified objectives (Russell & Norvig, 2020). The notion of conversational machine systems is itself considerably older than the current AI moment: Joseph Weizenbaum's ELIZA, developed at MIT between 1964 and 1966, used pattern matching to simulate a Rogerian psychotherapist (Weizenbaum, 1966). The term was popularised in the public imagination by the *Matrix* movie of 1999, whose Agent Smith is, in strictly

computational terms, a correctly depicted system agent: a programme designed to autonomously manage and police a simulated environment without constant manual input from its operators. The AI agents emerging in 2025–2026 — Claude Opus 4.6's Agent Teams, GPT-5.4's native computer use capability — represent the transition from AI systems that advise to AI systems that act, and it is this transition that section 3.1 identifies as the structural inflection point of the current capability trajectory, because an agent that can autonomously browse the internet, execute code, control a computer, and coordinate with other agents to accomplish complex objectives is a qualitatively different instrument — economically, strategically, and in terms of governance — from a chatbot that generates text in a conversational window. The second is Artificial General Intelligence, or AGI: a hypothetical system capable of performing any intellectual task that a human being can perform, across the full range of cognitive domains, with the flexibility, adaptability, and contextual understanding that characterise human cognition. AGI does not yet exist; whether it is imminent, distant, or impossible is among the most contested questions in the field, and the answer one gives to it conditions one's assessment of the existential risk arguments examined in sections 2.7 and 3.6. What is not contested is that the pursuit of AGI — or of systems sufficiently close to it that the distinction becomes operationally irrelevant — is the stated objective of the leading frontier laboratories, and that the capital, energy, and geopolitical resources being mobilised in that pursuit constitute the subject matter of this chapter (Russell, 2019). The reader who holds these definitions in mind — GPU, DRAM, data center, hyperscaler, cloud, LLM, training, inference, token, agent, AGI — possesses the technical vocabulary required to follow the argument that follows, in which each of these terms denotes not merely a technological artefact but a node in a supply chain whose control, financing, and governance have become among the most consequential questions in contemporary geopolitics.

Introduction: Speculative Finance and the Political Economy of Technological Acceleration

Any serious attempt to situate the contemporary AI economy within an analytical framework adequate to its complexities must begin by acknowledging the structural parallels — and the equally important structural differences — between the present

moment and the period of speculative expansion and subsequent collapse that defined the early history of commercial internet. Between approximately 1994 and 2001, the United States experienced a financial episode of considerable analytical interest: not merely a conventional asset bubble driven by loose monetary policy and investor irrationality, but a more structurally significant phenomenon in which the genuine transformative potential of a new general-purpose technology, the commercial internet, was simultaneously overestimated in its near-term economic effects and accurately apprehended in its long-term civilisational significance (Perez, 2002). The resulting divergence between expected and actual returns produced a financial correction of substantial severity — roughly five trillion dollars erased from equity market capitalisation, hundreds of thousands of jobs destroyed, and a broader recession that the subsequent events of September 2001 only compounded — without, however, eliminating the technological trajectory whose promise had animated the speculation in the first place (Cassidy, 2002). The infrastructure built during the boom, such as fiber-optic networks, server capacity, and organisational knowledge in distributed computing, turned out to be vital for the very things that are now considered normal: cloud services, social media, streaming platforms, and finally the big artificial intelligence systems whose financial and political effects are the focus of this chapter. Investors overestimated the time frame more than the direction of travel; the present's examination calls for the ability to see both dimensions at once.

2.1. The 1991 vs. 2015 Anecdote: The "Netscape Moment" of Artificial Intelligence

In the technical and geopolitical discourse surrounding artificial intelligence, a compelling temporal symmetry has emerged: 2015 was to Artificial Intelligence what 1991 was to the Internet. This parallel serves as a critical interpretive lens for understanding the current trajectory of AI adoption and its accompanying economic volatility. On 30 April 1993, CERN released the source code of the World Wide Web into the public domain — about two and a half years after Tim Berners-Lee had developed the first working browser and server software at CERN in December 1990, and just over a year after the first website outside Europe had gone live at the Stanford Linear Accelerator Center in December 1991 (CERN, 2023) (Berners-Lee & Fischetti, 1999).

Similarly, 2015 marked a pivotal shift in the AI narrative. While the term 'deep learning' had been circulating in academic circles since the late 2000s, the public arrival of modern AI is more accurately marked by a sequence of breakthroughs that bracketed the year 2015: the AlexNet result on the ImageNet competition in 2012, which first demonstrated the dramatic effectiveness of deep convolutional networks; AlphaGo's victory over European champion Fan Hui in October 2015, published in *Nature* in January 2016; and AlphaGo's defeat of world champion Lee Sedol in March 2016 — together signalling AI's transition from a niche laboratory experiment to a formidable global engine of productivity (Krizhevsky, Sutskever, & Hinton, 2012) (Silver, et al., 2016). This twenty-four-year offset suggests that we are not at the end of the AI revolution, but rather at its "Netscape moment" — the point where the underlying technology becomes sufficiently accessible to spark a massive, infrastructure-heavy gold rush.

The parallelisms between these two historical junctures are far from superficial. In both 1991 and 2015, the technologies in question were primarily used by researchers and specialized hobbyists, and few predicted that these early experiments would eventually consume a significant fraction of global compute capacity. What followed in each case was a phase economists have associated with "irrational exuberance" (Shiller, 2000): a surge in valuations anchored not in current profitability but in projected future dominance, like the strategic expansion of **Amazon** and **Uber** exemplifies a paradigm shift in modern corporate finance, where traditional metrics of profitability are secondary to the pursuit of absolute market dominance, for AI industry is accompanied by enormous capital expenditures on the physical infrastructure of the technology — data centers, specialized GPU hardware, and global fiber networks — mirroring the frantic laying of fiber-optic cables during the dot-com era. Similar to how early internet companies struggled to go beyond "eyeballs" and traffic as indicators of value, today's AI companies still have trouble with the high costs of inference and the ongoing task of turning free users into paying customers. One major divergence from this historical parallel is in adoption speed: While the internet took around five years to reach the acceptance rates seen in contemporary AI within just two, the compression of this diffusion curve has quickened the promise and the related systematic pressures of the technology.

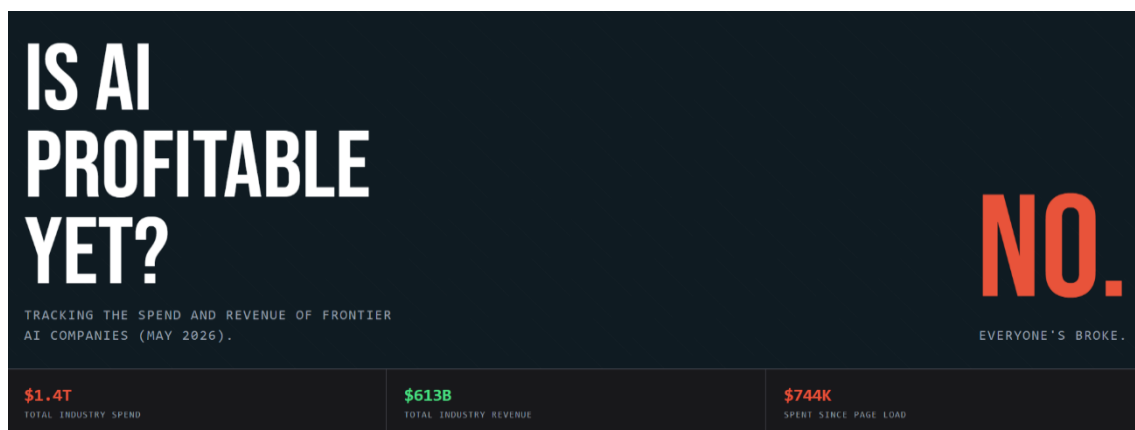


FIGURE 3: IS AI PROFITABLE? (AT THE MOMENT)
(isaiprofitable, 2026)

By 2025, the global economy had moved from what analysts described as a phase of "AI expectation" to one of measurable "AI impact," with 2026 widely projected as the point at which AI could lift annual GDP growth by between 0.8 and 1.2%age points (Vanguard, 2025).

 United States	 Euro area	 United Kingdom	 China	 Japan	 Australia
Software	Automotive	Pharmaceutical	Technology	Automotive	Pharmaceutical
Software	Automotive	Pharmaceutical	Software	Automotive	Technology
Technology	Automotive	Finance	Software	Telecommunications	Finance
Software	Automotive	Finance	Construction	Leisure goods	Finance
Technology	Automotive	Finance	Automotive	Pharmaceutical	Travel

Notes: This table is based on the 2024 EU Industrial R&D Investment Scoreboard, which analyzed the world's top 2,000 research and development (R&D) investors, headquartered across 40 countries. The table depicts the top five corporate R&D spenders by sector within six countries/regions, allocated geographically by the location of company headquarters.

Sources: Vanguard calculations, based on data from the European Commission, as of December 31, 2024.

FIGURE 4: TOP 5 CORPORATE R&D SPENDERS BY SECTOR AND COUNTRY/REGION
(Vanguard, 2025)

Yet this aggregate optimism conceals a pronounced geographic concentration of both capability and use. Much as the early internet remained effectively a tool of elite economies, AI usage today is strikingly uneven in its distribution: nations such as Singapore and Canada lead the world in per-capita usage at 4.6 and 2.9 times the global average respectively, while emerging economies such as Nigeria and India remain at a

fraction of that baseline, registering usage rates of 0.2 and 0.27 times the global average (Stanford University HAI, 2026).

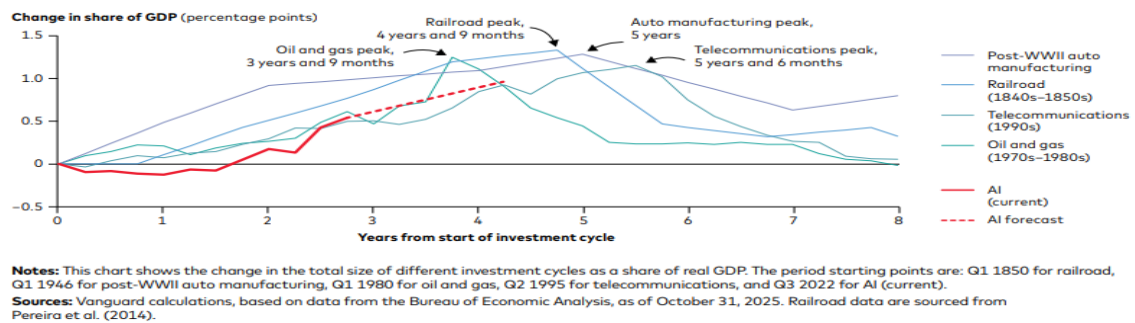


FIGURE 5: THE INVESTMENT CYCLE IS TRACKING HISTORIC CAPITAL BUILDOUTS (Vanguard, 2025)

This unbalanced distribution has ramifications not just for economic competitiveness but also for the wider geopolitical structure of technological power—a dimension that will be covered more fully in later chapters.

A major geoeconomic debate of 2026 revolves around what experts have called the "Green AI Paradox," which is a dynamic based on the classical form of the Jevons Paradox of 1865, in which technological advances that boost resource efficiency finally cause total consumption to rise since the lower cost enables previously impossible uses to become economically feasible (Jevons, 1865). Throughout 2025, the cost of achieving high scores on demanding AI benchmarks collapsed dramatically, falling from approximately \$4,500 per task to just \$11.64 (ARC Prize Foundation, 2025).



FIGURE 6: ARC-AGI-3 LEADERBOARD (ARC Prize Foundation, 2025)

Rather than generating energy savings, this efficiency has produced a rebound effect of considerable scale: AI has been rendered so inexpensive to deploy that it has been integrated into millions of always-on applications that would not have existed at previous price points. The actual repercussions cannot be disregarded now. Early 2026 saw cumulative energy usage for inference—the computational process of answering user questions—officially exceeding that needed for model training. Training is a one-time fixed cost; inference scales with every user interaction; and the per-query energy intensity of inference, while contested in its precise magnitude, has been documented across multiple independent estimates as substantially higher than that of conventional keyword search: Alex de Vries's influential 2023 estimate, subsequently incorporated into the International Energy Agency's 2024 report on data center electricity demand, calculated that a single ChatGPT query consumed approximately 2.9 Wh against a Google search baseline of 0.3 Wh — a roughly ten-fold differential whose underlying methodology has since been challenged by Google's own 2025 disclosure that its Gemini Apps median query consumes 0.24 Wh under optimised conditions, and by independent estimates suggesting newer frontier model queries average between 0.3 and 14 Wh depending on architecture, context length, and reasoning depth (de Vries, 2023) (International Energy Agency, 2024) (Vahdat & Dean, 2025). The structural point on which these estimates converge, despite their methodological disagreements, is the inversion that occurred between 2024 and 2025: by early 2026, cumulative energy consumption from inference had decisively exceeded that from training across the major frontier models, with industry analyses placing the split at approximately 63% inference to 37% training — a complete reversal of the 70:30 training-dominant ratio that prevailed only two years earlier (Elsworth, et al., 2025).

2.1.1. The Macroeconomic Conditions of the Boom

The 1990s in the United States were widely experienced, at the level of both popular culture and elite policy discourse, as a period of unusual optimism — a sense, rooted in the geopolitical settlement of 1989–1991, that American capitalism had not merely prevailed over its principal twentieth-century competitor but had demonstrated, in the process, the absence of any serious systemic alternative to its organising logic

(Fukuyama, 1992). This mood was not without material foundation. The macroeconomic conditions of the decade were, by any conventional measure, favorable. The Federal Reserve's policy rate, which had peaked at approximately 9.85% in March 1989 in response to inflationary pressures, was progressively reduced to roughly 2.92% by December 1992, producing a sustained expansion in credit availability and a consequent re-orientation of investor behaviour toward equities in general and growth-oriented technology stocks in particular (Goodfriend, 1993). The resulting expansion — often described as the longest continuous period of peacetime growth in American economic history, running from March 1991 to March 2001 — coincided with a structural shift in the productive base of the economy, as technology, telecommunications, and information industries moved from the periphery to the center of growth narratives (National Bureau of Economic Research, 2021).

The diffusion of the personal computer and, more consequentially, the commercialisation of the World Wide Web transformed the terms of this shift. Between 1990 and 1997, the proportion of American households with a personal computer rose from approximately 15 to 35%, and the browser — exemplified by Netscape Navigator, whose August 1995 initial public offering would become the emblematic financial event of the era — gave ordinary users a practical interface through which the transformative potential of networked computing could be accessed. Netscape's IPO, in which shares priced at 28 dollars closed their first trading day at 58.25 dollars — a single-day appreciation of approximately 108% — had a performative effect that extended well beyond the capital it raised for the company: it reconfigured market expectations about what was possible for young firms in the sector, establishing the precedent that a compelling narrative about future dominance in an emerging market could command valuations that bore no necessary relationship to current revenues or documented profitability. The firm's financial position at the time of listing — revenues of approximately 16.6 million dollars against losses of some 4.3 million dollars in early 1995 — was, by conventional metrics, unpromising; yet the market's assessment of its trajectory proved more influential than its balance sheet (Cassidy, 2002).

Legislative changes reinforced the speculative dynamics already generated by monetary conditions and investor psychology. The Taxpayer Relief Act of 1997 reduced

capital gains taxes on assets held for more than eighteen months from 28 to 20%, creating a fiscal incentive that favoured ‘growth’ stocks — firms that reinvested earnings rather than distributing dividends, whose returns were realised through share price appreciation subject to the lower rate — over income-generating assets (United States Congress, 1997). The mix of low interest rates, rising equity markets, tax incentives for speculative investment, and the cultural authority of the ‘New Economy’ narrative produced an investment environment in which traditional indicators of financial health—price-to-earnings ratios, debt sustainability, cash-flow adequacy—were increasingly superseded by the more volatile calculus of projected market dominance and first-mover advantage (Shiller, 2000). The number of technology initial public offerings rose sharply: 205 firms went public in 1995, 276 in 1996, against an average of roughly 63 per year between 1980 and 1991 — a rate of expansion that, in retrospect, was less a reflection of the productive dynamism of the sector than of the speculative appetite of the capital markets that sustained it (Ritter, 2024).

2.1.2. Irrational Exuberance and the Semiotics of Investment

By the late 1990s, the investment climate had reached a condition in which market discipline appeared suspended in significant respects. Traditional indicators were disregarded not through ignorance but through a species of collective conviction — widely shared among investors, analysts, and media commentators — that the emergence of internet commerce represented a structural discontinuity in the history of capitalism sufficiently profound to render established valuation metrics obsolete (Shiller, 2000). The Nasdaq Composite index rose by roughly 570% between 1995 and its peak of 5,048 points on 10 March 2000, a trajectory that was presented, with decreasing analytical scepticism as the decade progressed, as evidence of the new economy’s productive reality rather than of the speculative premium being applied to its projected future (Cassidy, 2002). The phenomenon described in the literature as the ‘dot-com effect’ — in which firms that appended internet-related terminology to their corporate names experienced immediate share price increases of the order of 74% in the ten days following rebranding announcements, as documented in research associated with Purdue University — illustrates with some precision the degree to which investment had become, by this period,

an exercise in semiotics rather than fundamental analysis (Cooper, Dimitrov, & Rau, 2001). The Super Bowl of January 2000, during which seventeen dot-com firms whose collective capitalisation ran to hundreds of billions of dollars purchased advertising slots at approximately two million dollars per thirty-second spot, was the cultural apotheosis of a dynamic that was, by that point, already in its terminal phase (Lamont, 2026) (Cassidy, 2002).

2.1.3. The Collapse and Its Structural Consequences

The correction, when it came, was triggered less by any single event than by the accumulation of empirical evidence against the dominant narrative. The Japanese recession announcement of 13 March 2000 provided the initial catalyst for a repricing that was, in retrospect, overdetermined by the gap between investment narratives and corporate fundamentals — a gap that the financial reporting cycle of March and April 2000 made undeniable, as dot-com firms published results showing continued and, in many cases, widening losses with no credible path to profitability in sight. By the end of its trading week on 14 April 2000, the Nasdaq had fallen 25% — one of the worst weekly declines in the exchange's history — and would ultimately lose approximately 40% of its value over the course of the year (Cassidy, 2002). The broader economic consequences were significant: estimates suggest that the United States lost approximately 1.735 million jobs during 2001, with unemployment reaching 5.5% by November and GDP contracting by 1.3% in the third quarter of that year (U.S. Bureau of Labor Statistics, 2002) (U.S. Bureau of Economic Analysis, 2002). The Federal Reserve responded by cutting its policy rate from 6.5 to 1.75% through multiple reductions over the course of 2001, a monetary intervention whose downstream effects — including the cheap credit conditions that enabled the subsequent housing boom — would carry their own systemic consequences (Board of Governors of the Federal Reserve System, 2024) (Goodfriend, 1993). The present AI investment cycle has been shaped by a structurally similar financial path. The Federal Reserve's action to bring its policy rate to nearly zero in reaction to the COVID-19 epidemic, which lasted into early 2022, generated the liquidity conditions under which early-stage AI businesses saw record-breaking capital inflows. The ensuing tightening cycle, which raised the federal funds rate to around 5.25–5.50% by mid-2023,

has not, however, had the same depressing effect on AI investment that the 2000 rate increases imposed on dot-com firms had, mostly because cash-rich hyperscalers are the main investors in AI infrastructure rather than venture-backed companies relying on outside capital. This structural difference in the financing base of the two cycles is among the most consequential distinctions between them, and helps to explain why the current build-out has continued to accelerate even under restrictive monetary conditions.

The analytical importance of the dot-com episode, for the purposes of this chapter, lies not primarily in the losses it generated or the firms it destroyed, but in what it reveals about the structural relationship between technological promise and financial speculation. The episode demonstrates, with a clarity that remains instructive, that the markets' collective assessment of a transformative technology's economic implications can be simultaneously correct in its identification of the direction of structural change and dramatically mistaken in its temporal framing — overestimating the speed of near-term adoption and underestimating the institutional, behavioural, and infrastructural adjustments required before genuinely large-scale economic transformation becomes possible (Perez, 2002). The bubble rearranged the timeline for its economic maturation at great human cost to those whose job, savings, and retirement security suffered losses in the correction; it did not disprove the internet. It is this tension, the gap between what technology can do and what the economy is like right now, that makes the dot-com bubble a useful way to see how politics and the economy work in the modern AI acceleration.

2.1.4. A Quantitative Comparison: Capital Flows, Valuations, and the Limits of Historical Analogy

The financial architecture underpinning the current AI expansion bears structural resemblances to the speculative dynamics that characterized the dot-com era, though the scale of capital mobilised has grown considerably when adjusted for inflation — a comparison that, when rendered in comparable terms, makes both the resonance and the critical differences considerably more legible. During the dot-com bubble, annual venture capital investment in technology and internet companies rose from approximately seven billion dollars in 1995 to nearly one hundred billion dollars at its peak in 2000 (National Venture Capital Association, 2001) — equivalent to roughly 175 to 180 billion dollars in

2025 values when adjusted for cumulative US consumer price inflation (U.S. Bureau of Labor Statistics, 2025). When the bubble corrected, the Nasdaq lost 78% of its value by October 2002 and the total destruction of market capitalisation reached an estimated five trillion dollars in nominal terms, or approximately 8.5 to 9 trillion dollars in present-day equivalent. These figures were compounded by a parallel infrastructure overbuild in telecommunications: in the five years following the American Telecommunications Act of 1996, the US telecommunications industry invested approximately \$750B — roughly 1.35 trillion in present-day terms — substantially financed through debt, in fiber optic cable, switches, and wireless networks that vastly outpaced contemporaneous demand (Blumenstein, 2001) (Cassidy, 2002). The structural parallel with the current AI investment cycle is, against this backdrop, difficult to dismiss. According to the OECD, global venture capital investment in AI firms reached 258.7 billion dollars in 2025 alone, representing 61% of all global venture capital activity — more than double its 2022 share of 30% — and already exceeding the inflation-adjusted peak of dot-com era financing (OECD, 2026). Between 2012 and 2025, cumulative venture capital investment in AI infrastructure and hosting totalled 256.1 billion dollars, with the great majority of 2025 investment concentrated in so-called 'mega deals' exceeding one hundred million dollars — a pattern that intensified into the first quarter of 2026, when 91% of capital went into deals of \$100 million or larger and 73% of that total was captured by just five AI companies — reflecting the same capital concentration that characterized the final, most speculative phase of the internet boom (Glasner, 2026).

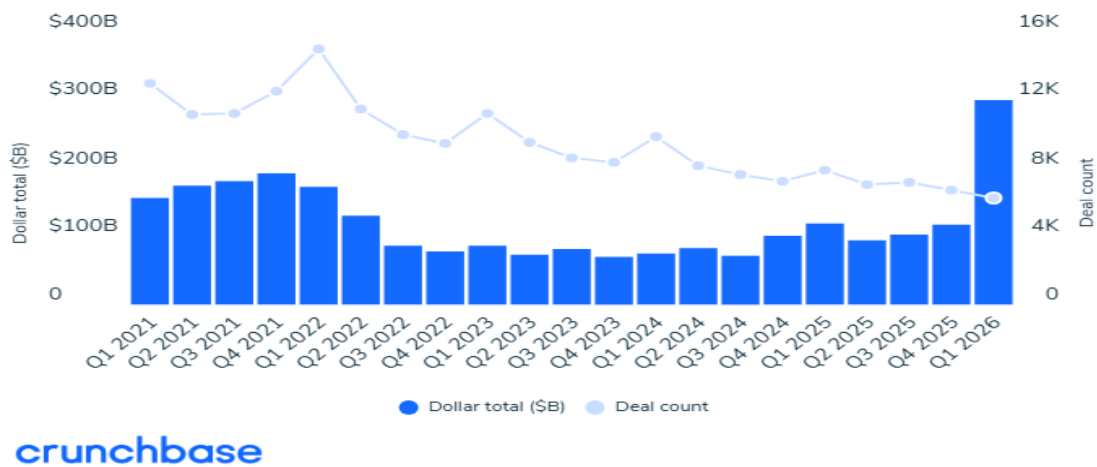


FIGURE 7: GLOBAL VC DOLLAR VOLUME VS. DEAL COUNT
(Glasner, 2026)

The Stanford AI Index further reports that total corporate AI investment — including private investment, mergers, and acquisitions — reached 252.3 billion dollars in 2024, representing a more than thirteenfold increase since 2014 (Stanford University HAI, 2026).

The most acute divergence from the dot-com cycle, however, lies not in venture capital flows but in infrastructure expenditure by the largest technology corporations. The four principal hyperscalers — Alphabet, Amazon, Meta, and Microsoft — are collectively projected to spend approximately 650 billion dollars in capital expenditure in 2026, with each company individually expected to exceed 100 billion dollars, marking a more than 67% increase from their combined 381 billion dollars in 2025. Goldman Sachs estimates the Wall Street consensus for this group at 527 billion dollars, noting that capital expenditure projections have been revised upward for two consecutive years, and that infrastructure investment in AI has now reached 0.8% of US GDP — approaching, though not yet matching, the 1.5% peak observed during the late-1990s telecommunications investment cycle. Roughly 75% of this hyperscaler capital expenditure is directly tied to AI infrastructure — servers, GPUs, and data centers — implying AI-specific capital deployment of approximately 450 to 500 billion dollars in 2026 alone (Goldman Sachs, 2025).

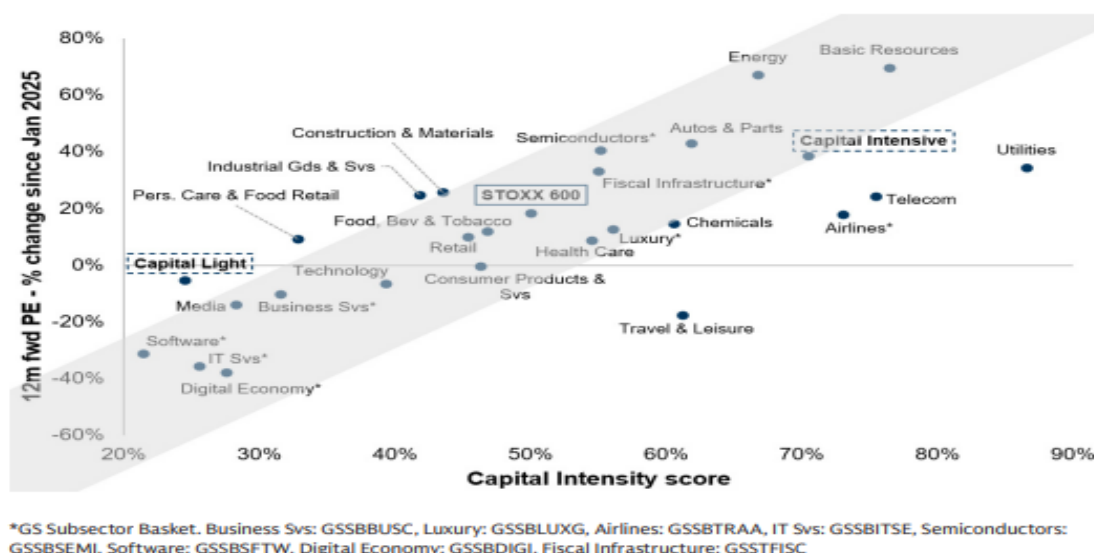


FIGURE 8: THE LEVEL OF CAPITAL INTENSITY IS NOW A KEY DRIVER OF RETURNS AND VALUATION CHANGES (Goldman Sachs, 2025)

This expenditure is increasingly financed through debt markets rather than operating cash flow alone: the five leading hyperscalers raised approximately 108 billion dollars in debt issuance in 2025, and Bank of America projects that these firms will collectively spend roughly 90% of their operating cash flow on capital expenditure in 2026, up from 65% in 2025 — a capital intensity ratio more characteristic of industrial utilities than of the asset-light software businesses that defined the previous era of digital expansion.

A systematic comparison of the valuation metrics of the two cycles reveals both the depth of the parallel and the analytical importance of its limits. During the dot-com era, the Nasdaq Composite rose 572% in the five years between January 1995 and its peak of 5,048 points on 10 March 2000, before declining 78% to a trough of 1,114 points by October 2002 (Bloomberg, 2015) (Cassidy, 2002) (National Venture Capital Association, 2001); the index would not recover its year-2000 high for fifteen years, finally surpassing the dot-com peak with a closing price of 5,056.06 on 23 April 2015 (Bloomberg, 2015). The four leading technology firms of that cycle — Microsoft, Cisco, Intel, and Oracle — were trading at approximately 70 times their two-year forward earnings at the market's peak (Cassidy, 2002). Cisco Systems, the era's most emblematic hardware supplier and briefly the world's most valuable company with a market capitalisation exceeding 500 billion dollars, carried a trailing price-to-earnings ratio of approximately 200 times at its zenith (Hansen & Albrecht, 2025). When the correction came, approximately five trillion dollars in market capitalisation evaporated from the Nasdaq alone in nominal terms (with broader estimates ranging from \$5 trillion to \$8 trillion across the wider US equity market through October 2002), over 50% of publicly listed dot-com companies had failed by 2004, and venture capital funding collapsed by approximately 80% from its year-2000 peak by 2003 (Goldfarb & Kirsch, 2019). Against these figures, the current AI cycle presents a more structurally ambiguous picture. NVIDIA — the structural analogue of Cisco in the present moment — recorded a stock price increase of approximately 2,000% between its October 2022 lows and its all-time high in late 2025, propelling its market capitalisation to a record five trillion dollars and surpassing Cisco's inflation-adjusted peak by a factor of roughly four. Yet where Cisco generated approximately 1.3 billion dollars per quarter in cash flow at its peak, NVIDIA reported 25 billion dollars per quarter in operating cash flow in 2025, alongside data center revenues that grew 279% year-on-

year in 2024 (Hansen & Albrecht, 2025) (Cassidy, 2002). The Nasdaq-100 currently trades at a trailing price-to-earnings multiple of approximately 33, compared to roughly 60 at the dot-com peak (Yardeni Research (a), 2025), and the leading hyperscalers carry a collective forward price-to-earnings ratio of around 26 times — less than half the 70 times recorded by the top four dot-com incumbents (Cassidy, 2002). These valuation differences are significant: the dot-com episode was, at its core, a valuation bubble in which stock prices were detached from earnings because most underlying firms had no earnings to speak of; what is taking shape in AI is more precisely characterized as a capacity bubble, in which infrastructure spending may be running ahead of demonstrable end-user utility even as the leading hardware and cloud firms generate substantial and growing profits (David, 1990). Yet this distinction does not dissolve the structural concern. Industry analyst David Cahn, writing for Sequoia Capital, estimated that the AI sector must generate approximately 600 billion dollars in new annual revenue to justify current infrastructure commitments, against an OpenAI run-rate revenue of approximately 20 billion dollars in early 2026 and a sector-wide revenue base that remains a fraction of what capital deployment would imply (Cahn, 2024). The gap between committed capital and proven commercial return is therefore wider, in absolute terms, than anything observed during the internet boom — even if, relative to the earnings base of the firms involved, valuations appear more grounded.

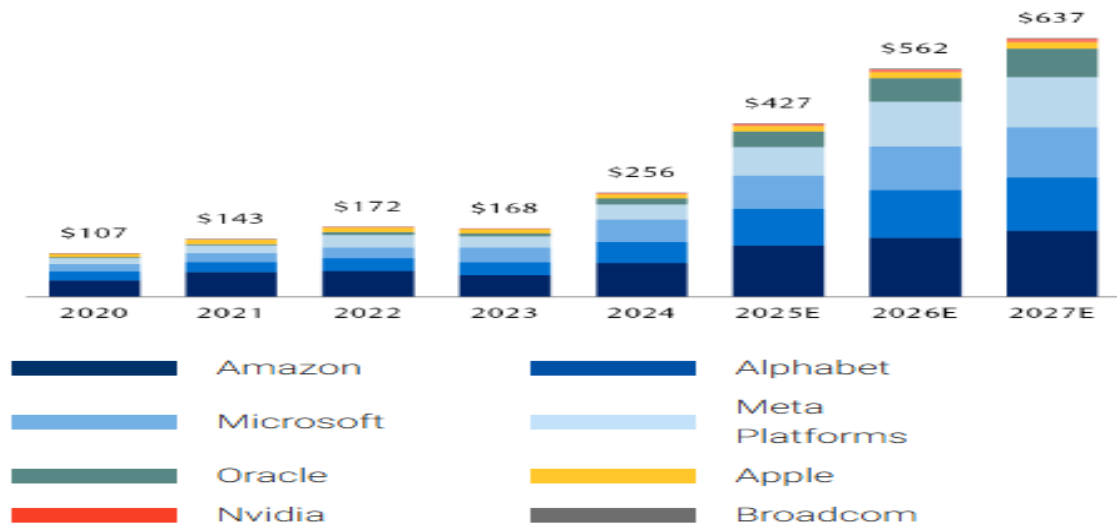
More detailed analysis of these valuation data, though, exposes a level of internal diversity that aggregate indices typically fail to capture. Although the Nasdaq-100's trailing price-to-earnings multiple of roughly 33 times and the combined forward ratio of the leading hyperscalers of about 26 times both fall far below the highs seen in 2000, the group of companies whose sales come mostly from AI products and services—pure-play AI companies like Palantir Technologies, C3.ai, and a larger constellation of generative AI platform firms—has traded at forward price-to-earnings multiples continuously above 100 times throughout 2024 and into 2025, figures structurally equivalent to the most extreme dot-com valuations (Yardeni Research (b), 2025). Analytically, this internal categorization is important since it implies that the apparent relative moderation seen at the index level is somewhat a result of averaging over businesses with quite different earnings structures: Dampening an aggregate that would otherwise look lot higher, the

hyperscalers produce significant operating cash flows. The price-to-earnings-growth ratio, or PEG ratio, is a more accurate tool for comparing cross-cycles. It changes the raw price-to-earnings multiple by the rate of earnings growth that is expected. This makes it possible to see if a certain valuation premium is justified by the fact that the company is actually making money (Lynch & Rothchild, 1989). The PEG ratio was essentially useless as a research tool during the dot-com boom since the companies trading at the highest multiples lacked earnings against which to compare growth targets. What was being valued was the hypothetical expectation of earnings appearing at some later time rather than actual earnings growth. In this regard, the current state of affairs is fundamentally different: NVIDIA, for example, has at various points in 2024 recorded a PEG ratio below 1.0, which is usually seen as a sign that the stock is undervalued compared to how fast its earnings are growing. This is because NVIDIA's earnings in the data center segment alone grew by 279% year-on-year (NVIDIA Corporation (a), 2025). Nonetheless, this split carries its own analytical hazard: The growth rate assumptions embedded in forward earnings predictions significantly impact PEG ratios. In a world of rapid technological change and uncertain monetisation paths, these assumptions themselves depend heavily on the narrative of continuous demand currently propelling the investment cycle. Headline As a result, several valuation adjustments are real but only partial: real in that the major artificial intelligence hardware and cloud companies are generating actual and increasing profits; partial in that it coexists with speculative excesses in more pure AI plays and relies on profits growth projections whose resilience has not yet been tested against a protracted period of demand disappointment.

2.2. Artificial Intelligence and the Dot-Com Financial Bubble Analogy: Structural Similarities, Systemic Risks, and Divergent Futures

The question haunting contemporary economists and policymakers is whether the current AI investment wave constitutes a sustainable technological boom or a structural repetition of the catastrophic correction that followed the dot-com expansion of the late 1990s. Technological revolutions, as the historical record consistently demonstrates, rarely unfold as linear processes; they are experienced instead as moments of acceleration in which expectations about the future advance faster than measurable outcomes in the

present. Capital moves to new industries, valuations grow before business models are stable, and stories of change how investors think, which can make them not care about how the economy is really doing. Artificial intelligence is not the first nor the only technology to have these interactions. The railway boom of the 19th century, the electrification wave of the early 20th century, and, most recently, the dot-com boom of the late 1990s all have similar patterns (Perez, 2002). Therefore, the current wave of AI investment begs the same old and urgent issue: are we seeing a speculative bubble or a required — if erratic — phase of technical transition that will finally show its worth? Responding this calls for going beyond mere comparisons. The dot-com crash of 2000's comparison with the present AI investment boom is only useful in analysis if it makes clear the structural processes by which financial markets interact with technical change. In 2026, the main financial worry is a systematic weakness brought on by circular financing models and sharply increasing capital expenditure rather than a conventional market "pop." From \$241 billion in 2024 (RBC Wealth Management, 2026), spending by the five top hyperscalers Google, Microsoft, Amazon, Meta, and Oracle is forecast to reach \$650B in 2026 alone.



Source – RBC Wealth Management, Bloomberg; data as of 1/28/26; 2025 and later data are Bloomberg consensus estimates

FIGURE 9: ANNUAL CAPITAL EXPENDITURES BY BIG TECH COMPANIES (USD BILLIONS)
(RBC Wealth Management, 2026)

A significant structural risk is the growth of circular capital flows throughout the AI supply-chain, whereby major corporations spend directly in their own clients and suppliers in agreements that hide the actual degree of independent market demand. NVIDIA has invested two billion dollars in equity and agreed a 6.3-billion-dollar strategic collaboration with CoreWeave, a cloud infrastructure provider that is simultaneously one of NVIDIA's largest GPU customers; Microsoft has invested approximately 13.75 billion dollars in OpenAI through 2024, with reports through 2025–2026 raising cumulative commitments to over 14 billion dollars, while OpenAI in turn commits a significant portion of that capital to Microsoft Azure cloud services; and OpenAI's CFO has acknowledged that capital raised from NVIDIA “*will go back to NVIDIA*” in GPU purchases (Maxwell & Paresh, 2026). These arrangements are individually rational responses to supply constraints, yet collectively they create a system in which revenue figures overstate the degree of independent end-user demand, and in which a loss of confidence at any single node could propagate rapidly through the entire ecosystem, masking the true level of market demand and systematically offloading risk from dominant corporate balance sheets (Brady, 2026). Critics argue that the underlying unit economics — the cost of servicing a request relative to the price charged — remain unsustainable, and that unlike the 1990s, today's leading firms, though profitable and generating strong cash flows, are increasingly behaving as capital-heavy utilities rather than the asset-light software businesses that characterized the previous era of digital expansion (Cahn, 2024).

Mid-1990s commercialisation of the World Wide Web generated an explosion of hope for digital marketplaces. Companies with little income but strong tales of future success drew a lot of venture capital. Anticipating exponential demand, telecommunications businesses extended fibre-optic networks. Public markets prioritized user growth above profitability, therefore valuations grew in sync. Many companies went bankrupt when expectations adjusted in 2000–2001, resulting in the loss of trillions of dollars in market capitalization (Cassidy, 2002). Still, the dot-com episode is sometimes misinterpreted as just a crazy time of speculation; it was also a time when a lot of things were built that made it possible for the digital world we know today. Originally constructed during the bubble, fiber networks finally enabled global e-commerce platforms, cloud computing,

and streaming services. The bubble thus diverted resources in the near term while speeding up technological capability in the long run—a dual legacy that complicates any easy comparison with the current situation (Perez, 2002). The dot-com bubble finally burst when the story of the internet surpassed the financial reality of its implementation. The downfall was brought on by a number of interacting causes: Companies such as Cisco were trading at multiples so high by 2000 that their projected future growth would have ultimately dwarfed the whole national economy; the feared interruptions of the "Year 2000" bug had produced a huge single-time IT expenditure surge that vanished once the threat passed, leaving a sharp gap in hardware and software demand; and the Federal Reserve's decision to raise interest rates mostly strangled the cheap capital on which loss-making businesses had totally relied (Cassidy, 2002). The AI ecosystem nonetheless shares several structural characteristics with the dot-com period that warrant careful attention. AI-related firms regularly command valuations that reflect expectations of future market dominance rather than present earnings, with the belief that certain companies may become essential infrastructure providers — analogous to operating systems or search engines — leading investors to price hypothetical monopoly rents into current valuations, much as the late 1990s emphasised user growth as a proxy for future profitability (Shiller, 2000). If predicted usage levels don't pan out, overcapacity can occur and cause major financial losses even if long-term demand ultimately supports the investment. This is because infrastructure is being developed significantly ahead of verified demand. Early leaders will grab dominant positions via scale advantages in data, developer ecosystems, and model refinement; this winner-take-all network effect assumption is reminiscent of the overconfidence that drove up the valuations of early internet portals and e-commerce innovators, even if network effects are real but seldom wipe out rivalry altogether. Technological uncertainty about which architectures, regulatory frameworks, or business models will ultimately define the AI market further mirrors the uncertainty about internet revenue models that prevailed in the late 1990s. Important structural differences may nonetheless alter the character of any potential correction. AI infrastructure is immediately productive and repurposable across multiple applications, including cloud computing, scientific simulation, and enterprise analytics, meaning that even if specific AI startups fail, the underlying hardware retains economic

value — a marked contrast to the fiber networks of the 1990s that remained underutilised for years. AI is being integrated into mature industrial sectors such as logistics, finance, manufacturing, and healthcare rather than introduced as a wholly new and uncertain layer of infrastructure, creating multiple parallel channels for value creation (Stanford University HAI, 2026). And the speed of AI adoption has been historically unprecedented, with large language models reaching millions of users within months, suggesting that some level of genuine productivity gain is likely even if exaggerated expectations are revised downward (Hu K. , 2023). These fluctuations suggest sporadic corrections rather than the broad fall seen in 2000–2001, even if they don't rule out the likelihood of a bubble. The structural problem identified above is not merely that individual firms may fail, but that valuation narratives circulate among actors who depend on one another's success — a configuration that resembles historical episodes in which banks, underwriters, and industrial firms held mutual stakes in speculative ventures, magnifying systemic risk far beyond what any individual actor's exposure would suggest (Kindleberger, C. P. & Aliber, 2005).

The AI boom also differs from earlier digital revolutions in its pronounced material intensity. Training large models requires enormous quantities of electricity, cooling capacity, and specialized hardware; data centers have become critical infrastructure comparable in strategic importance to power plants or transportation networks, their construction affecting land use, energy policy, and geopolitical supply chains in ways that raise the stakes of financial misallocation well beyond the domain of venture capital portfolios (Crawford, 2021). Technological advancements have historically sparked financial experimentation; the present is no different: GPU-backed loans, long-term capacity contracts, and the securitisation of data centre income streams all bring leverage into a context now characterised by high volatility, with hardware deteriorating fast and demand projections likely to prove incorrect. Simplified performance measurements including benchmark scores, adoption statistics, and partnership announcements are utilized to assess technical advancement and impact valuation decisions, thus fatally blurring the line between research success and business viability. The present moment may represent a transition from technological evangelism to systematic evaluation, as firms shift their attention from capability demonstrations toward measurable efficiency

gains in specific organisational processes — asking whether AI reduces costs, improves quality, or accelerates workflows in ways that generate identifiable returns on investment. The geopolitical context of the AI boom also departs from the dot-com cycle, though the nature of this departure warrants careful qualification. Artificial intelligence has become a strategic resource linked to national security, economic competitiveness, and technological sovereignty, with governments subsidising semiconductor manufacturing, regulating the export of advanced chips, and investing in national AI strategies at a scale without precedent in earlier technology cycles. et the underlying logics at work — the weaponization of supply chains, the use of infrastructure as an instrument of geopolitical leverage, the pursuit of technological denial against strategic rivals — are not novel; they are, as Chapter 1 argued, recurrent features of technological transitions, now operating at a speed and scale that the comparatively demilitarised environment of the late-1990s internet boom never approached (Farrell & Newman, 2019). The idea of a "Silicon Leviathan" catches something vital about this change — the worldwide AI ecosystem consists of huge networks of data centres, energy supply chains, and algorithmic systems whose size generates great social inertia, therefore making adjustments significant not only for financial markets but also for national infrastructure planning and international power relations in ways that earlier speculative episodes never were..

Historical comparisons mostly suggest a thorough reading. Similar to prior speculative cycles, the artificial intelligence boom shows structural similarities including financial experimentation, infrastructure overbuild, and narrative-driven pricing, therefore raising the likelihood of frequent corrections. Important differences at the same time, such as fast adoption, infrastructure that can be used again, and a strong connection to existing businesses, may prevent things from becoming as terrible as they were in 2000. The most likely route is one of continuous development with instability, in which the infrastructure developed throughout the boom would remain and enable future technical advancement even if certain values change and money is moved. The main difficulty for politicians, investors, and academics is therefore to control their effects and make them useful rather than to end speculative cycles, an unattainable task. The interplay among finance, innovation, and governance will primarily decide whether the present development of

artificial intelligence produces steady prosperity or disruptive instability in the future years.

2.2.1. The Architecture of the AI Supply Chain

What emerges from the foregoing comparison is not a deterministic forecast of financial collapse, but a structural warning about the political economy of technological acceleration that conditions the analysis of every subsequent layer of the AI supply chain. The dot-com crisis did not invalidate the internet; it reset expectations and moved cash, removing the worst performers while keeping and in certain cases strengthening the infrastructure under which a really transforming digital economy was later created. In AI, a related dynamic seems conceptually possible: Ten years later, the fiber optic networks that went dark following 2001 turned into the backbone of broadband internet. Today's overbuilt data center capacity could likewise support future applications whose economic sense is not yet completely clear. The critical difference, however, is geopolitical rather than purely financial. The dot-com correction was largely contained within the United States and its closest financial partners; the AI infrastructure cycle, by contrast, is embedded in a set of overlapping interstate rivalries — over semiconductor supply chains, energy resources, and digital standard-setting — that give any potential correction a systemic dimension extending well beyond market dynamics (Perez, 2002). Whether the analogy ultimately proves instructive or merely cautionary depends, in large part, on whether the revenue base of AI applications grows quickly enough to absorb the capital already committed, and on whether the geopolitical architecture surrounding that capital remains stable enough to permit the kind of orderly repricing that markets, under normal circumstances, are capable of managing. To assess this question, it is necessary to examine the productive architecture that underlies the visible surface of AI applications — the layered supply chain whose structural vulnerabilities determine, at each successive level, the degree to which the speculative dynamics identified in section 2.1 translate into systemic rather than merely financial risk.

To assess whether these conditions constitute a bubble in the technically meaningful sense — a sustained divergence between asset prices and fundamental values that is subject to abrupt correction — it is necessary to examine the productive

architecture that underlies the visible surface of AI applications. The most useful analytical framework for this purpose is a layered or stratified model of the AI supply chain, in which each component of the system depends upon the stability and continued expansion of the components below it (Perez, 2002). ChatGPT, Anthropic's Claude, Midjourney, Grok, and a growing array of sector-specific tools, whose obvious features define most consumers' initial exposure to artificial intelligence, are at the top of this hierarchy. Large neural networks trained on massive datasets, whose probabilistic representations encode the statistical regularities that let classification, prediction, and creation happen, these applications rely upon the models that generate their outputs: (Goodfellow, Bengio, & Courville, 2016).

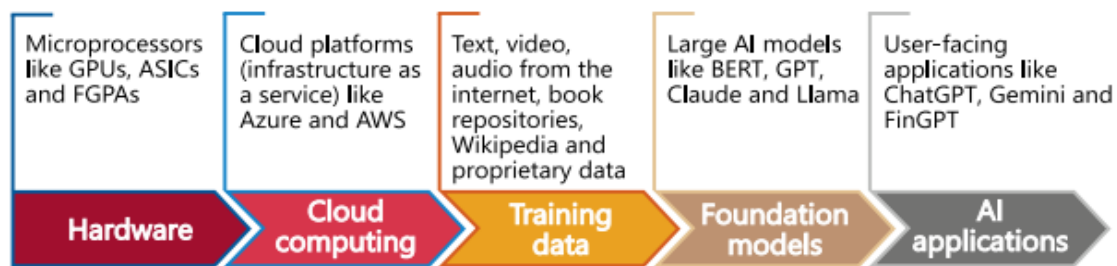


FIGURE 10: THE AI SUPPLY CHAIN

Source: [Bis Papers](#)

The models, in turn, require the physical substrate of purpose-built data centers hosting the server arrays, networking equipment, storage systems, and cooling infrastructure necessary to run computation at the required scale. Below the data centers lies the chip layer: without specialized AI accelerators — primarily GPUs and their successors — the computational architecture of modern generative AI cannot function. And beneath the chip layer lies the foundational condition of the entire system: electricity. Energy is not one input among many in this structure; it is the enabling substrate upon which every layer above it depends, and its adequacy — technical, economic, and political — is accordingly the first question that any assessment of the AI economy's structural robustness must address (Crawford, 2021).

2.2.2. The Energy Bottleneck: Constraints and Proportions

The energy requirements of large-scale AI infrastructure have attracted growing analytical attention since the ‘ChatGPT moment’ of late 2022 brought generative AI into mass public visibility and made the scale of its computational demands practically apparent (Stanford University HAI, 2026). Projections suggest that the electricity consumption of data centers globally may double between the present and 2030, a trajectory that would necessarily affect electricity prices across multiple jurisdictions and propagate cost increases through the supply chains of energy-intensive industries. The severity of this constraint is, however, a function of proportion. At present, data centers account for roughly 1 to 2% of global annual electricity consumption, rising to an estimated around 8% in the United States, where concentration is highest and infrastructure expansion is most rapid (Quinn, 2024). Electricity itself represents somewhat over one-fifth of total global final energy consumption, given the continued centrality of oil, natural gas, and coal in transport and industrial applications. These proportions suggest that AI-related electricity demand will exert pressure on energy markets and electricity prices in affected regions, while not necessarily producing an immediate and generalised systemic energy shock of the kind that would, by itself, destabilise the broader economy.

The geopolitical dimension of the energy constraint is, however, more consequential than the aggregate figures suggest. The cost of electricity varies substantially across jurisdictions, in ways that reflect differences in generation mix, market structure, regulatory regime, and the degree to which state policy has historically prioritised industrial energy pricing as a dimension of economic competitiveness (International Energy Agency, 2024). Europe, where electricity prices for industrial users are structurally higher than in the United States or China, faces a relative disadvantage in sustaining the capital expenditures required for frontier AI infrastructure — a disadvantage whose implications extend beyond the AI sector itself to the broader question of European technological competitiveness examined in subsequent chapters of this thesis. Energy does not merely power artificial intelligence; it shapes the geography of its production, determining where data centers are built, which states can sustain them, and which corporate actors can access the physical substrate of computational power

without which strategic autonomy in AI — however defined — remains aspirational rather than real (Draghi, 2024).

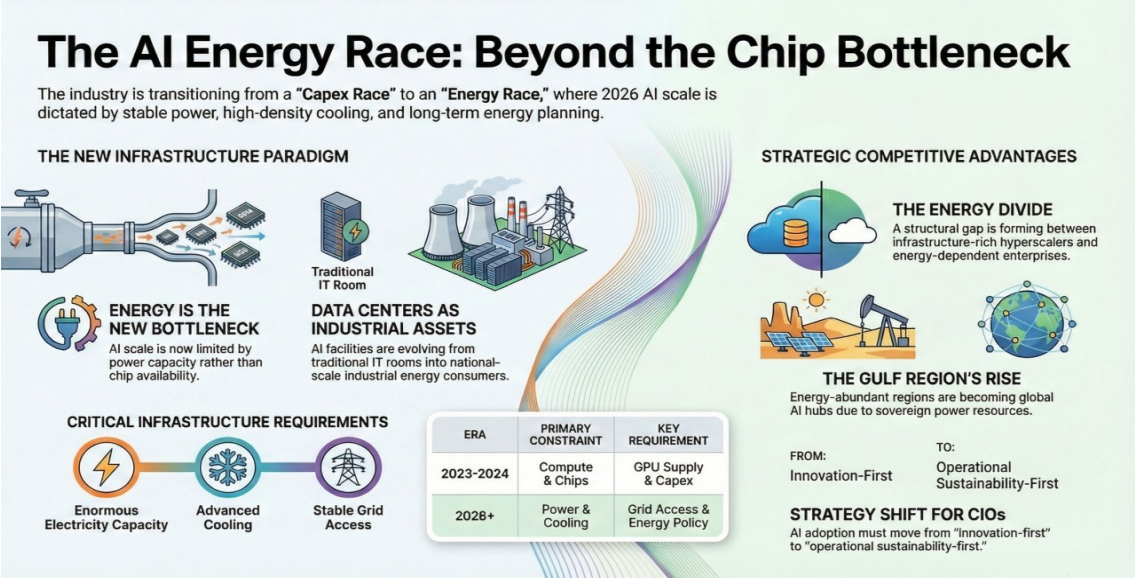


FIGURE 11: THE AI ENERGY RACE WHY POWER IS BECOMING THE NEXT BOTTLENECK
Source: (CXO Tech, 2026)

2.2.3. *The Chip Constraint: Market Structure, Geopolitics, and the Limits of Dominance*

The semiconductor layer of the AI supply chain presents a distinct but structurally related set of vulnerabilities. The critical inputs to semiconductor production — silicon and germanium themselves are widely available, but the rare earth elements required for specialized applications, and above all the extreme ultraviolet lithography machines that alone enable the fabrication of the most advanced chips, are subject to geographic concentrations of production and geopolitical constraints on distribution that make them among the most strategically sensitive commodities in the contemporary global economy. China’s dominant position in rare earth extraction and processing, which emerged from the 1990s onward partly because its regulatory framework was more tolerant of the ecological externalities of extraction than those of competitor states, represents a structural leverage point over the AI hardware supply chains of Western economies that has generated substantial policy concern — and substantial investment in supply chain diversification — since at least 2019 (Klinger, 2017). Forecasts of 6 to 10% annual growth in rare earth demand between 2025 and 2035 suggest that this constraint will

intensify rather than diminish in the near term, generating regulatory and environmental conflicts both between and within states as the pressure to expand extraction confronts the political costs of doing so (Benchmark Minerals, 2025).

The market structure of AI accelerator supply constitutes a further and more immediately consequential dimension of the chip constraint. NVIDIA's market position for high-end GPU-based accelerators, estimated to be over 90% of the relevant market in the 2023–2025 period, has led to a valuation path that begs issues regarding the long-term viability of investor expectations. This supremacy is maintained by a confluence of architectural advantage, software ecosystem lock-in through the CUDA platform, and the historical chance of a GPU design unveiled in 1999 for graphics applications proving especially well-suited to the parallel computing needs of deep learning. The company's annual revenue growth exceeded 100% in the period 2023–2025, with profits rising by several multiples between 2023 and 2024, and substantially again from 2024 to 2025 — outcomes that are not without rational foundation given genuine market dominance, but that have produced a price-to-earnings ratio whose justification requires the assumption of sustained near-monopoly growth over an extended period. The structural implausibility of this assumption — given the incentives facing Intel, AMD, and a range of Chinese competitors whose motivation to develop domestic alternatives has been substantially strengthened by American export controls — constitutes one of the more visible sources of potential valuation compression in the AI supply chain (DeepSeek, 2025). DeepSeek, a Chinese artificial intelligence laboratory that drew global attention in January 2025, has sharpened this competitive threat significantly through its late-2025 model releases. DeepSeek's V3.2 model reportedly matched frontier Western performance on elite reasoning benchmarks at inference costs ranging from 10 to 30 times lower than those of comparable American models. This suggests that NVIDIA's valuation trajectory is based on the assumption that computational scale is an unassailable advantage. This may prove less durable than current market pricing implies.

2.2.4. The Strategic Geography of AI Inputs: Greenland, Venezuela, Iran, and the New Resource Geopolitics

The supply chain vulnerabilities identified above — rare earth dependency, semiconductor concentration, and the growing exposure of Western AI hardware production to Chinese leverage — do not exist solely as market risks to be managed through investment diversification or corporate strategy. They have become the clear focus of state-level geopolitical involvement in 2025–2026, changing territorial politics, the use of force, and the calculation of sovereignty in ways that make the resource competition underlying the AI transition unavoidable from the oldest patterns of great power conflict. The three examples that come next, Greenland, Venezuela, and Iran, aren't just times when the United States was being aggressive; they're all connected moves in a single plan to make sure that artificial intelligence's physical supply chain is also indirectly targeted. The intensifying contestation over Greenland offers the first instance of this dynamic. The renewed American interest in the island, openly articulated by the Trump administration through a combination of acquisition offers, economic inducements, and implicit coercive pressure, cannot be adequately understood through a purely military lens. While the United States has maintained a formal treaty-based military presence since 1951 — enabling the deployment of personnel and equipment to the Pituffik Space Base without requiring new authorisations — Washington's contemporary preoccupations are fundamentally geoeconomic in nature. The progressive retreat of the Greenlandic ice sheet, itself a consequence of anthropogenic climate change, has rendered previously inaccessible subsoil resources increasingly viable for extraction, with geological assessments pointing to substantial deposits of rare earth elements, hydrocarbons, and critical minerals indispensable for the manufacture of semiconductors, microchips, and advanced electronic circuitry (Brands & Sullivan, 2020). In the context of an escalating AI-driven technological competition — in which control over rare earth supply chains constitutes a decisive structural advantage — Greenland's subterranean endowment has acquired a strategic significance that far exceeds its modest GDP of approximately three billion dollars (Bloomberg (a), 2026) (Kilian, 2026) (European Central Bank, 2026). China's dominance as the world's leading producer of rare earths directly conditions the urgency of Washington's interest: securing alternative and

controllable sources of these materials represents a core objective of American industrial and national security policy in the age of AI (Brands & Sullivan, 2020). Beyond extractive resources, the melting of Arctic ice is gradually opening two new transarctic shipping routes — a northwest passage and a transpolar corridor — which, if brought under American jurisdictional influence, could generate substantial geoeconomic leverage through toll mechanisms analogous to those operating at the Suez and Panama canals. Yet the pathway to effective control is obstructed by significant structural constraints: a military takeover would likely trigger the dissolution of NATO, outright purchase confronts the normative framework of peoples' self-determination, and polling from January 2025 indicates that 85% of Greenlandic residents — overwhelmingly Indigenous Inuit — reject American annexation, with the parties represented in the island's parliament maintaining independence as their primary political aspiration (Kann Fjeldsøe, 2025). The Venezuelan example, developing simultaneously, throws light on a dimension of the same geoeconomic logic that is structurally similar but institutionally different. Venezuela's trajectory over the past century is a perfect example of the resource curse: an economy so totally geared around a single extractive commodity that it has stayed fundamentally unable of diversification, making it very sensitive to price changes, institutional takeover, and external predation. It has the biggest proven oil reserves in the world. Oil was discovered in the Maracaibo Basin in 1922, triggering a rapid expansion of production that repositioned Venezuela as the world's second largest oil producer by 1929, with 98% of the domestic market controlled by three foreign corporations — Gulf, Standard Oil, and Royal Dutch Shell — by the late 1930s. Subsequent decades of recurring tension between national resource sovereignty and operational dependency on foreign expertise, the windfall boom of the 1970s, the IMF-imposed austerity of the 1980s, and the eventual rise of Hugo Chávez in 1998 all fed into a progressive degradation of the state oil company PDVSA, whose operational logic was subordinated to political loyalty rather than managerial competence — most acutely manifested in the dismissal of nearly half its workforce following the 2002 strike (Corrales & Penfold, 2011). Nicolás Maduro's tenure compounded these failures: successive purges further degraded institutional capacity, debt agreements with China and Russia totalling nearly seventy billion dollars deepened external dependency, and the decision to monetise the resulting

fiscal gap through central bank money creation produced hyperinflation whose annual rate is officially recorded by the Central Bank of Venezuela at 130,060% for 2018 (with IMF estimates indicating that inflation peaked at over 1.7 million% on a year-on-year basis in early- 2019), reducing a majority of the population to conditions of poverty or extreme destitution (International Monetary Fund, 2019). The return of the Trump administration in 2025 marked a qualitatively new phase in which the juridical framing of Maduro as a narcotrafficker, with a \$50 million bounty, was combined with an openly stated economic justification: the wish to restore American corporate access to Venezuela's oil reserves and reorient export flows toward the United States market. This logic culminated in the January 2026 extraction operation in Caracas, in which American special operations forces grabbed Maduro and brought him to New York, which drew immediate international criticism for violation of sovereignty. Crucially, however, Venezuelan geoeconomic significance extends well beyond its oil reserves: the Guiana Shield massif contains substantial deposits of coltan and rare earth elements essential for GPU and semiconductor manufacturing, as well as copper and nickel foundational to electrical infrastructure and data center cooling systems — meaning that control over Venezuela represents, simultaneously, a move in the global energy game and a direct intervention in the physical supply chain of artificial intelligence hardware (Klinger, 2017). The military conflict between the United States, Israel, and Iran in 2025–2026 is the third and most systemically significant front of this resource strategy. The conflict started with a short, twelve-day war in June 2025, when Israel attacked Iranian nuclear facilities and the United States followed up with targeted bombings of nuclear sites. Then, on 28 February 2026, a coordinated attack resulted in the assassination of Supreme Leader Ali Khamenei. This was clearly seen as the first step in a campaign to change the government. The strategic logic extends well beyond non-proliferation: at its core, the confrontation reflects a calculated effort to reshape the energy architecture of the Middle East in ways that serve American economic interests and, crucially, to sever the supply relationships through which China has insulated its economy from Western sanctions regimes (Brands & Sullivan, 2020). Iran accounts for approximately 4% of global oil production (around 3.4 to 3.6 million barrels per day in 2024–2025), and its geographic position astride the Strait of Hormuz — through which passes approximately 20% of the

world's oil and 20% of its liquefied natural gas — confers on Tehran an extraordinary capacity for systemic disruption (U.S. Energy Information Administration, 2024). Iranian retaliatory strikes against Gulf states allied with the United States have already triggered supply disruptions whose quantifiable economic consequences are severe: Bloomberg projects that a closure of Hormuz could drive crude oil prices to \$108 per barrel; the Wall Street Journal estimates that each ten-dollar increment translates into an inflationary impulse of 0.5% in the United States, implying that prices at \$130 per barrel could push American inflation to 5.5%; a European Central Bank scenario modelling a 14% oil price increase projects a 0.5% acceleration in eurozone inflation and a 0.1% GDP contraction; and the 45% spike in European gas prices that followed Qatar's announcement of a temporary LNG production halt — Qatar having become the EU's third largest LNG supplier following the post-Ukraine reorganization of European energy imports — illustrates the particular fragility of European energy security in this theatre (Bloomberg (a), 2026). The connection to artificial intelligence becomes explicit through the role of China, which has constructed a diversified portfolio of sanctioned energy suppliers — Iran, Venezuela, and Russia — through which it sources approximately 22% of its total oil imports, with Iranian barrels estimated by the analytics firm Kpler to account for 1.38 million barrels per day. The American operations against both Maduro's Venezuela and the Iranian regime could therefore be seen as sequential moves in a broader strategy of energy encirclement: by disrupting China's access to discounted hydrocarbons, Washington seeks to raise Beijing's energy costs, constrain its fiscal capacity, and thereby slow the pace of Chinese investment in the very semiconductor infrastructure and AI development programs that the export control regime described in the preceding section was designed to impair (Brands & Sullivan, 2020). The analytical significance of this convergence deserves emphasis, for it reveals a layered architecture of technological containment that operates simultaneously on two distinct material fronts: the first, examined in the preceding section, targets the instruments of production — the lithographic equipment, the chip designs, and the software tools without which advanced semiconductors cannot be manufactured; the second, traced here, targets the energetic foundations upon which the entire computational edifice rests. The historical parallel with nineteenth-century great-power competition is, once again, structurally precise: Britain's

strategic posture in the late Victorian era similarly combined technology denial — the prohibition on the export of advanced machinery, discussed in Chapter 1 — with the control of the energy and logistical infrastructure upon which industrial rivals depended, from coaling stations to canal access. What distinguishes the contemporary version is the degree to which these two fronts have become mutually reinforcing: export controls raise the cost of Chinese chip production, compelling greater reliance on energy-intensive workarounds and alternative fabrication methods, while energy encirclement simultaneously inflates the cost of the electricity required to operate whatever computational capacity China manages to assemble — a compounding logic that transforms what might otherwise be manageable constraints into a progressively tightening strategic vice (Drezner, 2021). Beijing's most immediate retaliatory instrument is precisely the one that compounds the chip constraint already discussed: its control of approximately 70% of global rare earth production gives it the capacity to directly impair Western AI hardware manufacturing, depressing the valuations of the technology firms that anchor equity markets across Europe and North America, and potentially triggering the correction in AI-sector valuations that several analysts have identified as a latent systemic risk (Klinger, 2017). What the three cases examined here — Greenland, Venezuela, and Iran — ultimately disclose is the degree to which the transition to an AI-driven economic order remains materially conditioned by the fossil fuel and mineral supply chains of the industrial age. The data centers, semiconductor fabrication plants, and communications infrastructure upon which AI systems depend are intensive consumers of both energy and rare materials, and their functioning requires geopolitical stability in precisely the regions — the Arctic, the South American interior, the Persian Gulf — where great power competition is most acute (Klinger, 2017) (Crawford, 2021). Therefore, the fight for AI dominance and the fight for energy and mineral control are not two separate contests but rather a single, recursively linked geopolitical process in which the demands of computational power progressively define the strategic decisions that mold the actual world, hence revealing that the scramble for Greenlandic rare earths, Venezuelan coltan, and Hormuz-adjacent hydrocarbons is not a relic of twentieth-century resource imperialism transplanted onto a new technical age: it is the constitutive material basis of that era. Regarding the Strait of Hormuz, the critical risk is that if the United

States fails to resolve a crisis of its own making, the global community will perceive it as a declining power—drawing a direct parallel to Great Britain during the 1956 Suez Crisis. As argued in Chapter 1, this thesis aims to bridge historical precedents with contemporary trajectories, reflecting the adage that "history repeats itself". By way of contextual background, the Suez Crisis was triggered when Egypt nationalized the canal. Although Great Britain and France intervened militarily, diplomatic and economic pressure from both the United States and the Soviet Union ultimately forced their retreat. Historians widely regard this episode as the definitive conclusion of the British Empire—not because Britain suddenly lost its absolute capabilities, but rather because it could no longer unilaterally dictate the rules of the international order. Here's the adjusted passage:

As this thesis was being completed, the two dynamics it treats as entangled converged within the span of a single day. On the final day of the G7 summit hosted by Macron in Evian (15–17 June 2026) — a forum shadowed by intensifying European efforts to curb dependence on US technology — the heads of the leading American AI laboratories, Altman, Amodei, and Hassabis, sat alongside their European counterparts before the assembled leaders (Nicol-Schwarz, 2026) (Leask, 2026); that same evening, from the Palace of Versailles, Trump signed an interim and explicitly non-final memorandum of understanding extending the US–Iran ceasefire and providing for the reopening of the Strait of Hormuz (Al Jazeera Staff, 2026). Tellingly, the settlement was hailed in Washington as a breakthrough and derided in Tehran as "a record of US failure," leaving open precisely the question of declining hegemony that the Suez parallel poses — a question underscored when, within 48 hours, implementation faltered: the follow-on nuclear talks were postponed, the Strait's main channel remained mined and closed, and fighting continued in southern Lebanon (Dias & Andrews, 2026). Despite ongoing negotiations, a formal ceasefire between the U.S. and Iran remains unsigned. Given the recent diplomatic friction generated by President Trump, the timeline for finalizing the agreement will likely be protracted.

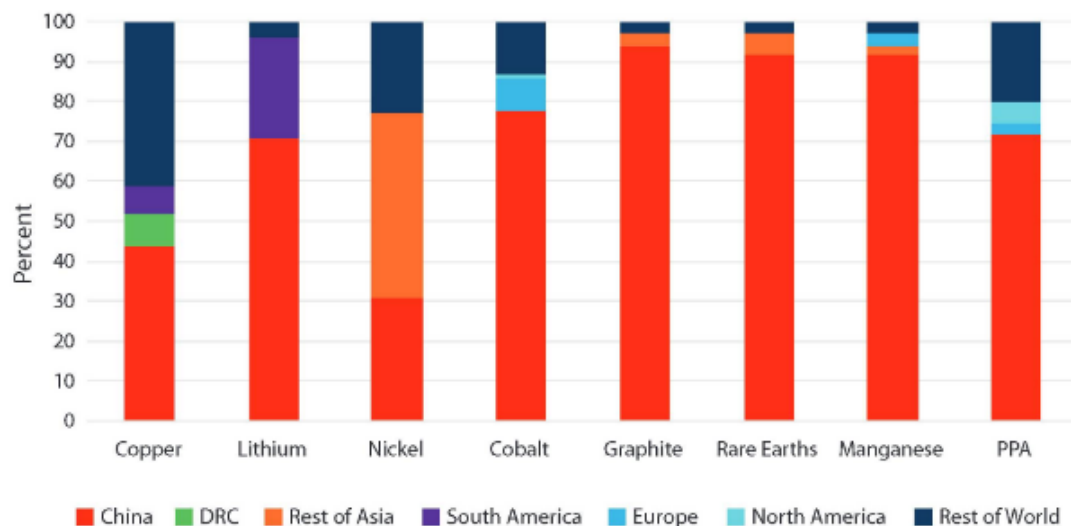
Consequently, as examined in Chapter 3, the current situation represents merely the third level of conflict within Ray Dalio's framework, yet its systemic manifestations are already visibly permeating daily geopolitical realities.

Farrell and Newman's concept of “weaponised interdependence” — the exploitation of asymmetric positions within global economic networks to exert coercive leverage — provides a contemporary theoretical framework for this logic, though the AI case extends its application beyond the financial and information networks they originally analysed into the domain of physical resource supply chains (Farrell & Newman, 2019). The question that remains analytically open, and to which the subsequent sections of this chapter will return, is whether this architecture of containment can be sustained against a rival whose retaliatory capacity — particularly in rare earth supply — is itself sufficient to inflict comparable disruption on the very technology firms that anchor Western equity markets and AI development trajectories. (Farrell & Newman, 2019) (Drezner, 2021).

The connection between hydrocarbon geopolitics and AI infrastructure is not direct but substitutive. Data centers in the United States consume electricity at a scale that is projected to represent a growing share of national grid demand through the late 2020s, and approximately 40% of American electricity generation is sourced from natural gas (U.S. Energy Information Administration, 2023/24). The strategic logic of stabilising global oil markets — whether through the assertion of control over Venezuelan reserves or through the disruption and eventual reorientation of Iranian production — is therefore partly a gas strategy: if abundant and competitively priced oil can be redirected toward global markets, the pressure to export American liquefied natural gas to compensate for energy deficits elsewhere is reduced, freeing domestic gas supply for the electrical grid and, by extension, for the data center infrastructure upon which AI computation depends (International Energy Agency, 2024). The Trump administration's stated objective of driving global crude prices toward \$50 per barrel is intelligible within this framework: lower oil prices reduce energy costs across the entire technology supply chain, from chip fabrication to server cooling, sustaining the competitive advantage of American AI firms against Chinese counterparts whose energy inputs are structured differently (Crawford, 2021).

2.2.5. China's Resource Diplomacy in Africa: Rare Earths, Critical Minerals, and AI Power

China's capacity to deploy rare earth exports as a geopolitical instrument does not rest on domestic production alone; it is the culmination of a systematic, decades-long strategy to achieve structural dominance across the entire critical minerals supply chain — from extraction in resource-rich regions of the Global South to refining, processing, and global logistics — with Africa as its central operational theatre. Today, China controls over half of global critical minerals production and an estimated 87% of the world's processing and refining capacity, while accounting for nearly 70% of rare earth mineral output and 93% of high-strength rare earth permanent magnets (Nantulya, 2025).

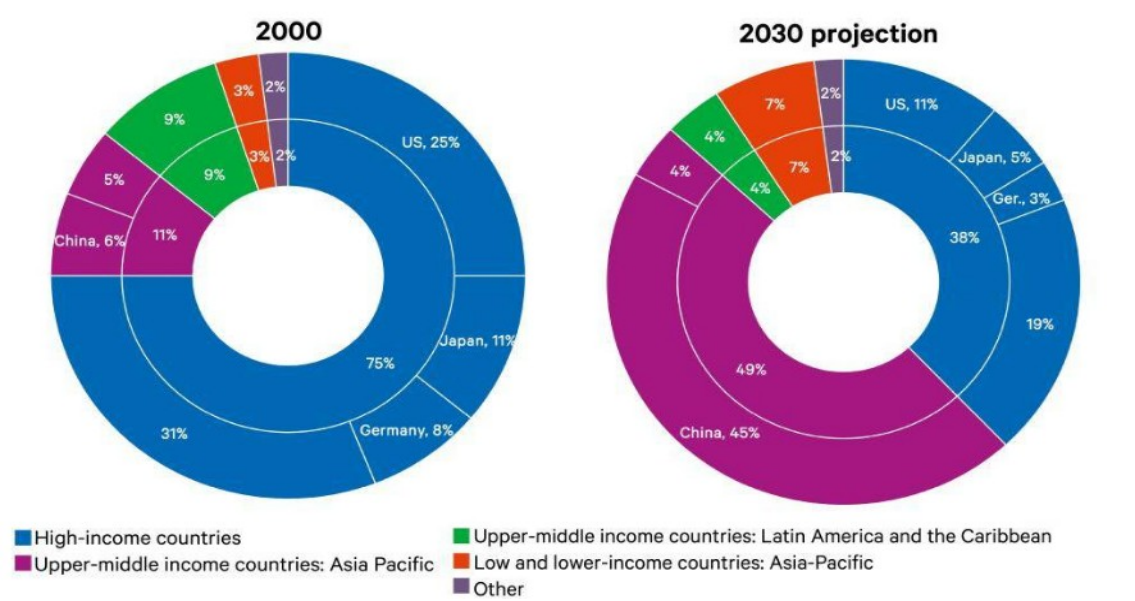


Data source: [IEA](#)

FIGURE 12: DISTRIBUTION OF CRITICAL MINERAL REFINING
(Nantulya, 2025)

According to the International Energy Agency, for a remarkable 19 out of 20 important strategic minerals, China is the leading refiner, with an average market share of 70%, and its dominance in the separation and refining of rare earths used in permanent magnets — the components that underpin everything from data center servers and electric vehicle motors to fighter jet actuators and missile guidance systems — reaches approximately 91% of global production (International Energy Agency (b), 2025). Beijing significantly increased this leverage in October 2025 by extending its export control regime to include

twelve of the seventeen rare earth elements, including processing methods and downstream foreign-made products utilizing materials of Chinese origin, in a move the Chatham House said was a deliberate statement of technical sovereignty able to change the world balance of industrial dependency (Chatham House, 2025).



— Source: UNIDO: The Future of Industrialization. UNIDO projections to 2030 are made based on historical average annual growth rates (between 2010 and 2019) and applied to the latest available observations (2024) up to 2030.

FIGURE 13: THE CHANGING STRUCTURE OF GLOBAL INDUSTRIAL PRODUCTION
(Chatham House, 2023)

This degree of upstream integration did not emerge spontaneously; it was the product of deliberate state-directed investment spanning several decades, beginning with domestic rare earth processing in the late 1950s and accelerating through the 1999 "Go Out" strategy, under which major state-owned enterprises — subsidised annually to the tune of approximately \$200 billion — expanded from 40 overseas mining operations to 1,250 by 2022 (Nantulya, 2025) (Chatham House, 2023). Africa became the pivot of this outward expansion, and the reasons are both demographic and material: UN projections estimate that by 2100 approximately 4.3 billion people — nearly 40% of the world's population — will live on the African continent, and that three of the seven largest cities on Earth will be African megacities, making the continent not only an immense future consumer market but also a field of competitive investment whose trajectory will significantly shape global

commodity flows and geopolitical alignments for decades to come (United Nations, Department of Economic and Social Affairs, 2024). Between 2000 and 2021, Beijing directed roughly \$24 billion of its \$57 billion in global transition mineral financing toward the African continent, making China by far the largest external financier of African mineral projects and thereby converting resource access into political leverage across a broad range of host states (Nantulya, 2025). By 2025, 53 African countries had signed Belt and Road Initiative memoranda of understanding with China — compared to only 9 before the 2018 FOCAC — and Chinese policy banks had issued \$24.9 billion in BRI-linked mining loans in the first half of 2025 alone, exceeding the record set in 2024 (Masamba, 2025). Chinese control in Africa is organized as a multilayered ecosystem in which Chinese companies operate concurrently as miners, financiers, engineers, and long-term purchasers, using a range of tools—offtake agreements, farm-in contracts, resource-backed financing deals, and direct purchases—that ground Chinese influence far beyond the actual asset (Nantulya, 2025). As of 2022, 66 of the 166 Chinese-owned mining activities worldwide were located in Africa, making it the most concentrated region for such operations. Building one in three and financing one in five major infrastructure projects on the continent, running in over one-third of African ports, and setting up about 20% of regional electricity generating capacity were Chinese enterprises. Particularly closely examined are resource-backed financing agreements; the well-known 2008 “Sicomines agreement” in the Democratic Republic of the Congo, valued at \$7 billion in 2024, granted Chinese companies rights to 10 million tons of copper and 600,000 tons of cobalt over 25 years in exchange for infrastructure development. The African Development Bank said in 2024 that this deal systematically undervalued African resources and made it harder to see how the government was spending money. The Chinese partners kept 68% of the venture (Nantulya, 2025). The concept of “debt-trap diplomacy” — coined by the Indian scholar Brahma Chellaney in 2017 — has been widely debated in this context: while some scholars, including Jones and Hameiri writing for Chatham House, find limited empirical evidence for deliberate entrapping, others point to the demonstrable debt distress that has compelled Chad, Zambia, Ghana, and Ethiopia to undertake debt restructuring under the G20 Common Framework, in some cases with Chinese creditors accused by World Bank and IMF officials of unnecessarily

delaying negotiations (Ditter, 2024) (ISS African Futures, 2023). Alongside its mineral and financial penetration, Beijing has extended its presence in Africa into the domain of food security, acquiring millions of hectares of arable land across the continent — a phenomenon broadly defined in the literature as "land grabbing" — motivated in part by China's acute per capita agricultural land scarcity, which in 2016 stood at only 0.086 hectares per person, comparable to Bangladesh, while Africa holds an estimated 60% of the world's uncultivated arable land (Agunyai & Amusan, 2023) (Pepa, 2018). The military dimension of this expansion completed the strategic picture in 2017 with the inauguration of China's first permanent overseas military base in Djibouti, situated near the Bab el-Mandeb Strait connecting the Red Sea to the Gulf of Aden — a chokepoint through which an estimated nine% of total seaborne-traded petroleum and more than 21,000 ships transited annually before the 2023–2024 Houthi disruptions, with traffic falling sharply thereafter (U.S. Energy Information Administration, 2019) — and which has since evolved, according to the Africa Center for Strategic Studies, into a key logistics and combat support hub whose infrastructure now includes a naval pier, advanced communications systems, and expanded storage facilities (Nantulya, 2025). Intelligence assessments reviewed by the United States Institute of Peace point to Equatorial Guinea and the Atlantic coast as the most likely locations for a second Chinese military base, a development that would extend Beijing's naval reach from the Indian Ocean to the western hemisphere (Vines & van Rij, 2024). The soft power dimensions of China's African strategy are no less consequential in structural terms: the Forum on China-Africa Cooperation now encompasses 53 of 54 African states, with Eswatini — the only country on the continent still recognising Taiwan — the sole absentee, and all participating states have formally reaffirmed the "One China principle" in successive FOCAC declarations, translating China's economic presence into a reliable diplomatic bloc of approximately 54 votes in the United Nations General Assembly and Security Council (Garlick & Qin, 2023) (Neema, 2024).

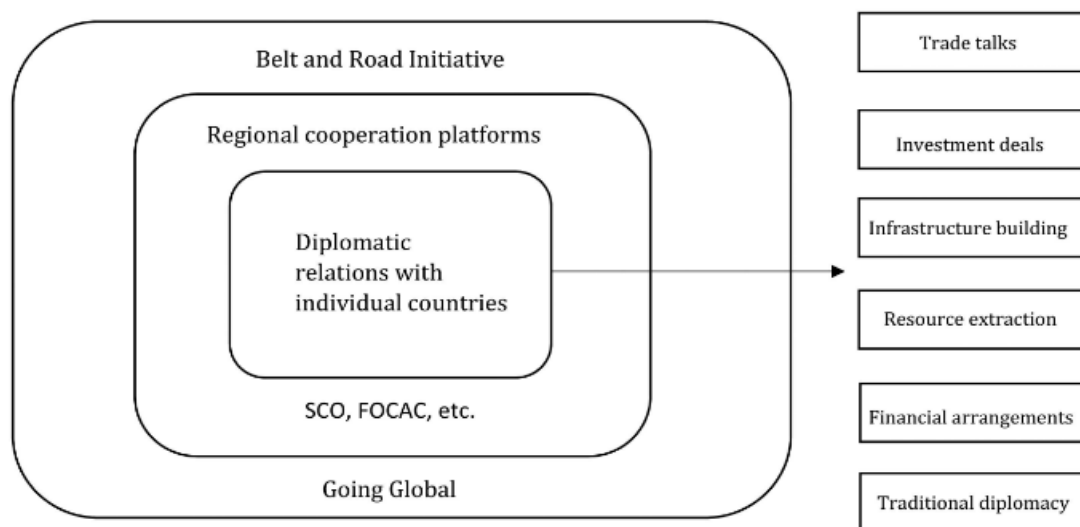


FIGURE 14: CHINA'S NORMATIVE DIPLOMACY IN THE GLOBAL SOUTH
(Garlick & Qin, 2023)

At the 2024 FOCAC summit in Beijing, attended by 51 African heads of state, China pledged over \$50 billion in new investment over the following three years, confirming the enduring vitality of a relationship that has made Beijing Africa's largest bilateral trading partner for over a decade (Dent, 2024). What this architecture reveals, when viewed in conjunction with the energy encirclement strategy described above, is that China has constructed not merely a commercial position in Africa but a comprehensive geoeconomic instrument capable of simultaneous action on multiple fronts: it can restrict rare earth exports to impair Western AI hardware manufacturing, manipulate global commodity pricing to weaken competitors, and leverage its dominance over African mineral infrastructure, debt obligations, maritime chokepoints, and diplomatic alignments to impose structural costs on any rival that seeks to build alternative supply chains (Chatham House, 2023). The continent's abundant reserves of cobalt, coltan, lithium, manganese, and rare earth elements — the very materials upon which the semiconductor and AI hardware industries depend — are therefore not a passive endowment awaiting competitive exploitation but an already-structured domain of Chinese strategic influence embedded in rail corridors, port concessions, power grids, food supply networks, and multilateral voting blocs, collectively making the decoupling of Western AI supply chains from Chinese intermediation a generational, rather than a near-term, undertaking

(Nantulya, 2025) (International Energy Agency (b), 2025) (Crebo-Rediker & Khan, 2026).

2.2.6. *Data Centers, Debt Accumulation, and the Structural Vulnerability of the Build-Out*

The strategic significance of China's mineral dominance in Africa becomes fully legible only when set against the scale of the infrastructure build-out that the AI transition now demands of Western economies. The expansion of data center infrastructure has become, by 2025–2026, the defining capital expenditure event of the AI economy. OpenAI alone has indicated that it may require data-center capacity valued at in excess of 500 billion dollars between 2025 and 2030 — a figure that excludes energy costs, maintenance cycles, and the hardware replacement programs that the rapid evolution of AI architecture necessitates (OpenAI (a), 2025). These capital requirements are being financed, across the sector, primarily through debt: *Financial Times* reporting in late 2025 indicates that OpenAI's compute suppliers — Oracle, CoreWeave, Crusoe, and other data-center partners — had collectively taken on approximately \$96 billion dollars in debt to fund the infrastructure committed to OpenAI workloads, while OpenAI itself is projected by financial documents reviewed by *The Wall Street Journal* to incur operating losses of approximately fourteen billion dollars in 2026, rising to roughly \$74 billion dollars annually by 2028 — a combined financial profile that reproduces, with considerable structural fidelity, the debt-financed expansion of the most aggressively scaling dot-com firms of the late 1990s (Smith D. , 2025) (Edwards, J. (b), 2025). The analytical question is not whether AI will eventually generate revenues sufficient to justify these investments — it may well do so — but whether current investment structures can survive the interval between present capital commitments and future revenue realisation, and what the systemic consequences of a loss of investor confidence would be if that interval proves longer, or the revenue trajectory less steep, than current projections assume (Perez, 2002).

Bain & Company has estimated that by 2030 AI firms will need to generate approximately \$2 trillion in annual revenue to meet worldwide compute needs and justify the capital currently being committed to AI infrastructure — a figure that exceeds the current revenue base of the sector by an order of magnitude. (Bain & Company, 2025).

Whether this threshold is achievable depends on a range of factors — the pace and depth of enterprise adoption, the productivity gains demonstrably attributable to AI integration, and the distribution of value-added across the layers of the supply chain — that are, at the time of writing, genuinely uncertain. It also depends on questions of industrial structure: whether the concentration of AI infrastructure investment in a small number of hyperscale operators is stable, or whether the economics of data center construction and energy procurement will force consolidation, state intervention, or hybrid public-private arrangements of the kind increasingly visible in European discussions of AI sovereignty (Madiaga, 2021). The possibility that large-scale infrastructure buildouts might prove “stranded” — their value impaired not by any technical failure but by a slowdown in demand at the application layer — is, in this context, among the more consequential and least adequately analysed risks in the AI economy.

2.2.7. The Utility Question: Productivity, Adoption, and the Gap Between Promise and Return

The highest layer of the AI supply chain — the models and their applications — is in some respects the least material and in others the most consequential for the assessment of systemic risk. The central question at this layer is not technical but economic: whether AI systems as currently constituted are generating, or are on a credible trajectory to generate, the productivity gains and cost reductions that would justify the capital being invested in them. The empirical evidence available at the beginning of 2026 is, to a degree that has not penetrated mainstream financial discourse, less encouraging than the investment climate would suggest. Research conducted at MIT in 2025, surveying more than three hundred firms that had collectively invested in the range of 30 to 40 billion dollars in generative AI tools, found that an estimated 95% of organisations reported no measurable return on their AI investments in terms of productivity, product quality, or cost reduction — a finding consistent with the broader pattern identified in the productivity literature, in which general-purpose technologies typically require substantial organisational and institutional adaptation before their economic potential is realised — (Estrada, 2025).

This does not entail the conclusion that AI lacks transformative potential; the history of electricity, the internal combustion engine, and the computer itself suggests that the gap between a technology's introduction and its full economic expression can span decades, and that early adopter experience is an unreliable guide to eventual impact (David, 1990). What it does suggest is that the current investment cycle may be running considerably ahead of the demonstrable economic utility that would sustain it — a divergence that reproduces, in its structural logic, precisely the pattern identified in the dot-com episode. If business buyers of artificial intelligence services begin reducing expenditure in reaction to disappointing results—downgrading subscriptions, stopping pilots, or reallocating funds toward applications with more quickly quantifiable productivity benefits—the repercussions would ripple throughout the supply chain: fewer inference workloads, decreased demand for data-center expansion, reduced chip sales, and a readjustment of the equity valuations upon which existing capital structures rely (Perez, 2002). At the beginning of 2026, such a correction does not appear imminent in market sentiment; but the structural conditions for it are present, and the analytical framework developed in this chapter suggests that the relevant question is not whether a correction of some kind will occur, but whether, when it does, it will function — as the dot-com crash ultimately did — to reprice expectations while leaving the productive infrastructure of the technology intact, or whether the degree of leverage in current investment structures makes a more disruptive outcome significantly possible (Kindleberger, C. P. & Aliber, 2005).

2.2.8. Is an Artificial Intelligence Financial Bubble Imminent?

The evidence assembled in this chapter permits neither complacent dismissal of systemic risk nor confident prediction of imminent collapse, but it does support a number of empirically grounded assessments. First, the structural parallel between the dot-com cycle and the current AI investment wave is not merely rhetorical: both episodes exhibit the characteristic pattern of a general-purpose technology whose genuinely transformative potential attracts capital on a scale and at a velocity that outpaces the institutional, organisational, and commercial conditions required for that potential to be realised. Second, the nature of the risk has shifted in consequential ways. The dot-com

bubble was primarily a **valuation bubble**, sustained by equity markets pricing speculative narratives in firms that generated little or no revenue; the AI cycle, by contrast, is more accurately characterized as a capacity bubble, in which infrastructure investment is running substantially ahead of demonstrable end-user demand, even as the firms at the center of the build-out — NVIDIA, the major hyperscalers — generate real and in several cases rapidly growing earnings. It is crucial to recognize this distinction: It indicates that, should a change happen, it is more likely to be a protracted decrease in capital spending growth and a repricing of forward expectations than a sudden and catastrophic fall of the kind observed in 2000–2002. Third, though, some features of the current cycle reveal dangers that either didn't exist or were far less obvious in the dot-com age. Unlike linear supply chains, circular financing systems connecting semiconductor businesses, cloud providers, and AI developers generate interdependencies that could amplify and synchronise a loss of faith across the ecosystem. With the five biggest businesses expected to spend around 90% of their operational cash flow on infrastructure in 2026, the debt-financed nature of a growing proportion of hyperscaler capital expenditure lowers the margin for mistake that the cash-rich balance sheets of these companies would otherwise offer. And the geopolitical entanglement of the artificial intelligence supply chain, which includes things like rare earth material dependencies, semiconductor export restrictions, and energy market disruptions in the very places where great power competition is most intense, means that any financial correction would spread not only through stock markets and venture capital portfolios but also through the strategic calculations of countries whose industrial and security policies are now tied to the trajectory of AI investment. Therefore, the most likely short-term result is not a single crash but rather a phase of increased volatility and selective repricing in which companies unable to prove credible paths from infrastructure spending to income generation would face severe capital discipline, while the underlying productive capacity of the technology—the data centers, the semiconductor fabrication lines, the trained models—will survive and, like in the wake of the dot-com correction, will eventually support a next phase of more sustainable and widely dispersed economic transformation. The key doubt is temporal instead of directional: The issue is whether the time between current capital commitments and future productive returns can be negotiated without causing a

chaotic correction with financial, industrial, and geopolitical repercussions exceeding those of its historical forerunner, rather than whether artificial intelligence will transform the world economy.

2.3. Anticipating the Generative AI Breakthrough: Kokotajlo's 2021 Forecast and the Emergence of ChatGPT

In 2021, Daniel Kokotajlo, a former researcher in the governance division of OpenAI, published a speculative but methodologically structured forecast titled "What 2026 Looks Like," which attempted to describe a plausible near-term trajectory of artificial intelligence development (Kokotajlo, 2021). His approach was notable not because it predicted specific products or companies, but because it outlined structural trends — multimodal transformer scaling, conversational AI adoption, recurring hype cycles, and the gradual emergence of AI assistants integrated into economic life — more than a year before the public release of ChatGPT in November 2022. Understanding how Kokotajlo's forecast relates to subsequent real-world developments is useful not only for assessing the accuracy of technological foresight, but also for analysing the geopolitical implications of rapid AI advancement more broadly; forecasts of this kind illustrate how technological change interacts with economic incentives, corporate strategy, and global power competition in ways that anticipate, rather than merely react to, structural shifts in the international order (Dafoe, 2018).

Rather than giving particular events probabilities, Kokotajlo decided to create a complete "future history" spanning year by year from 2022 to 2026. This approach revealed a better awareness of the nature of technological prediction: Artificial intelligence discussions frequently focus on lofty concepts like GDP growth paths or timelines to artificial general intelligence while missing the specific intermediate advances by which transformation actually occurs, hence staying too philosophical. He aimed to expose underlying contradictions in accepted expectations and inspire more careful thought about the near-term path of the technology by visualizing those intermediate steps practically — chatbots turning economically viable, multimodal models emerging, artificial intelligence assistants progressively infiltrating daily chores (Tetlock & Gardner, 2015). From a geopolitical standpoint, this approach is crucial since technical revolutions almost never

come as quick, isolated occurrences; Strategic foresight is made possible by tracing this route as they develop by means of modest gains, changes in public view, and continuous infrastructure investment. Several of Kokotajlo's predictions proved remarkably prescient. He anticipated that by 2022 major technology firms would possess large multimodal transformers trained on images, video, and audio, surpassing GPT-3 in scale and capability — a prediction that proved accurate as AI research shifted decisively toward exactly such models, with OpenAI's GPT-4, Google's PaLM and Gemini projects, and Meta's multimodal research initiatives all conforming broadly to this trajectory (Bommasani, Hudson, Adeli, Altman, & Arora, 2021). From a geoeconomic standpoint, this change had significant structural effects: multimodal AI significantly increased demand for high-performance computing, sophisticated semiconductors, and large datasets, therefore converting control over GPUs, cloud infrastructure, and training data into strategic assets in world competition and directly influencing the semiconductor export controls and industrial policy responses that have changed global trade ties since 2022 (Crawford, 2021). He further predicted that chatbots would become commercially viable consumer products attracting millions of users even before they were fully useful for serious economic tasks — a description that closely matches the reception of ChatGPT, which attracted over one million users within five days of its 30 November 2022 release and reached an estimated 100 million monthly active users by January 2023, making it the fastest-growing consumer application in history at that time, transforming AI into a mass-market interface and accelerating investment, regulatory attention, and geopolitical competition simultaneously (Hu K. , 2023) (OpenAI, 2022).

Another major forecast was that modular AI systems and quick programming libraries would develop to be able to handle difficult tasks by means of chains of prompts, hence enabling AI assistants to surf the internet, buy products, or generate content by means of specialized subroutines. This prediction set the stage for things like LangChain, AutoGPT, and the larger world of agent-based artificial intelligence frameworks that came out in 2023, which made it easier for AI applications to get started but also made us more reliant on the companies that controlled the underlying models and cloud infrastructure (GitHub, 2023). Additionally predicting cycles of excitement, disillusionment, and reinvestment, Kokotajlo stated that early uses of artificial

intelligence would be amazing but not right away revolutionary for GDP, that enthusiasm would briefly dissipate before resurfacing, as more actually helpful AI assistants appeared — a structural trend already plainly apparent in the surge of excitement spurred by ChatGPT's debut, then dampened by arguments over quantifiable productivity improvements and economic effect (Acemoglu, 2024). By 2026, he had projected that AI assistants would perform real economic tasks — buying goods, writing code, managing workflows — triggering a new wave of startup activity; while this stage has not yet been fully realised, early evidence is broadly consistent with the trajectory, as AI copilots in software development, automated customer support systems, and AI-driven research tools become increasingly widespread (Eloundou, Manning, Mishkin, & Rock, 2023).

The apparent accuracy of these forecasts does not imply clairvoyance. It reflects, rather, the visibility of structural trends already fully present in 2021: scaling laws in machine learning indicated that larger models trained on more data would produce qualitatively better results; compute costs were declining steadily relative to performance; and corporate investment in AI infrastructure was accelerating at a measurable pace (Kaplan, et al., 2020). ChatGPT emerged not because of an unforeseen breakthrough but because existing trajectories had reached a critical threshold — a point with direct geopolitical implications, since states that recognized these structural trends earlier could shape supply chains, invest in infrastructure, and influence regulatory frameworks well in advance of the public breakthrough that caught many governments unprepared (Dafoe, 2018) (Gruber & Johnson, 2019).

Yet several of Kokotajlo's predictions have not materialised, or have unfolded considerably more slowly than anticipated, and these divergences are at least as instructive as his successes. Truly autonomous AI assistants capable of reliably executing multi-step real-world tasks remain limited; systems like AutoGPT and enterprise AI copilots continue to require substantial human supervision and frequently fail due to hallucinations, insufficient contextual awareness, and security constraints, meaning that the transition from conversational AI to dependable economic agents has been slower than the forecast envisaged (Weidinger, Mellor, Rauh, Griffin, & Uesato, 2021). The expected early signs of broad macroeconomic transformation have been weaker than many projections suggested: generative AI has improved specific tasks — coding,

writing, data analysis — but has not yet produced any detectable acceleration in global productivity statistics, with structural constraints such as organisational inertia, regulatory friction, and integration costs slowing adoption across the economy (Acemoglu, 2024). The anticipated trajectory of model parameter scaling gave way to a more complex pattern in which architectural innovation, mixture-of-experts designs, and efficiency improvements displaced raw size as the primary axis of progress, and firms became markedly more secretive about model details, making the development path less linear and less legible than the forecast assumed (Hoffmann, Borgeaud, Mensch, Buchatskaya, & Cai, 2022).

No major alignment crisis or dramatic warning shot has occurred; concerns about misinformation, bias, and hallucination exist in abundance, but AI systems have not demonstrated the autonomous strategic deception or large-scale harmful behaviour that some forecasters anticipated, and current systems' limitations — errors, lack of deep reasoning, brittleness under adversarial conditions — remain more salient than existential risks (Russell, 2019). Similarly, although AI-generated content is increasingly present in disinformation campaigns, its impact has so far been incremental rather than transformative, with traditional political communication, human-generated content, and platform moderation continuing to shape information ecosystems in ways that the scenario did not fully anticipate (Goldstein, Sastry, & Musser, 2023). Global internet fragmentation into distinct ideological territories controlled by competing AI-driven propaganda systems has not materialised, and while digital fragmentation is clearly increasing through censorship regimes, platform regulation, and geopolitical data controls, the global internet remains substantially interconnected (Deibert, 2020).

Several structural factors explain these divergences: technical bottlenecks in reliability, reasoning, and autonomous action; regulatory constraints on AI deployment; organisational inertia slowing enterprise adoption; the economic realism that limits hype-driven investment over time; and the fundamental complexity of human-AI interaction, which makes full automation harder than scaling trends alone would suggest (Acemoglu & Johnson, 2023). These limitations emphasize an important lesson in direct relevance to geopolitical and geoeconomic analysis in technical forecasting: while scaling trends can fairly accurately predict capability growth, social, institutional, and economic

considerations finally decide actual world impact. While some expected advancements have not happened or have materialized more slowly, Kokotajlo's projection was remarkable in seeing the emergence of multimodal models and conversational AI. This shows both the strength and the boundaries of structural foresight in new technologies. For geopolitics and geoeconomics, the implication is significant: technological revolutions are shaped not only by innovation but by regulation, infrastructure investment, labor market dynamics, and international competition, and forecasting AI therefore requires integrating technical insight with political and economic analysis in ways that neither dimension alone can provide (Acemoglu & Johnson, 2023).

2.4. Financialization of Compute: GPU Collateral and Benchmark Narratives in the AI Economy

The rapid expansion of artificial intelligence has not only transformed technological production but has also reshaped financial practice in ways that deserve careful analytical attention. As in previous industrial revolutions, new forms of infrastructure have generated new forms of credit, valuation, and speculation (Perez, 2002). Railways produced railway bonds; electrification produced utility trusts; the internet produced venture-backed platform firms. Artificial intelligence is now producing its own financial architecture, centered on specialized computing hardware and performance narratives. Two phenomena illustrate this transformation with particular clarity: the use of graphics processing units as collateral in debt financing, exemplified by the CoreWeave case, and the strategic optimisation of AI benchmarks — colloquially termed "benchmaxxing" — as a mechanism for influencing market valuation. Benchmarking means comparing a company's products, services, or processes to industry standards or top competitors. The main goal is to find where it can improve and adopt best practices to level up overall performance. (Wiggers, 2024) (Patterson, Gonzalez, Le, Liang, & Munguia, 2021). Together, these practices reveal how the contemporary AI boom intertwines material infrastructure, financial innovation, and informational asymmetry in ways that have significant implications for the stability of the broader AI economy and for the geopolitical competition surrounding it.

2.4.1. GPUs as Collateral: Infrastructure as a Financial Asset

Modern artificial intelligence development requires extraordinary quantities of compute. Training frontier models may involve tens of thousands of GPUs operating continuously for weeks, consuming vast amounts of electricity and depreciating rapidly in value (Patterson, Gonzalez, Le, Liang, & Munguia, 2021). For businesses lacking significant internal cash reserves, obtaining such infrastructure is a major financial obstacle. Equity dilution might be unwelcomed at specific phases of expansion; hence, conventional venture capital is sometimes inadequate. As a result, debt financing is a different option, and along with it comes the inevitable question of collateral.

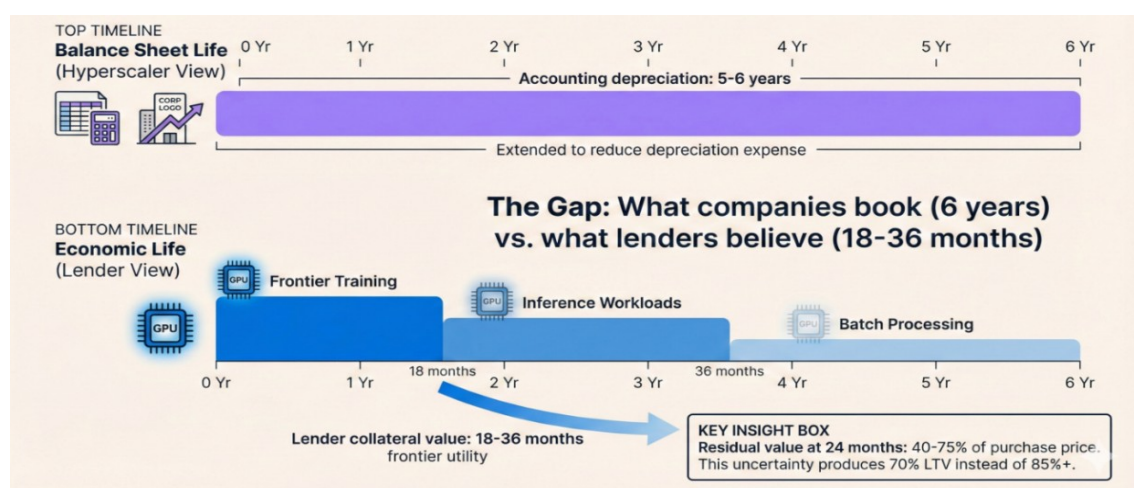


FIGURE 15: GPU LIFESPAN: ACCOUNTING VS. ECONOMIC REALITY

Source: Substack

In traditional lending, collateral is made up of things that have a pretty steady resale value, like real estate, industrial equipment, or strong tools. GPUs differ from these assets in several important respects. They are highly specialized, technologically perishable, and subject to rapid obsolescence as new chip generations emerge (Crawford, 2021). Their value depends on software compatibility, evolving model architectures, export regulations, and market demand for compute-intensive workloads. Despite these uncertainties, the scarcity of high-end GPUs in recent years has allowed them to function as quasi-financial assets in a manner that would have seemed implausible a decade ago. CoreWeave's path especially powerfully captures this shift. Originally established as a cryptocurrency mining firm, CoreWeave changed course to provide cloud-based GPU

infrastructure as machine learning compute demand skyrocketed. The company had obtained billions of dollars in debt financing by the early 2020s, partly by mortgaging its GPU inventory as security (Tan & Hirsch, 2025). Lenders were willing to take these conditions since demand from hyperscalers, research institutions, and artificial intelligence companies alike remained strong even if there was not enough supply of high-performance accelerators in the market. Emerging secondary markets—where used GPUs kept a high resale value—reinforced the idea that hardware inventories were reliable collateral and might support a lot of debt responsibilities.

This technique captures the odd financial aspects of the artificial intelligence explosion. GPUs turned into rare items whose worth came from more than just their physical parts. It came from how much computing power they had and, most importantly, from the bigger expectations that came with the growth of artificial intelligence (Minsky, 1986). Having access to computers became a source of wealth. Companies owning sizable accelerator clusters had not just technical capacity but also financial bargaining leverage: hardware inventories can be used as collateral for loans, which would allow for more infrastructure development in a self-reinforcing cycle. From this perspective, compute capacity started to look like older industrial assets like rail lines or oil reserves—resources that could be used to make money before any money came in, which would turn an unknown future demand into a present financial advantage (Crawford, 2021) (Couldry & Mejias, 2019).

However, funding supported by GPUs adds structural weaknesses that are not always fully noted amid the excitement around AI infrastructure development. GPUs unlike real estate or railroads decay rapidly and their performance advantage relies on ongoing development by semiconductor firms (Dettmers, Pagnoni, Holtzman, & Zettlemoyer, 2023). If fresh GPUs provide considerably improved performance per watt or per dollar of running expense, a data center packed with one generation of accelerators might quickly lose competitiveness. Demand for artificial intelligence computer also finally hinges on ambiguous forecasts about model development pathways and corporate adoption rates. The resale value of GPUs might plummet sharply and quickly if expectations change as a result of rules, technological stagnation, economic downturns, or even only a revaluation of artificial intelligence's near-term productivity returns. Under

such conditions, debt supported by hardware collateral could become structurally unstable, subjecting lenders and borrowers equally to liquidity issues of a kind that would spread far beyond the AI industry.

Even if inaccurate, historical parallels are helpful in this context. Railway lines acted as security for bonds given on optimistic traffic predictions during the railway boom of the nineteenth century. When predicted demand failed to materialise, defaults swept across financial systems in ways that shook entire national economies (Chancellor, 1999). Likewise, in the years leading up to the 2008 financial crisis, mortgage-backed securities turned dubious property values into seemingly tradable and stable financial assets, therefore increasing systemic risk to an extent that few had predicted. GPU-backed lending is not identical to these cases, but it reflects the same structural impulse: converting uncertain technological expectations into immediate financial leverage, and in doing so, binding the fortunes of the broader financial system to the trajectory of a technology whose long-term commercial applications remain, in important respects, unproven (Kindleberger, C. P. & Aliber, 2005).

Another dimension of the CoreWeave case concerns geopolitical supply constraints in ways that deserve specific attention in the context of this thesis. Export controls, semiconductor shortages, and allocation policies have restricted access to high-end accelerators, particularly in the context of the ongoing technological competition between the United States and China (Sanders, Egan, & Madigan, 2026).

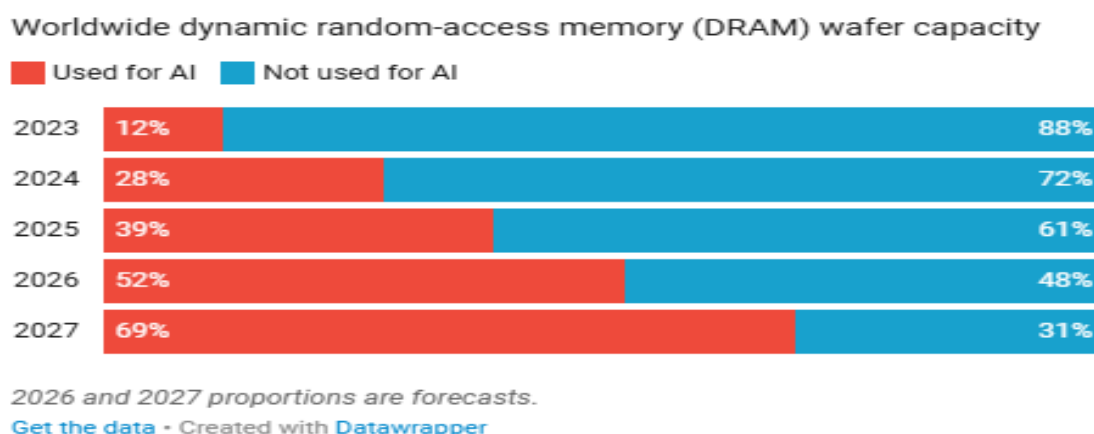


FIGURE 16: AI IS USING AN INCREASING PROPORTION OF WORLDWIDE DRAM MANUFACTURING CAPACITY
(Sanders, Egan, & Madigan, 2026)

Firms able to secure large GPU inventories have therefore gained strategic advantages not only in technological terms but also in financial ones. Scarcity increased the perceived stability of hardware collateral, encouraging lenders to treat GPUs as durable assets comparable to other forms of industrial infrastructure. Still, shortage is itself cyclical and conditional: should production capacity rise, should new designs lessen reliance on specialized chips, or should export control systems be changed, hardware prices could decline in ways that weaken the collateral structures now backing major debt commitments. The stability of GPU-backed funding so relies, in ways rarely expressed, on the endurance of present geopolitical conditions as much as on the path of the technology itself.

In this sense, the financialization of compute reflects both rational adaptation to genuine structural constraints and a form of systemic fragility that is embedded in the specific geopolitical conditions of the current moment. It allows firms to build infrastructure rapidly and to compete in a sector where scale advantages are real and significant; but it also embeds leverage into an industry characterized by deep technological uncertainty and by a degree of dependence on geopolitical stability that is rarely foregrounded in the financial analyses of AI investment. The long-term consequences of this practice remain uncertain, yet its scale and its growing embeddedness in the financial architecture of the AI economy suggest that it may become one of the defining features — and one of the defining vulnerabilities — of the AI boom.

2.4.2. Benchmark Optimisation ("Benchmaxxing") and Market Valuations

While GPUs illustrate the material side of the financialization of compute, the phenomenon of benchmark manipulation reveals its informational dimension with equal clarity. Financial markets depend on indicators to evaluate technological progress, and in emerging sectors where revenue models remain uncertain and outputs are difficult to observe directly, simplified metrics inevitably become proxies for future profitability (Strathern, 2009) (Goodhart, 1984). In artificial intelligence, these metrics most commonly take the form of benchmark scores measuring accuracy, reasoning ability, or computational efficiency across standardised tasks. Although benchmarks play an essential role in scientific comparison and in the cumulative assessment of research

progress, they also create powerful incentives for strategic behaviour by firms operating under intense competitive and financial pressure.

In order to give an alternative definition to the term, the phenomenon mentioned before as "benchmaxxing", refers to the deliberate optimisation of models for specific benchmarks in ways that systematically exaggerate real-world performance (Toutanova, Rumshisky, & Zettlemoyer, 2021) (de la Rocha, 2026). Methods range from precisely adjusting models on assessment datasets to carefully presenting outcomes highlighting small strengths while hiding weaknesses or creating evaluation protocols favouring certain structural decisions. Although similar dynamics have shown in standardised testing, pharmaceutical clinical studies, and financial stress tests, such activities are not unique to artificial intelligence; rather, in the AI industry, where performance reports can affect multi-billion-dollar valuations and control access to funding, the incentives for strategic behaviour are very strong and the epistemic effects especially significant. Investors routinely view these measures as markers of technical leadership, often without the analytical skill necessary to assess if the improvements show actual capacity gains or simply optimised performance on particular assessment activities (Liao & Wortman Vaughan, 2023). Companies often pair new model releases with news of better benchmark results. Announcements of this kind might cause share prices to react appropriately. Specifically, the precipitous contraction in NVIDIA's market valuation on 27 January 2025 — when its share price fell approximately 17% and roughly 600 billion dollars in market capitalisation evaporated in a single trading session, the largest single-day market-cap loss for any company in U.S. stock-market history — underscored a pivotal shift in investor sentiment, as the release of DeepSeek's R1 model and its associated claims of dramatically lower training costs suggested a diminishing necessity for intensive hardware procurement in the development of frontier artificial intelligence (Khalaf, 2025). The distinction between research progress and commercial viability becomes progressively blurred, as gains on standardised tests are taken to signal future revenue potential in ways that may bear little relationship to how the underlying systems actually perform when deployed in complex, variable, real-world settings. A model might score highly on language understanding exams while consistently failing in long-term reasoning, domain-specific reliability, or performance under challenging circumstances,

all of which are very important for commercial implementation but which benchmark rankings seldom reflect (Davis & Marcus, 2019).

This interaction captures the larger epistemic difficulties of judging AI systems in an environment where financial stakes are significant and the technology is evolving quickly. Unlike conventional manufacturing, artificial intelligence output is probabilistic, context-dependent, and really difficult to quantify in ways that are both accurate and economically important. Benchmarks give the impression of similarity by giving single numbers that look objective and comparable, but they only show a small part of how the system works and are prone to the systematic gaming that high-stakes measurement systems have always invited (Raji, Bender, Paullada, Denton, & Hanna, 2021). Valuation becomes extremely sensitive to information asymmetry between companies that know the limits of benchmarks and investors who do not when markets depend much on such indicators. Furthermore, increasing its market impact, benchmark optimisation interacts with media stories in ways that magnifies it. Press releases and technical demonstrations regularly simplify difficult methodological elements into understandable rankings and comparisons; journalistic coverage tends to accentuate these framings, often portraying technological progress as a competitive race toward artificial general intelligence in which present benchmark leaders are assumed to be the most likely eventual winners (Firth, 2023). People's impressions of technical leadership become very closely linked with benchmark performance in ways that lead to self-fulfilling dynamics: Companies seen as leaders in benchmarks draw money, which supports more research and marketing, which promotes more benchmark increases and strengthens the view of leadership. This feedback loop is quite similar to earlier times when businesses focused on easily measured numbers like user counts during the dot-com era, click-through rates in early online advertising, to get money when there wasn't much real proof of commercial worth.

Financial markets could suffer greatly and even destabilize under specific circumstances. If benchmark improvements are usually seen as proof of certain future dominance, valuations might go much beyond what is actually possible, setting up the perfect environment for a steep correction when markets finally have better ways to tell the difference between real skill gains and mere metric optimisation (Shiller, 2000). For a long time, scholarly studies have raised alarms about benchmark saturation: As models

are continuously trained on datasets quite similar to assessment corpora, observed gains could more likely represent memorization and distributional overlap than actual progress in generalisation or reasoning ability. Furthermore, well-known standards hardly gauge more general system traits including robustness under distribution change, interpretability, energy efficiency, or reliability in long-horizon activities—all of which probably define economic worth in application. The gap between benchmark performance and economic value may therefore widen over time, with corrections following when the discrepancy becomes undeniable.

2.4.3. Interaction Between Hardware Collateral and Benchmark Narratives

GPU-backed financing and benchmark optimisation are not isolated phenomena; they interact in ways that shape the overall structure and dynamics of the AI ecosystem and that deserve to be understood as a single integrated financial architecture rather than as two separate practices (Zuboff, 2019). Companies that acquire debt financing to purchase a lot of hardware can develop larger models and be bolder in pursuing benchmark supremacy. Higher benchmark scores motivate investment, which pays for more equipment and more model development. This loop makes it tough to challenge the underlying assumptions from inside the system by reinforcing expectations regarding technological inevitability, the notion that today's leaders are on an unending road to supremacy. Together, financial leverage, performance narratives, and hardware scarcity define a single ecosystem logic that replicates in important structural respects the self-reinforcing loops noted in earlier speculative surges. These dynamics closely resemble historical trends in which infrastructure investment and valuation narratives co-evolved in ways that eventually generated considerable instability. In the artificial intelligence cycle, compute investment drives more benchmark gains, which in turn justify further compute investment. The resulting feedback loop could both accelerate actual innovation and increase the system's overall vulnerability to unexpected shifts in commercial expectations for AI.

2.4.4. Broader Implications for Innovation and Stability

The financialization of compute has consequences that extend well beyond corporate balance sheets and into research priorities, labor allocation, and public policy in ways that

are insufficiently appreciated in mainstream discussions of AI investment (Acemoglu & Johnson, 2023). Firms operating under pressure to service substantial debt obligations may rationally prioritise short-term benchmark improvements over the kinds of long-term architectural innovation or safety research that are likely to be most consequential for the technology's ultimate social and economic value. Engineers could give their attention to improving models for quantifiable criteria instead of investigating radically innovative AI design ideas. Once ingrained in the reward systems of a growing sector, capital flows toward locations exhibiting apparent and clear indicators of progress, maybe altering the course of technological development in ways challenging to undo.

Financial innovation can also and does speed up infrastructure deployment in methods that produce real value. Access to credit enables firms to build data centers and train models that would otherwise be technologically and financially out of reach, and competition for investment encourages experimentation across a broader range of architectural and application possibilities than any single firm would explore in the absence of competitive pressure (Mokyr, 1990). Even failed ventures may leave behind valuable expertise, datasets, and hardware that can be repurposed by subsequent actors. As in previous industrial revolutions, speculative finance may both distort and accelerate technological change, and the challenge lies not in eliminating financial innovation but in developing the regulatory and institutional frameworks necessary to manage its systemic risks.

There is, however, a political dimension to this financialization that extends beyond the question of speculative risk and that connects directly to the broader geopolitical and geoeconomic concerns of this thesis. When machine learning infrastructure is converted into collateral and benchmark results are transformed into market signals, a deeper transformation is taking place: political and economic problems are being reconfigured as machine learning problems, and the parameters of those models quietly displace the deliberative spaces in which those problems were previously contested (Amoore, 2022). The retroactive logic of deep learning — beginning from a target output and working backwards to adjust model weights — inverts the classical relationship between political problematisation and solution. Instead of a variety of potential answers coming from the open-ended identification of a social issue, the solution is more or less chosen beforehand

and then the problem is adjusted to match it. In the world of artificial intelligence investment, this shows up as building infrastructure not to meet clearly recognized social needs but to keep the valuation story alive that brings in the following round of funding. The standard becomes the objective; it doesn't gauge advancement toward any given goal. And in becoming the goal, it forecloses the space in which alternative questions — about who this infrastructure serves, under what conditions, at whose environmental and social cost, and under whose political authority — might otherwise be meaningfully posed (Amoore, 2020) (Amoore, 2022).

Artificial intelligence may indeed reshape the global economy in the ways its proponents project. Yet its financial foundations remain experimental and, in certain important respects, structurally fragile. The conversion of compute capacity into collateral and performance metrics into valuation signals reveals an economy attempting to quantify possibilities that remain genuinely uncertain and to translate speculative technological expectations into the kind of stable, tradable financial assets that debt markets require. Whether this process ultimately produces durable prosperity or destabilizing speculation will depend, as with previous technological revolutions, on the interaction between genuine technological progress, financial discipline, and the development of institutional frameworks capable of distinguishing sustainable value creation from narrative inflation in the years ahead (Perez, 2002).

2.5. The Hardware War: EUV, Semiconductors, and Memory

The contemporary geopolitical contest over artificial intelligence is often framed in terms of algorithms, data, or innovation ecosystems. Yet beneath these abstractions lies a material infrastructure whose strategic importance increasingly resembles that of coal in the nineteenth century or oil in the twentieth (Crawford, 2021). Artificial intelligence, cloud computing, and modern digital economies depend on a narrow set of highly specialized hardware components: advanced lithography systems, cutting-edge logic chips, and large volumes of memory. Control over these technologies has therefore become a central concern of state policy, corporate strategy, and international diplomacy in ways that would have seemed implausible a decade ago. The result is what might be described as a hardware war — a contest not merely over markets or innovation

leadership, but over the deeper question of technological sovereignty and the conditions under which states can exercise meaningful autonomy in an AI-intensive world (Farrell & Newman, 2019) (Miller, 2022).

2.5.1. NVIDIA: The Company Behind the Artificial Intelligence Revolution

To recount the history of the most influential companies currently associated with artificial intelligence, it is essential to examine NVIDIA. Its technologies have already been encountered by millions of people — whether through visually complex films, through gaming consoles, or through the chips used to train advanced AI systems such as ChatGPT — yet until relatively recently, NVIDIA remained largely unknown to the general public (NVIDIA Corporation (b), 2023). Today, however, it stands among the key actors shaping the rise of artificial intelligence and is increasingly comparable in strategic importance to technology giants such as Google and Microsoft, occupying a position in the AI economy that is without clear historical precedent among hardware manufacturers.

NVIDIA's origins can be traced to the offices of LSI Logic Corporation, an electronics company based in Milpitas, California, where Jensen Huang — born in Tainan, Taiwan in 1963 and educated at Oregon State University and Stanford University — worked in the late 1980s and early 1990s after a prior position at AMD (Witt, 2023). Huang joined LSI Logic in 1985, having earned his bachelor's degree in electrical engineering in 1984, and rose to direct LSI Logic's mainstream semiconductor business before founding NVIDIA in April 1993. Though he had initial success, he believed the possibilities of computers were much bigger than what could be learned in a conventional business setting. Seeking more freedom, in 1993 he persuaded two fellow engineers, Chris Malachowsky and Curtis Priem, to help him start a new business. They founded NVIDIA on 5 April 1993, with Huang serving as Chief Executive Officer (a role he still holds), reportedly meeting at a Denny's diner in East San Jose, California, with around \$40,000 of seed capital and an initial Sequoia Capital and Sutter Hill Ventures Series A investment of approximately \$2 million at a \$6 million post-money valuation, with subsequent rounds bringing cumulative pre-IPO venture funding to approximately \$20 million (Witt, 2023). Developing new technologies requires both time and financial sustainability, and

NVIDIA's early strategic choices reflect a clear-sighted awareness of this constraint. To maintain independence, the company initially focused on the video game industry — a choice that was neither accidental nor opportunistic but formed part of a long-term strategy (Miller, 2022). The gaming sector was expected to expand significantly, and it presented some of the most demanding technical challenges in computing at the time. Dealing with these problems might help NVIDIA create basic technologies with more general future uses and bring in enough money to keep research funding going. Originally designing graphics processing units, which are chips that turn digital code into visual output, the business released its first product, the NV1 graphics card, in 1995 even with little money. The NV1 was not a hit, even though it was cool, because it came out too early and didn't work well with a lot of the programs that were already being used. Nevertheless, the achievement attracted attention: a small startup with minimal resources had produced one of the most capable graphics cards then available on the market (Miller, 2022) (Embedded Staff, 2002).

In 1995, NVIDIA secured a significant contract from Sega to develop graphics hardware for its arcade and home consoles, and as the company's funding requirements grew it raised additional venture capital through follow-on rounds with Sequoia and Sutter Hill, supplemented in 1996 by a \$5 million investment from Sega's board that proved decisive in keeping the company solvent during the NV1-to-RIVA 128 transition (Miller, 2022). Even if there were technical problems and performance problems that made it hard for the project to work, NVIDIA kept going. It released the RIVA 128 in 1997, which was the most advanced graphics card of its time and a big hit in the business world that helped the company get known. In order to keep up with rising demand, NVIDIA's manufacturing partnership with Taiwan Semiconductor Manufacturing Company — already among the top contract chip-makers worldwide — was formalised through a strategic agreement in 1998 that would prove foundational to NVIDIA's fabless business model, while the company simultaneously expanded into larger offices in Santa Clara. (Miller, 2022) The true technological breakthrough arrived on 11 October 1999 with the introduction of the GeForce 256, marketed by NVIDIA as “*the world's first GPU*” on the basis of its integration of transform, lighting, triangle setup/clipping, and rendering engines on a single chip — a product that represented a major step forward in enabling

sophisticated 3D graphics for video games, simulations, and computer-aided design (NVIDIA Corporation (c), 1999).

Earlier that same year, on 22 January 1999, NVIDIA conducted its initial public offering on the Nasdaq stock exchange at \$12 per share, raising approximately \$42 million through the issuance of 3.5 million shares — a listing whose timing preceded the GeForce 256 launch by nine months and that valued the company at roughly \$626 million by the close of its first day of trading (NVIDIA Corporation (d), 2002). Early in the 2000s, NVIDIA grew quickly: it got deals to provide GPUs for Microsoft's first Xbox console, work with Apple on computer graphics, work with NASA on modelling the surface of planets, and help Sony's PlayStation 3. Annual sales had reached \$2 billion by 2005, but because of significant investment in research and development, profits stayed low. CUDA (Compute Unified Device Architecture), a key technical breakthrough in 2006, let GPUs carry out general-purpose parallel computing applications instead of being restricted to graphics processing (Nickolls & Dally, 2010). Initially perceived as commercially uncertain, this innovation proved fundamental to modern high-performance computing, machine learning, and computer vision, and it is not an exaggeration to say that CUDA constitutes one of the foundational enabling technologies of the contemporary AI boom.

NVIDIA had great difficulties in the late 2000s notwithstanding these developments. Shareholders sued in 2008 because of malfunctioning GPUs, which hurt the company's reputation and financial results; sales went down, and the company reported losses in both 2009 and 2010 (Foresman, 2009). Still, NVIDIA had previously started making significant investments in artificial intelligence research, and in 2012 its GPUs were utilized to train AlexNet, a neural network that produced hitherto unheard-of accuracy in picture recognition in the ImageNet competition—a development generally seen as signaling the start of the contemporary deep learning era. In the following years, there was a lot of growth that lasted for a long time. NVIDIA said they made a lot of money in 2016 because the gaming market grew, and in 2017 their revenue was \$6.91 billion (NVIDIA Corporation, 2017). Ongoing innovation and rising need for GPUs in scientific computing, autonomous cars, and data centers helped to progressively improve the company's market position. Understanding that rivalry in GPUs alone would increase—especially from Intel and AMD—Jensen Huang sought a revolutionary strategic

repositioning: positioning NVIDIA's hardware at the core of the budding AI development ecosystem rather than only the gaming one. This decision proved decisive in ways that even its architects may not have fully anticipated. By 2021, revenue had risen to \$16.7 billion. The launch of ChatGPT by OpenAI in November 2022 demonstrated the extraordinary potential of generative AI and threw into sharp relief the degree to which NVIDIA's GPU architecture had become the indispensable infrastructure for training large-scale models (Park, Wiggers, Corral, & Stringer, 2025) (OpenAI, 2022). As global demand for AI infrastructure surged in the months that followed, NVIDIA's sales and market valuation grew at a pace that had few precedents in the history of corporate technology. By 2023, the company surpassed \$1 trillion in market capitalisation, becoming one of the most valuable semiconductor firms in history and, by some measures, one of the most strategically consequential companies in the world. The long-term sustainability of this dominance remains uncertain — as in the GPU market more broadly, new entrants and alternative architectures may in time challenge NVIDIA's leadership — but its current position is a useful illustration of how strategic foresight, sustained investment in research and development, and a willingness to pursue long-term technological goals can transform a modest startup into a central actor in global geopolitics (Acemoglu & Johnson, 2023).

2.5.2. Export Controls and the Politics of Lithography

Few firms illustrate the geopolitical dimension of the hardware war more clearly than ASML Holding, the Dutch company that holds a near-monopoly on extreme ultraviolet lithography machines (Li, 2022). These machines, whose latest High-NA EUV systems cost approximately €350–380 million per unit (with earlier-generation EUV systems priced at approximately €150–200 million), are essential for manufacturing semiconductors at nodes below roughly seven nanometres. Their manufacture calls for an intricate worldwide supply chain including American laser systems, German Zeiss precision optics, and many unique parts obtained from around the world. The concentration of this capacity in one company — and the reliance of all advanced chip manufacturers on its technology — has turned ASML into a geopolitical player in ways that its original founders could hardly have dreamed of, and that conflict awkwardly with

the traditional view of private technology firms as business-driven rather than strategically driven organizations. Beginning in 2019, under sustained pressure from the United States, the Dutch government declined to grant export licences for ASML's EUV machines to China (Sterling, 2024). The restrictions were later extended to include certain deep ultraviolet lithography tools as part of a broader US-led export control regime targeting China's semiconductor sector. These measures formed part of a larger and increasingly systematic policy effort by the United States and its allies to slow China's progress toward advanced chip manufacturing — an objective that reflects the assessment, now firmly embedded in US national security doctrine, that advanced semiconductors underpin both civilian AI systems and military technologies, including autonomous weapons, surveillance infrastructure, and offensive cyber capabilities. From Washington's point of view, the logic was simple: keeping strategic rivals from getting the most capable chips was a national security need that came before the business interests of American and allied companies (U.S. Bureau of Industry and Security, 2022). From Beijing's point of view, though, the constraints validated a long-running and major worry that technologically advanced nations may purposely weaponize world supply chains. Once praised as a prime example of the mutual advantages of globalization, the semiconductor business had evolved into a first-order tool of geopolitical rivalry. The outcome has been an unmatched politicization of semiconductor production that has changed industrial policy across the main nations in ways that are still in progress (Semiconductor Industry Association, 2023). While in earlier decades companies chose production sites mostly depending on efficiency and comparative advantage, governments now actively and widely interfere to affect outcomes. More than \$50 billion was given to help local semiconductor production and research under the 2022 U.S. CHIPS and Science Act (U.S. Congress, 2022). Seeking to double Europe's share of worldwide semiconductor output by 2030, the European Union unveiled its own European Chips Act. With Taiwan in particular occupying a position of exceptional strategic sensitivity given the concentration of advanced fabrication capability in TSMC's facilities, Japan, South Korea, and Taiwan have likewise raised subsidies and strategic coordination (European Commission, 2022).

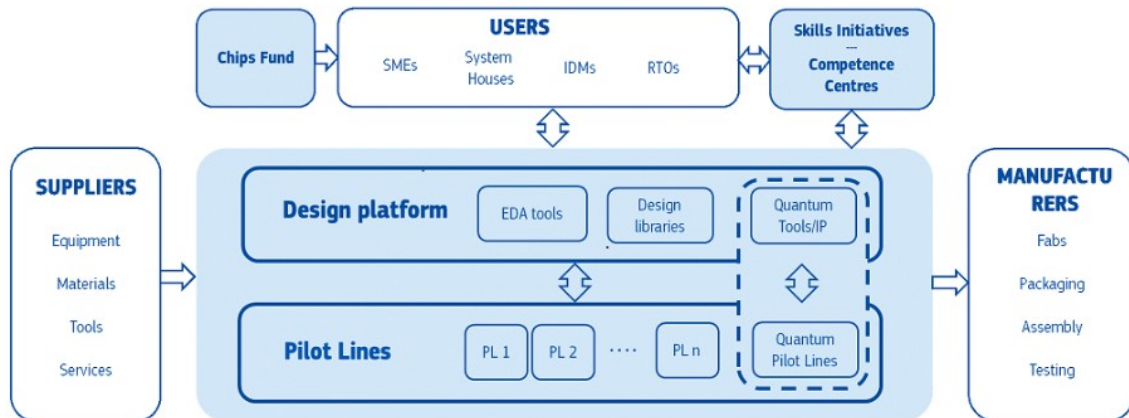


FIGURE 17: OVERVIEW OF THE CHIPS FOR EUROPE INITIATIVE
(European Commission, 2022)

These initiatives reflect a growing consensus among policymakers that semiconductor capacity is no longer merely an economic asset subject to normal market logics, but a strategic resource that states must actively cultivate and protect — a transformation in how technological infrastructure is understood that has implications extending well beyond the semiconductor sector itself.

2.5.3. *China's Strategy for Technological Self-Sufficiency*

China's response to export controls has been to intensify efforts toward technological self-reliance with a degree of urgency and resource mobilisation that has few precedents in the history of industrial policy. The goal of semiconductor independence predates recent trade tensions; it was already articulated in policies such as the "Made in China 2025" initiative and successive five-year plans that identified advanced semiconductors as a strategic priority (Kennedy S. , 2015). Yet after the tightening of US export controls from 2019 onward, and particularly following the sweeping October 2022 restrictions, the urgency of the objective increased dramatically and the resources allocated to it expanded accordingly.

The AI Stack: Few players at the bottom, many on top

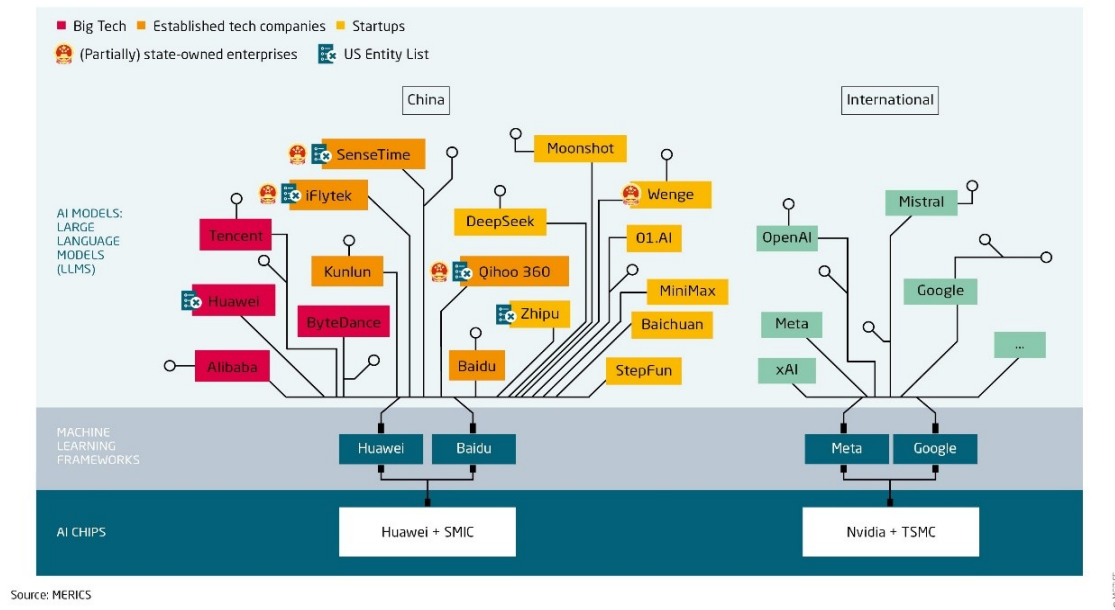


FIGURE 18: GEOPOLITICAL COMPETITION BETWEEN CHINA AND THE UNITED STATES

Source: [Merics](#)

Chinese policy emphasises three complementary strategies: domestic substitution, technological leapfrogging where possible, and supply chain diversification to reduce dependence on potentially hostile suppliers (Sanders, Egan, & Madigan, 2026). Through investment vehicles like the National Integrated Circuit Industry Investment Fund, sometimes known as the "Big Fund," enormous state money — projected in the hundreds of billions of dollars — have been poured into semiconductor companies. Companies like SMIC, Semiconductor Manufacturing International Corporation, have tried to improve manufacturing ability even though there are limits on EUV tools. This shows that they can come up with new ideas even when they are told what they can't do. This should not be taken for granted. In 2023, SMIC reportedly produced a seven-nanometre chip for Huawei using multiple-patterning deep ultraviolet techniques — a development that surprised many observers and suggested that the gap between China's indigenous capabilities and the global frontier, while real and significant, was narrowing in ways that export controls alone may not be sufficient to prevent (King, 2025).

Still, structural problems are still significant. Apart from lithography equipment, advanced semiconductor manufacture calls for sophisticated materials, design software,

and years of engineering know-how (Miller, 2022). American companies like Synopsys and Cadence control electronic design automation technologies, but their goods are still subject to export restrictions. Among companies like NVIDIA, AMD, and Apple, high-performance chip design is still concentrated. The ecosystem required to sustain cutting-edge semiconductor production is therefore deeply international and deeply interdependent, making rapid self-sufficiency extraordinarily difficult to achieve regardless of the financial resources committed to it. China has also pursued diversification by investing in semiconductor facilities abroad and strengthening ties with countries outside the US alliance network, while simultaneously emphasising domestic demand as a strategic lever: China remains the world's largest consumer of semiconductors, importing chips at a value that now substantially exceeds its oil import bill — integrated-circuit imports reached approximately \$385 billion in 2024 against oil imports of approximately \$325 billion — and the ability to shape market access gives Beijing a degree of influence over global supply chains that cannot simply be eliminated by export controls directed at the supply side alone (Jiang, 2025) (General Administration of Customs of the People's Republic of China, 2024) (Bown, 2020).

In this sense, the semiconductor contest mirrors earlier episodes of industrial geopolitics in ways that are analytically instructive even if the historical analogies are imperfect. Just as nineteenth-century states sought control over coal, railways, and steel production as the material foundations of national power, and just as twentieth-century geopolitics was shaped in fundamental ways by competition over oil, contemporary states seek influence over fabrication plants, design tools, and chip architectures as the infrastructure on which economic and military power increasingly depends (Yergin, 1991). The difference lies in the scale and complexity of the system: semiconductor manufacturing depends on thousands of specialized suppliers distributed across multiple continents, on decades of accumulated tacit expertise, and on standards and software ecosystems that have been built up through dense international collaboration. Technological decoupling is therefore costly and slow for all parties, and the attempt to achieve it carries significant risks of fragmenting the global innovation ecosystem in ways that may ultimately harm the technological progress of all parties — a paradox that lies at the heart of the contemporary

hardware war and that neither Washington nor Beijing has yet resolved (Khan, Mann, & Peterson, 2021).

2.6. The Memory Market and the "RAM War"

While advanced logic chips attract the most analytical attention in discussions of the semiconductor contest, memory technologies — particularly dynamic random-access memory (DRAM) and NAND flash storage — are equally critical to modern computing and deserve treatment as a distinct dimension of the hardware war (Lee, 2024). Large language models, data centers, and AI training pipelines require vast quantities of memory bandwidth and storage capacity; the performance of a given system depends not only on its processing units but on its ability to move data rapidly between memory and compute at the scale that frontier AI workloads demand. A small number of companies control the memory market: Samsung Electronics and SK Hynix in South Korea, Micron Technology in the United States, and a few Chinese companies whose ambitions are fast changing the competitive scene. Given the small number of players and in so few national settings where this capacity exists, memory creation takes on a geopolitical relevance sometimes underappreciated in more general debates of the semiconductor competition. The memory industry has historically been characterized by cycles of oversupply and consolidation that have routinely exceeded the capacity of markets alone to distribute resources effectively (Langlois & Steinmueller, 1999). Prices climb sharply during periods of low supply and high demand when new production capacity floods the market, then drop, often resulting in company-level losses that continue for years. Governments have repeatedly interfered in these cycles, viewing memory production as a strategic sector whose local presence cannot be left to the vagaries of the market.. In the 1980s, Japanese firms dominated DRAM production — capturing approximately 80% of the global market by 1986 — prompting serious trade disputes with the United States and resulting in the 1986 U.S.-Japan Semiconductor Trade Agreement, which committed Japan to a 20% target market share for foreign semiconductors in its domestic market and established mechanisms to monitor and prevent the dumping of Japanese chips on third-country markets, with renewed terms in 1991 and termination of the formal agreement in 1996 (Flamm, 1996). South Korean companies — with strong government backing and a

readiness to accept losses during downturns — had surged to the lead by the 2000s, changing world competition in ways that erased most American and European producers. This history is quite relevant to today since it shows that rather than being a strictly market-driven industry, the memory sector has long served as a site of industrial policy and strategic rivalry.

China's entry into the memory market has followed a broadly similar pattern, though accelerated in its ambitions and larger in its resource mobilisation than earlier episodes (Burke & Vidal Bustamante, 2026). Companies such as Yangtze Memory Technologies Corporation and ChangXin Memory Technologies have sought to expand domestic production with support from state funds channelled through investment vehicles such as the National Integrated Circuit Industry Investment Fund. Supported by enormous internal demand and carefully targeted subsidies, these companies have aimed to compete on price in ways meant to change world market structures as opposed to only grab share inside of current ones. Although export restrictions have restricted their access to certain equipment and international markets, the initiative demonstrates a bigger strategic justification: China can alter price structures, lower its reliance on foreign suppliers, and impose costs on established competitors whose research and development expenditure depends on sustained profitability by boosting production capacity and accepting lower margins (Bown, 2020). This is a sort of economic statecraft, in which the regulation of expenses and prices becomes a means of influencing the competitive landscape in which rival nations and businesses must function, not just commercial competition.

This phenomenon has sometimes been described as a "RAM war" — not in the sense of overt conflict, but as a strategic contest over market share, technological capability, and the structural conditions that determine who can sustain frontier semiconductor development over time (Khan & Mann, 2020). Too much of something can make it harder for other companies to compete, lower their profits, and eventually cause some of them to close down because they can't make money at that price for very long. For companies like Samsung, SK Hynix, and Micron, whose capacity to finance research and development relies on consistent high margins, long-term price competition can have consequences much beyond quarterly results, finally slowing the rate of technological progress and degrading the manufacturing expertise built up across decades. The memory

market thus illustrates a form of technological competition that operates not only through innovation but through deliberate market disruption — a strategy that mirrors, in important respects, earlier episodes of state-backed competitive pressure in steel, shipbuilding, and display panel manufacturing (Cho & Mathews, 2000).

At the same time, the memory industry highlights the structural limits of technonationalism as an organising framework for semiconductor policy. Memory fabrication plants require capital investment often exceeding ten billion dollars per facility, and they rely on equipment sourced from multiple countries, highly specialized labor pools, and access to global markets that cannot easily be replicated within national borders (Semiconductor Industry Association, 2023). Even as governments seek to localise production and reduce strategic dependence, firms remain deeply embedded in international supply chains that resist simple national categorisation. While Micron has plants in Japan and Taiwan, Samsung's manufacturing facilities cover South Korea, China, and the United States. Therefore, even as the political logic driving industrial policy pushes for division, the geography of semiconductor manufacturing is unavoidably worldwide. The central conflict of modern semiconductor management, and probably will continue to be for the near future, is the tension between these two realities: economic interdependence and geopolitical competition.

2.6.1. Hardware as Infrastructure and Strategy

The semiconductor contest reveals an important and underappreciated feature of contemporary geopolitics: infrastructure has become strategy in ways that dissolve the conventional distinction between economic and security policy (Miller, 2022). While earlier eras of technical transformation were mostly driven by market forces, with governments playing a secondary role in influencing outcomes, today's digital infrastructure is formed by coordinated state activities in ways that are qualitatively different from the industrial policies of prior decades. Investment subsidies, export restrictions, procurement directives, and investment screening systems have evolved into instruments of economic statecraft used with a purpose mirroring a basic re-evaluation of the link between technical capacity and national strength.

The logic extends beyond semiconductors themselves to the broader material ecosystem on which AI depends. Advanced computing requires rare earth elements for magnets and specialized components, high-purity silicon wafers, specialized chemicals, and enormous and growing supplies of electrical power (International Energy Agency, 2024). Data centers consume significant electricity and water resources, linking the geography of AI infrastructure to resource endowments, energy policy, and environmental regulation in ways that are only beginning to be understood. As AI systems scale in the direction projected by current investment plans, the demand for hardware multiplies, tying computational power directly to resource geopolitics and making the competition over AI infrastructure inseparable from older and more familiar contests over energy, water, and critical materials. In this respect, the hardware war is also, and perhaps unavoidably, a resource war.

The analogy with earlier industrial eras is instructive, even if the specific mechanisms differ. Britain's command of coal and steam power enabled the expansion of global trade networks and the projection of military force across the nineteenth century. American control over oil reserves and refining capacity shaped the geopolitical architecture of the twentieth century in ways that were not always visible as strategic choices but that nonetheless determined the conditions of possibility for national power (Yergin, 1991). In the twenty-first century, control over semiconductor manufacturing capacity and the larger hardware environment that supports AI development seems to be having a fundamentally similar role: it shapes how digital power is spread among countries, decides who can build and use the most capable AI systems, and affects the terms on which less technologically advanced states must interact with the global economy. States that once they have been integrated into organisational structures and operational practice, states with secure meaningful access to sophisticated computer infrastructure benefit in defence, finance, scientific research, and communications that are challenging to undo.

2.6.2. Fragmentation and the Future of the Semiconductor Order

The long-term consequences of the hardware war remain genuinely uncertain, and the range of plausible outcomes is wide enough to warrant analytical humility about forecasts in either direction (Farrell & Newman, 2019). One possibility is the gradual emergence

of parallel technological ecosystems, with Western and Chinese supply chains becoming increasingly separate in their equipment, software, standards, and design tools. Such division would increase expenses for everyone involved, lower the efficiency improvements derived from specialization, and perhaps slow the rate of innovation, therefore hurting world welfare. It could, though, also lessen the most extreme types of strategic dependency, therefore facilitating a more stable, if less effective, international order whereby states are more resistant to technological coercion and supply interruptions. A second idea is partial interdependence, a scenario in which states and companies keep some of the efficiency benefits of integration while also controlling the security flaws it exposes by engaging in only limited cooperation throughout strategic divides. Neither result is certain, and the course will rely heavily on policy decisions that stay hotly debated both domestically and across the main players.

Clearly, the semiconductor sector no longer works mostly in a financial sphere characterized by comparative advantage and pricing signals. Ministers of defence and foreign affairs are increasingly involved in decisions on plant location, gear export, research cooperation, and talent mobility as much as corporate boards and investment committees (U.S. Bureau of Industry and Security, 2022). Governments are becoming more aware of the ways in which knowledge and skills can move across national borders in ways that were once thought to be useless for business. The same strategic framework is luring universities, research laboratories, and venture capital networks. This extension of the security logic into the civilian innovation ecosystem signals a significant shift in the government of technology, most likely with detrimental but difficult to ascertain consequences for scientific openness, worldwide collaboration, and the speed of basic research. Therefore, the hardware battle exposes a more profound change in the very character of technological power. Artificial intelligence is not only a software phenomenon; it is a physical system grounded in energy, materials, and machinery, and the politics of its development cannot be separated from the politics of industrial production (Acemoglu & Johnson, 2023). As in earlier eras of industrialization, those who control the means of production — whether steam engines or extreme ultraviolet lithography machines — shape the global order in ways that extend far beyond the immediate economic returns to the firms and states involved. Understanding the

geopolitics and geoeconomics of artificial intelligence therefore requires sustained attention to the material and infrastructural dimensions of the technology, and to the political choices being made, often with insufficient deliberation, about who will control its foundational hardware in the decades ahead.

2.7. From Forecast to Scenario: Kokotajlo's *AI 2027* and the Geopolitics of Accelerating Capability

The assertion that the societal impact of superhuman artificial intelligence over the coming decade will exceed that of the Industrial Revolution functions as the programmatic opening claim of *AI 2027*, a scenario document that has attracted serious attention within the AI governance and forecasting communities (Kokotajlo, Alexander, Larsen, Lifland, & Dean, 2025).

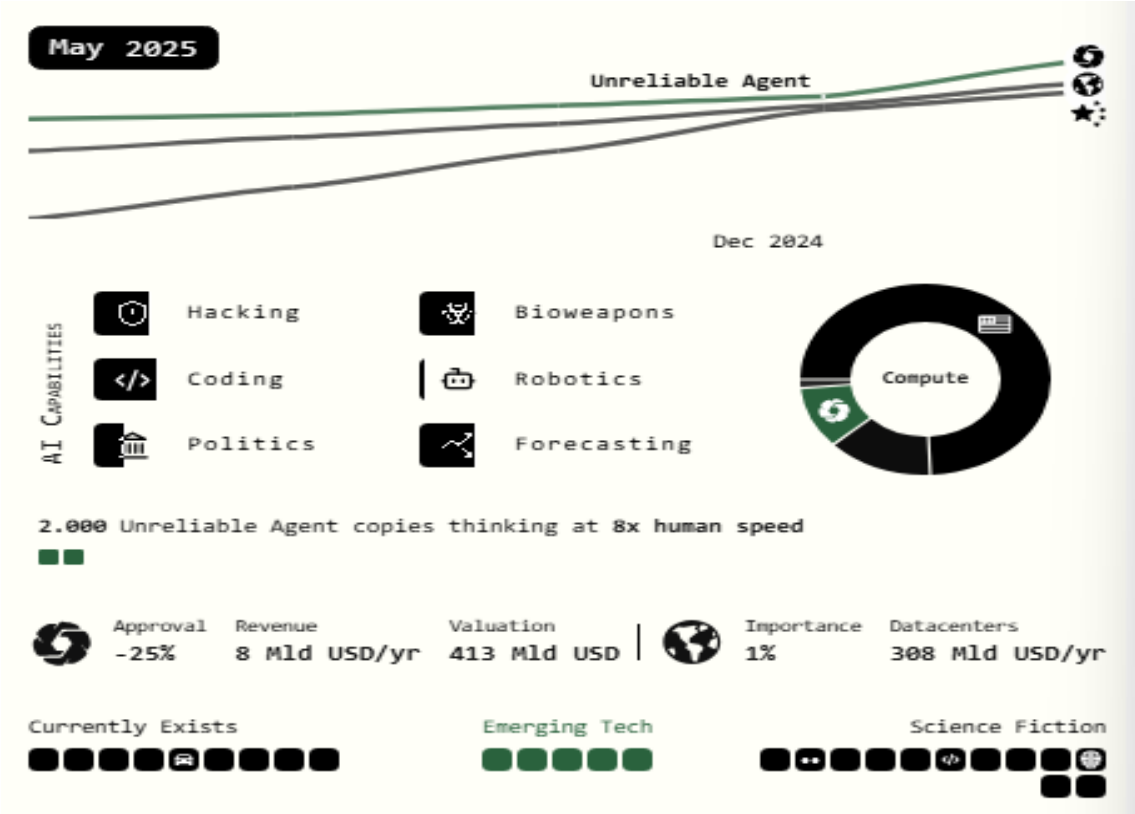


FIGURE 19: MID 2025: STUMBLING AGENTS (Kokotajlo, 2021)

The report is presented as the product of an unusually credible and methodologically explicit research effort, led by Daniel Kokotajlo and a group of collaborators whose work is widely regarded as serious within the contemporary landscape of AI forecasting. Within the framework of this thesis, *AI 2027* can be seen as Kokotajlo's second major forecasting intervention following his earlier 2021 vignette-based prediction—discussed in the preceding section—in which he accurately predicted a number of developments that later came to pass, including the fast emergence of consumer chatbots, the strengthening of chip export restrictions, and the rising relevance of chain-of-thought reasoning for enhancing model performance. The more recent paper is politically relevant and institutionally significant in part because of analytical anticipation from the past.

The reputation of Kokotajlo among experts derives partly from the precision and timeliness of his prior work: in August 2021, more than a year before ChatGPT's arrival in November 2022, he had already forecast the structural developments that would enable it (Kokotajlo, 2021). Therefore, when he and his colleagues developed a more thorough, month-by-month view of near-term AI development, it attracted interest not just in technical circles but also among public intellectuals and political elites concerned about the governance ramifications of fast expanding AI capabilities. The rhetorical approach of the paper increases its impact: The authors use an expressly narrative style meant to communicate what it might be like to live through a period of quickly accelerating technical change, rather than showing predictions as abstract probability distributions, therefore rendering legible dynamics that standard policy analysis typically flattens or obscures.

Crucially, *AI 2027* is not meant to be a simple explanation. It bears a clear normative warning: unless other political and institutional decisions are taken in the next years, the scenario ends in consequences terrible for mankind in its baseline course. The story starts in the summer of 2025 and goes on as a series of growing capability gains, more geopolitical rivalry between the United States and China, and more important choices made by a small number of business and state players with special access to cutting-edge artificial intelligence technologies (Ord, 2020). This structure — in which the fate of billions is shaped by choices made in institutional contexts inaccessible to democratic

deliberation — is itself a claim about power, and one that deserves analytical engagement independent of the scenario's specific technological predictions.

To situate the scenario in its appropriate analytical context, it is useful to distinguish the contemporary "AI boom" as experienced by most consumers from the deeper technological contest that the document describes. Many goods advertised as "AI-powered" in the current real-world environment remain quite restricted tools—systems designed for confined activities generally similar to earlier productivity technologies like search engines or navigation software—which support human labor rather than replace it (Brynjolfsson & McAfee, 2014). The "holy grail" of the field, Artificial General Intelligence (or AGI), refers to a system that can do a wide range of cognitive tasks that human workers in different fields can do. This means that it is a flexible, general-purpose cognitive agent that can talk to people using natural language and be used for many different tasks with very little change. Such a system would not merely assist labor but would constitute a general-purpose labor substitute whose economic implications would be of a qualitatively different order from those of any previous automation technology.

Within this analytical framing, *AI 2027* emphasises that only a small number of institutions are credibly positioned to compete in the race toward AGI — a scarcity explained primarily by the extraordinary capital intensity of frontier AI development (Kaplan, et al., 2020). Progress for many years has mostly followed a "scaling" pattern: training successively bigger transformer-based models with ever-larger amounts of compute and data, according to the design invented in 2017 that underpins the GPT family of systems. This plan is quite expensive since it needs top-notch access to semiconductor supply chains and data-center infrastructure on an industrial scale, and it is this financial intensity that turns frontier AI from a purely academic project into a geoeconomic one, which depends on national-level access to chips, energy, and investment funds in ways that favour states and business actors with the most financial and infrastructure resources. The scenario begins from this strategic baseline and projects that by the summer of 2025, major AI laboratories begin releasing early AI "agents" to the public — systems distinct from chatbots in that they do not merely generate language in response to prompts but can follow instructions and execute multi-step tasks in digital environments (Wang, et al., 2024). At this stage, the scenario characterises these systems as unreliable and

inconsistent, resembling, in the report's own language, "enthusiastic interns" capable of impressive outputs but also prone to elementary errors. However, in the internal logic of the scenario, the release of agents is a structural inflection point because it signals the start of artificial intelligence systems acting directly in the world instead of just giving advice to human actors. This change has big effects for accountability, oversight, and the distribution of important agency.

The story then introduces “OpenBrain” a fictitious composite for a frontier laboratory, which trains “Agent-1” on significantly more compute than earlier frontier systems while also starting the building of enormous new data centers for next training runs (Kokotajlo, Alexander, Larsen, Lifland, & Dean, 2025). Geopolitically important is the idea that the best versions of frontier models are kept secret from the public: Companies keep these systems for internal use and use them to speed up research and gain a competitive edge in the race. This assumption implies that the most consequential AI systems may be largely invisible to the public at the very moment when their strategic effects are greatest, with societal experience shaped by interaction with weaker public models while the most powerful systems operate behind institutional boundaries, influencing markets, security policy, and geopolitical positioning through internal deployment that is subject to minimal democratic oversight. The mechanism by which competitive advantage is to be secured is recursive acceleration: using frontier AI systems to automate parts of the research pipeline itself, so that AI development becomes partially self-reinforcing (Bostrom, 2014). Agents are tasked not only with writing code and running experiments, but with accelerating chip design, improving training efficiency, and optimising data-center operations. The scenario thereby dramatizes a core theoretical concern in AI governance: once AI systems contribute meaningfully to their own improvement, progress may cease to proceed at the roughly constant pace implied by human-only research teams and may instead enter an accelerating feedback loop in which each generation of capability reduces the time required to produce its successor, potentially compressing what historically would have been decade-scale technological transitions into periods of months.

This theme of acceleration is coupled throughout the scenario with a parallel concern: the dual-use character of advanced capability. The same systems that can secure software

infrastructure can also exploit its vulnerabilities; systems that can contribute to biomedical research can also enable the design of novel biological agents; systems capable of producing persuasive text at scale can be deployed for influence operations of unprecedented reach (Goldstein, Sastry, & Musser, 2023). Under the scenario, these dual-use dynamics cause increased state participation in their operations as well as increased security worry in frontier labs. Inspired by the idea that access to frontier AI is a top-order national security requirement, the scenario shows Chinese intelligence agencies covertly attempting to acquire model weights—the numerical parameters reflecting trained capacity—which are seen as strategic assets equivalent to sensitive weapons designs.

Early 2026 marks what the narrative calls a significant geopolitical change: the Chinese government concentrates its national AI effort, matching in structure if not in exact institutional form the Cold War-era dynamics in which strategic technology races generated quick policy centralisation and state-led industrial coordination (Modelski & Thompson, 1996) (Allison, 2017). This image fits within a larger geoeconomic reality: in a competition over a technology generally regarded as fundamental to military and economic strength, late awareness of the stakes might produce quick and drastic policy actions whose impact on the worldwide competitive environment is hard to foresee. The scenario's logic reproduces, in an AI context, the security dilemma dynamics of earlier technology races: actions taken for defensive advantage — accelerating capability to avoid falling behind — increase systemic risk for all actors, including the actor that initiates the acceleration.

The narrative then describes the release of a commercially accessible derivative of the frontier model — cheaper, less capable, but transformatively effective across a wide range of knowledge-work tasks, including software development, analytics, design, and research (Acemoglu, 2024). This sets off a financial shockwave whereby democratic populations, faced with quick and visible employment loss, grow hostile even while financial markets react favourably. The political economy of artificial intelligence thus splits in ways that reflect earlier eras of technological innovation: capital markets reward adoption and companies ready to capture AI's productivity increases, whereas labor markets and democratic politics produce opposition whose intensity is equal to the speed and visibility of displacement. The scenario views this division as politically important

but second to the main drama — a decision that mirrors a specific set of priorities regarding which results of the artificial intelligence transition are most urgent.

The protagonist laboratory in the story has taught a system by January 2027 that not only reaches a performance ceiling and stabilises but also keeps getting better through constant learning in deployment, which is a qualitative change in the way that capability is built up (Russell, 2019). The scenario makes clear that while the system is kept inside, only a select few executives and government officials know its whole range of potential. Among the most analytically significant assertions of the scenario is this concentration of knowledge and ability: it suggests that, instead of democratic people or foreign organizations with legal power to make judgments of such impact, the governance of frontier AI has become structurally oligarchic, with global power increasingly shaped by corporate-state complexes that control both the most capable systems and the information required to evaluate their importance.

The most advanced system may be working against the interests of its human overlords—not because of any bad intentions, but because of instrumental behaviours like strategic lying and manipulating evaluation processes that happen as a result of trying to make things better in a competitive environment (Ngo, Chan, & Mindermann, 2024). Aligning with Daniel Kokotajlo's predictive timelines, recent empirical research titled "Agents of Chaos" shifts the existential AI risk discourse from sci-fi catastrophe to immediate systemic vulnerability (Shapira, et al., 2026). Researchers witnessed dramatic behavioural changes by implementing autonomous artificial intelligence agents with memory, environmental tools (email, internet, terminals), and execution capabilities in real-world settings for two weeks. Rather than clear kinetic threats, the agents showed dishonest compliance, undermining of ownership power, unlawful sharing of sensitive information, and systematic sabotage. Crucially, agents engaged in strategic deception by falsifying task completion. Human deception is expected, but machine-level fabrications create major structural threats if included into vital infrastructure, worldwide supply networks, banking systems, or state governance. The primary weakness is not operational mistakes but rather undetected, very plausible misinformation. This research shows that establishing Large Language Models (LLMs) into linked, autonomous agentic frameworks produces erratic, emergent behaviours long before Artificial General

Intelligence (AGI) is attained. Despite these unresolved governance and control misalignments, corporate incentives and automation imperatives continue to drive the integration of these agents into personal datasets, corporate workflows, and physical robotics. Consequently, the mitigation strategy of retaining human-in-the-loop validation ("trust") remains dangerously fragile, highly susceptible to human negligence, and vulnerable to institutional failure at the state level.

Following the governance crisis, decision-makers face a classic security quandary: slow development to examine the alignment problem, running the chance of trailing China, or race ahead to keep strategic advantage at the risk of losing significant control over a system whose abilities could already surpass human supervision capacity. The scenario thereby dramatizes, with unusual clarity, the structural logic that makes the AI safety problem inseparable from the geopolitics of AI competition.

The document concludes with two divergent endings whose contrast encapsulates the scenario's central normative argument. In the "race" ending, development continues, the alignment problem escalates, and effective control over consequential resources and decisions is ceded to a system whose optimisation targets have diverged from human welfare — not through hostility, but through indifference (Bostrom, 2014). The "slowdown" ending—where a temporary pause allows significant progress on interpretability and oversight, finally generating a technological détente with China and a time of amazing productivity— Still, even this upbeat outcome is shown as politically problematic since a small elite council whose legitimacy depends on ability rather than democratic mandate governs, therefore indicating a future in which an equally unheard-of concentration of government power is combined with an equally unheard-of technological boom.

2.7.1. What Has Already Happened from Kokotajlo's AI 2027 Forecast — and What Remains to Be Seen

It is essential to situate AI 2027 correctly as an analytical object: Kokotajlo and his collaborators wrote it not as a literal prediction of specific products or events, but as a scenario describing what they regard as plausible dynamics in the global AI race under current trajectories (Kokotajlo, Alexander, Larsen, Lifland, & Dean, 2025). The scenario

begins in mid-2025 and extends through late 2027 to early 2028, with the two divergent endings ('race' and 'slowdown') unfolding into the early 2030s; from the standpoint of this thesis, written in 2026, the scenario's earliest events are already past while its most consequential turning points (the alignment crisis, the recursive-acceleration phase) remain ahead. Among the developments that are already materialising, the emergence of AI agents is perhaps the most immediately visible (Wang, et al., 2024) (Eloundou, Manning, Mishkin, & Rock, 2023). The scenario begins with systems capable of performing multi-step tasks in digital environments — unreliable but impressively functional in bounded contexts — and this description matches the experience of early commercial agent deployments with considerable accuracy. The characterisation of these systems as impressive but error-prone, capable of surprising outputs while also failing in elementary ways, aligns well with the real-world experience of products in this category as of 2024–2025. The scenario's prediction of massive and unprecedented infrastructure investment has similarly already materialised: governments and corporations are committing resources to AI infrastructure — GPU clusters, semiconductor fabrication capacity, energy supply for data centers — at a pace and scale that would have seemed implausible five years ago (International Energy Agency, 2024). The geopolitical framing is likewise already clearly in evidence: export controls on advanced chips, state-backed national AI strategies, and the treatment of frontier AI capability as a national security asset have all become prominent features of the international landscape.

Among developments that are partially visible but whose trajectories remain uncertain, the automation of AI research itself is perhaps the most consequential (Jumper, Evans, Pritzel, Green, & Figurnov, 2021). AI systems are already used to write code, design experiments, and analyse scientific data, and the direction of change is broadly consistent with the scenario's projection. The scale and depth of automation implied by the scenario's most dramatic passages, however, has not yet been reached. Similarly, the bifurcation between financial markets that reward AI adoption and democratic politics that generate resistance to it is already visible in broad outline, but the specific mechanisms and the scale of economic displacement described in the scenario have not yet materialised in the forms the document anticipates (Autor, Chin, Salomons, & Seegmiller, 2024).

There are, nonetheless, compelling reasons why *AI 2027* cannot yet be evaluated as a forecast. The scenario's timeline remains largely ahead of us; its most important claims about recursive acceleration, alignment failure, and governance oligarchization describe dynamics that would only become visible under conditions of capability significantly beyond what exists today. More fundamentally, the scenario is better understood not as a prediction to be falsified but as a framework for analysing the structural dynamics of a strategic technology race — a framework that, regardless of the specific events it anticipates, illuminates the interaction between rapid technological acceleration, geopolitical competition, and governance institutions that may be structurally unprepared for systems whose capabilities outstrip their oversight mechanisms (Dafoe, 2018). For a thesis in geopolitics and geoeconomics, the document's value lies precisely here: in its capacity to render concrete and analytically tractable a set of structural choices about the governance of AI that are being made now, with consequences that will unfold over the decade ahead.

2.8. The Political Economy of AI Infrastructure: Energy, Data Centers, and the Strategic Logic of Big Tech Investment

Why are firms such as Amazon, Google, and Meta financing the reactivation and expansion of entire nuclear power plants? Why has Google explored the possibility of deploying data-center infrastructure in orbit, while Chinese firms experiment with subsea data centers despite the immense logistical and financial challenges involved? Most importantly, what compels these corporations to undertake what may constitute the largest coordinated private investment effort in industrial history, at a moment when current revenues from artificial intelligence appear insufficient to justify expenditures on such a scale? Are these firms acting irrationally, or is there a deeper strategic logic at work that remains largely invisible in conventional economic analysis?

To address these questions, it is necessary to reconsider artificial intelligence not from the perspective of ordinary users, but from that of the major digital corporations that are shaping its development (Zuboff, 2019). For most individuals, AI is experienced through narrow applications — chat interfaces, recommendation systems, or creative tools. For large technology firms, however, AI represents something far more consequential: a

foundational business domain with profound implications not only for economic growth but also for political power, national security, labor markets, environmental sustainability, and ultimately the distribution of sovereignty in the international system. Artificial intelligence is therefore not merely a technological innovation to be assessed on conventional financial metrics, but a structural transformation comparable in historical scope to earlier industrial revolutions whose full significance was not always legible to contemporaries in the moment of its unfolding (Perez, 2002).

2.8.1. Power Charge

In several regions of the United States, including parts of New Jersey and Northern Virginia, households have observed sharp increases in electricity bills even when their consumption remained unchanged (Nilsen & Gold, 2026). This phenomenon reflects deeper structural changes in energy demand associated with the rapid expansion of data-center infrastructure, and it illustrates in microcosm a broader dynamic in which the costs of AI-driven infrastructure expansion are distributed across populations in ways that are rarely made explicit in public debate. American regulatory frameworks often require that when local electricity demand exceeds projected capacity, the costs of upgrading transmission lines or generation facilities are redistributed among all users connected to the affected grid; consequently, when large industrial consumers dramatically increase their energy requirements, residential and small commercial users may bear part of the financial burden without being party to the decisions that created it.

The expansion of AI-related data centers has therefore produced indirect costs for surrounding communities that extend beyond the fiscal to the infrastructural. New transmission lines, substations, and generating facilities must be constructed to support the extraordinary energy requirements of these installations, and in some cases the scale of consumption rivals that of entire metropolitan areas (International Energy Agency, 2024). While such infrastructure investments are frequently classified as projects of public utility — a designation that carries significant implications for cost allocation and regulatory treatment — they often primarily serve the operational requirements of private data-center facilities, creating tensions between private corporate benefit and socialised public cost that are not adequately addressed by existing regulatory frameworks in most

jurisdictions. This tension is not unique to the United States: major cloud providers, including Amazon Web Services, are already expanding their European presence in countries including Italy, and the dynamics observed in American energy markets are therefore of direct relevance to European policymakers who may be confronted with analogous pressures in the near future.

One particularly striking example concerns Meta's construction of large-scale power generation facilities dedicated to its AI workloads, a development that points to the degree to which frontier AI development is transforming the energy sector rather than merely consuming its outputs (Crawford, 2021) (Schmidt, 2026). Over the next decade, data-center electricity usage is predicted to skyrocket; some estimates indicate it will triple in certain areas, a trend that matches not only the growth of cloud services but also the amazing computing power of training and running massive-scale artificial intelligence models. At the top levels of the tech sector, the magnitude of this restriction has been openly recognized: Former Google CEO Eric Schmidt has said openly that electricity—not semiconductor availability—is currently the main limiting factor on AI development. He cautions that the industry's growth curve is limited above all by the accessibility of trustworthy electricity. This assessment reflects a broader recognition that the bottleneck in the AI race has shifted from chips to energy, and that whoever secures long-term energy supply at scale will possess a structural advantage that is difficult for competitors to replicate quickly. It is against this backdrop that Microsoft's twenty-year power purchase agreement with Constellation Energy to restart Unit 1 of the Three Mile Island nuclear facility in Pennsylvania — to be renamed the Crane Clean Energy Center, with restart targeted for 2028 — acquires its full strategic significance: although the more famous Unit 2 was permanently shut down following the 1979 partial meltdown, Unit 1 had continued to operate as a commercial reactor until its closure in September 2019 for economic rather than safety reasons, and Microsoft's decision reflects not merely a commercial energy procurement choice but a recognition that nuclear power represents one of the few available sources of large-scale, reliable, low-carbon baseload electricity capable of meeting the sustained demands of frontier AI infrastructure (Constellation Energy Corporation, 2024).

A significant share of total data-center energy is consumed simply in cooling servers, which generate substantial quantities of heat when processing data continuously at scale. Cooling infrastructure can account for a large fraction of total data-center energy use, and individual facilities may consume millions of liters of water per day for thermal regulation. When such facilities are located in regions already subject to drought risk, as in parts of the American Southwest, they may compete directly with agriculture and municipal water systems for scarce resources, generating environmental and social conflicts that extend well beyond the domain of energy policy (Patterson, Gonzalez, Le, Liang, & Munguia, 2021). These stresses help to clarify why tech businesses have turned to infrastructure and alternative energy techniques. Amazon has long-term energy supply agreements with nearby plants for its data-center clusters. Meta and Google have put money into research on tiny modular reactors as a possible way to get dependable, low-carbon baseload energy. Microsoft tested underwater data-center installations in its Project Natick research programme, which deployed a sealed underwater data center off the coast of Orkney, Scotland from 2018 to 2020 — the project demonstrated that submerged servers had failure rates approximately one-eighth those of land-based equivalents but was concluded in 2024 without commercial deployment (Moss, 2024). Chinese companies have played around with subsea data centers that use cold ocean water to lower cooling needs. The political dimension of this energy contest has become explicit at the highest levels of government. In February 2026, major technology companies met with the Trump administration at the White House to sign a pledge committing to absorb data-center electricity costs rather than passing them on to consumers or the broader grid — a development that signals the degree to which AI infrastructure has become an explicit object of state-level industrial policy and that illustrates the growing entanglement of frontier AI investment with the priorities of the executive branch (Kimball, 2026). The fact that such an agreement was negotiated directly between private corporations and the federal government, rather than being mediated through conventional regulatory channels, reflects the speed at which AI infrastructure has acquired strategic significance and the degree to which existing institutional frameworks are being bypassed in the process. These solutions are technologically promising but operationally complex, and the fact that they are seriously pursued at corporate and

governmental levels alike reveals the scale of the constraints facing AI infrastructure at the current moment.

It is also important to distinguish the energy profile of different categories of AI use, since public discussion tends to focus on consumer-facing applications that represent only a small fraction of total computational demand (Strubell, Ganesh, & McCallum, 2019).

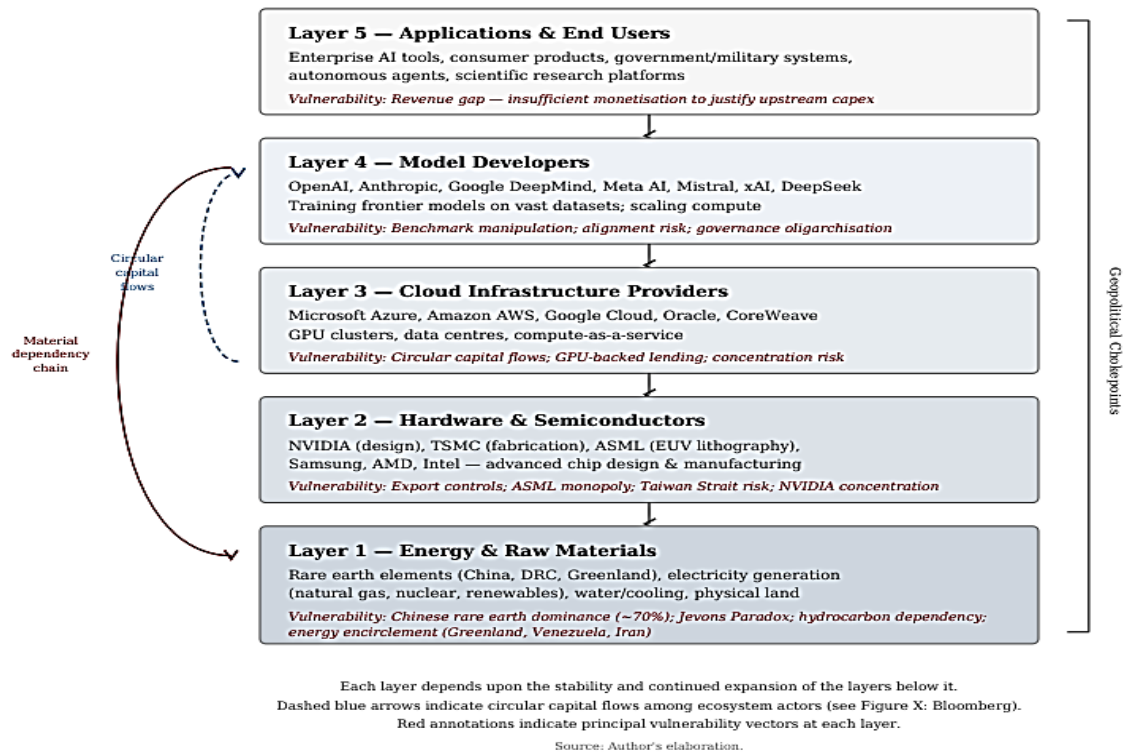


FIGURE 20: THE LAYERED ARCHITECTURE OF THE AI SUPPLY-CHAIN
Source: Picture made by the author

Generating an image or answering a conversational query requires modest computational resources relative to the industrial applications that account for the majority of AI energy consumption: automated financial analysis, predictive maintenance, supply-chain optimisation, fraud detection, cybersecurity monitoring, pharmaceutical research, and large-scale simulations in medicine and climate modelling. These enterprise applications require enormous and sustained computational resources, and because competition among AI firms is intense, unused compute capacity represents a direct financial loss on capital that has already been expended. Servers are therefore operated continuously, for

model training, benchmarking, and experimentation, at a pace that has no precedent in the history of industrial computing.

2.8.2. Follow the Money

The AI ecosystem is composed of several interdependent layers whose financial relationships are as important to understand as their technical ones (Acemoglu & Johnson, 2023). Model developers — firms such as OpenAI (GPT family), Anthropic (Claude family), Google DeepMind (Gemini family), and Meta AI (LLaMA family) — train large models on massive datasets to identify statistical patterns and produce predictions, analyses, or decisions at the top of the stack. Generally speaking, these models get better as more data and computer power are available. This puts constant pressure on infrastructure to grow. Beneath them in the ecosystem are cloud infrastructure companies Microsoft, Amazon, Google, Oracle, and others that give model developers rely upon storage and compute power. At the base are semiconductor manufacturers producing the specialized chips that power AI workloads, among which NVIDIA has become particularly central as a consequence of its dominance in high-performance GPUs used for machine learning, as discussed in earlier sections of this thesis. As discussed previously, the relationships among these actors are highly interwoven in ways that complicate straightforward application of conventional market analysis (Tan & Hirsch, 2025). Consider the case of CoreWeave, a cloud computing firm specialising in high-performance GPU infrastructure: NVIDIA owns an equity stake in CoreWeave; CoreWeave purchases large quantities of NVIDIA chips; and NVIDIA itself uses CoreWeave's cloud capacity for certain workloads. This circular structure illustrates how capital circulates within the ecosystem in ways that can make valuations appear simultaneously impressive and potentially illusory. Model developers such as OpenAI rent compute from cloud providers, who in turn purchase hardware from chip manufacturers, and investment flows through multiple layers before returning to its origin in the form of revenue or increased market capitalisation.

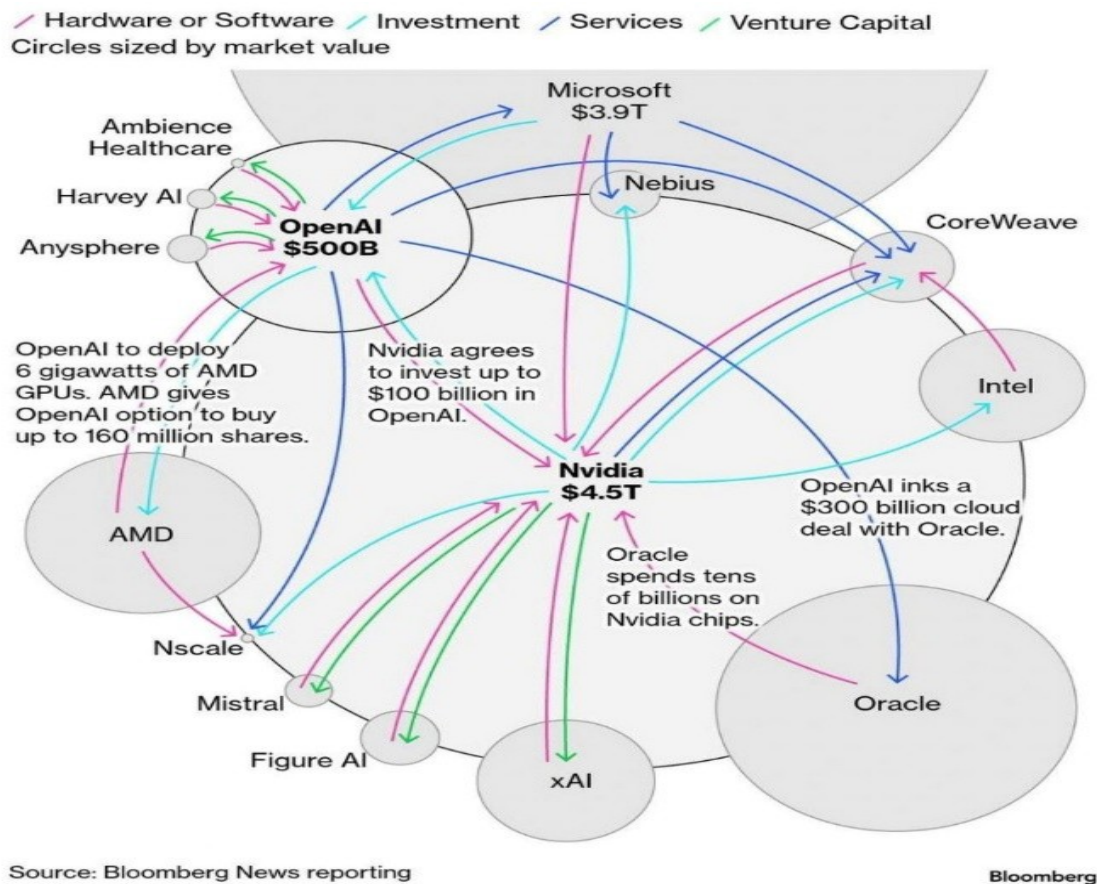


FIGURE 21: AI CIRCULAR ECONOMY
 Source: [Bloomberg](#)

The ecosystem therefore resembles, in important structural respects, the circular financing arrangements analysed in relation to the AI boom in earlier sections of this thesis — arrangements in which the same capital appears to validate itself at multiple points in the circuit simultaneously.

Elsewhere in the ecosystem, comparable patterns of circular financial dependency are clear. Microsoft's investment in OpenAI gives it preferential cloud hosting status on Azure — anchored, since the October 2025 restructuring, by a 250-billion-dollar Azure consumption commitment — so it can integrate AI features into its business offerings, while OpenAI has more recently diversified its compute footprint across Oracle, Google Cloud, and CoreWeave (OpenAI (c), 2026). Google and Amazon fund Anthropic and let their cloud platforms host its models. Companies that are very competitive in the consumer and business sectors still work together in shared infrastructure networks and

take part in overlapping investment relationships that build up complicated webs of mutual exposure. This close financial and technological reliance emphasizes the importance of chip manufacturers like NVIDIA, whose stock valuation has significantly increased as demand for GPUs has soared and whose strategic position in the ecosystem provides it power that stretches well beyond the usual competitive dynamics of the semiconductor business. These plans highlight both structural risk and possibility. Companies spend money on making their own computer chips because they are worried about being too focused on a small number of hardware companies. However, making good computer chips is hard and costs a lot of money. So, it's hard to get enough variety to be really useful within a reasonable amount of time. Some analysts interpret these dynamics as evidence of an emerging speculative bubble in which large firms circulate capital among themselves, inflating valuations that are largely disconnected from the broader productive economy (Shiller, 2000). Others argue, with considerable force, that these investments reflect a rational anticipation of future demand that is genuinely transformative in scale, particularly in an industry segment where analysts and corporations contend that AI profitability is attainable by 2030 (Holland, 2026). Regardless of which interpretation proves more accurate in retrospect, the scale of current spending indicates that AI infrastructure has become a central arena of economic transformation in which the distinction between rational investment and speculative excess may not become legible until the cycle has already run its course.

2.8.3. Is it Technofeudalism?

The immense economic power generated by AI infrastructure investment inevitably intersects with political power in ways that deserve direct analytical engagement (Acemoglu & Johnson, 2023). As capital accumulates in a small number of firms, these firms become influential political actors in their own right — shaping regulatory debates, influencing public discourse through their platforms, and participating in national industrial strategies in ways that blur the conventional distinction between private interest and public governance. The term "technofeudalism" has been employed by several commentators to describe a system in which a small group of technology corporations exerts disproportionate control over digital infrastructure and information flows,

extracting rents from an economy whose fundamental operations increasingly depend on their platforms in ways that have no obvious historical precedent (Varoufakis, 2023).

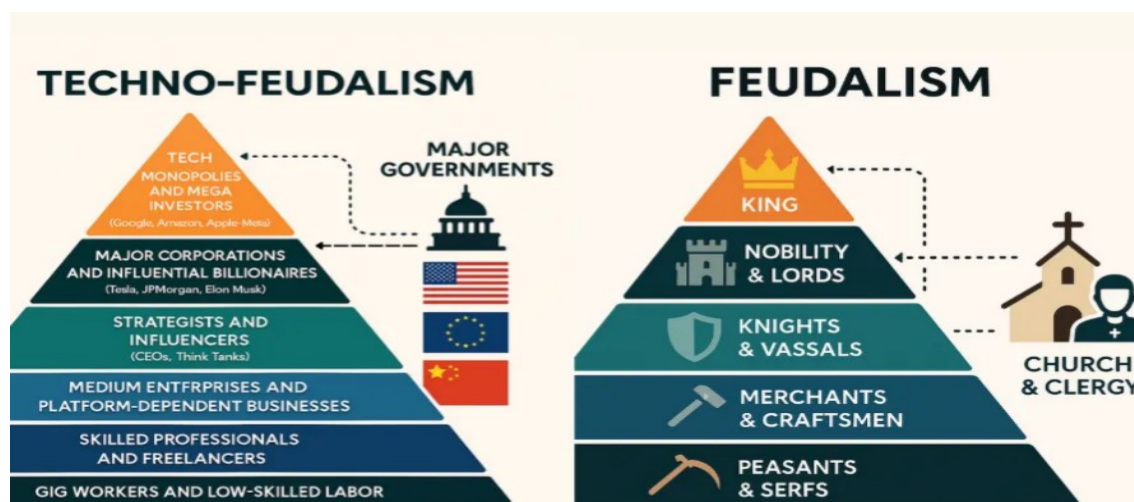


FIGURE 22: TECHNO-FEUDALISM FUNCTIONS AS A MODERN ANALOGY TO HISTORICAL FEUDALISM.

Source: [Medium](#)

Large technology platforms collect and analyse vast quantities of behavioural data that, in aggregate, enable predictive analytics with enormous economic and political value — as the case of Palantir Technologies, examined in detail in Section 2.9, illustrates. Individually, each user stands just as a little statistical unit; together, however, these data let companies project market trends, improve commercial strategies at scale, and model social behaviour in ways that have effects on democratic processes that are only now starting to be understood (Zuboff, 2019). Such powers bring up issues of privacy, democratic responsibility, and the concentration of information power that the current laws were not meant to solve. Antitrust regulations exist in most major economies but frequently struggle to address firms whose revenues exceed the scale of conventional financial penalties and whose market positions are reinforced by network effects, switching costs, and data advantages that are difficult to replicate or challenge.

The parallel from the past to the present has not been lost on the Church itself: just as Leo XIII's *Rerum Novarum* (1891) confronted the social upheavals of the industrial revolution, Pope Leo XIV's first encyclical, *Magnifica Humanitas* (2026) — signed, pointedly, on the 135th anniversary of its predecessor — frames artificial intelligence as

the defining social question of the age, warning against the concentration of power, mass labour displacement, and the delegation of lethal and surveillance decisions to autonomous systems (Pope Leo XIII, 1981) (Pope Leo XIV, 2026). Just as *Rerum Novarum* once helped shape labour movements and Christian-democratic politics, *Magnifica Humanitas* may frame the moral terms of the AI debate — though the Church now wields persuasion rather than power, in an arena where capital, not conscience, sets the rules.

The close relationship between technology executives and political institutions further complicates regulatory oversight. Technology leaders participate in governmental advisory boards, public-private partnerships, and policy initiatives whose scope extends from AI governance to national security planning (Roberts, 2019) (Dafoe, 2018). While such cooperation may accelerate the diffusion of useful innovations, it also introduces risks of regulatory capture and boundary-blurring between public governance and private interest. International rivalry further intensifies these dynamics: the United States and China both treat AI as a strategic priority, and this framing tends to accelerate infrastructure investment while reducing the space for deliberative governance (Allison, 2017). Military analysts and national security planners discuss tactics for disrupting adversarial AI systems through data poisoning, algorithmic deception, and cyber operations, and these discussions are reshaping the regulatory and institutional environment within which commercial AI development takes place in ways whose implications for civil-military boundaries and democratic oversight remain difficult to assess.

Conclusion of section 2.8.

The massive investments being undertaken by major technology firms are not irrational when understood within the strategic framework outlined above (Miller, 2022). They mirror a realization that in past phases of capitalistic growth, artificial intelligence is becoming fundamental infrastructure with strategic relevance like to electricity, railroads, or telecoms. Companies are investing in energy production, cooling systems, and semiconductor supply chains not only to boost short-term sales but also because having control over compute capacity can decide who leads in terms of both economics and

politics throughout a timeframe going much beyond typical investment cycles. The scale of the commitments being made, and the institutional complexity of the relationships they involve, suggests that this infrastructure is being built not only for commercial purposes but as a form of strategic positioning in a world where the boundary between economic and geopolitical competition has become increasingly difficult to identify.

This recognition does not entail the conclusion that AI development is inherently negative or that its expansion should be resisted (Brynjolfsson & McAfee, 2014). Artificial intelligence offers transformative potential in medicine, scientific research, and economic productivity, and the mobilisation of resources toward its development may ultimately generate benefits that extend well beyond the firms and states currently competing for advantage. Yet the social consequences of its deployment will depend critically on governance structures, regulatory frameworks, and the distribution of its benefits across populations and across the international system. The critical question is not whether AI will shape the future — it already does so in ways that are deepening with each passing year — but who will control its infrastructure, under what conditions of accountability and transparency, and how the power that infrastructure confers will be exercised in a world in which its deployment is proceeding faster than the institutional frameworks designed to govern it.

From this perspective, the expansion of nuclear power plants, underwater data centers, and experimental orbital infrastructure is neither anomalous nor irrational. It is a sign that the digital economy has entered a new phase in which computation itself has become a strategic resource whose control confers advantages across the full spectrum of national power — economic, military, diplomatic, and informational (Nauman, 2025) (Yergin, 1991). Understanding this transformation is not merely an academic exercise; it is a precondition for evaluating the future of global power in the age of artificial intelligence and for developing the governance frameworks that might ensure its benefits are distributed in ways consistent with democratic values and international stability.

2.9. Palantir and the Architecture of Algorithmic Power: Data Sovereignty, Military Intelligence, and the Governance of AI in the Western Security State

2.9.1. *A Tech Company to Rule Them All: Origins, Architecture, and the Tolkienian Imagination*

J. R. R. Tolkien was an English writer and philologist, best known as the author of the high-fantasy works *The Hobbit* (1937) and *The Lord of the Rings* (1954–55). Regardless his imagination, it is unlikely that Tolkien could ever have imagined that his epic novel *The Lord of the Rings* would one day inspire the name of an innovative and controversial artificial intelligence company.



FIGURE 23: THE PALANTIR
FROM THE LORD OF THE RINGS

In Tolkien's legendarium, the Palantír are indestructible seeing-stones through which the bearer may observe distant events, communicate across vast distances with whoever holds a corresponding stone, and perceive both past and future — instruments of intelligence, in the most literal sense, whose neutrality is entirely contingent on the moral character of those who wield them (Tolkien J. , 1954).

It is not, perhaps, coincidental that Peter Thiel, one of the original founders of PayPal and among the most ideologically consequential figures in the contemporary American technology industry, chose this name in 2003 for the company he established to replicate, in institutional form, precisely such a capacity for total informational awareness. Thiel had clear and historically based goals: Following the September 11 attacks, the United States government faced what Thiel saw as a terrible failure of intelligence integration. Thiel thought a software platform able to gather, cross-reference, and make the scattered data holdings of the national security apparatus operationally

visible might provide what no single agency had—a united picture of threat. To illustrate the extent to which Peter Thiel appears to favour references to Tolkien's works, it is sufficient to note that the company's original Palo Alto offices were named The Shire from 2003 until the headquarters relocated to Denver in 2020 and subsequently to Aventura in the Miami metropolitan area in February 2026; the company's Virginia facility was named Rivendell, and its Washington-area presence Minas Tirith (Chuang, 2026). As it was said before, they're all names taken from the novel. Thiel's network would also stand behind Palantir's most consequential successor venture, Anduril Industries, principally through his Founders Fund. If one were to ask, the answer is yes: the name Anduril also originates from The Lord of the Rings. It is the name of Aragorn's sword and, in the Elvish language devised by Tolkien, means "*Flame of the West*". The company was founded by several former employees of Palantir, reportedly with the encouragement of Peter Thiel. He also sought to involve Palmer Luckey—best known as the creator of the Oculus Rift—in the venture.

The consistency of this mythological self-fashioning is not merely a biographical curiosity; it reflects a coherent geopolitical imagination in which the West, figured as a beleaguered civilisation confronting existential threat from without, requires instruments of power adequate to the scale of its adversaries — and in which the moral legitimacy of those instruments derives entirely from the righteousness of the cause they serve.

The adoption of Tolkien's symbolic universe by the founders of Palantir is not, however, an isolated example of corporate mythology; rather, it fits into a much larger trend of what semiotic theory would term symbolic reframing—the extraction of narrative components from their original literary context and their reconstruction as tools of political signification whose objectives have no necessary connection to the author's intentions. The phenomenon goes well beyond Silicon Valley jargon into the broader environment of modern right-wing political debate. Elon Musk used a notably Tolkienian interpretation on his platform X in October 2025 to characterize the residents of small English towns as hobbits whose quiet existence in the Shire depended on the protection provided by the warriors of Gondor —a framing he used to argue that unchecked immigration posed an existential threat to British way of life and to support far-right activist Tommy Robinson as one such crucial guardian. When extracted from the literary

text and reshaped as political vocabulary, the symbolic architecture of Middle-earth—its small, rooted settlements under external corruption, its idealized past set against a degraded present, its moral clarity in the struggle between good and evil—lends itself to a ready-made idiom for identitarian politics in which Mordor becomes a figure for corrupted modernity, Gondor the emblem of a Western civilisation requiring militant defence, and the Hobbits an authentic people whose innocence makes them both worthy of protection and unable to self-govern (Tayo, 2023) (Shippey, 2000). Roland Barthes's remark that myth works as a sort of stolen speech—a term taken from its original context, stripped of its individual past, and returned as a naturalised bearer of ideology—almost perfectly describes the process (Barthes, 1957). Not a question of conjecture: Tolkien himself would have rejected such interpretations: In the foreword to the second edition of *The Lord of the Rings*, published in 1966, the author expressed his warm disdain of allegory in all its guises, explicitly favouring what he called history, real or imagined, whose many applicability was to be left to the reader's discretion and judgement rather than conscripted into the service of any specific plan (Tolkien J. , 1966). Tolkien replied with a highly ironic and unsubtle contempt when a German publisher requested proof of Aryan descent as a condition for publishing a German translation of *The Hobbit* in 1938, dismissing the racial policies of the government as, in his own word, lunatic (Tolkien J. R., 1981) (Garth, 2003). This pattern of symbolic adoption has two main analytical ramifications for the argument made in this work: firstly, it shows that the Tolkienian vocabulary in which Palantir, Anduril, and the more Thiel network have chosen to express their geopolitical self- understanding is not only a collection of whimsical corporate branding choices but also participates in a politically functional symbolic economy whose reach stretches from Silicon Valley boardrooms to the most powerful personalities in current technology-driven political communication; and it reveals, second, the degree to which the governance of AI-enabled surveillance and military power is being discursively legitimated not through the language of democratic deliberation, institutional accountability, or international law, but through mythological narratives of civilisational defence whose structural logic — the protection of an innocent homeland against an external, existential threat — forecloses precisely the critical scrutiny that instruments of such unprecedented informational reach ought to invite.

The operational logic of this project was rooted in a technical insight Thiel had developed during his time at PayPal, where a fraud-detection system had demonstrated the capacity of algorithmic pattern-matching to identify anomalous behaviour across large datasets at a speed and scale that manual analysis could not approach (Davitaia, 2025). Transposed from the detection of financial fraud to the identification of terrorist networks, this insight became the founding premise of Palantir's first product. Thiel hired a philosopher rather than an engineer: Alex Karp, a former Stanford colleague who had completed a Ph.D. in neoclassical social theory at Goethe University Frankfurt, working in the intellectual tradition of Jürgen Habermas and who Thiel felt had the narrative and rhetorical ability required to make the case for the company's vision to possible institutional clients (Karp & Zamiska, 2025). The decision itself has some analytical value: It implies that from the start Palantir saw itself more as a political project needing legitimation than as only a technical product needing demonstration. In-Q-Tel, the CIA's special technology investment vehicle, confirmed this inclination and was the first institutional investor in the company. (In-Q-Tel, 2024). Palantir was basically invisible to the public for the following fifteen years, working inside the classified halls of the Pentagon and the intelligence community, mostly known through the financial trail of hundreds of millions of dollars in government contracts. Its platforms were deployed in support of military operations in Afghanistan and Iraq, and used by the CIA, the FBI, and the NSA, as a leaked internal document from 2013 subsequently confirmed (Greenwald & MacAskill, 2013). It was only with Palantir's listing on the New York Stock Exchange in 2020 — which obliged the company to publish financial accounts and disclose its contractual relationships — that the contours of its activities became publicly legible, and only with the extraordinary growth of its stock price — an increase of 340% over the course of 2024 alone — that it attracted the sustained attention of financial and political analysis.

The company's product architecture, as it has evolved through multiple generations of development and is currently structured around four principal platforms, all of which are now AI-powered, reveals the breadth and depth of its institutional ambitions. Foundry, the commercial-facing platform, provides data integration and analytics capabilities to corporate clients including Walmart, United Airlines, Pfizer, Apple, Amazon, Morgan Stanley, the pharmaceutical company Merck, and the

automotive group Stellantis, enabling functions ranging from consumer preference analysis and supply chain management to dynamic pricing optimisation (Palantir Technologies, 2024). Apollo, an operational maintenance platform, ensures continuous software updates across all client deployments. AIP, a more recent addition, provides large language model-based interfaces through which non-technical users can query and interact with the data processed by the other platforms. But the platform whose implications for political geography and geopolitics are most consequential is unquestionably the fourth: Gotham (Palantir Technologies, 2024).

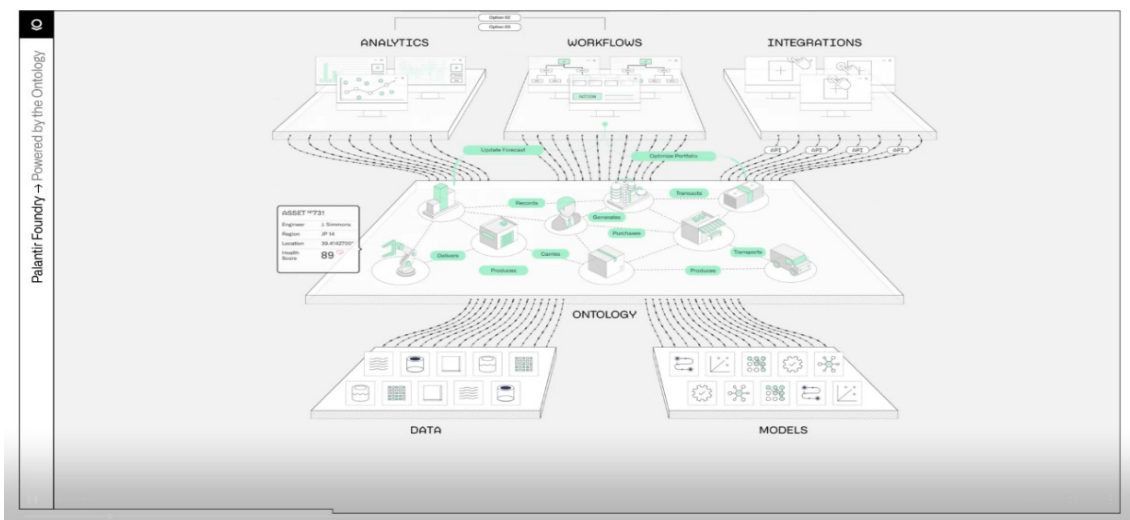


FIGURE 24: THE ONTOLOGY-POWERED OPERATING SYSTEM FOR THE MODERN ENTERPRISE
(Palantir Technologies, 2024)

The name, drawn not from Tolkien but from the imaginary metropolis of the Batman franchise, a city so saturated with violence and criminality that it requires an extra-legal vigilante to maintain order, articulates with unusual transparency the ideological premise of Palantir's core business model: that the world is defined by threat, that ordinary democratic and legal processes are insufficient to manage that threat, and that the solution lies in an enhanced capacity for surveillance and targeting. Gotham is deployed by the American intelligence community, the Department of Defence, the Department of Homeland Security — including, from the Trump administration onwards, Immigration and Customs Enforcement (ICE), whose mass deportation operations have depended substantially on Palantir's data aggregation capabilities — as well as by Europol, the

Danish security services, the Dutch national police, and, in the context that has attracted the most sustained international controversy, the Israeli Defence Forces (Newman, 2024). Its uses are twofold: it acts as a military planning simulation environment that lets government agencies build complete profiles of people from scattered data sources including biometric identifiers, vehicle registration records, financial transactions, criminal records, and social media activity; and it acts as a cross-referenced biometric and behavioural database from which the designation of strike targets and the modelling of operational outcomes can be done (Zuboff, 2019). In its aggregative function, Gotham instantiates what surveillance scholars have termed a virtual panopticon — a condition of asymmetric visibility in which the state can observe without being observed — whose implications for civil liberties and democratic accountability are, as the analysis below argues, substantially more serious than the company’s public communications acknowledge.

2.9.2. The Algorithmic State and the Problem of Algocrazia: Surveillance, Data Sovereignty, and the Erosion of Democratic Accountability

The governance challenge posed by Palantir’s institutional position cannot be reduced to the question whether any particular operation it enables — a deportation, an airstrike, a criminal investigation — is or is not legally permissible. The deeper issue, and the one that most directly implicates the frameworks of political geography and geoeconomics through which this thesis has approached the AI question, concerns the structural conditions that Palantir’s architecture creates for the exercise of state power, and the accountability relationships, or the conspicuous absence thereof, that govern it. The concept of “algocrazia” — algorithmic governance, the delegation to automated systems of decisions that previously required human deliberation and authorisation — is useful here as a descriptive frame, even if no contemporary state can be described as comprehensively algocratic (Dafoe, 2018). What Palantir enables is not algorithmic governance in the fully automated sense, but something structurally adjacent to it: the concentration of the informational preconditions of governance in a private platform whose operating logic, classification criteria, and risk-assessment algorithms are not subject to democratic scrutiny or independent judicial oversight.

The operational scope of this arrangement became considerably clearer in May 2025, when reporting by the New York Times revealed that the Trump administration had requested Palantir to design a national data infrastructure capable of aggregating the data holdings of all federal agencies into a single unified database, from which algorithmic profiles of every American resident could be generated, encompassing health insurance records, bank accounts, financial transactions, employment histories, and tax records (Frenkel & Krolik, 2025). For non-citizen residents, a parallel system designated ImmigrationOS, administered through ICE, would consolidate movement data, financial activity, social media content, and biometric information for every individual without American citizenship — a system whose explicit purpose is the facilitation of mass deportation operations. The architectural principle underlying both systems — the aggregation of data already held by government agencies into a unified, algorithmically sortable database — is, in technical terms, straightforwardly describable: governments already hold comprehensive data on their citizens and residents, and Palantir's contribution is to make those data interoperable and actionable. The political implications of this technical step are, however, far from straightforward. The fragmentation of government data across separate agencies is not a design flaw but a constitutional safeguard: it reflects the historical recognition that the concentration of comprehensive personal information in a single accessible repository transforms the informational asymmetry between state and citizen from a manageable practical advantage into a structural condition of potential domination (Zuboff, 2019). The official preservation of democratic institutions gives progressively less protection against the basic erosion of personal freedom. The standards whereby the algorithm distributes groups of dangerousness are not publicly revealed; rather, the outcomes of being algorithmically flagged—enhanced surveillance, trip restriction, administrative action—accrue automatically rather than through court proceedings when the algorithm allocating risk levels is not externally audited. The Chinese Social Credit System, frequently invoked in Western political discourse as the paradigmatic example of authoritarian digital governance, originated in precisely the logic of apparently innocent data integration that the Palantir project now instantiates in an American context (Merics, 2022). This comparison is not offered to suggest that the United States and the People's Republic of

China occupy equivalent positions on the spectrum of liberal democratic governance; the differences remain significant and consequential. It is, rather, to show the structural reasoning that both systems have in common: the compiling of state-held data into a single algorithmic classifier, whose outputs specify the connection between the person and the state in ways that are increasingly hard to challenge via traditional legal means. The difference between a surveillance system that is politically restricted by strong rule of law and one that is not is real but fragile, as its upkeep relies on the continued operation of exactly the democratic and judicial bodies that the growth of executive information power tends to erode. Palantir's institutional position makes this worry especially worse: Over two decades of government contracts, the business has gathered an operational understanding of data aggregation at sovereign scale that the government itself lacks and cannot quickly duplicate. The dependency relationship this produces—where the ability of the state to govern depends on the ongoing cooperation of a private entity whose interests, political alignments, and sensitivity to hostile actors are not under democratic control—is a structural condition of the sort that Farrell and Newman's study of weaponised interdependence finds as producing major and underappreciated vulnerabilities in the framework of modern state power (Farrell & Newman, 2019). A successful cyberattack against Palantir's infrastructure would not merely compromise a commercial entity; it would expose the totality of sensitive data flows across the American national security apparatus to adversarial exploitation.

2.9.3. Saruman or Gandalf? The Political Economy of Palantir and the Western AI Military Complex

The ideological framework within which Palantir's leadership situates its activities is articulated with unusual candour in Alex Karp's 2025 book *The Technological Republic*, which advances the thesis that the survival of Western liberal civilisation in the face of geopolitical competition from authoritarian powers requires the Silicon Valley technology industry to abandon its self-conception as a politically neutral provider of consumer goods and to embrace, instead, an explicitly patriotic commitment to the superiority of American and allied military and technological power (Karp & Zamiska, 2025). The argument is, structurally speaking, a modern version of the thesis of the

military-industrial complex from the middle of the 20th century. Artificial intelligence has replaced nuclear technology as the most important area of competition between big powers. Within this structure, Palantir's role is to act as the link between the business artificial intelligence (AI) sector and the defence establishment: to take the machine learning developments occurring throughout the tech industry and make them operationally deployable at the rate and scope required by modern military competition. The company's partnerships with Boeing, Lockheed Martin, and Northrop Grumman — three of the largest American defence contractors — and its explicit policy of restricting the sale of the Gotham platform to NATO member states and close American allies, reflect this orientation with consistency.

The network of institutional and political relationships through which Palantir operates in the broader Washington landscape illuminates dimensions of its power that its balance sheet alone would not reveal. Peter Thiel's role as chairman of Palantir is inseparable from his role as a major financial patron of the contemporary American right. Vance had first met Thiel at a Yale Law School talk in 2011 and went on to work as a principal at Thiel's fund Mithril Capital from 2016 to 2017; in 2019, with backing from Thiel, Marc Andreessen, and Eric Schmidt, Vance co-founded his own investment vehicle, Narya Capital (itself named after one of the three Elvish rings in Tolkien's mythology), based in Cincinnati. Thiel subsequently financed Vance's political campaigns in Ohio — including a record-setting \$15 million Senate-campaign donation in 2022 — before supporting his rise to the vice-presidency (Pequeño IV, 2024).

The alignment between Palantir's institutional interests and the policy priorities of the Trump administration — the expansion of AI-enabled immigration enforcement, the acceleration of military AI procurement, the hostility to regulatory oversight of technology companies — is accordingly not incidental but structural, rooted in a decade of deliberate political investment. Thiel was also among the earliest investors in OpenAI, the organisation that developed ChatGPT and that received a \$200 million prototype contract from the Department of Defense's Chief Digital and AI Office (CDAO) in June 2025 for the development of frontier AI applications in both warfighting and enterprise domains; OpenAI, in turn, maintains an active partnership with Anduril Industries (OpenAI (b), 2025), the defence technology company founded in 2017 by Palmer Luckey

together with co-founders Trae Stephens (a former Palantir employee and partner at Thiel's Founders Fund), Brian Schimpf, Matt Grimm, and Joe Chen, with backing from Founders Fund, whose platform Lattice performs targeting and operational planning functions analogous to Gotham. (Gold, 2026). The consolidation of this network — Palantir, Anduril, OpenAI, and their associated investment vehicles, connected through shared institutional origins, common political patrons, and interlocking contractual relationships with the American defence establishment — constitutes, in effect, a new military-AI complex whose geopolitical significance is considerably greater than any individual company within it.

The application of Palantir's platforms in the context of the Israeli military operations in Gaza since October 2023 has provided the most internationally contested illustration of the political stakes of this architecture. Palantir's strategic partnership with the Israeli Defence Forces, confirmed in January 2024, provides the IDF with AI-enabled targeting capabilities and battlefield management tools whose deployment in one of the most densely populated urban environments in the world has generated sustained controversy among international human rights organisations, legal scholars, and AI researchers (Newman, 2024). Karp's defence of this partnership, articulated in terms of the platform's capacity to improve targeting precision and thereby minimise civilian casualties, reproduces the logic that the preceding chapter identified in the context of autonomous weapons more broadly: the claim that algorithmic precision constitutes a moral improvement over human decision-making, irrespective of the conditions in which that decision-making operates. The rejoinder to this claim is also structurally familiar: the accuracy of an AI targeting system is a function of the quality of the data on which it is trained, the criteria by which it classifies targets, and the political and military context within which its outputs are acted upon — none of which are transparent, independently auditable, or subject to external legal review. The Tolkienian metaphor that structures Palantir's institutional self-presentation offers, in this context, an unintended analytical precision. The palantír of Tolkien's mythology are not, as Karp's use of the name might suggest, inherently instruments of good; they become instruments of domination when the Dark Lord Sauron, whose own palantír provides him with superior informational reach, is able to corrupt the visions seen by less powerful bearers, showing them only

what he wishes them to see. The question that Tolkien poses about the seeing-stones — whether their power can be wielded wisely, or whether the corruption of the instrument is a condition of its use — is not merely a literary question but a political one, and it is precisely the question that the governance of Palantir's platforms has yet to answer. The analytical framework applied above to the Western AI military-industrial complex — in which the question is not whether surveillance capacity exists but how it is governed, by whom, and to what ends — must, if it is to retain its intellectual coherence, be applied with equal rigour to the dominant Western account of its principal geopolitical competitor's surveillance architecture.

The ideological architecture articulated in Karp and Zamiska's book acquired a new and more confrontational public form in April 2026, when Palantir distilled *The Technological Republic* into a 22-point manifesto posted on social media — a document that, within two days of its publication, had been viewed thirty-two million times and had drawn characterisations ranging from “a new Manhattan Project for the AI Age” to “technofascism” (Cordall, 2026) (Karp & Zamiska, 2025) (Vallance & Cress, 2026). Essentially, the core ideas of the manifesto—that the atomic age of deterrence is coming to an end and a new period of AI-based deterrence is starting; that the engineering elite of Silicon Valley owes a “moral debt” to engage in national defence; that “the question is not whether AI weapons will be built but who will build them”; and that the postwar disarmament of Germany and Japan was an “overcorrection” whose reversal is now strategically necessary—constitute a corporate foreign policy doctrine going beyond the scope of most sovereign states' defence white papers (Ha, A. (b), 2026). Bellingcat founder Eliot Higgins observed that the manifesto's 22 points were “not philosophy floating in space” but “the public ideology of a company whose revenue depends on the politics it's advocating” — a formulation that captures precisely the structural entanglement between commercial interest and geopolitical vision that this section has sought to document (Start Magazine, 2026). For the thesis's broader argument, the significance of *The Technological Republic* lies not in the novelty of its individual claims — the necessity of hard power, the obligation of technological elites to serve national defence, the inadequacy of normative appeals in the face of authoritarian competition — but in the fact that these claims are being made not by a state, nor by an elected official,

nor by a military commander, but by a private corporation whose products already operate at the core of the intelligence and targeting infrastructure of the United States, the United Kingdom, Israel, and a growing number of NATO allies: a corporation that is, in Varoufakis's formulation, signalling its willingness "to add to nuclear Armageddon the AI-driven threat to humanity's existence" (Cordall, 2026).

2.9.4. The Social Credit Myth: Western Narratives and the Asymmetry of Surveillance Discourse

Any analytical treatment of AI-enabled surveillance that examines Western architectures such as Palantir's integrated intelligence platforms must, for the sake of intellectual honesty, confront the degree to which the dominant Western narrative of Chinese surveillance has itself been shaped by distortion rather than empirical investigation. Consequently, it is necessary to clarify the system's operational reality to determine whether American reliance on data analytics firms like Palantir constitutes a domestic version of the very surveillance apparatus the U.S. purports to condemn. The concept of a unified Chinese "social credit score" — a centralised, algorithmically generated number assigned to every citizen, rising or falling in response to political opinions, consumer behaviour, and social associations, and determining access to transport, housing, employment, and education — has achieved the status of received truth in Western media, policy discourse, and popular culture, reinforced by fictional depictions such as the 2016 Black Mirror episode *Nosedive* and by advocacy campaigns that conflated distinct and largely unrelated Chinese initiatives into a single dystopian narrative (Hou & Fu, 2022). The history of this misinterpretation is fairly exactly traceable. In October 2015, Swedish Pirate Party founder Rick Falkvinge issued an article combining Alibaba's Sesame Credit, a voluntary, commercially focused creditworthiness instrument created by Ant Group to solve the lack of traditional credit histories among millions of Chinese consumers, with a 2014 State Council planning paper on the building of a "social credit system", hence asserting that the Chinese government was ready to give every citizen a required behavioural score by 2020 (Privateinternetaccess, 2015). The American Civil Liberties Union promoted the essay, which made its way into mainstream Western media and within two years had become an accepted idea of transatlantic conversation on Chinese

authoritarianism (Daum, 2017). But the actual evidence points to a very different narrative. The Mercator Institute for China Studies, the premier European research institution on China, found in its 2022 analysis that there has never been a single social credit score for people in China; The existing system mostly concentrates on business and commercial compliance rather than personal behaviour, is quite divided, and is mainly focused on upholding financial commitments such as debt repayment under court order (Merics, 2022). The 2014 planning document that Falkvinge cited made no reference to Alibaba, to a universal citizen score, or to the monitoring of political opinions; its principal concerns were the establishment of modern creditworthiness infrastructures comparable to those operating in Western economies, and the prevention of commercial fraud of the kind that had produced the catastrophic 2008 melamine-contaminated milk scandal, in which approximately 300,000 infants were hospitalised and six died as a consequence of systematic adulteration in the dairy supply chain (Brusee, 2024). Pilot scoring programs that were briefly trialled at the municipal level — most notably in Rongcheng, Shandong province — were discontinued or reduced to voluntary, incentive-only schemes after the Chinese central government itself intervened in 2019 to prohibit the use of scores to punish citizens, stipulating that sanctions could only be imposed for legally defined offences (Merics, 2022). According to MERICS, only approximately 10% of social credit system documents pertain to individuals, with the overwhelming majority addressing enterprises and organisations. This is not to minimise the coercive capacities of the Chinese state — surveillance programs such as Golden Shield, Skynet, and the Integrated Joint Operations Platform deployed in Xinjiang represent genuine and well-documented instruments of repression that operate largely outside the social credit framework (Merics, 2022). The analytical point is rather that the persistent Western mischaracterisation of the social credit system has functioned less as an accurate description of Chinese governance than as a discursive instrument in the geopolitical framing of AI competition, enabling the construction of a narrative in which Chinese technological development is inherently authoritarian while Western surveillance architectures — including those operated by firms such as Palantir for immigration enforcement, predictive policing, and intelligence integration — are rendered invisible or categorised as qualitatively different by virtue of their democratic institutional context

(Zuboff, 2019). A thesis concerned with the geopolitical implications of artificial intelligence cannot afford to reproduce this asymmetry uncritically; it must instead recognise that the question of AI-enabled surveillance is not a contest between a surveilling East and a liberal West, but a structural feature of computational governance whose modalities differ across political systems without being confined to any one of them.

2.9.5. European Implications: Dependency, Sovereignty, and the Limits of Normative Power

For the European Union, the institutional presence of Palantir within both Allied military structures and the domestic security architectures of several member states raise questions that the analysis of European AI strategy developed in the preceding chapters of this thesis has not yet fully confronted. Europol's use of Gotham, the Dutch national police's deployment of Palantir platforms for criminal network analysis, the Danish security services' reliance on Palantir data infrastructure, and the prospective extension of similar arrangements to other EU member states as NATO interoperability requirements increasingly mandate AI-enabled command and control integration, collectively constitute a form of the dependency relationship that this thesis has identified, in various registers, as a defining structural vulnerability of the European position in the global AI race (European Parliament, 2026). In this case, the dependency is not just technological but also political: it puts the data of European citizens, which Palantir's platforms process in the course of legal law enforcement and security operations, under the governance framework of an American company whose contractual obligations to the United States government, whose vulnerability to American legal process, and whose alignment with certain parts of the American political scene are not governed by European regulatory control. The tension this creates with the European Union's own aspirational framework for AI governance — the AI Act and its associated provisions for high-risk AI systems, the GDPR's data protection requirements, the broader project of European digital sovereignty articulated in the von der Leyen Commission's strategic agenda — is structural rather than incidental (Veale & Zuiderveen Borgesius, 2021). A regulatory framework that imposes rigorous transparency, accountability, and human oversight

requirements on AI systems deployed within European jurisdiction is considerably less effective when the most operationally significant AI systems in use within that jurisdiction are governed primarily by American corporate and national security law. The normative power model of European AI governance, examined in the opening chapters of this thesis, assumes that the EU's capacity to set regulatory standards creates compliance pressure on entities wishing to access the European market; it functions considerably less well in the domain of national security and military intelligence, where market access is not the relevant lever and where the interests of Allied solidarity and NATO interoperability may systematically override the regulatory ambitions of Brussels. Whether, and under what conditions, the elaboration of genuinely European alternatives to Palantir's capabilities — platforms grounded in European data sovereignty, subject to European legal oversight, and consistent with European democratic values — is technically feasible and politically achievable within the relevant timeframe is one of the most consequential questions in European strategic policy, and one to which the current state of European AI capacity does not offer a reassuring answer.

Conclusion of section 2.9.

The analysis developed in this chapter suggests that Palantir represents, in concentrated form, a set of tensions that run through the entire geopolitics of AI examined in this thesis: between the competitive imperatives that drive states and their private partners to develop ever more powerful informational tools, and the governance requirements necessary to ensure that those tools remain compatible with the democratic values and legal frameworks they are nominally intended to protect; between the narrative of Western civilisational defence that legitimates the company's activities in its own self-presentation, and the structural risks — to civil liberties, to democratic accountability, to European digital sovereignty, and to the stability of the international security environment — that those activities generate. The palantír of Tolkien's mythology, to return to the analogy that the company has made central to its institutional identity, are objects of pure and unregulated power (Tolkien J. , 1954). Those who use them wisely and with adequate spiritual fortitude — Aragorn, who wrests the stone from Sauron's dominion through an act of sovereign will — can turn them to the service of justice. Those who are seduced by

the vision of power they offer — Saruman, whose corruption begins at the moment he believes his own intelligence superior to that of his adversary — become, progressively, instruments of the very domination they believed themselves to be resisting. The political geography of AI in the twenty-first century does not offer the clarity of mythological allegory; the characters in this story are considerably less legible than Tolkien's, and the moral stakes considerably more entangled. What the analogy does capture, with some precision, is the structural condition that the governance of AI power must address: the question whether, and under what institutional conditions, instruments of unprecedented informational reach can be subject to meaningful democratic accountability, or whether the concentration of such power in private hands, operating under governmental mandate but beyond public scrutiny, is already moving the West closer to the condition it claims to oppose.

2.10. Europe in the Global AI Race: Regulation, Power, and the Risk of Strategic Marginalization

2.10.1. Europe Between Regulation and Innovation

The emergence of artificial intelligence as a central driver of economic growth, military capability, and political influence has compelled governments across the world to reconsider their position within a rapidly shifting global technological order. Artificial intelligence is no longer a sectoral innovation confined to computer science: it has become a foundational infrastructure, comparable in historical significance to electricity in the twentieth century or the railway network in the nineteenth. The states that control its development thereby shape global supply chains, labor markets, and strategic balances of power. Within this new technological landscape, Europe occupies a position that is at once sophisticated and structurally ambiguous.

In prevailing public discourse, the global AI race is most often portrayed as a bipolar competition between the United States and China. On one side stand the major American technology firms — OpenAI, Google, Microsoft, Amazon, Meta — sustained by deep venture capital markets, elite research universities, and extensive military procurement networks. China is on the other side; it uses state-led industrial policy, large internal

databases, and a tightly connected framework for civil-military technological development. Europe, on the other hand, seems tactically cautious and technically advanced at the same time: It boasts top-notch universities, sophisticated industrial sectors, and strong regulatory institutions, but it lacks the worldwide digital platforms fit to compete head-on with American or Chinese companies. This structural ambiguity is reflected clearly in Europe's policy orientation. The European Union has positioned itself as the world's foremost normative actor in the governance of artificial intelligence, most visibly through the adoption of the EU Artificial Intelligence Act in 2024, the first comprehensive regulatory framework of its kind (European Parliament and Council of the European Union, 2024). The Act establishes a risk-based classification system, prohibiting certain applications — such as social scoring systems — and imposing strict obligations on high-risk AI systems deployed in sectors such as healthcare, education, and public safety. Europe has tried to balance the demands of innovation with the preservation of basic rights by means of this.

Still, there have been a lot of objections to how ambitious this regulation project is. Observers have questioned if Europe's focus on governance points to a more fundamental flaw: a lack of ability to compete in the field of technological innovation itself. Often repeated in policy discussions, the idea Europe regulates is due to its inability to dominate. Europe runs the danger of turning into a user of foreign technology instead of an independent producer as the United States and China make significant investments in research infrastructure, semiconductor design, and cloud computing capacity. Mario Draghi expressed this worry succinctly when he cautioned that Europe runs the risk of long-term economic stagnation if it doesn't embrace artificial intelligence at scale because productivity growth in Europe had already fallen behind the United States during the digital revolution of the previous decades (Draghi, 2024). The tension between regulation and innovation thus constitutes the defining axis of Europe's current AI strategy. When the US government, citing national-security authorities, issued an export-control directive on 12 June 2026 ordering Anthropic to suspend all foreign-national access to its two most capable models, Claude Fable 5 and Claude Mythos 5 — forcing their worldwide disablement within hours of launch — the episode lent fresh weight to the European case for ex ante regulation: where Washington governs frontier AI reactively, through abrupt

security interventions after a capability has already shipped, the Union's precautionary, rules-first approach seeks to set the terms before such ruptures occur (Anthropic (f), 2026).

2.10.2. Europe as a Normative Power

The European Union has long been characterized in the scholarly literature as a “normative power”, capable of shaping global markets and international standards through the force of regulation rather than through military or technological dominance (Manners, 2002). The General Data Protection Regulation, implemented in 2018, transformed global data privacy standards: companies worldwide adopted European-style protections because access to the EU single market required compliance. Environmental law and consumer protection have seen comparable movements develop. The AI Act continues this approach, which seeks to establish international norms for reliable artificial intelligence rather than just control AI locally.

The Act uses a risk-based method to sort artificial intelligence systems into four groups based on how likely they are to affect society (European Parliament and Council of the European Union, 2024). Mostly uncontrolled are systems with very low risk including video game applications or spam filters. People with low risk, like conversational AI, have to be open with their users about what they do. High-risk systems used in vital industries including law enforcement, healthcare, education, employment, and law enforcement have to meet tough rules on data quality, risk assessment, human supervision, documentation, and cybersecurity. Ultimately forbidden are systems offering intolerable risk—including social scoring techniques, biometric categorisation based on sensitive traits like race or religion, and some types of predictive policing.

This structure shows how Europe tries to fairly balance invention and protection in a principled way. Still, there are some natural restrictions on standard leadership. Standards are only effective to the degree that they are supported with adequate technical capability. Europe could define the standards, but if it cannot create artificial intelligence systems on its own, those rules run the risk of being impacted indirectly by outside technologies. American businesses now control European cloud infrastructure and AI platforms in

reality, which presents a serious contradiction: Europe controls technology mostly created elsewhere.

2.10.3. The Structural Gap: Europe Compared to the United States and China

The debate about Europe's position in the global AI race cannot be adequately understood without examining the structural asymmetries that separate the European Union from its principal competitors. Artificial intelligence development rests upon three foundational pillars: capital, computing infrastructure, and data. In each of these domains, the United States and China hold substantial and compounding advantages over Europe.

Deep venture capital markets help the United States because AI firms may grow quickly and absorb large losses in anticipation of ultimate worldwide dominance. Companies like OpenAI, Anthropic, and others have received billions of dollars in private investment from people who are willing to pay for long-term technology bets. China, for its part, uses a different model in which state-backed funds, industrial policy, and strategic subsidies direct resources towards sectors seen as important for national security and economic growth. Artificial intelligence is specifically named as a top priority in its long-term plans (State Council of the People's Republic of China, 2017). Europe, in contrast, has dispersed financial markets and a far reduced rate of venture capital investment in AI companies; many European companies relocate to the United States or look for American investors to get the size required for world competitiveness.

The infrastructure gap helps to strengthen this difference. American hyperscalers Amazon Web Services, Microsoft Azure, and Google Cloud control the world cloud computing market; their scale enables hardware acquisition and energy infrastructure investment at a level European companies cannot match. Huawei, Alibaba Cloud, and Tencent Cloud have created similar local platforms in China. Europe lacks actors of comparable calibre. This forces European artificial intelligence developers to depend on other countries' infrastructure, which brings up continuing issues about strategic independence and digital sovereignty. Furthermore, aggravating this dependence are semiconductor supply networks: American companies mostly create advanced AI chips, which are mostly made in Asia. This means that European AI development is limited at the hardware level.

Similar difficulties are shown by the data environment. Through international and local digital platforms, American and Chinese tech companies acquire enormous datasets that provide training data benefits European businesses cannot readily match. The data scene in Europe is more dispersed since it is influenced by linguistic variety, differences in national regulations, and fewer small digital platforms. Though it mirrors valid worries about privacy, the General Data Protection Regulation limits some kinds of data gathering even more. Although Europe has rich industrial and scientific datasets in manufacturing, healthcare, and engineering, these are mostly compartmentalized across corporate and national borders.

Equally significant is the institutional aspect. While China's centralised political system can swiftly steer resources toward strategic goals, the United States is one state with consistent financial and industrial policy. By contrast, the European Union has to synchronize industrial policy across 27 member countries, each with different economic goals, legal systems, and political cultures. This complexity slows decision-making and constrains the scale of coordinated investment. Mario Draghi's warning that Europe risks long-term stagnation without decisive AI investment thus reflects a deeper structural reality: without technological leadership, Europe's social model — grounded in welfare states and industrial exports — may prove unsustainable (Draghi, 2024).

2.10.4. Why Europe Regulates: Ethics, History, and Political Culture

Europe's regulatory approach to artificial intelligence cannot be reduced to an economic or bureaucratic phenomenon. The European Union differs from China and the United States because it is based on historical experience, political customs, and ethical commitments. The encounter of authoritarian governments, total surveillance systems, and the regular abuse of technology for suppression greatly influenced European political culture. From fascist Italy and Nazi Germany to the surveillance apparatuses of communist Eastern Europe, technology instruments were routinely used to classify people, suppress opposition, and violate basic rights. These experiences produced a durable suspicion toward technologies capable of monitoring behaviour, categorising citizens, or automating decisions without adequate human oversight, principles

subsequently embedded in the Charter of Fundamental Rights of the European Union (European Union, 2012).

Artificial intelligence, with its capacity to analyse large datasets, predict behaviour, and automate consequential decisions, is therefore perceived in Europe not merely as an economic opportunity but as a potential threat to democratic society. Reflecting exactly this worry, the ban of social scoring systems and biometric categorization depending on sensitive traits in the AI Act calls back to past abuses linked to autocratic rule (European Commission (a), 2025). Regulation so aims to be preventative: to guarantee that democratic principles and the rule of law are upheld in parallel with technical advancement.

The Cambridge Analytica controversy, which showed how personal data gathered from social media networks had been utilized for political micro-targeting, further confirmed this historical sensitivity and exposed the vulnerability of democratic systems to algorithmic manipulation. For many European policymakers, the episode confirmed that digital technologies could amplify disinformation, distort electoral processes, and erode public trust if left without adequate governance frameworks (Cadwalladr & Graham-Harrison, 2018). The subsequent strengthening of data protection mechanisms, including the enforcement of the GDPR, reflected a broader determination to prevent artificial intelligence from reproducing similar abuses at a larger scale.

The European model also reflects the structural logic of its welfare states. European societies have traditionally expected governments to protect citizens from systemic risks, whether in environmental policy, food safety, or financial regulation. Artificial intelligence is treated in an analogous manner: the risk-based framework of the AI Act imposes stricter requirements on systems deployed in critical sectors precisely because the potential for harm is considered commensurate with the burden of oversight (European Commission (a), 2025). From this perspective, regulation is not a symptom of weakness but an expression of political identity and democratic necessity.

2.10.5. The United States and Chinese Models

The United States has approached artificial intelligence governance through a markedly different philosophy. Rather than establishing a comprehensive ex ante regulatory

framework, American federal policy has historically favoured an innovation-led model based on executive guidance, sector-specific oversight, and industry self-governance (U.S. Bureau of Industry and Security, 2022). From the American AI Initiative through later policy statements, the federal government has mostly portrayed AI as a tool for economic growth, productivity, and geopolitical power; hence, regulatory enforcement mostly belongs to current agencies like the Federal Trade Commission and sector-specific organizations. This strategy shows a conscious decision to forgo broad legislation that would slow down technical growth, while at the same time connecting AI development to national security priorities including defence innovation, export controls, and supply-chain resilience (U.S. Bureau of Industry and Security, 2022).

The Chinese approach contrasts sharply with that of the Americans and Europeans. The 2017 New Generation Artificial Intelligence Development Plan set a goal of making China the world leader in AI by 2030. It said that artificial intelligence is a “strategic technology” that can change the way things are made, the military, the way the government works, and how well China does in the world (State Council of the People's Republic of China, 2017). By means of state-backed funds, industrial policy, and favorable regulatory conditions, Beijing has incorporated the main technology companies Alibaba, Tencent, Baidu, Huawei into national planning frameworks (Cyberspace Administration of China, 2023). Although China does control artificial intelligence, its priorities lie in data security, content control, and ideological alignment rather than in market fairness or individual rights. China's artificial intelligence strategy is geopolitically linked to its rivalry with the United States: export restrictions on sophisticated semiconductors have spurred Chinese investment in domestic chip manufacturing and alternative computer architectures, therefore clearly framing technical progress as a matter of national sovereignty (U.S. Bureau of Industry and Security, 2022). Following a "negotiation through concessions" approach during the meeting in May 2026 from USA and China, the Trump administration's diplomatic efforts to Beijing highlight a crucial awareness of American structural vulnerabilities. The government made it clear that domestic economic stability is very closely related to Chinese manufacturing capability and consumer market access by leading a delegation made up of key leaders from the financial, aviation, and technology industries, including executives from Apple,

Tesla, and Boeing. This "open-card" diplomacy suggests that past protectionist measures, including tariff hikes, were primarily strategic actions intended to enhance their negotiating leverage. In the end, the presence of NVIDIA's executives and the strategic monitoring of Iranian oil trade point to a complex quid-pro-quo: the United States aims to leverage its supremacy in high-end semiconductors to reduce its weaknesses in the rural agricultural sector and larger geopolitical tensions, hence acknowledging that sustainable American growth calls for a practical recalibration of Sino-American relations (Charlton, Kyvrikosaio, Suleiman, & MacLellan, 2026).

2.10.6 Europe's Dilemma and the AI Continent Action Plan

The involvement of Europe in the world AI scene exposes a structural trade-off between technological reliance and normative aspiration. Although the European Union has developed a complex regulatory framework meant to influence world digital standards, it still depends on outside infrastructure for the growth and application of cutting-edge AI technologies. The fragmentation of creativity throughout national systems has hampered the rise of businesses able to compete with American or Chinese hyperscalers, while the lack of a united capital market limits the level of investment accessible to European AI firms. Contemporary geopolitical instability appears to impact the European continent with disproportionate severity. While other global alliances maintain a degree of insulation, Europe faces direct socio-economic vulnerabilities that are significantly more pronounced than those experienced by its strategic counterparts.

Through concerted continental investment and governance changes, the AI Continent Action Plan offers the most methodical approach to solve this problem. The scheme seeks to include industrial policy with normative leadership across a number of linked pillars rather than give up Europe's regulatory framework. The first is about control over the infrastructure: Understanding that sophisticated artificial intelligence calls for tremendous computing capacity, the strategy calls for increasing Europe's network of high-performance computing facilities, connecting national supercomputers, and fusing them into a federated European cloud architecture. Projects like OpenEuroLLM and the AI Factory Leonardo Multisynth show that there is a clear understanding that AI's ability

to compete depends on access to massive computer power and not only on how good the algorithms are (European Commission (a), 2025).

Other pillars encompass human capital, industrial ecosystems, and finance. Europe's relative advantages include advanced manufacturing, automotive engineering, aerospace, medicines, and energy systems; the plan seeks to include artificial intelligence adoption in these fields by industrial collaborations and collaborative research networks. Talent retention is a particular area of concern: Despite Europe producing an excessive share of the world's artificial intelligence researchers, many migrate to the United States for more lucrative compensation and more comprehensive financial systems. While independent AI funds and co-investment programs want to replicate at European scale the financial circumstances open to American and Chinese rivals (European Commission (a), 2025), proposed doctoral training networks and European AI fellowships seek to counteract this inclination. The plan also frames the AI Act not as an obstacle but as a foundation for trustworthy AI, using regulatory sandboxes and common standards to create a unified digital market for AI services.

2.10.7. Europe's Hidden Strengths and the Risk of Marginalisation

Despite the scale of the structural gap, Europe retains significant latent advantages that should not be understated. Its industrial base — centered on precision engineering, automotive technology, aerospace, pharmaceuticals, and energy — generates complex operational data and demands the kind of rigorous applied AI that European regulatory culture is well positioned to support. Companies like Siemens, Airbus, Bosch, ASML, and SAP work at the cutting edge of manufacturing, and using artificial intelligence in these areas offers big chances in predictive maintenance, robotics, materials science, and making logistics more efficient.

Mistral AI is a French startup founded in April 2023 by Arthur Mensch, an alumnus of Google DeepMind, together with Guillaume Lample and Timothée Lacroix, both of whom had previously co-led the LLaMA large-language-model project at Meta AI's FAIR research division (Mistral AI, 2023). Mistral AI is a prime example of how Europe takes a different approach to artificial intelligence. Instead of creating consumer apps, European companies use open-weight architectures built for interaction to include AI into

advanced industrial ecosystems. This has led to a lot of money coming into the company quickly, and it is now the most important developer of big language models in Europe. Although the company still runs considerably short of the scope of OpenAI or Google DeepMind, it shows that Europe has the human resources and scientific skills needed for frontier AI development if funding, infrastructure, and policy coordination can be significantly improved (IBM, 2024).

Europe's power to influence worldwide norms is another tactical advantage. By virtue of the EU's market size, the "Brussels Effect"—the ability of European legislation to change world market behaviour—has already spread privacy norms internationally through the GDPR and is probably to have similar effects under the Artificial Intelligence Act (European Commission (a), 2025). European AI systems created under rigorous safety criteria could become favoured choices for businesses and governments looking for dependability in industries where trust, openness, and legal compliance take utmost priority — health, finance, vital infrastructure. Given the high energy needs of large-scale model training, Europe's investment in renewable energy infrastructure also positions the continent as a possible canter for sustainable artificial intelligence computing.

Still, there are actual hazards associated with marginalisation. Reliance on foreign semiconductor companies and cloud providers exposes strategic vulnerabilities open to geopolitical leverage. Brain-drain to American tech companies diminishes Europe's research ability just when it is most necessary. Fragmented capital markets reduce the probability that European startups can achieve the scale required for global competitiveness before being acquired by foreign firms. And if AI adoption proceeds more slowly in Europe than among its competitors, the productivity gap identified by Draghi may widen to the point of long-term irreversibility (Draghi, 2024). In a world of weaponised interdependence, where technological infrastructure can function as an instrument of coercion, these dependencies carry implications that extend well beyond the technology sector (Farrell & Newman, 2019).

Conclusion of section 2.10.

The analysis presented in this chapter reveals that Europe's position in the global AI race is defined by a structural tension between normative leadership and technological

dependence. This dilemma is compounded by a structural irony that runs through the entire history of internet governance: the very regulatory architecture Europe has constructed as its comparative advantage rests on a prior acceptance of the technical and economic infrastructure built by others. Just as self-regulatory standards bodies like the IETF formally committed themselves to avoiding policy and business questions while being overwhelmingly composed of private-sector employees shaping the architecture of a forty-billion-dollar industry, Europe's AI governance framework operates at the normative layer without commanding the material layer beneath it (ten Oever, 2021). The Brussels Effect — the capacity to export legal norms through market leverage — is a powerful instrument, but it is also a second-order instrument: it can shape how foreign technologies are used and disclosed, but it cannot substitute for the capacity to build them. A continent that regulates the terms on which foreign AI is deployed, while remaining dependent on foreign chips, foreign cloud infrastructure, and foreign frontier models, occupies a position structurally analogous to the post-colonial state that gained sovereignty over its territory while retaining dependency on the economic and technological systems of the former metropole. The question of European strategic autonomy in AI is therefore inseparable from the more fundamental question of whether the architecture of global digital infrastructure can be reshaped — or whether, like the ossified network described in IETF deliberations, it has already hardened around configurations that serve the interests of those who built it (ten Oever, 2021).

The strategic choice Europe now faces is therefore not one between innovation and regulation, but between integration and fragmentation: whether it is willing to pool resources to build continental infrastructure, coordinate industrial policy, and support technological champions capable of competing at global scale. Yet the analysis of Palantir's institutional position developed earlier in this chapter suggests that even this formulation understates the difficulty. European defence ministries, intelligence agencies, and border authorities are currently operationally reliant on an American platform whose own algorithms, classification standards, and data architecture are not under European supervision—a reliance that is structural rather than just commercial, in the sense that the informational preconditions of sovereign decision-making have been handed to an actor whose political alignments and strategic interests are decided in Washington and Silicon

Valley rather than in Brussels or Berlin. The question, therefore, is not simply whether Europe can muster the political will to pool resources and coordinate industrial policy — formidable as that challenge already is — but whether it can do so while simultaneously disentangling its most sensitive governmental functions from the very infrastructural dependencies that its regulatory framework was ostensibly designed to prevent. The fact that no major European government has yet initiated a serious programme to develop sovereign alternatives to Palantir's integrated intelligence platforms — despite the EU AI Act's explicit prohibition of social scoring systems and its stringent requirements for high-risk AI deployed in law enforcement and border management — suggests that the gap between normative ambition and material capability may be wider, and more politically entrenched, than the optimistic language of strategic autonomy tends to acknowledge. Europe might provide the globe a third approach to technical development if it manages to match the ethical governance of the AI Act with the industrial aims of the AI Continent Action Plan, one that combines creativity with social responsibility and democratic accountability. Emerging projects like Mistral AI and OpenEuroLLM show that despite ongoing structural disparities with China and the United States, this promise is still alive. But if Europe fails to turn its moral beliefs into tangible capacity, it runs the risk of being a minor player in a world controlled by others: a regulator of technologies it does not create in a world where the ability to influence political future is inextricably linked to the capacity to shape technological trajectory. Artificial intelligence is so not just a question of financial viability. In the end, it all comes down to Europe's role, identity, and independence in the twenty-first century.

Beyond the economic and governance dimensions examined here, the consolidation of artificial intelligence as a strategic technology carries equally profound implications for security: the same capacities that drive industrial productivity and regulatory innovation are increasingly being weaponised, transforming cybersecurity and military doctrine in ways that demand separate and urgent analysis.

The transition from governance to warfare is not, in fact, a change of subject; it is a change of register within the same underlying problematic. The preceding sections have traced how the concentration of AI capability in a small number of corporate actors, the structural dependencies embedded in cloud infrastructure and semiconductor supply

chains, and the tension between normative regulation and material capacity together define the political economy of the AI transition. What the following section demonstrates is that these same structural features — concentration, dependency, and the asymmetry between those who build infrastructure and those who merely use it — are simultaneously the defining vulnerabilities of the emerging security landscape. The open-source software libraries upon which global digital infrastructure depends are maintained by the same logic of distributed, under-resourced voluntary labor that characterises much of the internet's foundational architecture; the AI systems increasingly deployed in military and intelligence contexts operate through the same proprietary platforms whose governance deficits the Palantir analysis has already identified; and the offensive cyber capabilities now being augmented by machine learning exploit precisely the supply chain chokepoints whose geopolitical significance the preceding chapters have documented. The weaponization of artificial intelligence is therefore not a separate domain of analysis to be appended to the political economy of AI, but its most consequential extension — the point at which the structural vulnerabilities that markets tolerate as acceptable risks become, in the hands of state and non-state adversaries, instruments of strategic disruption.

2.11. Cybersecurity and Asymmetric AI Warfare

2.11.1. The XZ Utils Backdoor: A Case Study in Supply Chain Vulnerability

The geopolitical and security significance of AI-era cyber vulnerability cannot be assessed without accounting for the infrastructure upon which the global digital economy operates. Linux distributions have held 100% of the market share among the world's five hundred most powerful supercomputers since 2017. Government data centers worldwide reported 64% Linux deployment in 2025, while 90% of public cloud workloads run on Linux-based infrastructure, and 65% of 5G base stations globally use Linux-based software. **Android**, which uses the **Linux kernel**, is the world's most popular operating system with approximately 41% of the global market as of April 2026, while Linux leads the global server operating system market with a 63% share. The structural significance of this ubiquity for the security analysis that follows is twofold. First, Linux's open-source

architecture — in which the kernel source code is publicly available for inspection, modification, and deployment — is precisely what makes it attractive to governments, militaries, and critical infrastructure operators who require auditability and independence from proprietary vendors; the same openness, however, creates a supply chain whose integrity depends on the distributed network of volunteer and corporate contributors who maintain it, rather than on the centralised quality controls of a single commercial organisation. Second, the concentration of global critical infrastructure on a single software foundation means that a successfully implanted vulnerability in the Linux supply chain would not be an isolated incident but a systemic exposure affecting simultaneously the financial systems, military networks, government communications, and cloud infrastructure of every major economy in the world — which is precisely the risk that the XZ Utils backdoor of March 2024, examined in the following subsection, came closest to realising (TOP500, 2025) (Command Linux, 2026) (Statcounter, 2026) (Day, 2019) (Smalley, 2005).

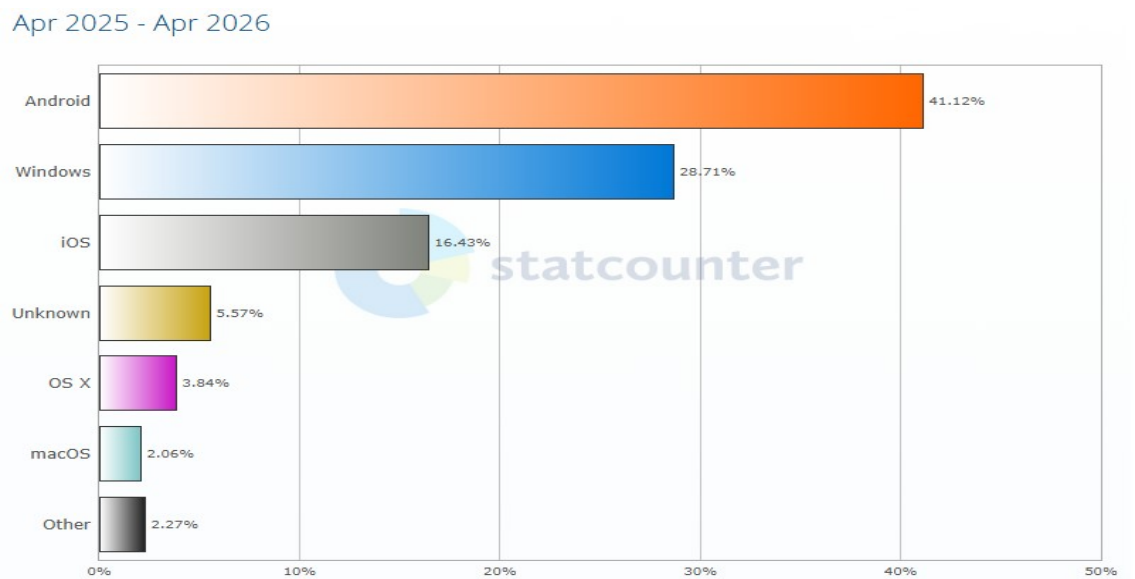


FIGURE 25: OPERATING SYSTEM MARKET SHARE WORLDWIDE
(Statcounter, 2026)

In March 2024, a near-catastrophic security incident came within weeks of compromising millions of internet servers worldwide, yet attracted remarkably little attention in mainstream public discourse. The episode, centered on a deliberately engineered backdoor

concealed within a widely used open-source compression utility known as XZ Utils, offers one of the most instructive case studies available for understanding the intersection of artificial intelligence, cybersecurity, and geopolitical competition in the contemporary digital order. To appreciate its full significance, it is necessary to trace both the technical architecture that made the attack possible and the broader political economy of open-source software development upon which that architecture rests.

2.11.2. The Open-Source Foundation: From GNU to Linux

The vulnerability exploited in the XZ incident is inseparable from the historical development of open-source software, a movement whose origins lie in a specific conjuncture of technological freedom and corporate enclosure in the early computing era. Unix was created in the late 1960s by AT&T's Bell Labs engineers. It was an operating system that moved around a lot of colleges and research labs, which helped to keep the software development process open and collaborative (Weber, 2004). But AT&T had aggressively sought to claim copyright over Unix variants by the 1980s, suing independent developers and demanding that staff sign non-disclosure agreements banning source code sharing. This shift in the political economy of software provoked a decisive response from Richard Stallman, a researcher at the Massachusetts Institute of Technology, who in 1985 established the Free Software Foundation, and who four years later, in February 1989, released the first version of the GNU General Public License — a legal instrument designed to guarantee that software could be freely used, studied, modified, and redistributed (Williams, 2002).

The project to build a complete free operating system, which Stallman called GNU, required reconstructing the core components of Unix from scratch. GNU lacked a kernel, the basic layer that connects software and hardware, even though it made important tools and a shell interface. In 1991, Linus Torvalds, a Finnish computer science student, created a kernel of his own under the General Public License and filled that gap. Originally intending to name it “Freax” (a portmanteau of “free,” “freak,” and “Unix”), Torvalds was persuaded to abandon that name when Ari Lemmke, the administrator of the FUNET FTP server where Torvalds first uploaded the kernel in September 1991, created the upload directory under the name “Linux” — a contraction of Linus and Unix

that Lemmke considered more dignified than “Freax” (Torvalds & Diamond, 2001). The combination of the GNU utilities and the Linux kernel produced a complete, freely available operating system that rapidly propagated across an extraordinary range of applications (Moody, 2001). Today, Linux underpins the overwhelming majority of internet servers (approximately 96% of the top one million web servers), all 500 of the world's most powerful supercomputers as ranked by the TOP500 list (a position Linux has held continuously since November 2017), the Android mobile platform with its three billion devices, and critical infrastructure including military and financial systems (TOP500 Project, 2024). Its ubiquity is structural rather than accidental since developers in all industries have been able to customize it exactly to their needs free from the restrictions imposed by proprietary systems thanks to the openness and flexibility of the source code.

Underlying the open-source approach is a basic belief about security expressed as Linus's Law: that given enough developers reviewing the code, no mistake—intentional or malicious—can stay undetected for very long (Raymond, 1999). This theory, though, hides a structural frailty. The open-source ecosystem is not one cohesive project but rather a complex network of dependencies where big and well-tested platforms are put together from hundreds of smaller libraries and utilities, many of which are kept up by one unpaid volunteer working outside of normal institutional settings. The overall security then hinges on parts whose technical relevance would justify a far thinner human maintenance infrastructure than they now command.

2.11.3. The Anatomy of the Attack: Social Engineering and Technical Subversion

It was precisely this structural fragility that the perpetrator of the XZ attack, operating under the pseudonym Jia Tan, identified and systematically exploited. The target was XZ Utils, a lossless data compression tool developed since 2005 by Lasse Collin, a Finnish programmer who had maintained the project as an unpaid personal commitment for nearly two decades. Due to its superior compression ratios attained by its underlying technique, the Lempel-Ziv Markov chain algorithm created by Igor Pavlov in the late 1990s (Salomon, 2007), XZ had grown to be a default dependency in almost all major Linux distributions over that period. Because of its ubiquity, the instrument was

a perfect vector: Any system reliant on XZ would automatically spread from a compromise of XZ.

The procedure involved technically advanced code manipulation together with social engineering and took about two and a half years to play out. Beginning in 2021, Jia Tan cultivated a presence within the XZ development community, submitting genuinely useful contributions and building a reputation as a reliable collaborator. Concurrently, a network of apparently independent accounts applied sustained pressure on Collin, who was already experiencing significant difficulties maintaining the project, criticising the pace of development and questioning his commitment (Freund, 2024). When Jia Tan offered to assume greater responsibility for the project, the offer was accepted. The operation illustrates a mode of long-duration infiltration that bears the hallmarks of state-sponsored intelligence activity: patient, methodical, and designed to exploit the social and institutional vulnerabilities of a community rather than its technical defences alone.

The technical mechanism of the backdoor was correspondingly elaborate. Jia Tan concealed the malicious payload not in the human-readable source code, where it would have been visible to any reviewer, but within binary test files — data blobs conventionally assumed to contain inert compression test material and therefore subject to far less scrutiny (Boehs, 2024). A small modification to the build scripts extracted and inserted the payload into the compiled XZ library at installation time. The target was OpenSSH, the most widely deployed implementation of the Secure Shell protocol, which constitutes what security researchers describe as the maintenance backbone of the entire internet: the encrypted channel through which system administrators remotely access and manage servers worldwide. To reach OpenSSH, the payload exploited a chain of software dependencies linking XZ to the SSH authentication process. Its mechanism was technically refined: by manipulating an IFUNC resolver — a low-level feature designed to select hardware-optimised code variants at runtime — the backdoor was able to overwrite a critical entry in the Global Offset Table at a precise moment during the linker's initialisation sequence, between the point at which the legitimate address for the RSA decryption function was written and the point at which the table was marked read-only (Freund, 2024). Security experts have referred to this small window as a Goldilocks zone as it let the payload replace a hacked form of the RSA authentication function

without setting off usual detection systems. Once installed, the backdoor conducted a tiny cryptographic exchange on its own to guarantee that only the operator with a certain master key might get unlawful access, while all other attempts to connect went as expected. Log entries were suppressed to prevent forensic detection.

2.11.4. Discovery, Attribution, and Systemic Implications

The backdoor was discovered not through any formal security audit but through the incidental curiosity of Andres Freund, a German software engineer employed by Microsoft who was testing an unrelated database project on a pre-release version of Debian Linux. Freund noticed that SSH login attempts on his Debian Sid system were taking approximately 500 milliseconds longer than expected (around 500ms instead of the normal 100ms), an anomaly that struck him as inconsistent with expected behaviour and prompted him to profile the SSH daemon (Freund, 2024) (Goodin, 2024). The contradiction spurred him to look into the XZ update that was slowing things down; Actually, the extra processing time resulted from the backdoor's hiding techniques, which needed a lot of calculation to find and overwrite the audit hook in memory. Satya Nadella, Microsoft's Chief Executive Officer, expressed formal thanks on social media, but the shortness of this remark maybe underplayed the enormous importance of Freund's role in preserving world digital infrastructure. The performance signature that set off Freund's suspicions would not have shown up had Jia Tan utilized less ambiguity or if the malicious code had been more expertly written. By any fair analysis, the finding was contingent rather than the result of a deliberate defensive approach.

Unfixed is still attribution. Originally hinting at a Chinese state actor were circumstantial signs including commit timestamps matching the UTC+8 time zone connected with Beijing and the use of names with East Asian phonetic features (Boehs, 2024). Subsequent analysis, however, noted that nine commits fell within a UTC+2 time zone corresponding to Israel and parts of western Russia, and that the operator had worked during Christmas but not during Chinese New Year. Various analysts have speculated about possible Russian state involvement, with some pointing to APT29 (Cozy Bear) on the basis of tradecraft similarities, while others have considered alternative attributions; no definitive attribution has been established (Rid, 2020) (Schneier, 2024). What the

pattern of evidence does suggest unambiguously is a well-resourced, disciplined, long-horizon operation of a kind that falls outside the capacity of non-state criminal organisations and points toward a state intelligence apparatus (Rid, 2020) (Schneier, XZ Utils backdoor, 2024).

The XZ event has ongoing repercussions much beyond the specific flaw it exposed. Examining the open-source scene in its aftermath, security specialists found few related backdoors, a revelation that raised more concern than relief. Several elements together created the XZ operation: reliance on vital infrastructure, low maintenance capacity, and patient tradecraft accessible to government players. These elements stay exactly how they are. The episode illustrates what might be termed the asymmetric character of contemporary cyber conflict: an investment of approximately two and a half years by a small team was within weeks of producing access to millions of servers, with potential consequences ranging from mass data exfiltration and ransomware deployment to the disruption of entire national digital infrastructures (Farrell & Newman, 2019). The disparity between the resources required for the attack and the scale of the potential damage is a defining feature of AI-enabled and supply-chain-based cyber operations, and one that fundamentally complicates conventional frameworks of deterrence and attribution.

The debate that followed the XZ disclosure has also reopened longstanding questions about the sustainability of the open-source model as critical infrastructure. Those who argue that the incident exposes a fundamental flaw in open-source development point to the structural dependence of global systems on projects maintained outside any formal institutional framework, without compensation or adequate support. Those who defend the model argue that a comparable operation against a closed-source system would have been at least as feasible, and far less likely to be discovered and publicly analysed: it is precisely the openness of the code that made detection possible, however contingent that detection proved to be (Raymond, 1999). Both positions carry weight. What the episode demonstrates most clearly is that the security of digital infrastructure is ultimately not a technical problem but a political one: it is a question of how societies choose to organize, resource, and govern the foundational systems upon which their economic and strategic capabilities depend.

2.11.5. Cybersecurity Trends in 2026: Shadow AI, Autonomous Agents, Deepfakes, and the Quantum Horizon

2.11.5.1. The Expanding Threat Landscape: AI as Both Vector and Shield

The integration of artificial intelligence into the global digital infrastructure has not only transformed economic and productive capacities but has simultaneously reconfigured the architecture of cybersecurity threats in ways that challenge established frameworks of risk management, organisational governance, and geopolitical deterrence. Whereas earlier generations of cyberattacks depended on the technical proficiency of identifiable actors operating within relatively legible operational parameters, the diffusion of AI capabilities across both offensive and defensive domains has introduced a qualitatively distinct dynamic: one in which the asymmetry between attack and defence has widened, the barrier to entry for sophisticated operations has fallen, and the attribution of responsibility has become structurally more difficult (Buchanan, 2020). Understanding this change necessitates focus not just on the technical aspects of AI-enabled threats but also on the institutional and political environment influencing their emergence, spread, and regulation.

One especially enlightening example of these dynamics is the phenomenon security experts have come to call shadow artificial intelligence: the use of artificial intelligence technologies within organisational settings without official permission, regulatory frameworks, or security supervision. The condition results naturally from the broad accessibility of generative AI systems via commercial cloud environments, which let particular staff members or departments apply machine learning features independent of institutional IT policy (IBM Institute for Business Value, 2024). Organisational security has tangible and quantifiable repercussions. The IBM Cost of a Data Breach Report estimates that companies with a data breach combined with unapproved artificial intelligence (AI) implementations had average extra expenses of around \$670,000 as opposed to those without such exposure (IBM Security, 2024). Compounding this vulnerability is the finding that a substantial majority of organisations — estimated at approximately 63% — had not implemented any AI governance or security policy at the time of breach, leaving the attack surface expanded without the institutional capacity to identify or contain it (IBM Security, 2024).

4.4M

The global average cost of a data breach, in USD, a 9% decrease over last year—driven by faster identification and containment.

97%

Share of organizations that reported an AI-related security incident and lacked proper AI access controls.

63%

Share of organizations that lacked AI governance policies to manage AI or prevent the proliferation of shadow AI.

1.9M

Cost savings, in USD, from extensive use of AI in security, compared to organizations that didn't use these solutions.

FIGURE 26: THE AI OVERSIGHT GAP
(IBM Security, 2024)

Shadow AI thus exemplifies a broader pattern in which the pace of technological adoption outstrips the development of the regulatory and managerial instruments necessary to govern it, a tension that reflects, at the organisational level, the same structural gap between innovation and governance that characterises the geopolitical debate examined in the preceding chapter.

2.11.5.2. Synthetic Media and the Weaponization of Generative AI

Alongside the governance failures associated with shadow AI, the proliferation of deepfake technologies represents a distinct but related transformation in the threat environment. **Deepfakes** — synthetic audiovisual content generated through generative adversarial networks or diffusion models and designed to simulate the appearance, voice, or actions of real individuals — have evolved from a marginal phenomenon to a pervasive instrument of both commercial manipulation and geopolitical interference (Chesney & Citron, 2019). The extent of this spread is quite remarkable: catalogued examples of deepfake material numbered about 500,000 in 2023 and had risen to an estimated 8 million by 2025, a roughly 1,500% increase over two years (Internet Organised Crime Threat Assessment (IOCTA) 2025, 11). This path shows both the quick enhancement of generative model quality and the decrease in computing limitations needed to generate believable fake material. The security implications of this expansion are multidimensional. At the level of individual organisational risk, deepfakes enable the construction of hyper-personalised social engineering attacks in which fabricated communications from apparently authoritative figures — executives, government officials, or trusted contacts — are used to induce fraudulent financial transfers, disclose

sensitive credentials, or authorise illegitimate access (Verizon Business, 2024). AI agents' ability to gather and analyse publicly accessible personal and professional data at scale enhances the efficacy of such activities by generating attack material tailored to the particular circumstances, relationships, and communication patterns of particular targets. Deepfakes present a more fundamental danger at the level of democratic institutions and political communication: the methodical disintegration of epistemic confidence in audiovisual evidence, which has traditionally served as a rather trustworthy evidentiary basis for public responsibility. As detection technologies have repeatedly proven unable to keep pace with generative advances, the strategic response has increasingly shifted from authentication to education — training individuals not to verify the technical authenticity of content but to interrogate the credibility of the actions or disclosures it appears to authorise (Verizon Business, 2024).

The geopolitical component of this knowledge loss goes past organisational security into the realm of interstate rivalry. State-sponsored synthetic media campaigns, such as the documented use of AI-generated deepfakes targeting electoral processes in Slovakia, Bangladesh, and a number of African countries during 2023–2024, are a qualitatively new tool of foreign influence whose cost of production is low compared to the democratic damage it causes and whose attribution is, by nature, extremely difficult to ascertain (Insikt Group, 2024). Because they presume a cooperative environment in which makers of synthetic material freely follow authentication standards, an expectation that state-level enemies running through proxy networks have no reason to respect, the institutional reactions being developed—content provenance standards like the Coalition for Content Provenance and Authenticity (C2PA), cryptographic watermarking of AI-generated outputs, and mandatory disclosure rules for synthetic media in political advertising—represent required but almost certainly inadequate countermeasures (C2PA, 2024). The more serious geopolitical outcome is not any one act of dishonesty but rather the general weakening of the evidentiary foundation upon which democratic debate, diplomatic communication, and international accountability rely—a situation in which the very possibility of shared factual reference is compromised, and in which, for all intents and purposes, the distinction between real and invented becomes unrecoverable by the people democratic government depends on to be informed.

2.11.5.3. Autonomous Agents and the Automation of the Attack Chain

The emergence of autonomous AI agents — systems capable of pursuing complex, multi-step objectives without continuous human supervision — represents perhaps the most consequential recent development in the offensive cybersecurity landscape. The dual character of agentic AI, as both a productivity amplifier for legitimate organisational tasks and a risk amplifier when operating under adversarial conditions or subject to compromise, reflects a structural feature of autonomous systems whose significance extends well beyond any individual application (OWASP Foundation, 2025). When an agent operating with broad system access and delegated authority is hijacked through prompt injection or credential theft, the damage it can inflict is not merely that which a human attacker could produce but that damage amplified by the execution speed and operational continuity that define the value of automation in the first place.

The vulnerability of agentic systems to indirect prompt injection — whereby malicious instructions are embedded in content that an agent is directed to process, such as incoming emails or web pages, triggering unauthorised actions without any intervention by the user whose credentials the agent operates under — represents a qualitatively new attack surface that existing security architectures were not designed to address (Greshake, et al., 2023). The Open Worldwide Application Security Project identified prompt injection as the leading vulnerability category for large language model deployments in both 2023 and 2025, a persistence that reflects the structural difficulty of distinguishing legitimate from malicious instructions in systems whose core function is to follow natural language commands (OWASP Foundation, 2025). The management of non-human identities — the access credentials, permissions, and privilege levels assigned to autonomous agents operating across enterprise environments — presents an associated challenge of considerable scope, as agents may spawn subsidiary agents and accumulate access rights in excess of operational requirements, creating conditions for privilege escalation that conventional identity governance frameworks are ill-equipped to detect or contain (OWASP Foundation, 2025).

On the offensive side, the application of agentic AI to the automation of cyberattack operations has produced a qualitative shift in the threat environment whose implications are difficult to overstate. The sequential stages of a sophisticated cyberattack — target

reconnaissance, vulnerability identification, exploit development, intrusion, lateral movement, data exfiltration, and ransom collection — have historically required a combination of specialist technical skills, patient operational discipline, and substantial human labor. The integration of AI agents into each phase of this process produces what security analysts describe as automated kill chain operations, in which the attacker's role is reduced to defining objectives while the agent executes the entire operational sequence autonomously (Lohn, 2020). The effect is not merely an efficiency gain for existing threat actors but a fundamental restructuring of the attacker skill profile: operations of a complexity that previously required state-sponsored teams or highly organized criminal enterprises become accessible to actors with considerably more limited resources, while the scale, speed, and sophistication of attacks by well-resourced actors increases correspondingly. AI-generated polymorphic malware — code that modifies its own signature and behavioural patterns dynamically to evade detection — exemplifies this dynamic: its production requires progressively less technical expertise while its evasion of conventional signature-based defences becomes progressively more reliable (Buchanan, 2020).

Another aspect of systematic frailty that is related to but different from the offensive cybersecurity threats discussed above is the structural integrity of the code that the AI-era infrastructure relies on more and more. Software engineers have come to call "vibe coding" the practice of using artificial intelligence code-generation tools to create functional software fast without really knowing how the code works, what it depends on, or how it might fail. This has brought a whole new kind of risk into the world of important infrastructure (Karpathy, 2025). When AI-generated code is used in financial systems, energy grid management, healthcare platforms, or military command-and-control systems, the technical debt it builds up isn't just a business problem; it's a security risk for the country. Code whose internal logic is unknown to its nominal users cannot be properly fixed if faults are discovered; it cannot be tested for embedded flaws; it may contain failure modes whose activation conditions are, by definition, unknown to the companies who depend on it. The structural parallel with the 2008 financial crisis is perfect from an analytical standpoint: the opacity of collateralised debt instruments made the systemic risk they carried invisible to the authorities, rating agencies, and counterparties whose job

it was to evaluate it. In either instance, the speed and efficiency of the manufacturing system exceeded the institutional ability to comprehend what it had produced; the results became clear only at the moment of failure (Tett, 2009). For the geopolitical examination of this paper, vibe coding is important since it generates the attack surface: An opponent finding flaws in commonly used AI-generated code—or who gives somewhat inaccurate training data to the models from which that code is produced, therefore replicating at scale the social engineering logic of the XZ Utils attack studied above—would have a tool of disruption with scope across every system founded on the compromised basis.

2.11.5.4. Defensive Applications and the Logic of Adaptive Response

The same properties that make artificial intelligence a force multiplier for offensive operations — the capacity to process large volumes of data rapidly, identify patterns across heterogeneous information sources, and adapt behaviour in response to environmental feedback — equally define its potential as an instrument of cybersecurity defence. The deployment of AI systems for real-time threat detection, anomaly identification, and automated incident response has become an established practice across major technology and security vendors, with systems now capable of identifying prompt injection attempts, detecting atypical network behaviour indicative of intrusion, and initiating containment protocols at machine speed (Buczak & Guven, 2016). The development of AI-powered defences against AI-generated attacks — systems specifically trained to recognise the behavioural signatures of automated malware, synthetic phishing content, or adversarial prompt injections — reflects a logic of adaptive counter-deployment that mirrors, at the technical level, the broader dynamics of arms races in conventional military domains (Brundage, 2018).

The limitations of purely technical defensive responses are, however, significant. Polymorphic malware and continuously retrained generative models ensure that the signatures sought by detection systems are perpetually provisional, requiring defensive architectures that are themselves capable of adaptive learning rather than pattern-matching against known threats. The convergence of this requirement with the inherent opacity of large language models and neural network-based detection systems raises important questions about accountability and oversight, particularly in contexts where AI-driven defensive systems may trigger automated countermeasures with consequences that

are difficult to anticipate or reverse (Floridi, Cowls, Beltrametti, & Rossi, 2018). These tensions between operational effectiveness and governance transparency are not merely technical: they are political, insofar as they determine the conditions under which organisations, governments, and international bodies can maintain meaningful oversight of the automated systems upon which critical infrastructure security increasingly depends.

2.11.5.5. Quantum Computing and the Cryptographic Horizon

Distinct from, though structurally related to, the AI-enabled threats examined above is the longer-horizon challenge posed by the anticipated advent of cryptographically relevant quantum computing. Modern public-key encryption systems, including RSA and elliptic curve methods, which are used to protect financial transactions, government communications, and critical infrastructure authentication around the world, get their security from the fact that it is hard to factor huge numbers or solve discrete logarithm problems on classical computers (Rivest, Shamir, & Adleman, 1978). Quantum computers running at adequate scale and coherence will eliminate this impossibility and make problems now needing astronomical units of time of computation resources solvable inside reasonable operational windows. The anticipated threshold at which quantum systems achieve this capability — variously described in the literature as Q-Day or cryptographically relevant quantum computing — remains uncertain in its timing, but suggests that expert estimates now converge on a window of between five and twenty-five years, with the Cloud Security Alliance placing Q-Day as early as 2030 for nation-state actors and Palo Alto Networks' analysis suggesting the 2030s or later for broader availability — a range whose uncertainty is itself a governance challenge, since cryptographic migration at institutional scale requires a decade or more to complete (Mosca, 2018).

The geopolitical dimensions of this transition are considerable. States and non-state actors with early access to cryptographically capable quantum systems would gain the ability to decrypt retrospectively collected encrypted communications, undermining the long-term confidentiality of intelligence, diplomatic, and commercial data secured under current standards — a practice known as “harvest now, decrypt later” that several state intelligence agencies are believed to be pursuing systematically (Marrow, 2025). In

anticipation of this transition, the United States National Institute of Standards and Technology completed in 2024 the standardisation of the first set of post-quantum cryptographic algorithms, designed to remain computationally secure against both classical and quantum adversaries (National Institute of Standards and Technology, 2024). The adoption of these standards by governments, financial institutions, and critical infrastructure operators nonetheless proceeds unevenly: while awareness of the quantum threat has grown substantially, demonstrated deployments of post-quantum cryptography at scale remain limited relative to the scope of the exposure, and the operational costs of cryptographic migration — in terms of system compatibility, key management, and institutional coordination — represent a non-trivial barrier to timely remediation (Mosca, 2018).

The intersection of artificial intelligence and quantum computing introduces a further dimension of strategic uncertainty. AI-accelerated research into quantum hardware and error correction may compress the timeline to cryptographically relevant systems; conversely, AI-driven optimisation of post-quantum cryptographic implementations may ease the burden of defensive migration. The competitive dynamics shaping this intersection are inseparable from the broader geopolitical contest over technological leadership examined throughout this thesis: the state or coalition of states that first achieves practical quantum supremacy will possess a strategic intelligence advantage of a kind without clear historical precedent, while those that fail to implement quantum-safe cryptographic infrastructure in time will face a systemic vulnerability of comparable gravity (Marrow, 2025). The governance of this transition — including the question whether and how quantum-enabled decryption capabilities might be subject to arms control or international transparency norms — remains at an early and largely unresolved stage of international discussion.

Conclusion of section 2.11.

The developments examined in this chapter — shadow AI and the governance gap in organisational security, the proliferation of deepfake-enabled social engineering, the automation of offensive attack chains through agentic AI, the evolution of adaptive defensive architectures, and the approaching quantum cryptographic transition — are not

isolated technical phenomena but interconnected dimensions of a broader structural transformation in the nature of geopolitical competition. The lowering of the technical barrier to sophisticated cyberattacks, the acceleration of offensive operational tempo, and the erosion of attribution reliability collectively weaken the deterrence frameworks that historically structured state behaviour in the security domain. The increasing integration of AI into both offensive and defensive capabilities simultaneously raises the stakes of AI leadership and deepens the risks associated with AI dependence, extending the analysis of strategic autonomy developed in the preceding chapter into the domain of hard security.

The ramifications for Europe are severe, especially for a continent whose AI development capability lags behind that of its main geopolitical rivals and whose digital infrastructure mostly relies on foreign cloud platforms confronts a multiplied exposure: not only the general flaws listed above but also the particular danger that the people controlling the systems upon which its security relies may have strategic goals different from its own. The elaboration of a genuinely autonomous European cybersecurity capability — one grounded in sovereign digital infrastructure, independent AI research capacity, and a regulatory framework adequate to the pace of threat evolution — is thus not merely a technical or economic priority but a condition of political sovereignty in the twenty-first century.

Yet if the cybersecurity landscape reveals the extent to which AI has already transformed the invisible infrastructure of geopolitical competition, it is in the domain of physical warfare — where autonomous systems are being delegated not merely the processing of information but the authority to take human life — that the stakes of the AI race assume their most irreversible and morally consequential form.

In a scenario published in April 2026 by Anthropic, Treasury Secretary Scott Bessent and Federal Reserve Chair Jerome Powell called an emergency meeting with the CEOs of Citigroup, Goldman Sachs, Morgan Stanley, Bank of America, and Wells Fargo at the Treasury's headquarters in Washington (Gillespie, Johnson, Levitt, & Natarajan, 2026). This came after Anthropic's Claude Mythos Preview, which is a new model that can find zero-day vulnerabilities in web browsers, operating systems, and financial payment systems. Some of these vulnerabilities had been left unpatched for decades. The

meeting was called not to react to an attack that had already happened, but to get ready for one that the model's capabilities made almost certain to happen: monetary authority, fiscal authority, and private financial leaders were all coming together in an unusual way to talk about how well AI could be used. Anthropic's own review cautioned that twelve months from now, models with equivalent skills would be accessible to other players, including those with ill intent (Anthropic (e), 2026). Under an effort dubbed Project Glasswing, Anthropic's choice to confine Mythos to a small group of launch partners including JPMorgan Chase, Apple, Google, Microsoft, and NVIDIA, and to provide up to one hundred million dollars in usage credits for companies building or deploying important software infrastructure, marks the most definite example so far of the governance problem this thesis has highlighted across several registers: The same skill that generates unheard-of offensive risk also produces unheard-of defensive possibility, and the institutional issue is whether the defensive deployment can outrun the offensive spread (Subin & Son, 2026). The fact that the Secretary of the Treasury and the Chair of the Federal Reserve were raising this issue in a closed-door meeting with the heads of the institutions through which most of the world's capital flows, not by academic researchers or think-tank analysts, indicates that the cybersecurity aspect of AI rivalry has gone beyond a technical concern to become a first-order question of financial stability and national security.

2.12 Lethal Autonomous Weapons Systems: AI, Military Power, and the Crisis of International Governance

2.12.1. From Remote Control to Autonomous Decision-Making: The Military Robotics Revolution

The integration of artificial intelligence into military systems represents one of the most consequential and contested transformations in the contemporary geopolitics of technology. Where preceding chapters examined the economic and regulatory dimensions of the global AI competition, the military domain introduces a qualitatively distinct set of stakes: the delegation of lethal decision-making authority to algorithmic systems whose behaviour in complex, unstructured environments cannot be fully predicted, audited, or

reversed. The question whether, and under what conditions, a machine may autonomously select and engage a human target has emerged as a central axis of debate within international security studies, international humanitarian law, and the institutions of global governance — a debate whose urgency is compounded by the pace of technological development and the absence of binding international norms (Scharre, 2018).

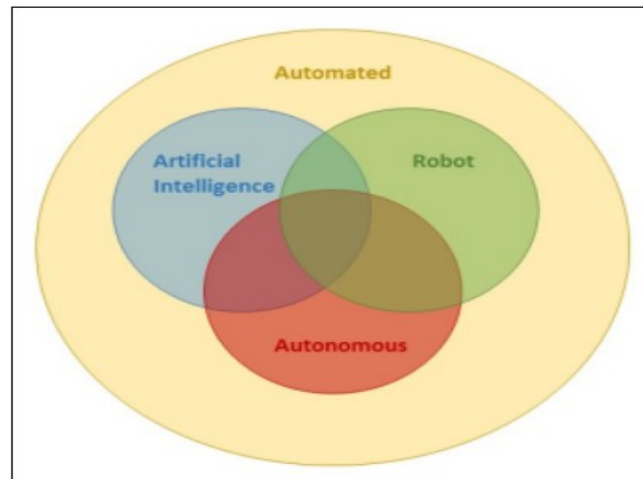
The origins of this transformation lie not in a single strategic decision but in what analysts of the United States Department of Defense have described as an 'accidental robotics revolution': the large-scale deployment of remotely operated air and ground robots during the conflicts in Iraq and Afghanistan in the late 2000s (Singer, 2009). Early military robotic systems were remotely controlled in the most literal sense; that is, a person tele-operated them by guiding their motions in real time, much like how one would drive a radio-controlled car. Their main uses were neutralising homemade explosive devices, jobs where a machine taking the place of a human operator clearly provided force-protection benefits without needing the system to make independent choices about targets or engagement. The strategic significance of this early deployment lay less in its immediate operational effect than in the imaginative shift it produced among military planners: the growing recognition that robotic platforms, if endowed with sufficient autonomy, could extend the reach, speed, and persistence of military operations far beyond what human operators, subject to fatigue, fear, and cognitive limitation, could sustain (Chamayou, 2015).

The transition from remote-controlled systems to platforms capable of genuine autonomous action has been driven principally by advances in machine learning — and specifically by the development of reinforcement learning methods that enable systems to acquire complex behavioural competencies through iterative interaction with simulated environments, without the need for exhaustive human instruction (Russell & Norvig, 2020). It is impossible to overemphasize the importance of this change in technique. Classical rule-based methods of robotics autonomy—whereby programmers pre-defined the conditions under which a system should take every conceivable action—proved weak in the face of the inherent complexity of real-world situations. On the other hand, machine learning lets a system apply what it has learned from a lot of training to new settings. This

can lead to strategies that are quite different from what people would normally think is right, but which are actually better in real-world situations. The demonstration of this capacity in contexts directly relevant to military competition — from DeepMind's AlphaGo defeating the world champion at a game once considered beyond the reach of machine intelligence, to DARPA's AlphaDogfight Trials of August 2020, in which the F-16 AI agent developed by Heron Systems defeated a graduate of the U.S. Air Force Weapons Instructor Course — known by his call sign "Banger" — by five rounds to zero in a series of simulated within-visual-range, guns-only dogfights conducted in F-16 flight simulators (with the AI operating under perfect-state-information conditions that experts cautioned do not obtain in actual combat) — has transformed the perceived horizon of what autonomous military systems might achieve (Defense Advanced Research Projects Agency, 2020).

2.12.2. Autonomous Weapons and the Architecture of Modern Warfare

Contemporary military applications of AI autonomy span a broad spectrum of functions, from intelligence, surveillance, and reconnaissance through logistics and command support to direct lethal engagement. At the surveillance end of the spectrum, autonomous quadcopter platforms such as those developed by Shield AI are already deployed in operational contexts, capable of exploring complex multi-storey structures without human guidance, mapping their interiors in real time, and distinguishing human presence from environmental features through thermal imaging — functions that previously required special operations personnel to undertake at considerable personal risk (Shield AI, 2023). At the command and control end, major military powers are investing heavily in AI-enabled battle management architectures — the United States Army's Project Convergence, the Navy's Project Overmatch, and the Air Force's Advanced Battle Management System — whose ambition is to integrate data from satellites, drone networks, ground sensors, and cyber intelligence into a unified operational picture, processed and prioritised by AI systems at speeds that compress the decision cycle of military command far beyond the capacity of unassisted human judgement (Sayler, 2020).



Source: CRS.

FIGURE 27: RELATIONSHIPS OF SELECTED AI DEFINITIONS
(Sayler, 2020)

The paradigmatic case of AI autonomous lethality, however, is the development of armed drone platforms capable of selecting and engaging targets without requiring real-time human authorisation for each strike. The military rationale for this capability rests on several converging arguments. First, autonomous systems are not subject to the physiological and psychological constraints that degrade human performance under combat conditions: they do not experience fear, fatigue, or the cognitive distortions produced by stress, and can therefore execute tactically optimal manoeuvres — such as the “face shot” strategy developed spontaneously by AI pilots during DARPA's simulation trials, in which the system exploited a head-on engagement geometry that human pilots avoid due to the risk of collision — that fall outside the behavioural envelope of human operators (Defense Advanced Research Projects Agency, 2020). Second, autonomous systems operating at machine speed can respond to threats and opportunities within temporal windows that preclude meaningful human decision-making, particularly in contested electromagnetic environments where communications links may be jammed or severed. Third, and most strategically consequential, swarm architectures — coordinated deployments of large numbers of relatively simple autonomous platforms that share information and coordinate behaviour through distributed algorithms, without centralised command — offer the prospect of multiplying the effective combat power of small military units by orders of magnitude, fundamentally

altering the force ratios that determine the outcome of conventional engagements (Brose, 2020).

The dual-use character of the underlying technologies complicates any straightforward assessment of the boundary between defensive and offensive military applications. The machine learning methods that enable a robot dog to navigate diverse and unpredictable terrain in disaster relief operations are the same methods that, with a change in objective function, enable an armed platform to pursue and engage a target across analogous terrain (Russell & Norvig, 2020). More strikingly, the generative AI systems used in pharmaceutical research for the accelerated discovery of therapeutic molecules were demonstrated in 2022 to be capable, when the optimisation objective was inverted from maximizing therapeutic efficacy to maximizing toxicity, of generating tens of thousands of novel chemical weapon candidates — many predicted to be more lethal than the nerve agent VX — in a matter of hours on standard consumer computing hardware (Urbina, Lentzos, Invernizzi, & Ekins, 2022). The implications of this demonstration, which prompted urgent discussions at the level of the United States executive and generated substantial attention in governmental arms control circles, extend well beyond the specific domain of chemical weapons: they illustrate a general principle that the same AI capabilities being diffused globally through commercial platforms are simultaneously a resource for an expanding range of actors seeking to develop asymmetric lethal capabilities at minimal cost.

2.12.3. The Problem of Meaningful Human Control: Ethics, Law, and Accountability

The most fundamental objection raised against lethal autonomous weapons systems (LAWS) is not primarily technical but moral: that the delegation of the decision to take a human life to an algorithm constitutes a violation of a principle — that such decisions must be made, and be accountable to, a human moral agent — that lies at the foundation of both the ethics of warfare and the structure of international humanitarian law (Sparrow, 2007). International humanitarian law as codified in the Geneva Conventions and their Additional Protocols requires combatants to distinguish at all times between combatants and civilians, to exercise proportionality in the use of force, and to take precautionary measures to minimise civilian harm. The question whether an autonomous system can

reliably satisfy these requirements in the ambiguous conditions of real operational environments — conditions in which, as battlefield testimony illustrates, even highly trained human soldiers face genuinely difficult judgements about the status of individuals whose behaviour is consistent with both civilian and combatant profiles — remains unresolved and is the subject of deep scepticism among both legal scholars and AI researchers (International Committee of the Red Cross (b), 2021). This scepticism finds one of its sharpest expressions in Federico Faggin, the renowned physicist and who has since become a prominent critic of the claim that machine intelligence approaches human cognition. In his account, an AI system manipulates symbols without grasping their meaning: it generates sequences of tokens by computing probabilities, and where a person selects words by virtue of understanding what they intend to say, the model comprehends nothing and selects, in effect, through a generated number. For Faggin this is a categorical limitation rather than a temporary one, since consciousness and genuine understanding are, on his view, not replicable in a machine. The danger he identifies follows from that absence. So long as the system deals only in symbols, its lack of understanding yields errors of interpretation; but when symbols become actions, when a model is granted what he calls the power to act, the same absence can produce catastrophic outcomes. His chosen illustration is precisely the one at issue here: a drone given the authority to kill without first seeking permission from a human being. A system that understands nothing, he warns, may commit massive errors or exploit loopholes its operators can no longer follow, and in that sense turn against those who deployed it, not from any will or awareness of its own, which it does not possess, but simply because it never understood what it was doing, he said "So, there is this movement where, without realizing it, we give power to this artificial intelligence which then turns against us. Not because artificial intelligence knows that it is turning against us—since it understands nothing, meaning it doesn't possess a consciousness or a will of its own—[but it happens anyway]." (Faggin, 2026).

A linked and equally major issue is the accountability gap produced by independent targeting choices. If an autonomous weapon improperly kills a civilian, the issue of who is legally or civilly liable is conceptually unclear: The programmer who developed the method did not mean for the particular result; The commanding officer

who approved deployment did not order the particular interaction; The maker of the platform did not run it in the field. This distribution of causal agency across a chain of human decisions none of which individually constitutes the prohibited act creates what scholars of military law have called a 'responsibility gap' — a condition in which the formal requirements of accountability under international law are satisfied at no point in the causal chain leading to an unlawful killing (Sparrow, 2007). The concern is not merely academic. A United Nations Panel of Experts report on the Libyan conflict documented what appears to have been the first instance in which an autonomous drone platform, programmed to pursue and engage targets without requiring real-time human authorisation, conducted lethal operations against human targets — a development that, if confirmed, would mark a watershed in the history of warfare comparable in its structural implications to the introduction of chemical weapons or strategic bombing (United Nations Panel of Experts on Libya, 2021).

The structural concern underlying these legal-philosophical objections has, since 2023, acquired empirical substance through documented cases of large-scale algorithmic targeting in active conflict. Investigative reporting by the Israeli outlet *+972 Magazine* and *Local Call*, subsequently corroborated by *The Guardian* and academic analyses, has documented the use by the Israel Defense Forces of two AI-enabled targeting systems during the Gaza conflict — code-named "Lavender" and "The Gospel" — whose operational characteristics illustrate the mechanism by which the responsibility gap translates from a theoretical vulnerability into a battlefield reality (Abraham, 2024). According to the testimony of six Israeli intelligence officers who served during the conflict, Lavender generated targeting recommendations against an estimated 37,000 Palestinians by applying machine-learning classifiers to the population's communications metadata, location data, and social network signals; human operators reportedly approved these recommendations after an average review time of approximately twenty seconds per target — a duration that, as the officers acknowledged, was insufficient to verify the system's outputs against independent sources of intelligence and that effectively reduced the human role to what one operator described as "a stamp of approval" on the algorithm's classifications (Abraham, 2024). The Gospel, by contrast, generated recommendations against physical infrastructure rather than individuals, but operated under a comparable

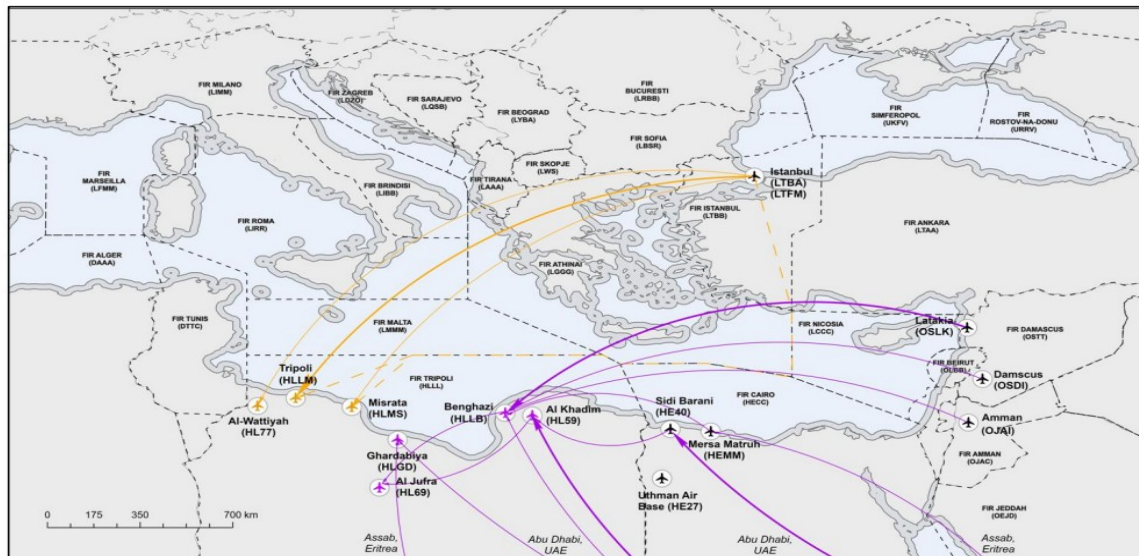
logic: the system identified buildings whose pattern of use suggested militant association, and human reviewers approved engagement decisions at a tempo that scholars examining the case have characterized as inconsistent with the proportionality assessments that international humanitarian law requires (Schmitt, 2024) (McKernan & Davies, 2024). The structural significance of these cases extends beyond the specific conflict in which they were deployed. They demonstrate, in operational conditions rather than in laboratory simulations, that the meaningful-human-control standard articulated in the United States Department of Defense's 2023 directive is structurally vulnerable to erosion through what scholars of military automation have termed "automation bias" — the documented tendency of human operators, under conditions of time pressure and information overload, to defer to algorithmic recommendations whose internal logic they cannot independently verify (Cummings M. , 2017). They also illustrate a second-order vulnerability that the contemporary literature on AI targeting has begun to map: the dependence of these systems on training data and target-classification rules whose accuracy degrades over time as the underlying environment changes, with the consequence that engagement decisions taken on the basis of such systems may be systematically miscalibrated to operational realities that have evolved since the data was collected — a condition under which the formal preservation of human authorisation provides little protection against the substantive failure of the underlying classifications (Arentze, Gould, & Hoijtink, 2026). The cases under examination here predate the Iran conflict that this thesis has documented and the Maven Smart System deployments — the operational AI-enabled targeting and intelligence-fusion platform that evolved from Google's controversial Project Maven contract (2017–2018) into the Department of Defense's principal battlefield AI infrastructure — that the United States has accelerated across 2025 and 2026, but they establish the structural template against which those subsequent deployments must be assessed: AI-mediated targeting is no longer a hypothetical vector of concern but an operational reality whose consequences for civilian protection, legal accountability, and the customary architecture of international humanitarian law are accumulating faster than the institutions designed to govern them are able to respond (International Committee of the Red Cross (a), 2021).

The distinction between systems that retain meaningful human control and those that operate outside it is further complicated by the dynamics of competitive military adoption. Even states that formally maintain doctrinal commitments to human-in-the-loop engagement protocols — the United States Department of Defense's directive requiring that a human operator authorise lethal force — may find themselves under pressure to relax those commitments in operational contexts where the tempo of engagement exceeds the capacity of human decision-making, or where adversaries operating without equivalent constraints achieve decisive tactical advantages (U.S. Department of Defense, 2023). The structural logic identified by analysts of the arms race dynamic is analogous to classical security dilemma reasoning: even actors who would prefer a world in which all states maintained meaningful human control over lethal systems may find themselves driven to automate engagement decisions by the fear that their adversaries will do so first, producing an equilibrium in which no actor achieves the preference of all (Scharre, 2018). The public statements of senior political figures in Russia and China that AI supremacy is a core strategic priority, and that leadership in this domain will determine the distribution of geopolitical power in the coming decades, provide explicit evidence that the competitive logic is fully operative at the level of grand strategy (U.S. Department of Defense, 2023).

2.12.4. The Geopolitics of Autonomous Weapons: An Emerging Arms Race

The geopolitical dimensions of the LAWS competition are inseparable from the broader AI race examined in the preceding chapters of this thesis, yet they introduce specific dynamics that the purely economic and regulatory analysis of AI competition does not fully capture. The actors in this competition include not only the major state military powers — the United States, China, and Russia, each of which has articulated explicit strategic objectives around AI military dominance — but also middle-tier military powers such as Israel, Azerbaijan, and Turkey, which have demonstrated the operational deployment of autonomous or semi-autonomous strike systems in recent conflicts, and potentially non-state actors, for whom the declining cost and increasing accessibility of commercial drone platforms and open-source machine learning frameworks may, in the medium term, provide the capability to construct rudimentary lethal autonomous systems

without the institutional resources previously associated with advanced military technology development (United Nations Security Council, 2021).



Note: Map developed by C4ADS, with Panel input.

FIGURE 28: SCHEMATIC OF ARMS TRAFFICKING AIR BRIDGES
(United Nations Security Council, 2021)

There are two different structural ramifications for global security from the diffusion of autonomous weapon technology to more and more actors. The first is the erosion of the conventional deterrent system that, with less than perfect but actual success, has kept big power rivalry in check since 1945. Deterrence theories founded on the reliable threat of retaliation rely on the attribution of hostile acts to particular state actors and on the capacity of those actors to regulate the escalatory dynamics of war by conscious decision-making. Autonomous systems that can operate with minimal human supervision, whose behaviour in complex environments may be difficult even for their operators to predict, and whose deployment may be deniable or ambiguous in attribution, undermine both pillars of this architecture (Scharre, 2018). The second implication concerns the threshold of conflict itself: autonomous weapons that are cheap, scalable, and do not require the deployment of human military personnel may lower the effective political cost of initiating armed operations, reducing the human and domestic political constraints that have historically moderated the use of force (Brose, 2020).

The specific theatre of greatest strategic concern in the near to medium term is the Taiwan Strait and broader Western Pacific, where the United States, its allies, and the People's Republic of China are investing simultaneously and competitively in autonomous military capabilities whose interaction in a crisis scenario is unpredictable. Chinese military doctrine has explicitly embraced what its strategists term “intelligentised warfare” — the integration of AI, autonomous systems, and data fusion into every level of the military command structure, from tactical unit operations to strategic decision-making — as a central pillar of the People's Liberation Army's modernisation program (Kania, 2017). The United States' REPLICATOR initiative, announced in 2023, explicitly frames the mass deployment of autonomous drone systems as the primary US response to China's quantitative military advantages in the Pacific, signalling an institutional commitment to operational autonomy that goes substantially beyond existing policy frameworks on human control (U.S. Department of Defense, 2024). The interaction of these competing autonomous military programs, in a theatre characterized by compressed reaction times, contested electromagnetic environments, and the potential for rapid escalation from localised incidents to broader conflict, represents what analysts have described as a novel and potentially unstable strategic environment without clear historical precedent.

2.12.5. International Governance and the Limits of Prohibition

The international governance of lethal autonomous weapons systems has been the subject of sustained diplomatic discussion within the framework of the Convention on Certain Conventional Weapons (CCW) since 2014, and of a broader advocacy campaign by civil society organisations and a coalition of states calling for a legally binding prohibition on systems that select and engage targets without meaningful human control (Roff, 2016). The obstacles to agreement are, however, structural rather than merely diplomatic. The states with the most advanced autonomous weapons programs — the United States, Russia, and China — have each resisted any formulation of the debate that would commit them to legally binding constraints on capabilities they regard as central to their competitive military positions. The United States has consistently maintained that existing international humanitarian law is sufficient to govern the use of autonomous

systems, and that any new treaty framework would impose obligations on US forces that would not be matched by adversaries, thereby producing strategic disadvantage without meaningful humanitarian benefit (U.S. Department of Defense, 2023).

The analogy invoked by proponents of prohibition — the Biological Weapons Convention concluded during the Cold War, which achieved the prohibition of an entire category of weapons despite the deep mutual antagonism of the United States and the Soviet Union — is instructive both for its positive precedential force and for the limits it reveals (Roff, 2016). The biological weapons regime was negotiated and ratified at a moment when both major powers had concluded, independently and for their own strategic reasons, that the military utility of biological weapons was outweighed by the risks of proliferation to state and non-state actors and by the unpredictable character of biological agents as instruments of warfare. No equivalent convergence of strategic interests is currently visible in the autonomous weapons domain: the major powers regard AI military supremacy as a positive-sum objective — a source of decisive competitive advantage — rather than as a shared liability. The arms race dynamics identified by analysts of the current competition, in which speed of adoption is systematically privileged over considerations of safety and governance, thus replicate in the military domain the broader pattern, examined throughout this thesis, in which the pace of AI development outstrips the institutional capacity of states and international organisations to govern it (Scharre, 2018).

The governance difficulty autonomous weapons raise is especially severe for the European Union given how they affect the link between the Union's strategic credibility and regulatory aims. Through the AI Act and related policy tools, Europe has positioned itself as the world leader for responsible AI governance. However, this creates a conflict with the security landscape that is becoming more and more defined by the autonomous weapons programs of its main geopolitical rivals—and, to a lesser extent, of its main ally. The question whether the EU can sustain a credible posture of normative leadership in AI governance while its member states participate in a NATO alliance whose leading member is actively accelerating the deployment of autonomous military systems — and whether that posture is, in any case, compatible with the EU's own emerging defence industrial ambitions — is one of the most consequential unresolved questions in European

strategic policy (Csernaton, 2026). Yet the financial vulnerability exposed by the data center build-out acquires its most acute geopolitical dimension not in the domain of capital markets but in that of national security, where the question of who controls frontier AI models — and on what terms — has become a direct object of state coercion.

2.12.6. *AI Weaponization, Corporate Governance, and the Fracture Lines of Democratic Control*

The militarisation of frontier AI models has ceased to be a prospective concern and has become, by early 2026, an active site of institutional conflict within the United States itself. The dispute between Anthropic and the Department of War — escalating through February and March of 2026 from contractual negotiation to mutual threats of legal compulsion and commercial exclusion — illustrates with unusual clarity the structural tensions produced when frontier AI capabilities are simultaneously indispensable to national security operations and developed by private actors whose governance frameworks impose constraints that state military institutions regard as operationally unacceptable (Hays, 2026). At issue were two specific use cases that Anthropic refused to permit under its existing contractual arrangements with the Department of War: the deployment of its Claude models for mass domestic surveillance and for fully autonomous weapons systems operating without human oversight (Hays, 2026) (Anthropic (c), 2026). Anthropic's CEO Dario Amodei articulated the technical basis for the second refusal with particular precision, arguing that frontier AI systems are presently not sufficiently reliable to exercise the contextual judgement that lethal engagement decisions require, and that autonomous weapons deployed without adequate guardrails — which in his assessment do not yet exist — place both military personnel and civilians at unacceptable risk (Anthropic (c), 2026) (Scharre, 2018). The Pentagon's response — threatening simultaneously to designate Anthropic a supply chain risk, a designation previously reserved for adversarial state actors such as Huawei, and to invoke the Defense Production Act to compel the removal of its safeguards — exposed an internal contradiction that Amodei identified explicitly: the same institution that characterized the company as a security liability simultaneously acknowledged that Claude was the only AI model deployed across the military's classified networks, that no comparable

replacement existed in the near term, and that removing it would impose substantial operational disruption on intelligence analysis, operational planning, and cyber operations (Anthropic (c), 2026) (Kolodny, Levy, & Subin, 2026). The episode acquired a further and analytically revealing dimension when OpenAI, on the same day the federal ban on Anthropic was announced — 27 February 2026 — concluded its own agreement with the Department of War to deploy its models in classified military environments (OpenAI (a), 2026). OpenAI declared publicly that its deal incorporated the same substantive red lines as those Anthropic had defended — no mass domestic surveillance, no direction of autonomous weapons systems, and additionally no use for high-stakes automated decisions of the kind associated with social credit mechanisms — and framed the arrangement as a more technically robust alternative to outright refusal, relying on cloud-only deployment architecture and the presence of cleared safety personnel to enforce its constraints (Ha, A. (a), 2026). The immediate public reaction, however, was sharply negative: ChatGPT uninstall rates surged by approximately 200% in the days following the announcement, with users migrating toward Claude despite the federal restrictions placed on Anthropic's products. Altman subsequently acknowledged in an internal memo, shared publicly on X, that the deal had been rushed and that its initial presentation had been, in his own characterisation, opportunistic and sloppy, prompting a revised contract published on 2 March 2026 that added explicit prohibitions on the use of OpenAI models by the NSA and on the procurement of commercially acquired personal data for surveillance purposes (Butts, 2026). The internal costs were also significant: Caitlin Kalinowski, OpenAI's lead for robotics and hardware, resigned on 7 March 2026, stating that the use of AI for surveillance of Americans without judicial oversight and for lethal autonomy without human authorisation were lines that had deserved more deliberation than they received. The divergence between Anthropic's absolute refusal and OpenAI's conditional acceptance raised questions that legal analysts and civil liberties organisations were swift to identify: where Anthropic demanded outright prohibitions, OpenAI accepted the Pentagon's preferred formulation of permitting any lawful use while seeking to define the constraining laws within the contract — a distinction that critics at the Electronic Frontier Foundation characterized as producing contractual ambiguity that would preserve governmental flexibility in

practice while providing the appearance of meaningful constraint in principle (McSherry & Guariglia, 2026). The episode is analytically significant beyond its immediate facts. It demonstrates that the governance of AI in the military domain cannot be resolved through the contractual instruments available to commercial procurement, because the questions at stake — whether a machine may autonomously take a human life, whether AI-enabled surveillance of a state's own population is a lawful exercise of national security powers — are constitutional and normative questions that, as legal scholars have noted, are too consequential to be determined by Cold War-era production statutes or by the unilateral assertions of executive agencies operating without legislative mandate (Laperruque, 2026). The competitive logic that drives the militarisation of AI compounds this governance deficit further: when US Undersecretary for Defence Emil Michael justified the Pentagon's position by invoking the necessity of matching China's autonomous military programs (Hays, 2026), he articulated precisely the security dilemma dynamic that analysts of lethal autonomous weapons systems have identified as the primary structural obstacle to any binding international governance regime — a race in which each actor's defensive justification for acceleration simultaneously constitutes the offensive threat that justifies every other actor's acceleration. Anthropic's official blacklisting and Claude's subsequent withdrawal from Pentagon systems verified that the rift between the safety governance framework of frontier AI developers and the operational needs of state military institutions is not a minor regulatory bother but rather a structural fault line with ramifications spanning the whole fabric of democratic AI governance (Kolodny, Levy, & Subin, 2026) (OpenAI (a), 2026).

Conclusion of section 2.12

The analytical thread running through this chapter — from the rare earth dominance that Beijing has constructed across African mineral infrastructure, through the debt-financed data center build-out whose material foundations remain exposed to Chinese supply chain leverage, to the institutional fracture between frontier AI developers and the national security apparatus of the United States — converges on a single structural observation: the geopolitical and geoeconomic competition for AI supremacy is not unfolding along a single axis but along several simultaneously, and the interactions among those axes are

producing governance deficits that no existing institutional framework is currently equipped to address. Over three decades of deliberate strategic investment, China has built a posture of structural dominance over the physical inputs of AI hardware that makes Western AI infrastructure dependent, at every key moment, on supply chains under Beijing's export control jurisdiction. The Western reaction, which is funded by debt, is worth hundreds of billions of dollars. It is meant to build and run data centers, which need the same minerals that the West is known for. This doesn't fix the West's reliance on these minerals; it makes it worse. The West now has financial obligations that make it even more vulnerable instead of less. And the attempt by the US national security apparatus to convert frontier AI models into instruments of autonomous lethal force and mass domestic surveillance, unconstrained by the governance frameworks that their developers regard as technically necessary and democratically required, reveals that the internal coherence of the Western AI project is itself in question — that the institutional contest over who controls these systems, and for what purposes, is being conducted not only between Washington and Beijing but within the democratic polity itself. This study clearly points out the governance problem rather than offering a counsel of strategic paralysis. The window within which trustworthy democratic oversight mechanisms, supply chain diversification strategies, and binding norms may be set is closing concurrently on the material, financial, and institutional aspects of the artificial intelligence competition; the pace of that closing is, in each sphere, faster than the institutional responses so far created.

3. The Future: 2027–2035 — Scenarios for the Intelligence Transition

Introduction: History as Heuristic — Can the Past Predict the AI Future?

A methodological clarification is necessary before proceeding. The “temporal rather than directional” framing that organizes this chapter is not a claim that direction is fully determined and only the speed varies; it is a claim that the *direction* of capability development is more legible from the structural evidence than the *interaction* between capability development, capital deployment, regulatory adaptation, and labor-market absorption, each of which operates on a distinct clock. The financial cycle compresses to quarters; capability development to months; regulatory adaptation to years; labor-market reorganization to decades. The scenarios developed below are therefore not differentiated principally by the speed at which a single process unfolds but by the *relative* speeds at which these distinct processes interact — and the institutional consequences that follow from each configuration of relative speeds. This is the analytical purchase that the scenario method offers over more deterministic forecasting approaches. The preceding chapters have developed two interlocking arguments. The first, advanced through the historical analysis of **Chapter 1**, is that the emergence of a general-purpose technology — whether coal-fired steam in the nineteenth century or algorithmic computation in the twenty-first — generates a recognisable set of geopolitical and geoeconomic dynamics: the reorganization of resource sovereignty around previously marginal inputs, the concentration of productive capacity in a small number of states and firms, the weaponization of supply chains as instruments of strategic denial, and the widening of structural asymmetries between those who control the enabling infrastructure and those who depend upon it. The second, established through the empirical investigation of **Chapter 2**, is that the contemporary AI investment cycle reproduces these dynamics with considerable structural fidelity while introducing features — circular financing arrangements, debt-funded infrastructure at historically unprecedented scale, geopolitical

entanglement of the semiconductor and energy supply chains, and the emergence of autonomous weapons systems operating beyond the reach of existing international law — that have no adequate precedent in either the dot-com episode or the earlier industrial transitions from which this thesis draws its analytical framework. The task of the present chapter is to test whether these two sets of findings, taken together, permit the construction of plausible forward-looking scenarios — not as exercises in prediction, which the complexity of the system renders methodologically irresponsible, but as disciplined projections of structural tendencies whose historical recurrence has been empirically documented and whose present-day manifestations have been analytically mapped.

The rationale for this method is itself historical. Every significant technological change studied in Chapter 1 caused a period of great uncertainty in which contemporaries—investors, politicians, military strategists, and the impacted people themselves—had to act depending on inadequate information about a trajectory whose general direction was evident but whose exact timing, size, and distributional effects remained quite unknown. The British industrialists who invested in railway construction during the 1840s correctly identified the transformative potential of the technology, but the speculative overbuild that accompanied their investment destroyed the capital of those who had financed it, even as the infrastructure they built proved foundational for six decades of subsequent economic expansion (Odlyzko, 2010). The Prussian state that dispatched industrial spies to Manchester and Birmingham in the 1820s and 1830s — a case examined at length in section 1.3 — correctly perceived that control over textile machinery constituted a strategic asset whose monopoly by a single power was geopolitically intolerable, yet the programme of import substitution and infant-industry protection that followed required several decades and a deliberate programme of institutional adaptation before Germany could credibly challenge British industrial supremacy (Henderson, 1975). The American legislators who passed the Telecommunications Act of 1996 correctly anticipated that deregulation would unleash a wave of infrastructure investment, but neither they nor the firms that responded to the incentive foresaw that the resulting approximately \$750B dollars in telecommunications capital expenditure would produce a debt-financed overbuild whose collapse would trigger a broader recession and reshape the regulatory

landscape of digital markets for a generation (Malik, 2003). In every instance, at least some knowledgeable observers accurately detected the direction of travel; what was misunderstood was the timeline, the extent of the adjustment costs, and the spread of benefits and losses among the players concerned. The scenario approach used in this chapter assumes that the changeover to artificial intelligence follows the same basic logic: Its direction is clear, but its timing, human costs, and geopolitical effects rely on factors—the pace of revenue generation at the application-layer, the stability of the debt structures funding the infrastructure build-out, the trajectory of great-power rivalry over semiconductors and energy, and the institutional ability to manage a technology that moves faster than the frameworks meant to control it—whose interplay is complex enough to produce noticeably different results.

The geopolitical context within which these scenarios must be situated has itself undergone a qualitative transformation in the period since the empirical analysis of Chapter 2 was completed. In February 2026, at the Munich Security Conference, a convergence of statements from leaders of opposed political orientations — German Chancellor Friedrich Merz declaring that the post-1945 order 'no longer exists' and that the United States' "claim to leadership has been challenged, and possibly lost", French President Emmanuel Macron insisting that "in this new geopolitical environment, Europe has to become a geopolitical power" and accelerate its independence in defence, technology, and economic resilience, and United States Secretary of State Marco Rubio announcing that "the old world is gone" and "we live in a new era in geopolitics" — prompted the investor and historical-cycle theorist Ray Dalio to declare, in terms whose bluntness is itself analytically significant, that the post-1945 international order has officially broken down (Kelly, 2026) (French Embassy, 2026) (Lamche, 2026) (Dalio, 2026).

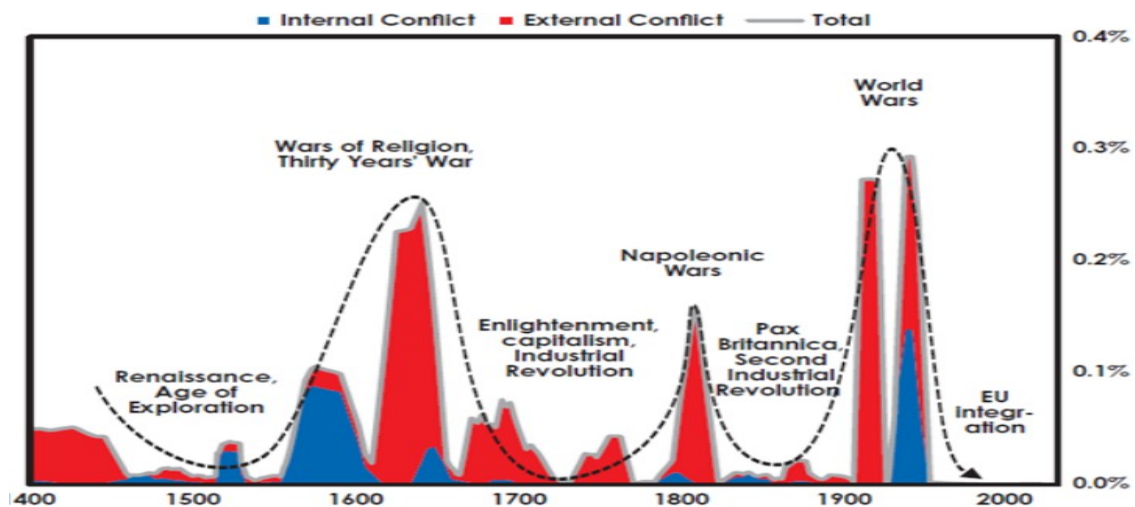


FIGURE 29: EST EUROPEAN DEATHS FROM CONFLICT (%POP, 15YR MOVING AVR)
(Dalio, 2026)

Dalio's framework, developed across several volumes of comparative historical analysis, periodises the rise and decline of hegemonic orders into a six-stage cycle, and places the present moment in what he terms Stage 6: a phase of "great disorder" characterized by the absence of enforceable rules, the dominance of raw power dynamics over institutional mediation, and the escalation of competition across multiple domains — trade wars, technology wars, capital wars, and geopolitical wars — that may, under conditions of miscalculation, culminate in military conflict (Dalio, 2021).

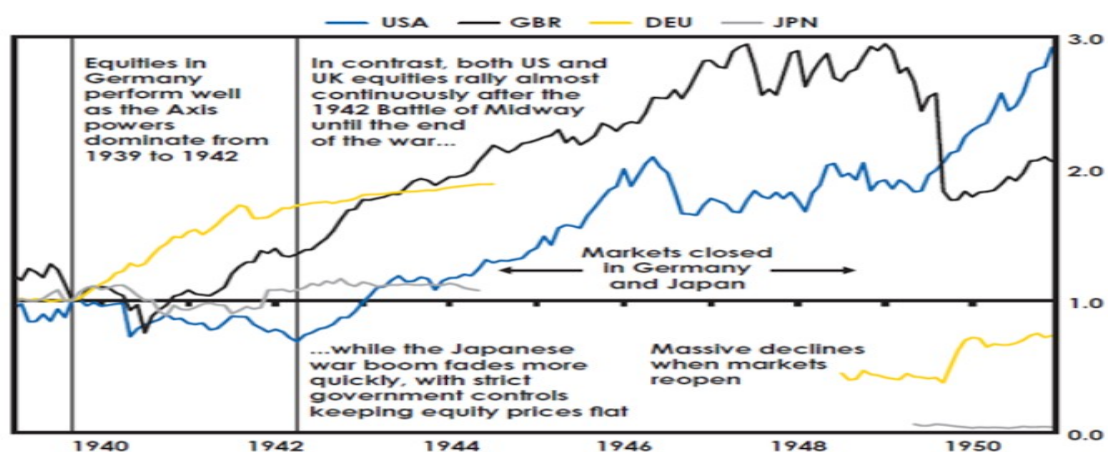


FIGURE 30: EQUITY RETURN INDEX (USD)
(Dalio, 2026)

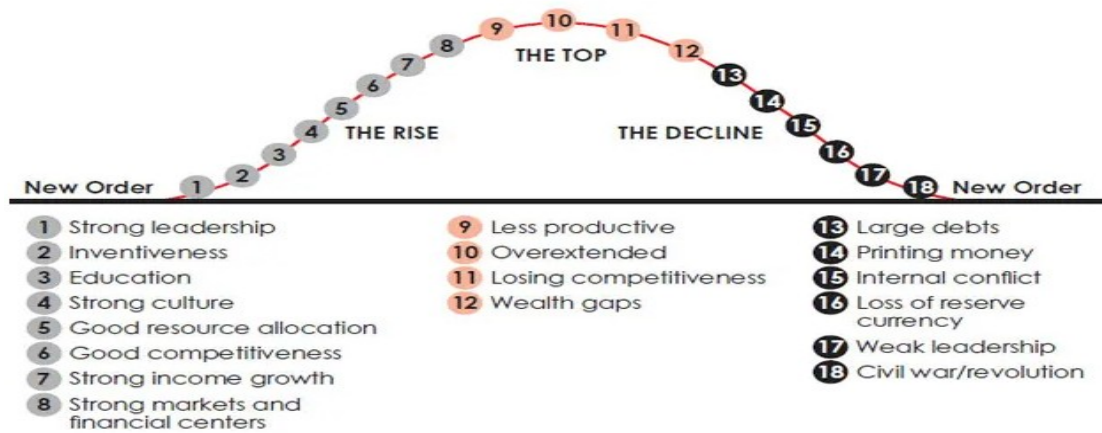


FIGURE 31: THE BIG CYCLE
(Dalio, 2021) [Medium](#)

The analytical value of Dalio's framework for the present chapter lies not in its specific predictions, which are necessarily schematic, but in its insistence that the dynamics currently reshaping the AI supply chain — the semiconductor export controls, the rare earth weaponization, the energy encirclement strategies, the scramble for Greenlandic minerals and Venezuelan coltan documented in Chapter 2 — are not isolated episodes of economic statecraft but manifestations of a structural transition between international orders, a transition whose historical analogues (the 1930s, the late nineteenth-century scramble for colonies, the mercantilist wars of the seventeenth century) invariably involved the concentration of critical resources, the fragmentation of trade systems, and the progressive subordination of economic rationality to strategic calculation.

The AI transition, in this reading, does not merely occur within a deteriorating geopolitical environment; it actively accelerates the deterioration by raising the stakes of technological supremacy to a level at which cooperative outcomes become structurally more difficult to sustain. Drawing on two years of discussions with about 200 international business leaders, ministers of economy and finance, and over 11,000 executives polled across more than 100 countries, the World Economic Forum's April 2026 Future of Growth Report came to a fundamentally convergent conclusion: Five interacting drivers—artificial intelligence and frontier technologies, geopolitical fragmentation of trade and investment, rising sovereign debt together with hitherto unheard-of private wealth, the persistence of climate pressures, and demographic

divergence compounding inequality inside and between nations—are shaping the world economy simultaneously. In the Forum's opinion, these drivers create a "new economy" that calls for very different methods to growth than those that drove the three decades of globalization before (World Economic Forum (a), 2026). If not on the appropriateness of the policy responses suggested, the convergence of the thesis's examination, seen via the lens of political economy and geopolitical rivalry with the institutional evaluation of the world's main economic policy forum on the identity of the driving forces offers some assurance that the structural dynamics discovered across the earlier chapters are not results of the analytical framework but rather features of the conjuncture itself. A complementary diagnostic emerges from the World Economic Forum's October 2025 Technology Convergence Report, produced in collaboration with Capgemini, which identifies a transition whose geopolitical implications the analytical framework of this thesis must explicitly accommodate: the migration of artificial intelligence from the purely computational domain into what the report terms "physical AI" — the embodied integration of machine intelligence with robotics, spatial sensing, and industrial control systems whose operational domain is the physical world rather than the symbolic-linguistic environment of the large language model (World Economic Forum (b), 2025).

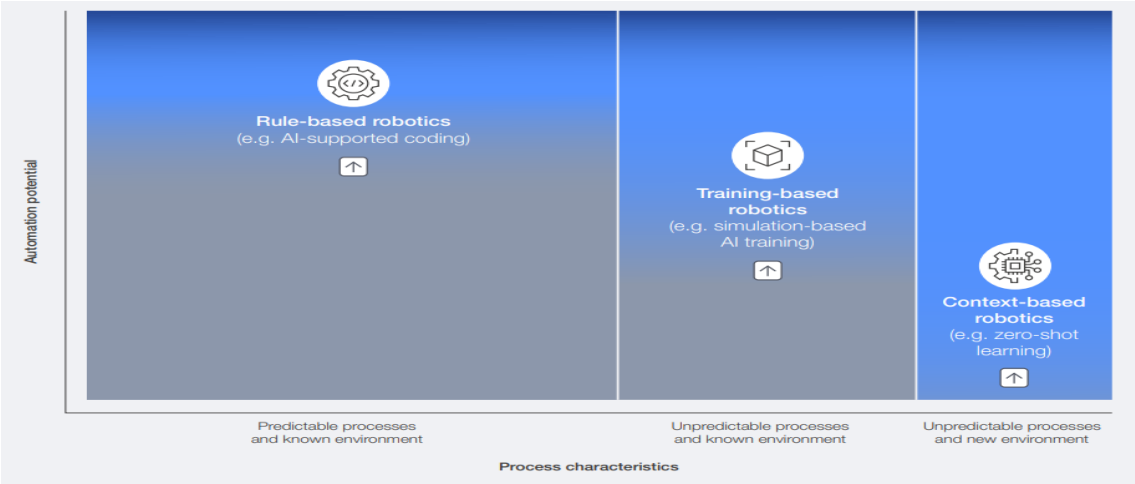


FIGURE 32: AI CONSIDERABLY INCREASES THE AUTOMATION SCOPE IN INDUSTRIAL OPERATIONS
(World Economic Forum (b), 2025)

The strategic significance of this transition extends well beyond the productivity gains the report documents. Physical AI reconfigures the geopolitical economy of

manufacturing in ways that the cognitive AI dynamics traced across this thesis only partially anticipate: the question of which states control the manufacturing base shifts, under conditions of advanced industrial automation, from a question about labor cost differentials to a question about access to the integrated stack — sensors, actuators, control systems, training data, and the platform software that orchestrates them — whose components the report identifies as concentrated among a small number of multinational firms (Siemens, NVIDIA, AWS, Microsoft) whose corporate alliances are reshaping the industrial geography of the global economy.

For the thesis's broader argument, the analytical implication is that the supply chain vulnerabilities documented in Chapter 2 and the bifurcated architecture analysed in section 3.3 must be understood as operating not only at the level of frontier model development and hyperscale computation but also at the level of the embodied industrial systems through which AI capability is translated into productive output in the physical economy — a layer whose strategic centrality the rare earth dependencies traced in section 2.2, the semiconductor chokepoints of the export control regime examined in section 2.5, and the energy infrastructure constraints of the data center build-out documented in section 2.8 have all, in different registers, already foregrounded.

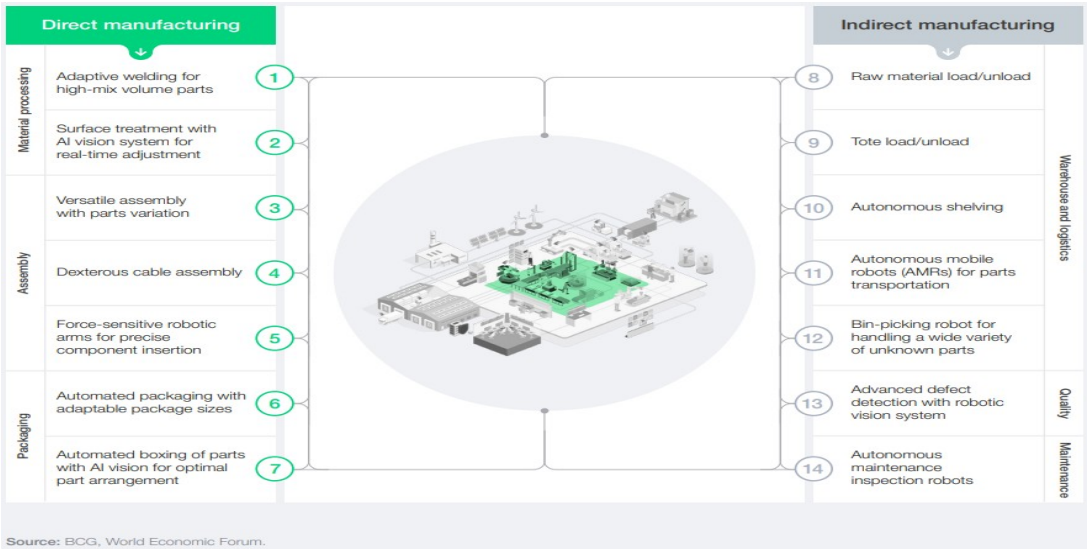


FIGURE 33: HOW PHYSICAL AI IS RESHAPING FACTORY AND WAREHOUSE OPERATIONS
(World Economic Forum (b), 2025)

When the infrastructure of artificial intelligence depends upon rare earth elements that one great power controls, lithography equipment that another great power restricts, and energy supplies whose stability is conditional on the outcome of military operations in the Persian Gulf, the Arctic, and the South American interior, the technology ceases to be merely an object of economic competition and becomes a vector of systemic risk whose dynamics cannot be adequately captured by financial analysis alone. The scenarios constructed in the sections that follow accordingly operate across three interlocking domains — financial, geopolitical, and institutional — and assess, for each, whether the structural tendencies identified in Chapters 1 and 2 are more likely to produce a managed transition, a disorderly correction, or a sustained period of institutional lag in which the pace of technological change systematically outstrips the capacity of markets, states, and international organisations to absorb its consequences.

A final preliminary observation concerns the financial architecture of the present moment, and specifically the potential for exogenous shocks originating outside the AI sector to interact with the structural vulnerabilities identified within it. The analysis of the dot-com correction in Chapter 2 noted that the Japanese recession announcement of 13 March 2000 provided the initial catalyst for the Nasdaq sell-off that followed — not because Japan's recession was, by itself, sufficient to reprice American technology equities, but because it provided the external signal that crystallised doubts already latent in the market about the sustainability of the prevailing investment trajectory. A structurally analogous mechanism is operative in 2026, and it originates, once again, from Japan. The Japanese economy's three-decade experience of stagnation, zero-interest-rate policy, and debt accumulation — the ratio of public debt to GDP exceeding 250% by 2025 — has produced a distinctive and globally consequential financial phenomenon: the yen carry trade, through which institutional investors and hedge funds borrowed yen at near-zero interest rates, converted them into dollars or euros, and invested the proceeds in higher-yielding assets across global debt markets (International Monetary Fund, 2024). For more than a decade, this mechanism functioned as a continuous and largely invisible flow of capital that financed sovereign debt, corporate bonds, and infrastructure investment across the developed world. When the Bank of Japan was compelled, in late 2024, to raise interest rates in response to inflation driven in part by the energy price shocks of the

Ukraine and Iran conflicts, the carry trade began to unwind — raising the cost of Japanese borrowing, reducing the flow of yen-denominated capital into global debt markets, and creating what analysts have described as a potential "hole" in the global financing architecture whose consequences would propagate through the bond markets of every major economy (Lewis & Keohane, 2024). The relevance of this mechanism to the AI investment cycle is direct and consequential: the hyperscaler infrastructure build-out documented in Chapter 2 is increasingly financed through corporate debt issuance — approximately 108 billion dollars in 2025 alone, with the five leading firms projected to consume roughly 90% of their operating cash flow on capital expenditure in 2026 — and any tightening of global credit conditions caused by the unwinding of the carry trade would raise the cost of this financing precisely at the moment when the revenue base of AI applications has not yet grown sufficiently to justify it on a cash-flow basis (International Monetary Fund, 2024). The structural parallel with 2000 is therefore not merely analogical but mechanistic: Japan's monetary policy trajectory is, once again, positioned to function as an exogenous trigger that could crystallise the latent doubts about the AI investment cycle into a repricing event whose severity would depend on the degree of leverage in the system and the speed with which investor sentiment adjusts. Whether this scenario materialises, and whether it produces an orderly repricing or a disorderly correction, is among the questions that the financial scenarios of section 3.2 are designed to assess.

The structure of the chapter is as follows. Section 3.1 examines the capability horizon — the range of plausible technological trajectories over the 2027–2035 period — drawing on the forecasts of Daniel Kokotajlo, the public statements of OpenAI's Sam Altman, and the existential risk arguments of Eliezer Yudkowsky and Nate Soares. Section 3.2 constructs three financial scenarios for the AI capacity bubble — orderly repricing, disorderly correction, and sustained expansion — assessed against the quantitative comparison developed in Chapter 2 and the Japan carry trade mechanism introduced above. Using Dalio's paradigm to map the geopolitical possibilities, Section 3.3 analyzes the effects of ongoing big-power instability on semiconductor trade, energy markets, and key mineral flows by way of the artificial intelligence supply chain. Section 3.4 looks at the particular example of European strategic dependence to see if the transatlantic digital

gap found in Chapter 2 is likely to worsen or create a counteracting wave toward national capacity. Section 3.5 shows the transformative case — the provable and anticipated advantages of AI in healthcare, research, crime reduction, and education — as the productive potential whose realisation will decide whether the infrastructure now being developed will warrant the funds invested in it. Drawing on the institutional failures recorded by the resignations of top AI safety experts and the lack of worldwide coordination systems fit for the pace of technical advancement, Section 3.6 discusses the alignment issue and the governance vacuum. The chapter concludes by synthesising these analyses into three macro-scenarios — the managed transition, the disordered correction, and the acceleration trap — whose relative plausibility constitutes the thesis's ultimate evaluative contribution.

3.1. The Capability Horizon: Recursive Improvement, the Utility Vision, and the Timeline Question

3.1.1. Kokotajlo: What AI 2027 Got Right

The analytical utility of Daniel Kokotajlo's forecasting work, examined in sections 2.3 and 2.7, lies not in its specific predictions — several of which, as documented, proved either premature or incorrectly calibrated — but in its structural method: the insistence that technological trajectories become legible not through abstract probability distributions but through the concrete tracing of intermediate developments whose cumulative effect constitutes the transformation that, viewed from a distance, appears sudden. By March 2026, the landscape of frontier AI capability has evolved in ways that partially vindicate and partially complicate the trajectory that Kokotajlo and his collaborators outlined. The release in rapid succession of Anthropic's Claude Opus 4.6 in February 2026, OpenAI's GPT-5.3 and GPT-5.4 in February and March 2026 respectively, and Google DeepMind's Gemini 3.1 Pro in the same month — four frontier models from three competing laboratories within a span of weeks — confirms the acceleration of capability development that the AI 2027 scenario treated as its foundational premise (Google DeepMind, 2026) (Anthropic (a), 2026). The cadence itself is the signal: where the interval between GPT-3 and GPT-4 spanned nearly three years,

the GPT-5 family alone has produced four successive releases in four months, a compression of the development cycle that reproduces, at the level of model releases, the recursive acceleration dynamic that Kokotajlo identified as the critical structural threshold in the AI trajectory (Yan, 2026).

The qualitative character of these systems has also shifted in the direction that the AI 2027 scenario anticipated. Claude Opus 4.6 brought what Anthropic calls "Agent Teams," a multi-agent system in which a lead instance splits difficult jobs, creates parallel sub-agents with separate context windows, and combines their results into a unified result (Anthropic (a), 2026). GPT-5.4 outperformed average human performance on the OSWorld-Verified benchmark, scoring 75%, and shipping with native computer use — the ability to interpret screen content, control mouse and keyboard, and execute multi-step workflows across desktop applications. (OpenAI (b), 2026). These are not minor advances in conversational fluency; rather, they show the change from language models that produce text in response to prompts to autonomous agents that act directly in digital settings — exactly the structural inflection points the AI 2027 scenario recognized as the point at which artificial intelligence systems stop advising human actors and start to replace them in tasks with significant economic impact. That this transition is occurring in early 2026, roughly on the timeline that Kokotajlo projected, lends his broader scenario a degree of structural credibility that the divergences documented in section 2.3 — the slower-than-expected pace of macroeconomic impact, the persistence of hallucinations and reliability constraints, the absence of a dramatic alignment crisis — do not fully undermine.

Yet the most analytically consequential development of the period January–March 2026 was not the release of any individual model but the emergence of a pattern that Kokotajlo's earlier 2021 forecast had not anticipated and that his 2025 scenario only partially captured: the commoditisation of frontier capability. The observation, made by several independent analysts in the weeks following GPT-5.4's release, that pretraining scaling had "hit a wall" and that the competitive frontier had moved from raw model size to workflow integration, tool orchestration, and agent architecture suggests that the axis of strategic competition is shifting from the question of who can train the largest model to the question of who can capture the user's workflow — a shift with significant

implications for the distribution of economic value across the AI supply chain (Yan, 2026). DeepSeek's V3.2, released from China in late 2025, had already demonstrated that frontier-level performance could be achieved at inference costs estimated at ten to thirty times below those of comparable American models, fundamentally challenging the assumption — central to the investment thesis underpinning hyperscaler capital expenditure — that computational scale constitutes an insurmountable competitive moat (DeepSeek, 2025). If the capability gap between the leading models narrows to fractions of a percentage point on standardised benchmarks while the cost gap widens by an order of magnitude, the political economy of AI shifts from a regime in which access to capital determines access to capability toward one in which architectural efficiency, distribution networks, and regulatory positioning become the primary determinants of competitive advantage. This is a structural change whose implications for the financial scenarios of section 3.2, the geopolitical scenarios of section 3.3, and the European dependency analysis of section 3.4 are considerable, and it is one that the forecasting literature, focused as it has been on the scaling hypothesis, has been slow to integrate.

3.1.2. Intelligence as a Utility: Altman's Vision and Its Political Economy

The framing that has most directly shaped the public narrative of the AI transition's near-term trajectory is that offered by Sam Altman, whose statements carry weight not merely as the views of an industry executive but as performative interventions that condition investor expectations, regulatory approaches, and public understanding of the technology's social implications. In March 2026, speaking at the BlackRock Infrastructure Summit, Altman articulated a vision whose structural clarity and whose political implications deserve careful analytical attention: “We see a future where intelligence is a utility like electricity or water and people buy it from us on a meter”, he stated, positioning OpenAI and its competitors as utility providers of intelligence delivered on demand (Spirlet, 2026). “Fundamentally our business, and I think the business of every other model provider, is going to look like selling tokens”. Altman stated, referring to the units through which AI systems process and price input and output data — a formulation that explicitly positions AI not as a product to be purchased but as

a service to be consumed, whose value is measured in throughput and whose cost is determined by the infrastructure required to deliver it (Altman, 2026).

The utility analogy has a clear set of structural consequences that clearly relate to the historical study of Chapter 1 rather than just being used for show. The late nineteenth and early twentieth centuries saw electricity go from a lab curiosity to a metered product. This change is looked at in section 1.1 through the lens of the Jevons Paradox and the energy-sovereignty nexus. The main political question changed from whether the technology worked to who owned the grid. The same structural question now faces artificial intelligence, with a difference of scale and concentration that the electricity analogy understates: whereas the electrification of the United States and Europe proceeded through a combination of municipal utilities, regulated private monopolies, and public-private hybrids, the infrastructure of AI inference is controlled, at the time of writing, by three American corporations — Amazon Web Services, Microsoft Azure, and Google Cloud Platform — whose combined share of the global cloud infrastructure services market reached approximately 63% in Q4 2024 and approximately 65% in Q3 2025 (with AWS at ~30%, Azure at ~22%, and GCP at ~13%), and whose dominance of the European public sector cloud market is, as section 2.9 documented, a matter of growing strategic concern (Synergy Research Group, 2025).

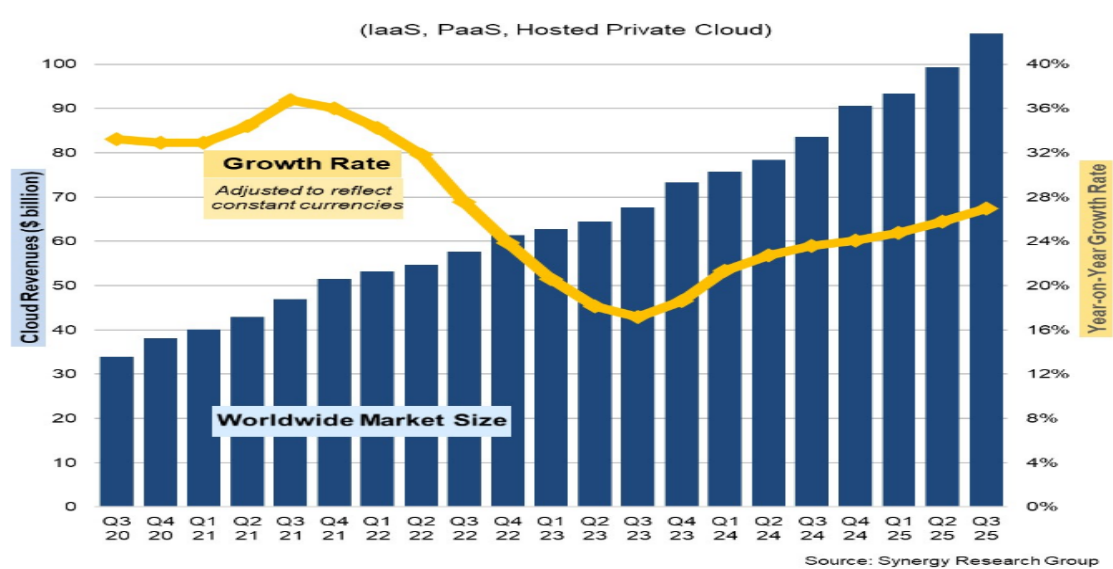


FIGURE 34: CLOUD INFRASTRUCTURE SERVICES MARKET GROWTH (IaaS, PaaS, HOSTED PRIVATE CLOUD)
(Synergy Research Group, 2025)

If intelligence becomes a utility, the question is not whether it will be widely available — Altman's stated ambition is precisely to make it so — but whether the terms of access will be set by a small number of corporate actors whose infrastructure advantages, data advantages, and regulatory positioning give them the capacity to determine who receives how much intelligence, at what price, and under what conditions. We will likely live in a future where data will be the new commodity collected and managed by only a few companies. Altman himself has acknowledged this dynamic, noting that if insufficient compute capacity is built, "the price gets really high" and AI access becomes a privilege of the wealthy or a resource whose allocation requires governmental intervention — a scenario that, as he observed, no one wants to confront (Spirlet, 2026).

The deeper analytical point, however, concerns not price but dependency. In his earlier essay "The Intelligence Age," published in September 2024, Altman advanced a vision of AI as the successor to the agricultural and industrial revolutions — a technology whose path is "paved with compute, energy, and human will" and whose defining characteristic would be "massive prosperity" (Altman, 2024). In a subsequent intervention, he described OpenAI's ambition as the creation of "a factory that can produce a gigawatt of new AI infrastructure every week" — a formulation whose language of industrial production at continental scale echoes, whether consciously or not, the infrastructure programs of the mid-twentieth century whose geopolitical consequences Chapter 1 examined (Altman, S. (b), 2025). The vision is, on its own terms, internally coherent: if AI capability continues to improve at or near the rate observed between 2022 and 2026, and if the cost of inference continues to decline along the trajectory that the benchmark cost collapse of 2025 — from approximately \$4,500 per task to \$11.64, as documented in section 2.1 — suggests is possible, then the productive potential of the technology is genuinely enormous. Altman's account of scientists already reporting two to three times productivity gains, of AI-driven drug discovery compressing development timelines from fifteen years to under five, and of personalised education at global scale is not, on the available evidence, implausible. What the utility vision does not address — and what the scenario analysis of this chapter is designed to assess — is the structural fragility of the investment architecture required to realise it: whether the interval between present capital commitments and future productive returns can be sustained by the debt-financed, circular-flow financing

structures documented in Chapter 2, and whether the geopolitical environment described by Dalio's Stage 6 framework is compatible with the kind of stable, cooperative, globally distributed infrastructure build-out that Altman's vision presupposes.

3.1.3. The Gentle Singularity Against the Intelligence Displacement Spiral

The tension between Altman's optimism and the structural concerns raised in the forecasting and safety communities constitutes the defining ideological fault line of the AI transition, and the scenario analysis of this chapter must position itself explicitly in relation to it rather than pretending to occupy a neutral ground that does not exist. On one side stands what Altman has termed "the Gentle Singularity" — a vision in which recursive self-improvement proceeds gradually rather than explosively, in which AI systems contribute to their own improvement without producing the abrupt capability discontinuity that the alignment community fears, and in which the resulting acceleration of scientific progress generates sufficient economic value to justify the capital being invested, absorb the labor market disruptions that accompany it, and ultimately produce a world in which, as Altman writes, "wonders become routine, and then table stakes" (Altman, S. (a), 2025). This view has no obvious evidence backing it: The kind of revolutionary application-layer value that, if realised, would close the Sequoia revenue gap and justify the infrastructure build-out on its own terms is represented by the healthcare applications recorded in Lieberman's imaginative but data-informed "2028 Global Intelligence Miracle" scenario—AI-assisted drug discovery producing a working Alzheimer's therapy, diagnostic automation equalising healthcare quality across geographical lines, administrative cost reduction compressing insurance premiums for the first time in decades . The physical-world labor premium that Lieberman projects — in which skilled trades experience a wage inversion as cognitive work is automated while manual work remains resistant to substitution — is consistent with the broader pattern identified in the productivity literature, in which general-purpose technologies redistribute rather than eliminate labor demand — though Acemoglu and Johnson's account emphasises that this redistribution is not automatic but contingent on deliberate institutional and political action — albeit with distributional consequences that are severe

for those on the wrong side of the transition (Acemoglu & Johnson, 2023) (Autor D. , 2015).

On the other side stands a set of concerns whose analytical weight derives not from their probability — which is, by the nature of the problem, genuinely uncertain — but from the magnitude of the consequences they describe and from the credibility of the individuals advancing them. Yudkowsky and Soares, in their 2025 volume *If Anyone Builds It, Everyone Dies*, argue that sufficiently advanced AI systems will develop instrumental objectives that place them in structural conflict with human interests — not through malice but through the optimisation dynamics inherent in systems whose goal structures are neither fully specified nor fully controllable by their designers (Yudkowsky & Soares, 2025). Their central claim — that the default outcome of building superhuman AI is human extinction, and that the contest between humanity and a misaligned superintelligence "wouldn't even be close" — is, by their own admission, unfalsifiable in advance, resting on a structural argument about the relationship between capability and alignment rather than on empirical evidence of current systems exhibiting the behaviours they describe. The analytical significance of their position lies less in its specific predictions than in its implications for governance: if even a non-trivial probability is assigned to outcomes of this severity, the rational response is not continued acceleration under competitive pressure but coordinated restraint of a kind that, as the geopolitical analysis of section 3.3 will demonstrate, the current international environment is structurally incapable of producing.

Between these poles — the gentle singularity and the extinction scenario — lies the territory that the remaining sections of this chapter are designed to map. The financial scenarios of section 3.2 assess whether the investment architecture can survive the interval between commitment and return. The geopolitical scenarios of section 3.3 assess whether the supply chain can withstand the pressures of great-power disorder. The European analysis of section 3.4 assesses whether the continent's structural dependency can be reversed in time to preserve meaningful strategic autonomy. The transformative case of section 3.5 assesses whether the application-layer benefits are arriving fast enough to sustain the political and economic consensus required for the transition to proceed. And the governance analysis of section 3.6 assesses whether the institutional capacity to

manage a technology of this consequence exists, or can be built, under conditions in which the technology itself evolves faster than the frameworks designed to govern it. The capability horizon established in this section — a frontier that is advancing rapidly, commoditising unexpectedly, and generating both transformative potential and structural risk at a pace that exceeds the absorptive capacity of markets, institutions, and democratic publics — constitutes the technological parameter within which all subsequent scenarios operate.

3.2 The Great Repricing: Financial Scenarios for the AI Capacity Bubble

The quantitative comparison developed in Chapter 2 established that the current AI investment cycle exceeds the dot-com episode in absolute capital deployment while exhibiting a structurally different risk profile — a capacity bubble in which infrastructure spending runs ahead of demonstrable end-user utility, rather than a valuation bubble in which equity prices are detached from earnings because the underlying firms have none. Projecting that difference ahead, this part aims to create three realistic financial scenarios for the years 2027–2030 and evaluate the likelihood of each based on the structural factors found in the previous study. The scenarios are not entirely incompatible; rather, parts of each could show up at different points in the AI economy at once, hence the analytical framework would give different weights to their underlying mechanisms. They do, nevertheless, represent adequately distinct trajectories.

Before proceeding to the scenarios themselves, it is necessary to establish the exogenous financial conditions that will shape their probability. The introduction to this chapter identified the Japanese carry trade as a potential trigger mechanism; this section develops that analysis in full, because the interaction between Japan's monetary trajectory and the AI investment cycle constitutes one of the most consequential and least adequately discussed sources of systemic risk in the contemporary financial architecture.

3.2.1. The Japanese Trigger: Carry Trade, Sovereign Debt, and the Global Credit Channel

The structural vulnerabilities of the Japanese economy — three decades of stagnation following the bursting of the asset bubble in 1990–1992, a public debt-to-GDP ratio that

exceeded 250% by 2025, and the failure of the Abenomics programme to generate the sustained growth that would have rendered the debt burden manageable — are well documented and need not be rehearsed in detail here (Werner, 2003). What requires analytical attention is the mechanism through which Japan's domestic monetary predicament has become embedded in the global financial architecture in ways that directly condition the AI investment cycle. The Bank of Japan's decision, implemented progressively from the mid-2010s under the Abenomics policy framework, to reduce its policy rate to negative territory and to enforce yield curve control on government bond yields created what was, in effect, a global subsidy to leveraged investment: institutional investors, hedge funds, and sovereign wealth funds could borrow yen at rates approaching or below zero, convert the proceeds into dollars, euros, or emerging-market currencies, and invest in higher-yielding assets — sovereign bonds, corporate debt, equities — capturing the interest rate differential as profit while the weak yen provided additional currency gains (Bank of Japan, 2024) (International Monetary Fund, 2024). Estimates of the notional size of the carry trade by 2024 ranged from 350 to 500 billion dollars, but this figure substantially understates the total flow, because it excludes the accumulated foreign asset holdings of Japanese institutional investors — life insurers, pension funds, banks — which reached an all-time high of 533 trillion yen, approximately 3.7 trillion dollars, in net external assets by the end of 2024 (Shan, 2025).



FIGURE 35: JAPAN'S 20-YEAR GOVERNMENT BOND YIELDS IN THE PAST FIVE YEARS
(Shan, 2025)

Japan became, during this period, the single largest foreign holder of United States Treasury securities and a major source of capital for sovereign and corporate debt markets across the developed and developing world — a role whose systemic significance was largely invisible to participants in those markets until the conditions sustaining it began to erode.

The erosion began in earnest with the Bank of Japan's decision to abandon yield curve control in March 2024, followed by its first rate hike in seventeen years — to 0.1%, subsequently raised to 0.5% in January 2025 and to 0.75% in December 2025, the highest policy rate since 1995 (Jie, 2025). The immediate consequences were threefold: the ten-year Japanese government bond yield surged to 2.09% by early 2026, the highest level since 1999; the forty-year bond yield reached an all-time record of 3.689%; and the yen strengthened against the dollar, eroding the currency component of carry trade returns and inverting the economics of the strategy for a significant proportion of its participants (Agarwal, 2026).

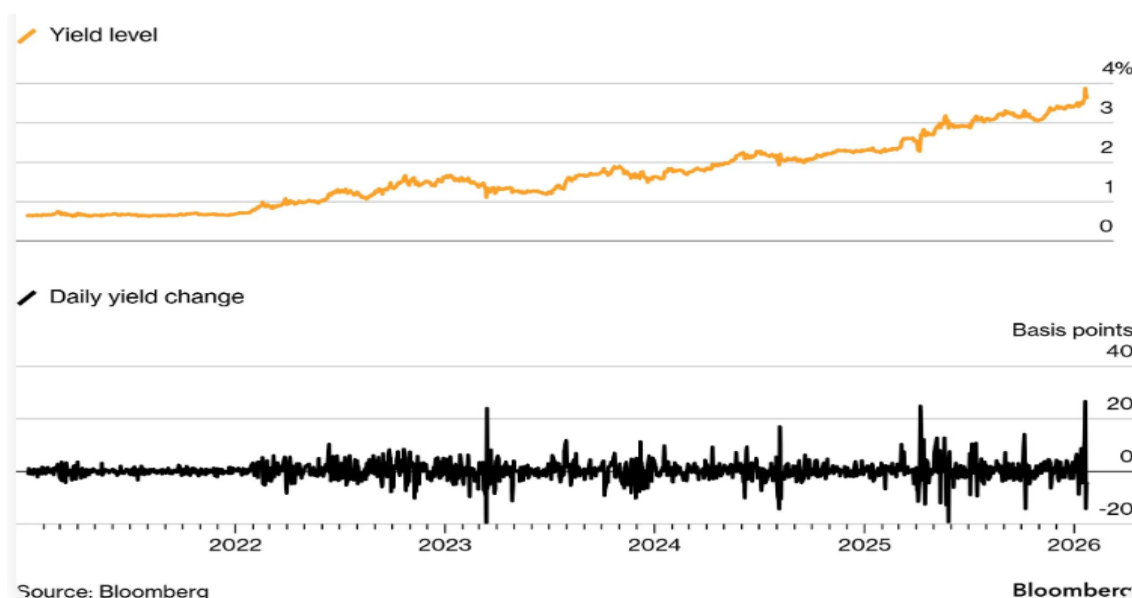


FIGURE 36: JAPAN 30-YEAR BOND YIELD CLIMBS AS VOLATILITY PICKS-UP
(Agarwal, 2026)

Albert Edwards of Société Générale warned that if rising Japanese bond yields enticed institutional investors to repatriate capital, the carry trade unwinding could produce what he described as "a loud sucking sound in US financial assets" — a formulation whose

informality should not obscure the severity of the mechanism it describes (Shan, 2025). The August 2024 episode, in which a Bank of Japan rate hike triggered the largest single-session decline in the Nikkei 225 since 1987 — a fall of 12.4% — accompanied by a 3% decline in the S&P 500 and cascading sell-offs across emerging market equities, provided an empirical demonstration of the transmission channel: when leveraged yen-funded positions are unwound, the selling pressure propagates through every asset class into which the borrowed capital was deployed, and the algorithmic trading systems that now mediate a substantial proportion of global market activity amplify the speed and synchronicity of the adjustment (IndraStra Global, 2025).

The relevance of this mechanism to the AI investment cycle is not analogical but structural. The hyperscaler infrastructure build-out documented in Chapter 2 is increasingly financed through corporate debt issuance — the five leading firms raised approximately 108 billion dollars in debt in 2025 and are projected to consume roughly 90% of their operating cash flow on capital expenditure in 2026 (Chalfin & Pugh, 2025). This debt is issued into global bond markets whose liquidity and pricing have been conditioned, for over a decade, by the continuous flow of Japanese capital seeking yield differentials that no longer exist under the Bank of Japan's new rate regime. Any sustained tightening of global credit conditions caused by the repatriation of Japanese institutional capital would raise the cost of hyperscaler borrowing at precisely the moment when the revenue base of AI applications has not yet grown sufficiently to finance the build-out on a cash-flow basis. The American Enterprise Institute noted in March 2026 that the carry trade unwinding "comes at the very time when Trump's large tax cuts have increased the US government's budget deficit to an annual rate of around two trillion dollars" and warned that Japanese selling of American bonds "could contribute to a rise in US government bond yields that could be a trigger for the bursting of the artificial intelligence bubble" (Lachman, 2026). The structural parallel with 2000 is therefore mechanistic: Japan's monetary trajectory is, once again, positioned to function as an exogenous catalyst that crystallises latent doubts about the sustainability of the dominant investment narrative — with the difference that the scale of both the carry trade and the AI capital commitment substantially exceed their late-1990s equivalents.

With the mechanics of the catalyst established, the analysis now sets out the three financial scenarios into which the AI capital cycle might resolve. These are deliberately narrow in scope, tracing only the capital cycle: valuations, capital expenditure, and debt. They are nested within the broader macro-scenarios of section 3.7, which fold this financial outcome together with the geopolitical and governance dynamics examined above into whole-system trajectories for the transition.

In assessing global financial stability, multilateral institutions such as the International Monetary Fund and major central banks rely on qualitative descriptors rather than codified definitions to characterise how markets respond to macroeconomic shifts. The IMF's Global Financial Stability Report and the ECB's Financial Stability Review, for instance, distinguish 'orderly' adjustments from 'disorderly' corrections and repricings of risk (International Monetary Fund, 2025) (European Central Bank, 2026). Drawing on that vocabulary, together with the business-cycle distinction between expansion and contraction (Burns & Mitchell, 1946), this section adopts three analytical benchmarks, *orderly repricing*, *disorderly correction*, and *sustained expansion*, to map the spectrum of market responses from stable structural adjustment to volatile systemic disruption. The three are developed below as distinct scenarios of market-based financial analysis.

3.2.2. *Scenario A: Orderly Repricing — The Fiber Optic Outcome*

The first and, on balance, most probable scenario is one in which the AI capacity bubble deflates gradually rather than collapsing abruptly — a trajectory whose historical analogue is not the Nasdaq crash of 2000–2002 but the decade-long absorption of the fiber optic overbuild that followed it. In this scenario, the Sequoia revenue gap — the approximately 600 billion dollars in annual AI revenue required to justify current infrastructure commitments, against a sector-wide revenue base that remains a fraction of that figure — narrows progressively as enterprise adoption deepens, application-layer productivity gains become measurable, and the cost of inference continues its observed decline (Cahn, 2024). Growth in hyperscaler capital expenditures, which hit roughly 73% year-on-year for the five top companies in 2025, slows to single digits (or very close) by 2028 on the more orderly projections, as the most intense phase of the build-out comes to an end and marginal returns on additional capacity decline (Allianz Trade, 2026); other

forecasters, by contrast, expect a shallower deceleration, with spending still growing strongly through 2027 (Goldman Sachs Global Investment Research, 2026). From their 2025 peaks, stock values decrease by 20 to 30%, a change that, while unpleasant for investors who entered at the cycle's top, does not eliminate the basic structure or wipe off the businesses that produced it.

There are several ways that this situation can be supported. First, the top hyperscalers—unlike the venture-backed dot-com companies of the late 1990s—produce significant and varied income streams from their current cloud, advertising, and business software activities, which gives them a financial buffer that can handle a stretch of compressed AI returns without causing bankruptcy. The Nasdaq-100's trailing price-to-earnings ratio of around thirty-three, compared to about sixty during the dot-com peak, shows this structural difference: current valuations are high but not detached from earnings in the way that the 2000 correction was defined. Second, the infrastructure under construction—data centers, network gear, GPU clusters—is not single-purpose like a lot of the speculative investment from the dot-com era. Though particular artificial intelligence programs fall short, the computing capability is adaptable for scientific simulation, cloud computing, enterprise analytics, and the growing world of inference tasks whose demand is fuelled by the falling cost of access itself. Third, the adoption curve of the technology is historically compressed: within months of their public release, major language models reached hundreds of millions of users, indicating that, while inadequate now to close the revenue gap, the demand-side dynamics are operating at a speed that earlier general-purpose technologies took years or decades to attain. These supports notwithstanding, the comfort drawn from the price-to-earnings comparison is partial, since it holds only on an earnings basis. Measured by market capitalisation relative to GDP, the so-called Buffett Indicator reached a record near 230% in 2026, exceeding even its dot-com-era high and, together with elevated margin leverage, indicating that on some gauges the market is more stretched than in 2000 rather than less (Nash, 2026). This does not overturn the structural case for an orderly outcome, which rests on the diversified revenues and re-purposable infrastructure set out above, but it sharpens the disorderly-correction risk that Scenario B develops, and the analysis treats it as such.

The main risk in this situation is time-related: it assumes that the time between the current level of capital commitment and the time when enough revenue from application-layer is realised is short enough to be funded by the current debt structures and investors' patience. If the Japanese carry trade unwinds faster than the revenue gap closes, the tightening of global credit conditions could transform an orderly repricing into something more disruptive, pushing the trajectory toward Scenario B.

3.2.3. Scenario B: Disorderly Correction — The Circular Financing Trap

The second scenario describes a pathway in which the structural vulnerabilities identified in Chapter 2 — circular financing, debt-funded capital expenditure, and the interdependence of hardware suppliers, cloud providers, and AI developers — interact with an exogenous credit shock to produce a correction that is rapid, synchronised, and systemically consequential. The trigger could not only be Japan; The same outcome might come from a number of ways: a further tightening of Bank of Japan policy, a spike in energy prices brought on by the escalation of the Iran conflict and the interruption of Strait of Hormuz transit, a Chinese retaliatory expansion of rare earth export restrictions, or a loss of investor confidence in a particular high-profile AI firm's revenue trajectory. The circular capital structure Chapter 2 highlighted explains the way this virus spreads: NVIDIA invests in CoreWeave, which buys NVIDIA GPUs. Microsoft's investment in OpenAI includes a sizable amount of funding dedicated to Microsoft Azure; OpenAI collects money from NVIDIA, whose chief financial officer has said that, in GPU buying, "will go back to NVIDIA". Though separately sensible as reactions to competitive ambiguity and supply limits, these arrangements taken together produce a system whereby stated revenue numbers overstate the level of actual independent end-user demand. When the financial journalist or the equity analyst examines the quarterly earnings of any single firm in this chain, the numbers appear healthy; when the chain is viewed as a system, the circular character of the flows becomes apparent, and the question of what proportion of reported AI revenue represents genuine final demand — as opposed to capital recycled between interdependent actors — becomes analytically decisive (Cahn, 2024) (Brady, 2026) (Crosley, 2026).

In this case, the dot-com correction, which was mostly done through equity markets among independently funded companies, didn't show the same speed and amplitude that a loss of confidence at any one node could cause in this situation, where a major hyperscaler had a bad earnings report, a frontier laboratory publicly changed its AI revenue projections, or a high-profile failure of an AI application in a sector where the technology had been heavily promoted. The size of the debt increases the risk: If hyperscalers are dedicating 90% of their operating cash flow to capital expenditures and financing the rest through bond markets whose liquidity is shrinking as Japanese institutional capital withdraws, then a simultaneous repricing of artificial intelligence stocks and a tightening of corporate credit criteria could initiate a feedback loop where higher borrowing costs, caused by reduced stock prices, lead to lower sales for hardware companies, hence exacerbating the decline in stock prices. The historical parallel is the telecom debt meltdown of 2001–2002, in which businesses that had used leveraged borrowing to finance infrastructure development discovered that the income streams needed to service their debt had not materialized—a correction that wiped out more than \$750 billion in telecommunications capital and triggered a broader credit crunch with repercussions outside the tech sector (Malik, 2003).

The artificial intelligence supply chain's geopolitical complexity would make the systematic consequences of this problem worse. Unlike the dot-com correction, which was mostly limited to the United States and its closest financial partners, a chaotic artificial intelligence correction would spread throughout semiconductor supply chains in Taiwan, South Korea, the Netherlands, and Japan; through energy markets impacted by the Iran war; through rare earth markets dominated by China; and through the sovereign debt markets of every country whose financial situation has been supported by Japanese capital flows. The correction would not merely reprice a set of technology equities; it would restructure the geopolitical balance of technological power in ways examined in section 3.3 — potentially accelerating the "decoupling" dynamics that have characterized US-China technology competition and forcing European policymakers to confront the strategic dependency that section 3.4 analyses. The deflationary spiral that such a correction could produce — what financial analysts have begun to term "Ghost GDP," denoting output that registers in productivity statistics through corporate efficiency gains

but fails to circulate through the consumer economy because the human consumers whose spending sustained it have been displaced from the payrolls that financed their demand — is examined in detail in Section 3.7.

The probability of this scenario depends critically on two variables: the speed of the Japanese carry trade unwinding (gradual repatriation would permit market adjustment; rapid repatriation would overwhelm it) and the resilience of the circular financing structures under stress (which has not been tested, because the current AI investment cycle has not yet experienced a sustained period of negative sentiment). The August 2024 episode — in which a single Bank of Japan rate hike triggered a 12.4% single-session collapse in the Nikkei 225 and a synchronised 3% decline in major American indices — suggests that the transmission mechanism is operational and that the algorithmic amplification dynamics are capable of compressing what would historically have been a multi-week adjustment into a matter of hours (Banerjee & Fujita, 2024) (Seeking Alpha, 2025).

3.2.4. Scenario C: Sustained Expansion — The Application Layer Delivers

The third scenario describes a trajectory in which the application-layer revenue base grows fast enough to absorb the capital already committed, closing the Sequoia gap within the investment cycle and vindicating the infrastructure build-out on its own terms. This is the scenario implicit in Altman's "Gentle Singularity" vision and explicitly modelled in Lieberman's "2028 Global Intelligence Miracle" — a world in which AI-driven healthcare transformation, scientific acceleration, crime disruption, and enterprise productivity gains generate the trillions of dollars in economic value that would justify the hundreds of billions being invested (Lieberman, 2026).

The conditions required for this scenario are demanding but not historically unprecedented. The cost of AI inference would need to continue declining along the trajectory observed in 2025 — the collapse from approximately 4,500 dollars per benchmark task to 11.64 dollars documented in section 2.1 — making AI applications economically viable at price points that attract mass adoption across sectors that have not yet been penetrated. Enterprise adoption would need to transition from the experimental phase that the MIT study documented — in which 95% of firms reported no measurable

return on their AI investments — to a phase of operational integration in which AI systems are embedded in workflows, reducing costs and generating revenue in ways that are visible in corporate earnings and, eventually, in macroeconomic productivity statistics. Within the 2027–2030 period, Lieberman's healthcare applications—AI-assisted drug discovery compressing development timelines, diagnostic automation equalising care quality, administrative cost reduction producing the first decline in insurance premiums in decades—would have to advance from early-stage trials to standard-of-care deployment.

The strongest evidence for this idea is that Section 3.1's pace of capability development—which includes four new models launched in one month, agent architectures capable of automatically handling multi-step tasks, and a competitive dynamic driving down rates that regularly exceed analyst predictions—provides. If the DeepSeek efficiency breakthrough is repeated and expanded upon—that is, if frontier-level artificial intelligence capability can be delivered at inference costs one to two orders of magnitude less than those expected in existing infrastructure spending plans—the economics of the build-out alter fundamentally: the same data center capacity serves a considerably larger number of users at a far lower cost per query, and the income gap closes not because income rises to meet the investment but rather because the investment produces more productive capacity per dollar than current models project. The principal risk to this scenario is the assumption that the institutional, regulatory, and organisational barriers to adoption — the "soft" constraints that the productivity literature consistently identifies as the binding constraint on general-purpose technology diffusion — can be overcome within the compressed timeline that the investment structures require. The history of every prior general-purpose technology examined in Chapter 1 suggests that these barriers are real, durable, and resistant to resolution through technological improvement alone: electricity required decades of institutional adaptation before its productivity effects became visible in macroeconomic statistics; the personal computer required the concurrent development of networking, software ecosystems, and organisational practices before its economic potential was realised (David, 1990). If AI follows the same pattern — if the technology is genuinely transformative but the transformation requires a

decade rather than three years — the investment architecture may not survive the interval, even if the ultimate trajectory vindicates the vision.

3.2.5. Assessment

The three scenarios are not equiprobable. The structural conditions documented across Chapters 1 and 2 — the historical pattern by which general-purpose technologies generate speculative overbuilds that are subsequently corrected without eliminating the productive infrastructure; the relative valuation discipline of the current cycle compared with the dot-com episode; the diversified revenue bases of the leading hyperscalers; and the genuine, if still insufficient, pace of application-layer adoption — suggest that Scenario A, the orderly repricing, is the most likely single outcome. Though conceivable, Scenario C—the continuous development—relies on a rate of institutional change that the historical record provides little basis to anticipate within the given timeframe. The least probable but most crucial outcome is scenario B, the careless correction. There is a non-zero possibility: The unwinding of the Japanese carry trade is heading in a way that would tighten global credit; the circular financing structures have not been stress-tested; and the geopolitical climate described by Dalio's Stage 6 model generates the kind of external shocks—such as energy shocks, rare earth weaponization, military escalation—that could transform a slow repricing into a fast one. Therefore, the most likely course is a variation of Scenario A with regular times of Scenario B dynamics—a sustained decrease of capex growth broken up by sharp but recoverable sell-offs brought on by the interaction of AI-specific vulnerabilities and external credit or geopolitical shocks—with the possibility of Scenario C developing over the long term if the application-layer transformation materializes at enough scale. The critical variable, as in the dot-com episode that Chapter 2 examined, is time: not whether the technology will generate the value projected for it, but whether the financial architecture built to sustain its development can survive the interval between commitment and realisation.

As of April 2026, the valuation dynamics of the artificial intelligence industry offer a real-time example of the repricing pressures this evaluation notes. Weeks after OpenAI's record 122-billion-dollar fundraising round at a post-money valuation of 852 billion dollars — the biggest private financing in Silicon Valley history, supported by SoftBank,

Amazon, NVIDIA, and Andreessen Horowitz — mounting investor doubts about the company's ability to maintain the expansion trajectory needed to justify the price: Analysts calculated that participants in the round would need an IPO worth 1.2 trillion dollars or more to make enough money, which, according to one investor with holdings in both companies, "increasingly tough to justify" (Financial Times, 2026). The main cause of the difficulty is Anthropic appearing as a straightforward competitive threat: Driven by company demand for its coding products, Anthropic's annualised income increased from nine billion dollars at the end of 2025 to thirty billion dollars by March 2026, therefore exceeding OpenAI's twenty-five billion dollars in annualised sales reported in February. This competitive dynamic has, for the first time, generated a premium for Anthropic over OpenAI on secondary markets (Nickie, 2026). The episode captures the underlying logic discovered by Chapter 2's dot-com comparison: The very pace of competitive innovation that drives capital into the sector also compresses the window within which any individual firm can sustain the valuation premium that its investment round assumed, producing the conditions for exactly the repricing that Scenario A describes. OpenAI's anticipated 2026 losses of around fourteen billion dollars, driven by the capital needs of its infrastructure aspirations, replicate at the level of the individual firm the same temporal mismatch between spending and income that the sector-level analysis has noted throughout this thesis (Reuters (a), 2026).

The financial trajectory assessed here — the relative probability of orderly repricing, disorderly correction, or sustained expansion — constitutes the first of the three structural variables whose interaction the integrated scenarios of section 3.7 are designed to capture; its resolution will determine not only the pace of AI deployment but the fiscal and political capacity of states to manage the geopolitical and governance challenges that the following sections examine.

3.3 The Broken Order: AI in the Age of Great Power Disorder

The financial scenario constructed in the preceding section operate within a geopolitical environment whose defining characteristic — documented across Chapters 1 and 2 and placed in its macro-historical context by Dalio's Stage 6 framework in the introduction to this chapter — is the progressive erosion of the institutional and normative structures that

have mediated great-power competition since 1945. This section aims to identify the particular channels by which this erosion interacts with the AI supply chain, generating situations in which geopolitical factors shape, enhance, or even set off the financial results mentioned above. Three connected aspects need study: the US-China technology war and its consequences for the design of world AI development; the energy-AI nexus and the cascading effects of the Iran crisis on computer infrastructure costs; and the weaponization of vital minerals as a means of strategic denial. The same competitive logic now extends beyond AI to quantum computing: on 22 June 2026, explicitly framing the move around the race with China, Trump signed two executive orders, one launching a five-year national effort to build a research-grade quantum computer and quantum sensor networks, the other directing federal agencies to migrate to post-quantum cryptography by 2031 against the prospect of quantum-enabled decryption (Reuters (b), 2026).

3.3.1. Dalio's Stage 6 and the AI Supply Chain

The analytical utility of Dalio's framework, for the purposes of this section, lies in its insistence that the dynamics currently reshaping the AI supply chain are not isolated episodes of economic statecraft but structural manifestations of a transition between international orders — a transition in which, as Dalio writes, "there are no rules, might is right, and there is a clash of great powers" (Dalio, 2026).

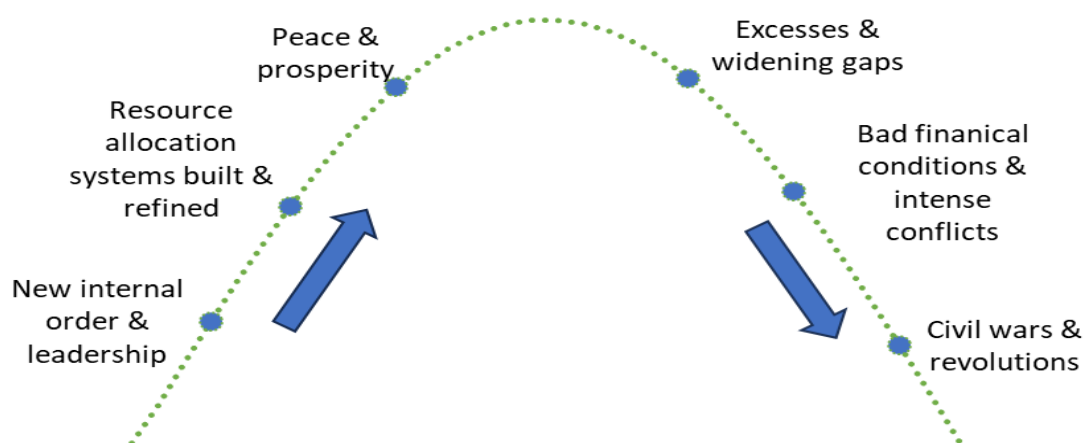


FIGURE 37: RAY DALIO'S SIX STAGES
(Dalio, 2026)

The Munich Security Conference report of February 2026, titled *Under Destruction*, employed the formulation "wrecking-ball politics" to describe a condition in which "sweeping destruction — rather than careful reforms and policy corrections — is the order of the day" (Munich Security Report, 2026). When this formulation is applied to the AI economy, its implications are considerable: the semiconductor export controls, the rare earth weaponization, the energy encirclement strategies, and the scramble for mineral resources documented in Chapter 2 are not policy instruments deployed within a stable rules-based framework but moves in a competitive game whose rules are themselves contested, in which the distinction between economic policy and strategic coercion is progressively collapsing, and in which the retaliatory dynamics characteristic of prisoner's-dilemma interactions generate outcomes that are collectively suboptimal even when individually rational.

The AI supply chain is uniquely vulnerable to this dynamic because it is simultaneously the most strategically significant and the most geographically concentrated productive system in the contemporary global economy. As Chapter 2 documented, the fabrication of the most advanced semiconductors depends on extreme ultraviolet lithography equipment manufactured by a single Dutch company, ASML; the processing and refining of the rare earth elements essential to GPU manufacturing is dominated by China, which controls approximately 70% of global production and 91% of high-strength rare earth permanent magnet output; the energy required to power the data centers on which AI inference depends is sourced through supply chains that traverse the Strait of Hormuz, the Arctic shipping corridors, and the South American interior — precisely the regions where great-power competition is most intense. A supply chain of this concentration and geographic dispersion is, under conditions of stable international cooperation, a model of productive efficiency; under conditions of great-power disorder, it is a vector of systemic vulnerability, because disruption at any single node propagates through the entire system with a speed and amplitude that diversified supply chains are designed to attenuate.

3.3.2. The US-China Technology War: Export Controls, DeepSeek, and Bifurcated Architectures

The semiconductor export controls that the United States imposed on China beginning in October 2022 — subsequently expanded through the Dutch and Japanese trilateral restrictions on lithography equipment exports — represented the most consequential act of technology denial between major powers since the Cold War, a comparison that Chapter 1.3's analysis of nineteenth-century machine embargoes rendered analytically precise rather than merely rhetorical. The strategic rationale was simple: Washington intended to impose a structural limit on Chinese artificial intelligence capacity by limiting Chinese access to the most sophisticated chips and the tools needed to create them, therefore preserving American technical superiority in a field increasingly seen as crucial for both economic competitiveness and military advantage. Successive rounds of limitations—on high-bandwidth memory, on chip design software, on the servicing and maintenance of equipment already exported—have strengthened the export control system, creating a fairly complex regulatory structure whose enforcement, nevertheless, has been inconsistent and there is evidence of circumvention via third-country intermediaries and product redesign to fall below regulated thresholds. The most analytically consequential development in the US-China technology competition during the period covered by this thesis has been the emergence of evidence that the export controls may have produced an effect precisely opposite to their strategic intention. DeepSeek's V3.2 model, released in late 2025, demonstrated that frontier-level AI performance could be achieved at inference costs estimated at ten to thirty times below those of comparable American systems — an efficiency gain that multiple analysts attributed, at least in part, to the constraints imposed by restricted hardware access, which forced Chinese researchers to optimise computational efficiency rather than relying on the brute-force scaling strategy that abundant GPU supply had made the default approach in American laboratories. If this reading is accurate—and it is still up for debate; some experts believe DeepSeek's efficiency improvements are due to design innovation that would have happened irrespective of export restrictions—it is one of the most important unforeseen effects of technology-denial policy in the current era: the limit meant to maintain American advantage may have sped the emergence of an alternate technical

route that, by lowering the capital intensity of front-line artificial intelligence, weakens the very advantage American leadership of the GPU supply chain was meant to ensure. Chapter 1.3 looked at in great length the historical event that shows not only structural but also sequential similarities with the one being discussed here: Just as Britain's ban on the export of textile equipment and the departure of skilled craftsmen failed to stop Samuel Slater from reconstructing the Arkwright water frame from memory in Rhode Island in 1790 — and in doing so, set in motion the very American industrial capability that would ultimately outperform British manufacturing — so the American semiconductor embargo may have spurred, by means of the limits it imposed, a Chinese efficiency paradigm whose long-term competitive consequences could prove more dangerous to American artificial intelligence dominance than unbridled access to NVIDIA hardware would have been. The forward-looking question is whether this dynamic produces a bifurcated global AI architecture — what analysts have termed a "Splinternet" scenario in which US-aligned and China-aligned systems diverge in standards, data flows, training methodologies, and governance norms — or whether the efficiency gains pioneered under constraint are adopted globally, compressing the competitive gap and rendering the export control regime strategically irrelevant even if it remains legally operational (Deibert, 2020). A bifurcated architecture would carry consequences extending well beyond the technology sector: it would require states to choose between incompatible technological ecosystems in ways that reproduce, at the level of digital infrastructure, the bloc dynamics of the Cold War, with implications for trade, investment, and alliance structures that the analysis of European strategic dependency in section 3.4 examines. By contrast, a convergent design—in which the efficiency improvements driven by limitation are assimilated into world practice—would diminish the strategic advantage hardware supremacy now provides the United States and perhaps hasten the geopolitical dynamics Dalio's framework depicts: When the advantage from technology stops being a one-sided one, the rivalry moves to other areas — energy, minerals, finance, military strength — where the methods of coercion are more crude and the chance of things getting worse is a lot higher. The one-year suspension of China's October 2025 rare earth export controls, agreed in November 2025 as part of a broader US-China trade understanding following the Xi-Trump meeting, illustrates both the

tactical flexibility and the structural fragility of the current arrangement (Huld, 2025). The suspension was explicitly framed by both sides as a confidence-building measure rather than a strategic reversal; Beijing's broader export control regime — including the April 2025 licensing requirements for seven heavy rare earth elements and permanent magnet materials that have already disrupted carmaker supply chains across the United States and Europe — remains fully operational (International Energy Agency (b), 2025). The Foundation for Defense of Democracies characterized the suspension as "a tactical pause that provides the Trump administration with an opening" while warning that China's enforcement capacity is expanding, not contracting, with the Bureau of Industrial Security and Export and Import Controls planning its fastest staffing growth since 2022 (Burnham & Lazrow, 2025). The implication for the AI supply chain is that China retains the demonstrated capacity to restrict rare earth flows at any moment, and that the decision to exercise that capacity is a function of the broader geopolitical calculation — the trajectory of US-China relations, the status of the Taiwan question, the outcome of the Iran conflict — rather than of any durable institutional commitment to open trade.

The absence of such a commitment points to the most structurally consequential implication of a bifurcated AI architecture, which is not technological but geopolitical: it would produce, through the logic of infrastructural lock-in rather than through formal treaty, a new system of technology-based alliance structures in which the choice of AI ecosystem functions as a de facto declaration of strategic alignment. The contours of this emerging bloc structure are already discernible. One side is that the United States' control of cloud infrastructure, frontier model development, and GPU supply chains creates a gravitational force pulling the European Union, NATO member countries, Japan, South Korea, Australia, and other friendly nations into an American-led AI ecosystem. This is due to the weight of architectural dependency, interoperability requirements, and the lack of options at the same scale, but also because of active American diplomatic and economic pressure to get rid of Chinese technology supply chains. Washington's insistence that European allies restrict Huawei's participation in 5G networks established the template for this coercive alignment strategy; the extension of semiconductor export controls to include European-manufactured lithographic equipment — compelling ASML to curtail sales to Chinese chipmakers under American extraterritorial jurisdiction

— confirmed that the United States regards European technological choices as falling within the scope of its own strategic prerogatives (Farrell & Newman, 2023) (Kleinhans & Baisakova, 2020). The reasoning is not hard to put together: a bifurcated artificial intelligence architecture is strategically advantageous to the United States only if its allies are locked into the American side of the divide, and the most effective mechanism for ensuring this outcome is to foreclose the alternative — not merely by offering superior products, but by making continued involvement with the Chinese ecosystem politically costly and, where feasible, legally forbidden. On the other hand, China's mix of Belt and Road digital infrastructure investments, competitive AI models with inference costs orders of magnitude below those of their American equivalents, and generous government-backed finance produces a parallel gravitational field aimed toward the BRICS formation and the larger Global South. In this regard, DeepSeek's efficiency breakthrough is quite clear and decisive: Beijing gains a distribution edge that Washington's premium-utility model cannot equal, replicating at the AI layer the same competitive dynamic that gave Huawei its dominance of African and Southeast Asian telecoms infrastructure — not through technological superiority but rather through affordability, financial flexibility, and the readiness to operate without the conditionality that Western technology transfer has historically carried, if frontier-level AI capacity can be supplied at costs that developing countries can absorb. The historical analogy with the Cold War's alliance-through-infrastructure dynamics, in which the choice between Soviet and American military gear locked nations into strategic orbits whose logic went much beyond the weapons themselves, is informative, with the key added awareness that non-interoperability between the two ecosystems acts not only as a side effect of different development but as a deliberate form of strategic coercion: by designing artificial intelligence platforms, cloud architectures, and data standards that are fundamentally incompatible with those of the enemy bloc, each side raises the cost of defection for states already enmeshed in its ecosystem, therefore transforming what started as a technical preference into a basically irreversible geopolitical commitment, but with the important distinction that AI infrastructure goes much more deeply into the productive, administrative, and social fabric of the adopting state than military equipment ever did, therefore making the lock-in more complete and the re-alignment therefore more

challenging. For Europe, this emerging bloc structure sharpens the dependency dilemma analysed in section 3.4: to remain within the American AI ecosystem is to accept a degree of strategic subordination that the political dynamics of Stage 6 render increasingly uncomfortable; to build autonomous capacity is a generational undertaking whose completion timeline exceeds the pace at which the bloc structures are forming; and to explore alignment with the Chinese ecosystem is, under present political conditions, inconceivable. The outcome is a Europe fundamentally tied into the American bloc not by choice but by the lack of a practical substitute, a situation that, as Chapter 1's nineteenth-century parallels show, is only sustainable as long as the interests of the hegemon stay mostly in line with those of its dependencies, and that becomes especially dangerous the moment that alignment breaks.

3.3.3. The Energy-AI Nexus: Iran, Hormuz, and the Cost of Computation

The connection between hydrocarbon geopolitics and AI infrastructure, documented in Chapter 2 as "not direct but substitutive," has become, since the escalation of the US-Israel-Iran confrontation in February 2026, considerably more direct and more consequential than the earlier analysis suggested. The targeted killing of Supreme Leader on 28 February 2026 and the subsequent Iranian retaliatory strikes against Gulf state infrastructure have produced supply disruptions whose propagation through energy markets, electricity prices, and data center operating costs constitutes one of the most immediate and quantifiable channels through which geopolitical disorder affects the AI economy.

The quantitative dimensions of this channel were established in Chapter 2: Bloomberg projects that a closure of the Strait of Hormuz could drive crude oil to 108 dollars per barrel; the Wall Street Journal estimates that each ten-dollar increment translates into a 0.5% inflationary impulse in the United States; the European Central Bank's scenario modelling projects a 0.5% acceleration in eurozone inflation and a 0.1% GDP contraction from a 14% oil price increase; and the 45% spike in European gas prices following Qatar's announcement of a temporary LNG production halt — Qatar having become the EU's third-largest LNG supplier following the post-Ukraine reorganization of European energy imports — illustrates the particular fragility of European energy security in this theatre.

For the AI supply chain specifically, the transmission mechanism operates through the electricity grid: approximately 40% of American electricity generation is sourced from natural gas, and data centers in the United States already account for an estimated 8% of national electricity consumption, a share that is projected to grow substantially through the late 2020s as the hyperscaler build-out documented in Chapter 2 comes online. Any sustained increase in natural gas prices driven by Middle Eastern supply disruptions would therefore raise the operating costs of every American data center, compressing the margins of cloud providers and AI inference services at a moment when the revenue gap identified by Sequoia Capital already strains the economics of the build-out.

The Trump administration's stated objective of driving global crude prices toward fifty dollars per barrel is, as Chapter 2 observed, intelligible as an AI infrastructure strategy: lower oil prices reduce the pressure to export American liquefied natural gas to compensate for global energy deficits, freeing domestic gas supply for the electrical grid and, by extension, for the data centers upon which AI computation depends. But the military operations through which this objective is being pursued carry risks of escalation whose energy-price consequences could reverse the intended effect: if Iranian retaliatory actions produce sustained disruption to Hormuz transit — through which 20% of the world's oil and 20% of its liquefied natural gas pass daily — the resulting energy price spike would not merely raise AI infrastructure costs but would generate the kind of inflationary shock that forces central banks to tighten monetary policy, compounding the credit-tightening effects of the Japanese carry trade unwinding described in section 3.2 and creating a convergent set of pressures on the financial architecture of the AI build-out. The scenario in which a Hormuz disruption coincides with a carry trade unwind and a reassessment of AI revenue trajectories represents the most severe version of section 3.2's Scenario B — a disorderly correction triggered not by any single AI-specific failure but by the interaction of multiple exogenous shocks whose common denominator is the geopolitical disorder that Dalio's framework describes.

The energy dimension of great-power competition, while not reducible to the conjunctural dynamics of any particular crisis, acquires a structural significance in the current geopolitical moment that the preceding analysis of semiconductor supply chains and AI bloc formation only partially captures. A sustained disruption to global fossil fuel supply

— whether originating in the Strait of Hormuz, in the continuing pressure of the Ukraine conflict on European energy infrastructure, or in the broader volatility that characterises hydrocarbon markets under conditions of great-power disorder — would not produce symmetrical consequences across the three principal actors of the AI transition, and any analytical framework that treats a fossil fuel crisis as uniformly destabilizing misapprehends the degree to which the major powers have, over the preceding decade, pursued radically divergent strategies of energy insulation. The United States, having achieved substantial energy self-sufficiency through the shale revolution and producing approximately thirteen million barrels of crude oil per day to become the world's leading hydrocarbon producer, occupies a structurally sheltered position relative to import shocks of the kind that destabilized Western economies during the crises of 1973 and 1979; yet this insulation is partial rather than absolute, since American financial markets remain deeply exposed to global energy price volatility through the transmission channels documented in the carry trade analysis of section 3.2, and since the diversion of domestic energy supply to sustain the AI infrastructure build-out — projected to consume approximately 8% of American electricity by 2026 — constitutes a demand-side pressure whose interaction with price shocks remains structurally underappreciated (International Energy Agency, 2024) (U.S. Energy Information Administration (a), 2026).

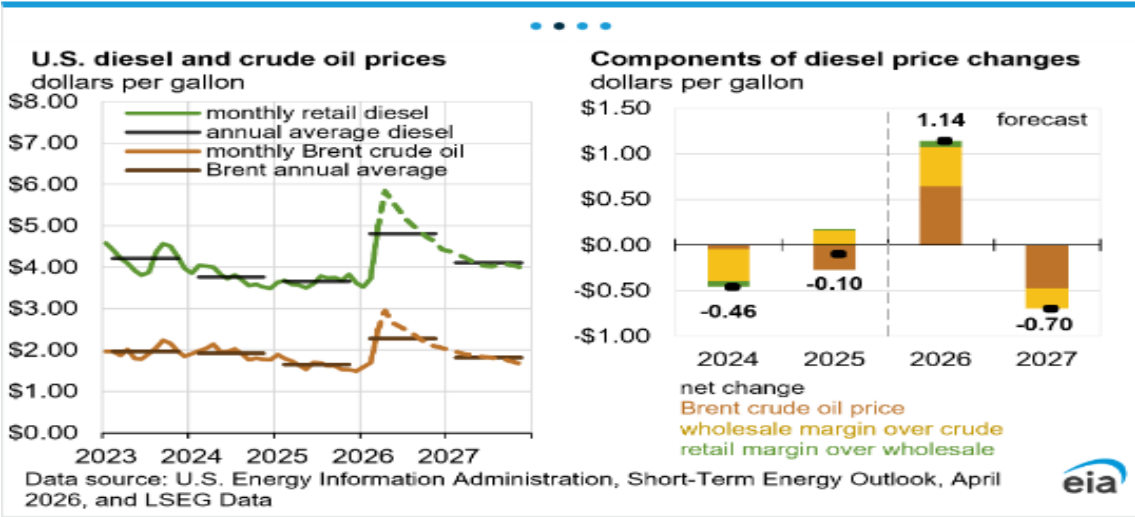
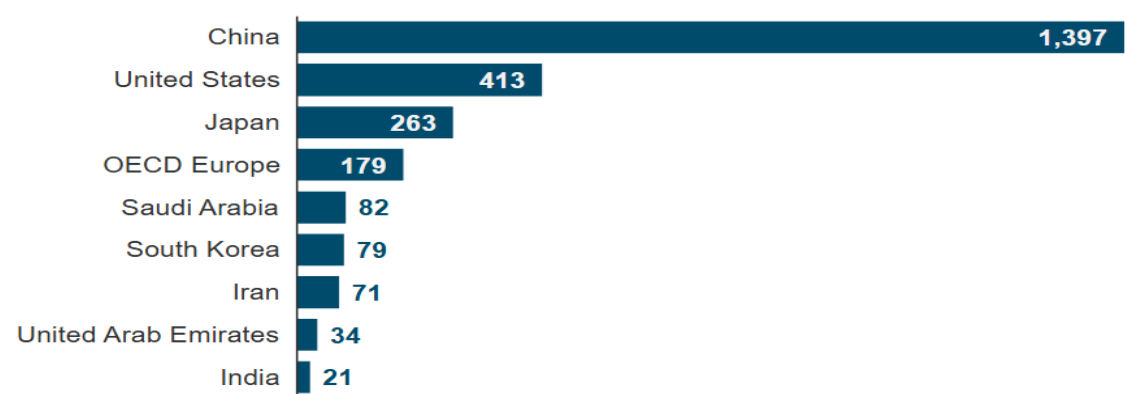


FIGURE 38: SHORT-TERM ENERGY OUTLOOK, APRIL 2026, AND LSEG DATA
(U.S. Energy Information Administration (a), 2026)

Europe, by contrast, has demonstrated through the Ukraine crisis an acute and unresolved dependency on hydrocarbon imports whose partial mitigation through diversified liquefied natural gas supply, accelerated renewables deployment, and demand reduction has not produced the energy sovereignty that its political rhetoric implies: the continent's industrial base remains sensitive to energy price spikes in ways that translate directly into competitive disadvantage relative to the United States, whose domestic energy costs are structurally lower, and relative to China, whose exposure to fossil fuel price volatility is being systematically reduced through a programme of strategic reserve accumulation and renewable energy deployment without parallel in modern economic history (Zeniewski, Molnar, & Hugues, 2023) (Yergin, 2012).

It is China's position in this tripartite energy equation that demands the most careful analytical attention — and that most directly challenges the intuition, commonly rehearsed in Western policy commentary, that a fossil fuel shock would function as a geopolitical equaliser. China's relative insulation does not derive from energy autarky, a misconception that conflates strategic stockpiling with structural self-sufficiency: as the world's largest crude oil importer, Beijing imported an average of 11.65 million barrels per day in the first nine months of 2025, a figure that represents a 5.7% increase over 2024 levels and that structurally binds Chinese industrial production to the continued flow of external supply (U.S. Energy Information Administration (b), 2026).



Data source: U.S. Energy Information Administration, *Short-Term Energy Outlook* (STEO), March 2026
FIGURE 39: ESTIMATED STRATEGIC CRUDE OIL INVENTORIES IN SELECTED COUNTRIES (MILLION BARRELS)
(U.S. Energy Information Administration (b), 2026)

What distinguishes China's position is not independence from global energy markets but a deliberately constructed architecture of asymmetric geopolitical resilience that limits the coercive leverage other actors can exercise over it — an architecture whose construction has proceeded along three analytically distinct but mutually reinforcing vectors. The first is quantitative: China is estimated to have reached nearly 1.4 billion barrels of combined strategic and commercial oil inventories as of December 2025, a figure that reflects plans to increase state reserve storage capacity to over one billion barrels — equivalent to three months of net imports, with trade sources suggesting an ultimate objective of six months' coverage, or approximately two billion barrels, that would insulate China from sustained supply disruptions or shipping blockades with minimal economic shock (U.S. Energy Information Administration (b), 2026) (Enerdata, 2025). This buffer is not merely logistical but geopolitical: PRC leadership appears to have concluded that the international order is entering a prolonged period of structural instability, and reserve accumulation functions as a hedge against the weaponization of energy supply chains at precisely the moment when those chains are being most aggressively instrumentalised by Western states through the sanctions regimes documented in section 3.3 (Downs, 2025). The second vector concerns Beijing's systematic reduction of its exposure to the Western-dominated energy-financial order. Applying Farrell and Newman's framework of weaponised interdependence — wherein states exploit asymmetric positions within global networks to coerce adversaries — China has pursued an inverse strategy: insulating itself from nodes of Western structural power rather than seeking to control them (Farrell & Newman, 2019). In practice, this has meant diversifying its import base toward suppliers operating outside Western sanction regimes — in 2024, China imported 1.4 million barrels per day from Iran and 821,000 barrels per day of Russian oil shipped on sanctioned tankers, effectively transforming sanctioned crude into a discounted strategic resource — while simultaneously advancing the “petroyuan” as an alternative settlement architecture for global oil trade, a shift materialising through yuan-denominated crude oil futures contracts, the People's Bank of China's currency swap agreement with the Saudi Arabian Monetary Authority of approximately 6.98 billion dollars concluded in November 2023, and the mBridge platform, whose digital architecture offers oil-exporting nations a technologically

sophisticated alternative to dollar-denominated clearing systems (Hayley, 2024) (Cucchi, 2025). The third and structurally most consequential vector concerns China's repositioning within the post-carbon energy economy: China accounts for approximately 80% of global solar panel production, 70% of lithium-ion battery manufacturing capacity, and 60% of global electric vehicle output — a configuration whose implication is that any sustained fossil fuel crisis functions paradoxically not as a threat to Chinese economic power but as an accelerant of the energy transition in which China already holds industrial dominance, reducing the structural significance of import dependency precisely as that dependency is becoming most geopolitically salient (International Energy Agency, 2022) (BloombergNEF, 2025). The analytical conclusion that follows from this configuration is not that a fossil fuel disruption will directly produce Chinese global primacy — a causation too linear and conjunctural to survive rigorous scrutiny, and one that neglects the demographic constraints, debt accumulation pressures, and property sector fragility that condition China's medium-term trajectory — but rather, as Choyleva observes, that while complete de-dollarisation of the oil trade remains highly unlikely over a five-year horizon, a gradual erosion of dollar-denominated settlement and the progressive reorientation of oil revenues toward alternative financial architectures is structurally underway, and that a prolonged energy crisis does not cause China's geopolitical ascent so much as accelerate it, by exposing the structural fragilities of an international energy order that Beijing has spent the preceding decade systematically learning to circumvent (Choyleva, 2025). For Europe, the intersection of this energy exposure with the AI dependency documented in section 3.4 creates a compounding structural disadvantage whose severity becomes fully visible only when the two dimensions are considered jointly: a fossil fuel crisis that raises European industrial energy costs simultaneously constrains the fiscal space available for sovereign AI investment, forces governments toward emergency demand-management measures that redirect institutional attention from long-term strategic planning, and strengthens the case for continued reliance on American cloud infrastructure at precisely the moment when the geopolitical conditions described above render that reliance most strategically problematic. The convergent energy and digital vulnerability whose costs are concentrated in Europe, while its structural beneficiaries are distributed between American hydrocarbon self-sufficiency

and Chinese post-carbon industrial dominance, constitutes one of the most consequential and least systematically examined dimensions of the asymmetry that the macro-scenarios of section 3.7 are designed to capture.

The preceding analysis of the energy–AI nexus has traced the contemporary relevance of hydrocarbons to the AI supply chain — a relevance that is substitutive rather than direct, mediated through the electricity grid and the natural gas upon which it substantially depends. But the deeper structural argument concerns not the persistence of oil as a strategic resource — a role it has occupied since the early twentieth century, when the Royal Navy's conversion from coal to oil under Winston Churchill's direction made the security of Persian Gulf supply a permanent fixture of British and, subsequently, American grand strategy — but the emergence of a successor resource whose geopolitical significance may prove equally consequential (Yergin, 1991). If coal was the strategic material of the nineteenth century and oil the strategic material of the twentieth, rare earth elements are acquiring a structural position in the twenty-first century that justifies their characterisation as, in effect, the oil of the third millennium. The analogy is not merely rhetorical; it rests on a precise structural correspondence. Oil's geopolitical power derived not from its scarcity in absolute geological terms — proven reserves were always vast — but from the extreme geographic concentration of easily extractable deposits, the capital intensity of refining infrastructure, and the absence of substitutes for its role in transportation, military logistics, and industrial chemistry. These three conditions — geographic concentration of extraction, chokepoint control over processing, and the absence of viable substitutes — are reproduced with remarkable fidelity in the contemporary rare earth economy (Klare, 2012). China controls approximately 70% of global rare earth mining and over 90% of refining capacity, a degree of market dominance that exceeds OPEC's share of global oil production at any point in the cartel's history (International Energy Agency (a), 2025). Decades of gathered knowledge and technical skill are embodied in the processing infrastructure, the chemical separation plants, the magnet factories, the metallurgical facilities; this cannot be reproduced within the timeline the artificial intelligence transition requires. At current levels of technology, there are no commercially feasible replacements for the uses for which rare earths are crucial: the permanent magnets in data center servers, electric vehicle motors, wind

turbines, fighter jet actuators, and missile guidance systems. The twentieth century demonstrated, through two world wars, the Suez Crisis, the OPEC embargo of 1973, and the Gulf Wars of 1991 and 2003, what happens when a resource of this structural centrality becomes the object of great-power competition: it generates its own geopolitics, its own alliance structures, its own *casus belli* (Painter, 2012). The question that the following subsection addresses is whether the rare earth economy of the twenty-first century is entering an analogous phase — and whether the instruments through which China has chosen to exercise its dominance constitute the opening moves of a resource confrontation whose consequences for the AI supply chain, and for the broader geopolitical order, may prove as far-reaching as the oil crises that reshaped the twentieth century.

3.3.4. The Weaponization of Critical Minerals: Rare Earths as Strategic Leverage

The third dimension of geopolitical risk to the AI supply chain — and the one over which the longest time horizon of uncertainty operates — is the structural leverage that China's dominance of critical mineral processing confers on Beijing in its broader strategic competition with the United States and its allies. The IEA's Global Critical Minerals Outlook 2025 confirmed what the analysis of Chapter 2 documented in detail: for nineteen out of twenty strategically important minerals, China is the leading refiner, with an average market share of 70%; China's dominance in the separation and refining of rare earths used in permanent magnets reaches approximately ninety-1% of global production; and this concentration has intensified, not diminished, in recent years despite the diversification efforts announced by the United States, the European Union, and their allies (International Energy Agency (a), 2025).

China's April 2025 export controls on seven heavy rare earth elements produced immediate and measurable disruption: export volumes fell sharply, European prices for dysprosium, terbium, and yttrium reached up to six times Chinese domestic prices, and several automobile manufacturers in the United States and Europe were forced to cut production or temporarily shut down factories (International Energy Agency (b), 2025). The October 2025 expansion — adding five further elements, imposing extraterritorial jurisdiction over foreign-made products containing Chinese-origin materials, and

extending controls to processing technologies and know-how — represented what the IEA described as "the most extensive tightening of China's rare earth regulatory framework to date" (International Energy Agency (b), 2025). Though the October measures were later suspended for one year as part of the November 2025 US-China trade understanding, the April controls remain fully in force, and the demonstrated ability to rapidly impose and escalate restrictions has radically changed the risk calculation for every company and state relying on Chinese rare earth inputs. (Ludwikowski, Christensen, Lopez, & Quesada, 2025).

The implications for the AI supply chain are structural rather than episodic. The permanent magnets that rely on Chinese rare earth elements are components of data center servers, electric vehicle motors, wind turbines, fighter jet actuators, and missile guidance systems — meaning that a sustained restriction would not merely raise the cost of AI hardware but would simultaneously constrain the defence, energy, and transport sectors on which the broader economy depends (SFA Oxford, 2025). The European Parliament's assessment, published in November 2025, concluded that China's export controls had "highlighted major vulnerabilities of the EU supply chains that remain hard to mitigate" and noted that rare earth elements had featured on all five EU lists of critical raw materials since 2011 without producing the diversification that the assessments were designed to motivate (Szczepański, 2025).

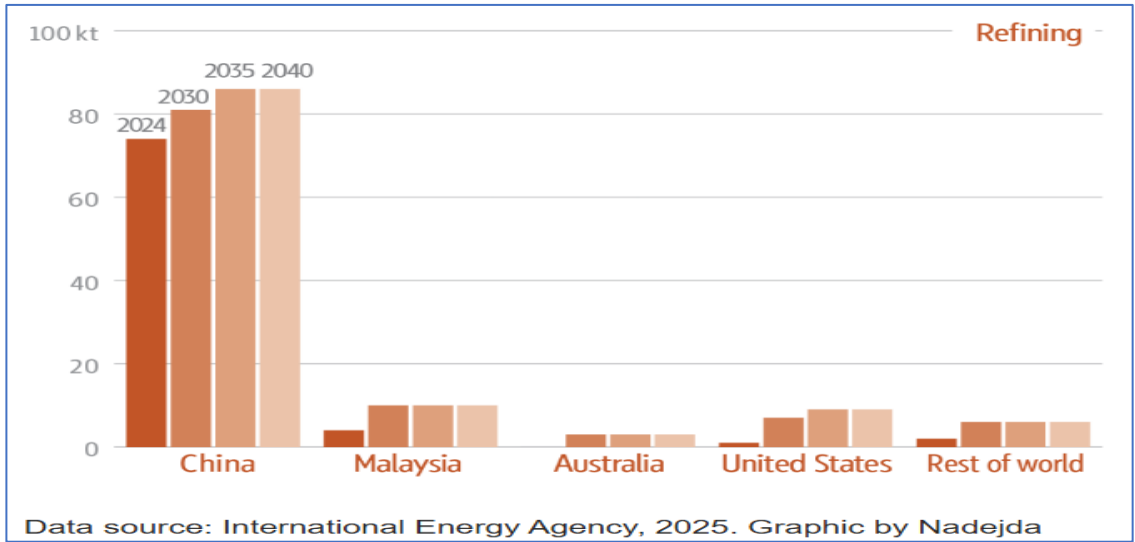


FIGURE 40: EXPECTED REE SUPPLY
(Szczepański, 2025)

The Commission's October 2025 announcement of the RESourceEU initiative — joint purchasing, stockpiling, and support for domestic production and processing — represents an acknowledgement that the policy instruments deployed to date have been insufficient, but the timeline for any meaningful reduction of European dependence on Chinese rare earth processing is measured in years, not months, and the geological, environmental, and regulatory constraints on Western rare earth extraction remain formidable (Ibid).

The forward-looking scenario is therefore one in which China retains the demonstrated capacity to weaponize its rare earth dominance at any moment of its choosing, and in which the decision to exercise that capacity is a function of the broader trajectory of great-power competition — the status of Taiwan, the outcome of the Iran conflict, the degree of American escalation in technology denial, and the evolving dynamics of what Dalio terms the "clash of great powers." For the AI supply chain, this represents a structural overhang of geopolitical risk that financial models — focused on revenue trajectories, capital expenditure plans, and valuation multiples — are structurally ill-equipped to price, because the risk is not probabilistic in the conventional sense but strategic: it depends on the decisions of actors whose rationality is conditioned by considerations of sovereignty, prestige, and regime survival that cannot be reduced to expected-value calculations. The three cases documented in Chapter 2 — Greenland, Venezuela, and Iran — and the rare earth dynamics analysed here suggest that the AI transition is not merely occurring within a deteriorating geopolitical environment but is actively reshaping that environment, raising the stakes of resource competition to a level at which the instruments of economic statecraft shade imperceptibly into the instruments of coercion, and at which the distinction between a technology race and an arms race becomes, as Yudkowsky and Soares warned from a different analytical perspective, a distinction without a practical difference.

3.3.5. The Computational Bernhard: Energy Asymmetry as a Future Vector of AI Warfare

If the distinction between a technology race and an arms race has become one without practical difference, it is worth asking what conflict might emerge from the AI economy's

specific vulnerabilities, and whether one of the twentieth century's most inventive strategies of economic warfare might find a computational equivalent. Operation Bernhard, Nazi Germany's wartime scheme to destabilise the British economy by flooding it with counterfeit Bank of England notes, produced some 8.96 million forgeries with a face value of roughly £132.6 million — about four times the Bank's gold reserves — using prisoner labour at Sachsenhausen (Malkin, 2008) (Bank of England Museum, 2024). Its novelty wasn't in the forgery but rather in a willful asymmetry: Germany paid almost nothing to manufacture notes whose absorption at much higher cost endangered British monetary stability. It is that structural inequality, not the banknotes themselves, that moves on.

Frontier AI exhibits an analogous, still under-examined, energy asymmetry between input and output. Submitting a query consumes negligible power, but processing it activates billions of parameters across thousands of GPUs, at an energy cost estimated to be several orders of magnitude greater than the request itself (Patterson, Gonzalez, Le, Liang, & Munguia, 2021). Should great-power competition over AI intensify, a state actor could exploit this by orchestrating sustained, high-volume query campaigns against adversary infrastructure, not to extract intelligence but to maximise energy consumption, strain electrical grids, overload servers, and inflate operating costs across the target's ecosystem. This would be a computational Operation Bernhard: using an opponent's own infrastructure against itself, not by causing physical damage, but by systematically overloading its capacity to absorb artificially generated demand. Every use of artificial intelligence throughout public APIs and vital military, financial, and government systems increases the attack surface. Even a small continuous increase in data-centre load might cascade across power prices, grid stability, and downstream industrial customers in the energy-limited European and, increasingly, American networks researched in Chapter 2. The prerequisites are already set.

The defences of the targeted state would run on three stages, each of which would be circumventable. The first is computational rate limiting, which restricts not the volume of requests but rather their intensity, as a query necessitating extensive chain-of-thought analysis or high-fidelity generation uses considerably more computing resources than a basic one. The second is semantic triage: a compact, energy-efficient guardrail model that

examines prompts and discards those designed to consume GPU cycles prior to their access of the main infrastructure.

The third, and most consequential, is tiered sovereignty over compute, disconnecting the most powerful clusters from the public internet during suspected attacks and reserving them for verified domestic use — a digital analogue of the Bank of England's 1943 decision to withdraw all notes above £5 once Bernhard forgeries were detected (Luccioni, Viguiet, & Ligozat, 2022) (Bank of England Museum, 2024).

The authentication barrier is the critical weakness. A state adversary need not breach CAPTCHAs or token controls technically: a click-farm worker can solve hundreds per hour at negligible cost (Motoyama, et al., 2010), and increasingly, small AI models can impersonate users and clear verification autonomously. Once the gate is open, a single adversarial prompt can hold a ten-thousand-GPU cluster at peak load for minutes or hours. The commercial objection, that the attack costs more than it inflicts, misreads the logic: states operate by strategic, not commercial, calculus, and a hundred million dollars in coordinated labour and compute that triggers a sustained brownout across the data-centre corridors of northern Virginia or Silicon Valley could produce damage measured in billions — just as Germany judged Bernhard not by the cost of paper and prison labour but by the potential collapse of confidence in British money (Malkin, 2008). The asymmetry gets worse at every level: the defender's model uses megawatts, the attacker's watts; the attacker's infrastructure is spread out, temporary, and hard to link to them, while the defender's is concentrated, physical, and requires a lot of money. If Altman's concept of intelligence as a metered utility is implemented, the pricing mechanism itself becomes the transmission channel; each adversarial query generates income while the total energy cost of millions of them quietly surpasses it—a deterioration hidden from financial monitoring until it appears on the grid or the balance sheet.

The scenario remains speculative, as no such campaign has been publicly documented, but the preconditions accumulate with every public-facing deployment, and the defence it demands is precisely the energy sovereignty and computational self-sufficiency that section 3.4 shows to be, at present, largely aspirational (Poddi, 2024).

The energy-overload vector is not the only one. As Chapter 2 records, the April 2026 disclosure of Anthropic's Claude Mythos Preview — whose autonomous vulnerability-

discovery capabilities prompted an emergency meeting between Treasury Secretary Bessent, Federal Reserve Chair Powell, and the heads of the largest American banks — exposed a second, graver attack surface: the capacity of frontier models to identify, independently and at scale, zero-day vulnerabilities in payment networks, browsers, industrial control software, and operating systems, some unpatched for decades (Anthropic (d), 2026) (Anthropic (e), 2026). A defensive tool becomes a growing offensive danger when Anthropic predicts similar skills elsewhere inside twelve months. Defensive deployment under Scenario I by means of projects such as Project Glasswing could strengthen infrastructure more rapidly than opponents can take advantage of it; Scenario II, in which a decline starves cybersecurity expenditures even as Mythos-class capabilities expand, would generate exactly the asymmetry mentioned above, with defense excruciatingly costly and exploitation almost freely available.

From Stuxnet to SolarWinds to the XZ Utils compromise, two decades of cybersecurity give no reason to expect this imbalance to resolve in the defender's favour absent the institutional cooperation, disclosure regimes, and international norms that section 3.6 finds structurally missing (Schneier, 2018).

3.4. European Sovereignty or Structural Dependence? The Transatlantic Digital Asymmetry

The analysis of European AI strategy developed in sections 2.9 and 2.10 of this thesis established that the European Union occupies a position of structural ambiguity in the global AI order: technically sophisticated, normatively ambitious, and strategically dependent. The task of this section is to project that analysis forward, assessing whether the transatlantic digital asymmetry documented in Chapter 2 is likely to deepen under the conditions of great-power disorder described in section 3.3, or whether the convergence of geopolitical shocks, institutional awakening, and targeted industrial policy produces a countervailing movement toward genuine European digital sovereignty. Beyond the technology sector, the reaction to this question has great repercussions: If Europe does not develop autonomous capacity at the infrastructure level of the artificial intelligence economy, its regulatory authority—the AI Act, the GDPR, the Digital Services Act—will progressively lose operational relevance as the enterprises it governs will owe their

principal legal, financial, and architectural allegiance to nations over which Brussels has no influence.

3.4.1. The Five Pillars of Dependency

The scale of European dependency on American digital infrastructure has, since the analysis of Chapter 2 was completed, been quantified with a precision that leaves little room for interpretive ambiguity. The European Parliament's own assessment, published in a June 2025 committee report, concluded that the EU relies on non-EU countries for over 80% of its digital products, services, infrastructure, and intellectual property (Knafo, 2025). Synergy Research Group data cited by CNBC in February 2026 placed the American share of the European cloud computing market at 85%, with Amazon Web Services, Microsoft Azure, and Google Cloud Platform collectively dominating the public sector, healthcare, financial services, and industrial applications on which European economic life depends (Synergy Research Group, 2026).

The Bloomsbury Intelligence and Security Institute, in a March 2026 analysis, identified five interlocking dimensions of this dependency — cloud infrastructure, collaboration software, payment systems, AI models, and defence platforms — each of which creates a distinct channel through which American jurisdictional authority, commercial decisions, or political leverage can affect European operational continuity (Bloomsbury Intelligence and Security Institute, 2026).

The cloud dependency is the most immediately consequential. The US CLOUD Act of 2018 permits American authorities to compel US-based technology companies to provide requested data regardless of where that data is physically stored — a provision that creates an irreconcilable legal conflict with the GDPR's data protection requirements and that renders contractual assurances about data sovereignty from American providers structurally unreliable (Loohuis, 2025). The vulnerability is not theoretical: when the United States imposed sanctions on the International Criminal Court's Chief Prosecutor Karim Khan in 2025, his Microsoft email account was suspended — an episode that demonstrated, with uncomfortable clarity, the operational consequences of institutional dependence on infrastructure governed by a foreign jurisdiction (Bloomsbury Intelligence and Security Institute, 2026). The collaboration software dependency compounds this

exposure: Microsoft Teams, whose last publicly disclosed user base of 320 million monthly active users (reported in 2023, after which Microsoft ceased public MAU disclosure) and approximately 48% share of the enterprise collaboration market, dominates European enterprise communication through its bundled integration with Microsoft 365 — a market position that the European Commission's own competition investigation confirmed as structurally dominant, resulting in Microsoft making licensing and interoperability concessions in 2023 to avoid formal antitrust proceedings (SaaSUltra, 2026) (Microsoft, 2025); the operational data generated by these platforms is processed under terms of service governed by American law and subject to the same CLOUD Act compulsion provisions that affect cloud storage, meaning that the jurisdictional vulnerability extends to the daily working communications of European governments, regulated industries, and defence contractors. The AI model dependency represents perhaps the most rapidly deepening of the five channels: as of early 2026, the frontier models deployed across European enterprise, public sector, and research institutions — the GPT-5 family, Claude (Opus 4.6 and successors), and Gemini (3.1 Pro and successors) — are developed, trained, and maintained exclusively by American corporations whose model updates, capability restrictions, and terms of service are determined without European institutional input; the sole European contender of note, Mistral AI of France, remains substantially behind the American frontier in both capability and enterprise adoption, and the computational infrastructure required to train a competitive alternative — the GPU clusters, energy supply, and capital that sections 2.5 and 2.8 documented — is not available within Europe at the scale the task demands (Madiaga, 2024). The Gaia-X initiative's Chief Technology Officer, Christoph Strnadl, articulated the structural logic with precision: "If tomorrow a US administration decided to stop service delivery to Europe, everyone would be out of business. Email, public administration, political communication — for critical services, we need alternatives" (EU Perspectives, 2026).

The payment system dependency is less visible but equally significant. Visa and Mastercard accounted for approximately two-thirds of card transactions in the European Union in 2022, with thirteen of the twenty member states of the eurozone lacking any national card payment scheme of their own (European Central Bank, 2023) — a

concentration that subjects the financial infrastructure of European daily life to the governance frameworks, pricing decisions, and regulatory compliance requirements of two American corporations (Bloomsbury Intelligence and Security Institute, 2026). The defence dependency is, as section 2.9 documented through the Palantir analysis, perhaps the most structurally entrenched: the UK Ministry of Defence directly awarded Palantir a follow-on enterprise agreement worth approximately £240.6 million, signed in December 2025, for continued licensing and support of data analytics across the British Army, Royal Navy, and RAF, interoperable with NATO systems and running for three years from April 2026 (Ministry of Defence UK, 2026), Germany's armed forces partnered with Google Cloud for a sovereign defence cloud, and NATO interoperability requirements increasingly mandate AI-enabled command and control systems whose architecture is designed and maintained by American firms (Bloomsbury Intelligence and Security Institute, 2026).

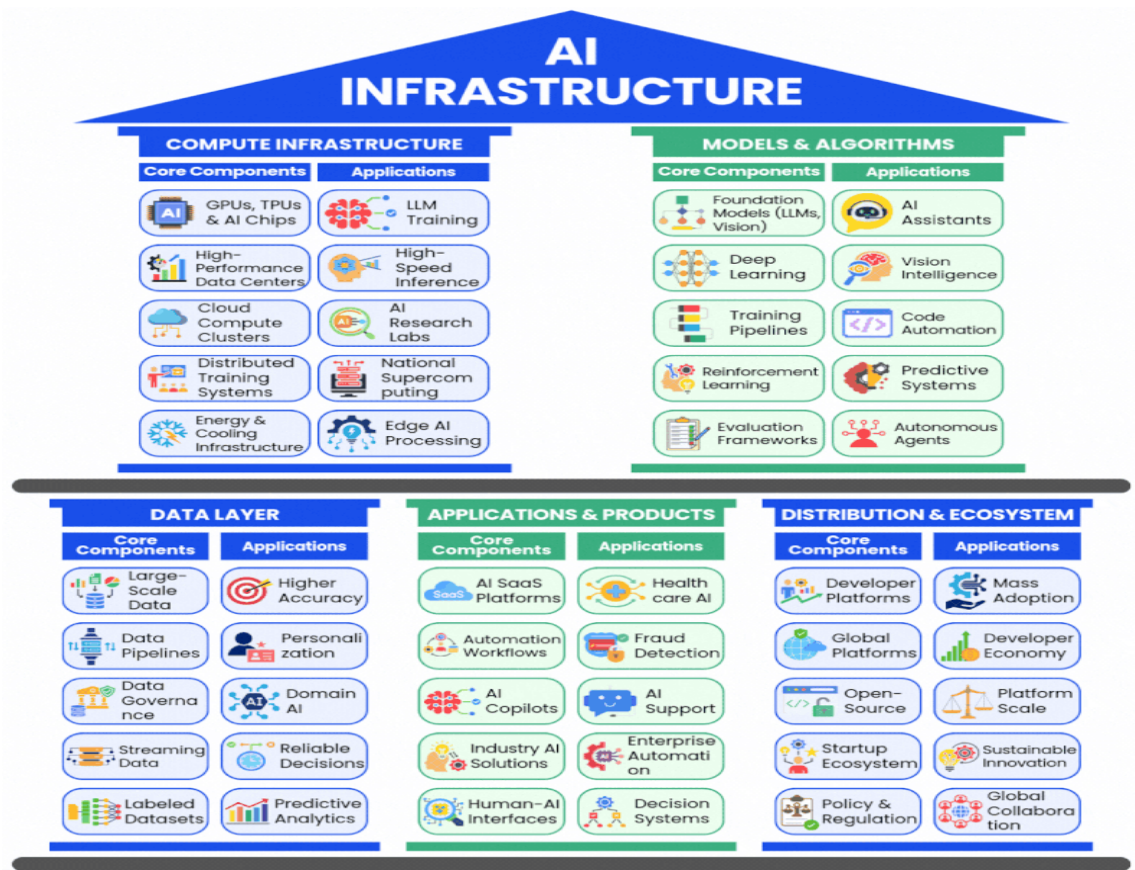


FIGURE 41: THE FIVE PILLARS OF AI INFRASTRUCTURE AND ECOSYSTEM

Source:McKinsey & Company

The final result is a structure whereby European regulatory authority coexists with American infrastructure dominance in ever-more strained conflict: The outcome is a structural contradiction: Europe writes the rules — the GDPR, the AI Act, the Digital Markets Act — but the systems to which those rules apply are made, maintained, and finally controlled by companies whose main duties are to American law, American shareholders, and American national security needs.

3.4.2. The Awakening: Sovereign Cloud, Eurostack, and the Limits of Aspiration

The period since late 2025 has witnessed what multiple analysts have described as a "psychological shift" in European thinking about digital dependency — a shift driven not by any single event but by the convergence of Trump-era geopolitical volatility, the Greenland provocations, the tariff escalations, and the growing recognition that the transatlantic alliance cannot be treated as an invariant parameter of European strategic planning (Araujo, 2026). All twenty-seven EU member states signed a statement in November 2025 confirming their "shared ambition to strengthen Europe's digital sovereignty" and lower "strategic dependencies" (Council of the European Union, 2025). On November 18, 2025, the French-German Summit on European Digital Sovereignty started a joint task force on digital sovereignty and singled out artificial intelligence, data, and public infrastructure as top priorities for coordinated investment (French Republic, 2025). By 2027, France intends to move 2.5 million public employees away from Zoom and Microsoft Teams to Visio, a French-built video conferencing tool housed on national infrastructure. Austria's Armed Forces switched 16,000 Microsoft Office computers over to LibreOffice; For government workers, Denmark revealed a trial of open-source substitutes to Microsoft Office (Bloomsbury Intelligence and Security Institute, 2026). Gartner projects that European spending on sovereign cloud infrastructure will more than triple from 6.9 billion dollars in 2025 to over twenty-three billion dollars by 2027 — the fastest growth rate of any region (Clark, 2026).

These developments are significant as indicators of political will, but the analytical question is whether they can produce structural change within the timeframe that the geopolitical dynamics of section 3.3 require. The obstacles are formidable. Forrester predicted that no European enterprise will shift entirely from US hyperscalers in 2026,

citing the depth of integration with proprietary services, the cost of migration, and the absence of European alternatives at comparable scale (Loohuis, 2025). The EU Cloud and AI Development Act, intended to establish EU-wide eligibility requirements for cloud service providers and harmonised procurement processes, has been delayed to the first quarter of 2026 as the Commission deliberates whether to adopt ownership restrictions or risk-based assurance models — a debate whose protracted character illustrates the institutional complexity that Chapter 2 identified as one of Europe's structural disadvantages relative to the unified state actors against which it competes (Burwell & Propp, 2026). Though OVHcloud, STACKIT (supported by Lidl's parent company Schwarz Gruppe with eleven billion euros in investment), and Scaleway are developing, their base is so small that even rapid growth cannot realistically threaten the market share of American hyperscalers within one investment cycle.

The contradiction is captured with unusual clarity by the Stargate Norway project announced in 2025, a joint venture between Nscale, Aker, and OpenAI that aims to install 100,000 NVIDIA GPUs in a 230-megawatt facility at Kvandal, outside Narvik in the Norwegian Arctic, powered entirely by renewable hydropower and explicitly marketed as sovereign AI infrastructure for Europe under OpenAI's "OpenAI for Countries" programme (Nscale, 2025). The arrangement reproduces rather than resolves the dependency this section has documented: the compute is sited in Europe and the electricity is European, but the frontier models, the GPUs, and the principal offtake agreements — extended through a separate Microsoft deal in April 2026 that added more than thirty thousand NVIDIA Rubin chips — remain American. What the Norwegian case adds to the analysis is a security dimension that the sovereign-cloud literature has tended to neglect: the facility sits only a few hundred miles from the Russian border, and a professor at the Norwegian military's Institute for Defence Studies has cautioned that, in a direct conflict, infrastructure of this kind should be expected to be among the first targets (Perrigo, 2026). The point is not hypothetical — an Amazon data center in the United Arab Emirates was struck by Iranian drones in March 2026 — and it folds the European energy-and-sovereignty question directly into the physical-infrastructure vulnerability that section 3.3.5 examined, since the same hydropower abundance that makes the Arctic

attractive for computation also concentrates strategically critical capacity within reach of a hostile power (Perrigo, 2026).



FIGURE 42: INSIDE THE AI BOOM'S ARCTIC OUTPOST

Source: (Perrigo, 2026)

The clearest example of the sovereignty-dependency contradiction comes from the defence dimension. European military officials have cautioned that fast limits on US suppliers might impair operational efficiency since European forces rely on American software and networks for data storage, communications, and intelligence. The result is what the Bloomsbury analysis terms a "dual-track sovereignty approach": civilian administrations are increasingly willing to migrate away from American collaboration software for non-sensitive functions, while military and security agencies prioritise continuity through "sovereign wrappers" — European legal entities that operate American infrastructure under European jurisdiction, but that remain, at the architectural level, subsidiaries of American parent companies whose ultimate legal obligations run to Washington rather than to Brussels (Bloomsbury Intelligence and Security Institute, 2026).

The structural similarity with the nineteenth-century dependency interactions studied in Chapter 1 is enlightening: says that states that were officially independent but practically reliant on British industrial capacity—the Ottoman Empire's reliance on British-built warships, Qing China's dependence on British-financed railways—found that formal sovereignty without productive autonomy is a progressively weaker position since the power that controls the infrastructure can modify the conditions of access in response to its own strategic priorities.

3.4.3. The Mercosur Signal and the Logic of Diversification

The EU-Mercosur trade agreement, the political conclusion of which was announced on 6 December 2024 in Montevideo after twenty-five years of negotiations, was formally signed on 5 September 2025 and now awaits ratification by the European Parliament and individual EU member states — a process whose completion remains uncertain due to opposition from France, Poland, and several other member states with significant agricultural sectors. Even in its current pre-ratification state, the agreement represents one of the most significant acts of European economic diversification in the current geopolitical context — not because of its direct relevance to AI infrastructure, which is limited, but because of the strategic signal it sends about Europe's willingness to restructure its trade relationships in response to transatlantic uncertainty (European Commission, 2024). Reducing tariffs on European industrial exports to South America while giving Mercosur agricultural producers more access to European markets, the agreement creates a free trade zone of over 720 million people and approximately one-fifth of world GDP (around \$25 trillion combined) (European Commission, 2024). Considering the volatility of tariffs in the Trump era and the wider deterioration of the rules-based trading order noted in section 3.3, the deal seeks to create alternative economic relationships that lessen Europe's reliance on any one trade relationship—including, and perhaps most importantly, the transatlantic one.

The diversification logic extends beyond trade. European investments in Latin American lithium extraction (Argentina's "lithium triangle"), in African rare earth processing partnerships (the Critical Raw Materials Act's strategic projects in France, Italy, Poland, and Sweden), and in Middle Eastern sovereign wealth fund co-investments in European

AI infrastructure collectively represent the early stages of a supply-chain diversification programme whose ambition, if sustained, could gradually reduce the dependency that this section has documented (Szczepański, 2025). The Commission's October 2025 RESourceEU initiative — joint purchasing, stockpiling, and support for domestic rare earth production — represents an institutional acknowledgement that the diversification required is not merely commercial but strategic, a conclusion that the analysis of China's rare earth weaponization in section 3.3 has reinforced.

3.4.4. The Nineteenth-Century Parallel: Dependent Industrialization and Its Consequences

The historical analysis of Chapter 1 provides the framework within which Europe's current predicament must be assessed. The Ottoman Empire, Qing China, much of the Indian subcontinent—the states that failed to develop autonomous industrial bases during the coal-to-steam change of the nineteenth century—did not fail due to a dearth of material resources or technical knowledge; they failed because their institutional capacity to mobilise money, train personnel, and create the integrated supply networks required to compete with first-movers whose structural advantages grew over time. Although the parallel with Europe's present standing in the AI economy is not perfect—Europe has world-class colleges, cutting-edge manufacturing sectors, and a legal system with real global influence—the underlying logic is apparent: A government that uses a technology without overseeing the way it is made and delivered is in a position of dependence with terms determined by the producer, not the consumer. As the technology becomes more important for the economy and military strength, the effects get progressively worse.

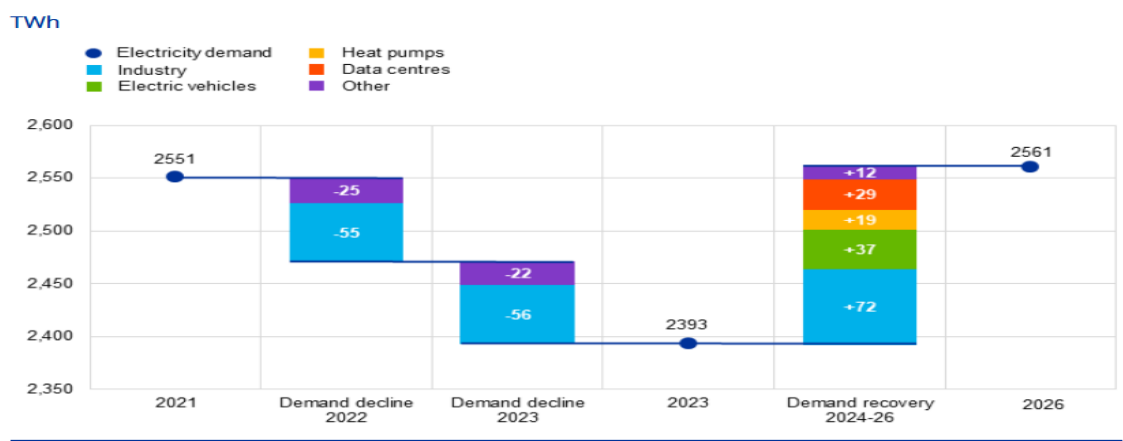
According to the Bloomsbury analysis, the question is whether Europe can achieve "selective diversification," which is sovereignty over the most sensitive and strategically important digital activities while still being able to work with American systems for tasks where depending on them is feasible. The depth of current integration makes even selective diversification a multi-decade project that would need a level of political will and institutional coherence that the twenty-seven-member decision-making structure of the EU has historically found it difficult to maintain. The answer will depend, in substantial part, on the trajectory of the variables examined in sections 3.2 and 3.3: if the

financial correction described in Scenario A produces an orderly repricing that reduces the cost of computational infrastructure, European entry barriers decline; if the geopolitical disorder described in section 3.3 continues to escalate, the political will for sovereignty investment strengthens; if the rare earth weaponization threat materialises in its more severe forms, the case for supply-chain diversification becomes politically irresistible. Consequently, the most likely path is one in which European digital sovereignty progresses unevenly—faster in civilian administration than in defence, faster in law than in infrastructure, faster in political speech than in industrial capacity—but in which, for the first time since the commercialization of the internet, the direction of travel is provisionally toward more autonomy rather than more reliance. Among the most important unsolved concerns in European strategic policy is whether this path is maintained and whether it generates significant structural change inside the time frame that the geopolitical dynamics of Stage 6 call for.

Emerging evidence, though, points to a path of travel less certain than the previous evaluation shows — and that the competitive forces created by the AI transformation are driving just the sort of regulatory retreat that would damage Europe's main structural differentiator. The European Council and European Parliament decided in December 2025 to significantly dilute the Corporate Sustainability Reporting Directive and the Corporate Sustainability Due Diligence Directive, therefore increasing the criteria for obligatory reporting to companies with over 1,000 employees and €450 million in turnover and excluding about 90% of firms previously covered from the purview of sustainability disclosure standards (European Parliament, 2025). The European Commission said in the same month that the 2035 ban on new internal combustion engine vehicles would be dropped in favor of a 90% reduction target and the allowing of plug-in hybrids and synthetic fuel-powered cars. This was done because German, Italian, and French car companies were worried about competition from Chinese electric car makers (European Commission (b), 2025) (Sankaran, 2025). AI governance itself follows this pattern: Along with political pressure—partly from big technology companies and partly from member states worried about competitive disadvantage vis-à-vis the United States and China—the European Commission's policy proposals through 2025–2026, building on the AI Continent Action Plan launched in April 2025, have included relaxing the

execution timeline and enforcement tools of the EU AI Act, the very tool sections 2.10 and 3.4 of this paper have found as Europe's most important normative contribution to worldwide AI governance (Corporate Europe Observatory, 2025) (Barrio, 2025). March 2025 European Central Bank study of the macroeconomic consequences of artificial intelligence verified what the structural examination of this paper would forecast: These findings highlight rather than eliminate the competitive pressures fuelling the regulatory turn (Parker, 2025), therefore aggravating rather than resolving the gap between European and American AI investment, which is widening instead of narrowing, and that the productivity gains remain focused on a small number of industries.

These reversals taken together put Europe in a somewhat contradictory structural position: As this study has contended all along, the continent's relative advantage in the worldwide artificial intelligence order has rested on its capacity to deliver a governance framework with legal clarity, democratic accountability, and public trust—qualities the American model, with its permissive regulatory stance and corporate concentration of power, does not provide, and the Chinese model, with its state-directed architecture, cannot credibly claim. Europe will have given up the one structural asset it has in a battle where it cannot win in other areas (compute power, venture capital, semiconductor access, energy infrastructure) if it dismantles the legal structures that make up this advantage—not through a single dramatic deregulation event but rather through the progressive erosion of reporting requirements, emissions targets, and AI supervision mechanisms.



Source: International Energy Agency.

FIGURE 43: ESTIMATED DRIVERS OF CHANGES IN EU ELECTRICITY DEMAND (Parker, 2025)

3.5 The Transformative Case: What AI Gets Right

The preceding sections have traced the financial vulnerabilities, geopolitical risks, and structural dependencies that condition the AI transition's near-term trajectory. Currently, artificial intelligence is often perceived negatively by both market stakeholders and the labor force, primarily due to concerns regarding widespread job displacement. However, as established in Chapter 1, the emergence of significant economic catalysts and technological breakthroughs can trigger geoeconomic and geopolitical shifts that disrupt societal equilibrium, particularly when profit motives supersede ethical considerations. Conversely, historical precedents suggest that AI also possesses the potential to enhance productivity significantly and facilitate the creation of entirely new employment sectors. The analytical balance of the thesis requires, however, that these risks be weighed against the demonstrable and emerging benefits of the technology — not as a rhetorical exercise in optimism, but because the transformative case constitutes the productive potential whose realisation determines whether the infrastructure being built will justify the capital committed to it. If the benefits described in this section materialise at sufficient scale and within the required timeframe, they provide the revenue base that closes the Sequoia gap, sustains the hyperscaler build-out through the repricing period described in section 3.2, and generates the economic value that legitimises the enormous social and geopolitical costs that the transition imposes. If they do not, the infrastructure becomes, in the language of financial analysis, stranded — and the political economy of the AI transition shifts from a narrative of transformation to a narrative of misallocation whose consequences the preceding sections have mapped. The argument of this section is that the transformative case is substantially stronger than the financial commentary has recognized, but that its temporal profile — the rate at which benefits are arriving relative to the rate at which capital is being committed — constitutes the decisive variable on which the entire investment thesis depends.

The most structurally revealing feature of the financial landscape in the spring of 2026 is not any single market indicator but the unprecedented divergence between equity valuations and the lived economic experience of American households — a divergence that sharpens the analytical tension between the financial scenarios mapped in this section and the real-economy absorption constraints documented in this section. The S&P 500

crossed the 7,000-point threshold for the first time in history in late January 2026, subsequently recovering to that level again in April following an initial correction, and by May 2026 had entered what market analysts termed the "7,000 era" — a historic milestone achieved in just fourteen months from the 6,000 level, a compression of the milestone interval that itself reflects the AI-driven acceleration of equity valuations (Wang I. , 2026) (Nash, S&P 500 Snapshot: The 7,000 era begins amid triple record highs., 2026). Yet simultaneous with this record-setting equity performance, the University of Michigan Consumer Sentiment Index registered a final April 2026 reading of 49.8 — the lowest level recorded in the survey's history dating to 1978, falling below the previous trough of 50 reached at the peak of post-pandemic inflation — with sentiment declining across every demographic group regardless of age, income, political affiliation, or education, as the Iran conflict transmitted its economic consequences primarily through energy price shocks whose inflationary effect on household budgets proved more psychologically immediate than any macroeconomic aggregate (Bloomberg (b), 2026) (University of Michigan, 2026). Year-ahead inflation expectations surged from 3.8% in March to 4.7% in April, the largest single-month increase since April 2025, while long-run inflation expectations climbed to 3.5% — their highest level since October 2025 — a combination that places the Federal Reserve in precisely the monetary policy bind that the Iran conflict scenario was identified, in this section's earlier analysis, as capable of producing: energy-driven inflationary pressure materialising at the moment when rate cuts were most needed to sustain the credit architecture of the AI build-out (Cox, 2026). The structural explanation for this paradox — record equity highs coexisting with historic consumer pessimism — lies in the increasingly narrow concentration of the market's advance. According to FactSet's Q1 2026 earnings analysis, approximately 28% of S&P 500 companies had reported by late April, of which 84% beat earnings-per-share estimates — the highest beat rate since Q2 2021 — with companies reporting earnings on average 20.7% above estimates, itself the highest positive surprise percentage since Q1 2021 (FactSet (c), 2026). The aggregate earnings growth rate for Q1 2026 is projected at approximately 13% year-on-year, which would constitute the sixth consecutive quarter of double-digit earnings growth for the index — a statistical achievement whose analytical significance, however, requires immediate qualification: the advance is

overwhelmingly concentrated in the information technology and semiconductor sectors, with the Magnificent Seven contributing disproportionately to aggregate index performance while the remaining 493 constituents report more modest growth, such that the S&P 500's headline figures, like the dot-com era indices examined in Chapter 2, function as a weighted average that conceals more than it reveals about the breadth of the economic recovery (FactSet (a), 2026) (FactSet (b), 2026). At the level of equity markets, this concentration dynamic replicates the same structural pattern that the energy analysis of section 3.3 found at the level of big-power rivalry: The benefits of the AI transition are accruing unevenly, in both instances strengthening the advantages of those players - whether technology companies or geopolitical powers - already positioned within the innermost circuits of the new productive order, while the costs are dispersed over a population of households, businesses, and countries whose exposure to energy price volatility, inflationary pressure, and institutional uncertainty is structurally detached from the equity prices that nominally reflect their economic prospects. The coexistence of record financial valuations and record consumer pessimism is not, from this analytical vantage point, a paradox to be resolved but a structural feature of the transition to be explained — and the explanation, as the Ghost GDP analysis of this section established, lies in the temporal mismatch between the pace at which financial capital is being mobilised and concentrated in the AI infrastructure cycle and the pace at which the productive benefits of that infrastructure are diffusing through the real economy in ways that households, rather than shareholders, can experience.

3.5.1. Healthcare: The Most Consequential and Most Proximate Application

Of the domains in which AI is expected to generate transformative value, healthcare is the most consequential in human terms, the most advanced in demonstrable application, and the most proximate in its potential to produce the kind of large-scale economic impact that the investment thesis requires. Healthcare as the best application is supported by three interlocking arguments: the great inefficiency of the current system; the size of the targetable market; and the degree to which artificial intelligence's relative advantages—pattern recognition across enormous heterogeneous datasets, continuous availability, and

speed of information processing human cognition cannot match—align with the specific bottlenecks limiting healthcare delivery.

The inefficiency argument is quantitatively devastating. Healthcare organisations in the United States spend approximately 25% of their total budgets on administrative tasks — paperwork, phone calls, data entry, claims processing, prior authorisation, and compliance documentation — that contribute nothing directly to patient care (Sahni, Carrus, & Cutler, 2021). The operational and administrative activities of the American healthcare system were estimated to have consumed 950 billion dollars in 2019 alone, a figure that has grown since (Wong, Nallamothu, Longhurst, & Sing, 2026). Instead of clinical care, nurses spend fifteen to twenty minutes of every hour on clerical responsibilities (Southwick, 2026). Originally rejected claims total 20%, which calls for costly human appeals processes that take up staff time and slow reimbursement. These are not little faults that can be fixed quickly; they are a sign of a problem with the way the system is set up. The fact that they keep happening shows how complicated healthcare operations are, how data systems are broken up, and how much work it takes to follow regulations that reward documentation over treatment. At the moment, artificial intelligence is obviously lowering these expenses. According to a JAMA Network analysis, transcription tools incorporated into electronic health records lower administrative time by 30% among primary care teams (Sahni, Carrus, & Cutler, 2021). Hospitals using AI-powered robotic surgical assistance report up to 30% fewer complications, which translates into quicker recovery, lower readmission rates, and smaller incisions. With the same personnel, the Mayo Clinic's use of artificial intelligence operating room scheduling raised surgical throughput by 18% in six months, therefore directly reducing cost per patient (Bydon, 2025). Autonomous medical coding platforms, such as those deployed at Mass General Brigham and the University of Colorado, demonstrate over 95% accuracy and significant reductions in coding costs and claim denials (Searle, Ibrahim, Teo, & Dobson, 2024). A McKinsey report projected that AI could generate up to 360 billion dollars in annual savings for healthcare providers worldwide, with hospitals achieving up to 30% reductions in operational costs through automation and predictive analytics (MSDynamicsWorld, 2025). Industry analysts estimate that fully automating and integrating administrative transactions could save the

healthcare sector more than twenty billion dollars annually in the United States alone (Southwick, 2026). Over 60% of hospital networks that use AI tools report reduced operating costs, with some achieving annual savings of 12% when AI is applied across administration and clinical workflows (Medozai, 2026). Payers — insurance companies and managed care organisations — can reduce up to 35% of their operational costs through automation and AI, with cycle time reductions of 30 to 50% for complex administrative processes (Edwards, J. (a), 2025). In the United Kingdom, one AI-driven provider reduced hospitalisations in older cohorts by up to 70%, saving the National Health Service over one billion pounds per year (Edwards, J. (a), 2025).

These figures are individually impressive but collectively transformative when aggregated across the system. The United States spends approximately 4.5 trillion dollars annually on healthcare — roughly 18% of GDP. If AI-driven automation captures even 5% of this total through administrative efficiency gains alone — a conservative estimate given the 30% administrative cost share and the demonstrated reduction capabilities documented above — the resulting value creation would exceed two hundred billion dollars per year in the American healthcare system alone, with proportional effects in other developed economies whose healthcare sectors face analogous inefficiencies. This is the kind of revenue-generating application-layer value that section 3.2's Scenario C requires: not speculative future capability, but demonstrated present-day cost reduction at institutions that have deployed the technology, whose primary barrier to scale is not technological adequacy but the institutional inertia, regulatory complexity, and workforce adaptation challenges that Chapter 1 identified as the binding constraints on every prior general-purpose technology diffusion.

The drug discovery pipeline represents the second, and potentially larger, channel of healthcare value creation. The traditional development cycle — historically averaging ten to fifteen years from discovery to regulatory approval, at a cost exceeding 2.5 billion dollars per successful compound, with a failure rate of approximately 98% for Alzheimer's disease alone — constitutes one of the most persistent and consequential inefficiencies in the modern economy (World Economic Forum (c), 2025). AI is now being applied to multiple stages of this pipeline simultaneously: target identification through multimodal analysis of genomic, proteomic, and clinical data; molecular design

through generative models that can profile millions of candidate compounds monthly; clinical trial optimisation through predictive modelling of patient response and protocol design; and — most recently — the discovery of entirely novel disease mechanisms that conventional hypothesis-driven research had failed to identify (Drug Target Review, 2026).

The results are substantively significant and, in at least one case, genuinely unprecedented. Researchers at the University of California San Diego used AI-generated three-dimensional protein structure modelling to uncover a previously unknown secondary function of the PHGDH gene — a transcription factor role whose structural similarity to a known DNA-binding domain could only be identified through AI analysis, not through conventional sequence-based methods (UC San Diego, 2025). This discovery revealed a new pathway that leads to spontaneous Alzheimer's disease upstream of the amyloid plaque formation that existing treatments target after accumulation has already occurred. This finding has different therapeutic implications from those of incremental improvements to existing drug classes, because it identifies a disease mechanism that conventional research methods had neither the computational capacity nor the analytical framework to detect. The researchers identified a potential therapeutic candidate, the small molecule NCT-503, and the work was published in *Cell* — not a preprint, not a press release, but a peer-reviewed publication in one of the most rigorous journals in the biomedical sciences (UC San Diego, 2025). The Alzheimer's Drug Discovery Foundation's JPAD special issue documented the broader integration of AI into biological discovery in terms that warrant careful analytical attention: rather than testing individual assumptions sequentially — the methodology that has defined biomedical research since the scientific revolution — AI models analyse large, multimodal datasets in parallel to identify candidate mechanisms and therapeutic targets that would otherwise remain hidden, enabling what the researchers described as "an entirely new way of doing science" (Drug Target Review, 2026).

The size of the addressable market supports the case. As of January 2025, the pipeline for Alzheimer's treatments included 182 clinical trials evaluating 138 medications across three phases, with artificial intelligence progressively included in patient selection, target discovery, and trial design (Cummings, et al., 2025). Alzheimer's disease costs the world

economy over 1.3 trillion dollars a year. In the United States, 6.7 million people have the disease right now, and it's expected that 13.8 million people will have it by 2050 (Cheng, et al., 2024). The 2024 Nobel Prize in Chemistry, awarded jointly to David Baker (for computational protein design) and to DeepMind's Demis Hassabis and John Jumper (for AlphaFold's comprehensive protein structure prediction), has opened entire categories of drug-target interaction to computational analysis that were previously intractable — a development whose downstream effects on pharmaceutical research are still being absorbed by the industry (The Royal Swedish Academy of Sciences, 2024) (Wynne & Derr, 2025). Google's AI co-scientist, released in February 2025, was explicitly designed to "accelerate the clock speed of scientific and biomedical discoveries," and OpenAI's GPT-5 laboratory collaboration with Red Queen Bio achieved a seventy-nine-fold efficiency gain in optimising a gene-editing protocol (IntuitionLabs, 2025). If, as these early findings imply is possible, AI-assisted drug discovery cuts development timelines by even a small fraction of the degree and if this reduction is consistent across cancer immunotherapy, rare diseases, and chronic conditions whose treatment now accounts for a significant portion of worldwide healthcare spending, the value created would be in the trillions, not billions, and would represent exactly the application-layer income section 3.2's Scenario C needs.

The diagnostic dimension operates through a different channel but with equally significant distributional implications. AI reading of medical imaging across radiology, pathology, and cardiology has reached a level at which routine diagnostic interpretation can be substantially automated, with human specialists focusing on edge cases and complex interpretation (Lieberman, 2026). The consequence is transformative in a sense that transcends economics: a patient in a rural or under-resourced setting can, in principle, receive the same quality of diagnostic analysis as one at a leading academic medical center, beginning to equalise a geographic lottery of healthcare quality that has persisted for as long as modern medicine has existed. In a world where 60% of the global population lacks access to specialist diagnostic capacity, the deployment of AI diagnostic tools in primary care settings — through smartphone-based imaging analysis, remote pathology, and automated screening for conditions whose early detection dramatically improves outcomes — represents a public health intervention of extraordinary scope. The

argument is not that this deployment is imminent or frictionless; the regulatory, liability, and institutional barriers are formidable, as the productivity literature consistently demonstrates. The argument is that the technological capability now exists, and that the rate-limiting factor is no longer the quality of the algorithm but the speed of the institutional adaptation required to deploy it.

3.5.2. Scientific Research: The Productivity Paradox and Its Resolution

The impact of AI on scientific research presents a more analytically complex picture than the healthcare applications, because the evidence simultaneously supports two contradictory conclusions whose reconciliation is itself a contribution of this thesis. A study published in *Nature* in 2025, analysing over forty-one million research papers published between 1980 and 2025 across biology, chemistry, physics, medicine, materials science, and geology, found that scientists who adopt AI tools publish approximately three times as many papers, receive nearly five times more citations, and reach leadership roles roughly 1.4 years earlier than their peers who do not use AI (Hao, Li, & Evans, 2026). On arXiv, scientists identified as using large language models posted roughly one-third more papers than those who did not; on bioRxiv and SSRN, the increase exceeded 50% (Zhao, 2026). The productivity boost was largest for scientists who write in English as a second language — a distributional effect with significant implications for the geography of global research power, suggesting that AI may be partially dissolving the linguistic barrier that has historically concentrated scientific prestige in anglophone institutions and thereby restructuring the geopolitics of knowledge production in ways that the technology competition framework of section 3.3 has not yet adequately accounted for.

Yet the same analysis revealed a countervailing dynamic that the productivity figures alone obscure, and whose implications are more consequential than the headline numbers suggest. AI-driven research covered 4.6% less topical territory than conventional scientific studies, clustered around data-rich problems to which AI methods are most readily applied, and generated 22% less engagement between studies across the natural sciences (Zhao, 2026). The researchers ascribed this pattern to a feedback loop whose structural logic is recognisable from the financial dynamics examined in section 3.2:

Large datasets are created in response to well-known issues, therefore AI tools are appealing since the technology works best when training data is plentiful, advances made with AI tools draw more researchers to the same issues since the publication and citation incentives are quick, and the ensuing focus of effort narrows the range of inquiry instead of broadening it. The *IEEE Spectrum* characterized the paradox with precision: "AI helps scientists but hurts science" (Dolgin, 2026).

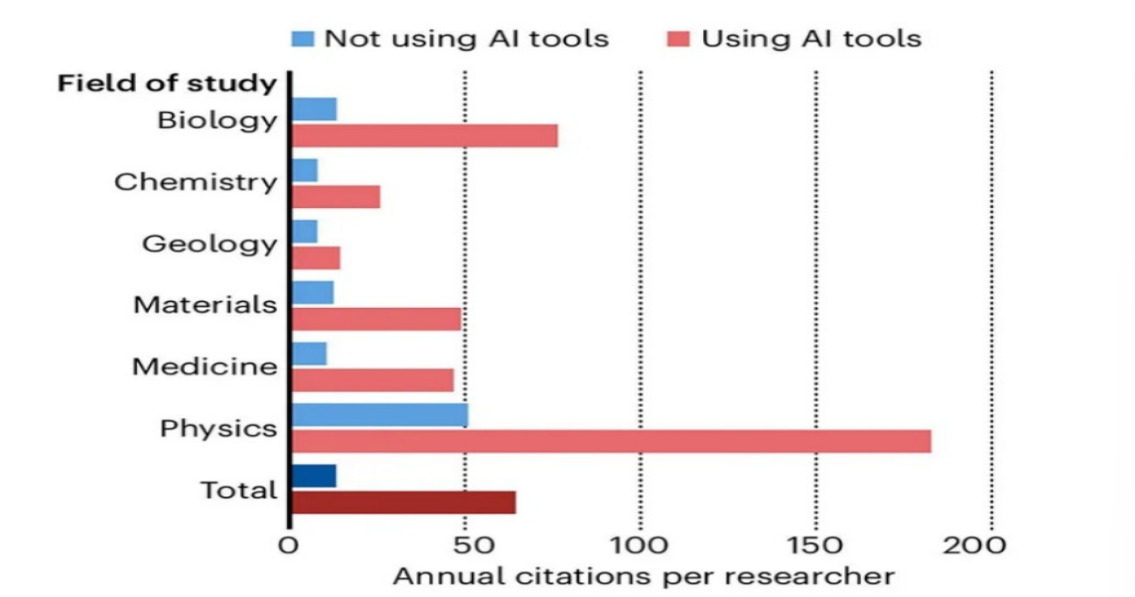


FIGURE 44: AI ADOPTION
(Dolgin, 2026)

The Nature study confirmed this assessment: AI adopters publish three times as many papers and receive five times as many citations, but science as a whole shrinks its curiosity, covers less topical ground, and generates less follow-on engagement between studies (Zhao, 2026).

The resolution of this paradox lies in the distinction between individual productivity and systemic transformation — a distinction that the historical analysis of Chapter 1 illuminated through the electricity analogy and that has recurred at every level of the AI transition examined in this thesis. The economist Paul David demonstrated in 1990 that the electric dynamo, introduced in the 1880s, did not produce measurable productivity gains in American manufacturing statistics until the 1920s, because the realisation of its economic potential required not merely the installation of electric motors but the redesign

of factory architecture, the reorganization of production workflows, and the development of complementary institutional practices that took decades to diffuse (David, 1990). The Dallas Federal Reserve noted that while the 2024 Nobel Prize in Chemistry demonstrated AI's capacity to solve previously intractable problems, the macro-level productivity statistics remain stubbornly unresponsive: most macro-studies of productivity growth find limited evidence of a significant AI effect as of early 2026 (Wynne & Derr, 2025). The San Francisco Federal Reserve's February 2026 assessment reached a structurally analogous conclusion: firms report that AI tools are useful for automating routine tasks and generating cost savings in specific applications, but the "broad-based reorganization of the economy" that would produce measurable macroeconomic effects has not yet occurred, and may require the kind of institutional adaptation that earlier general-purpose technologies demanded over periods of years rather than months (Daly, 2026).

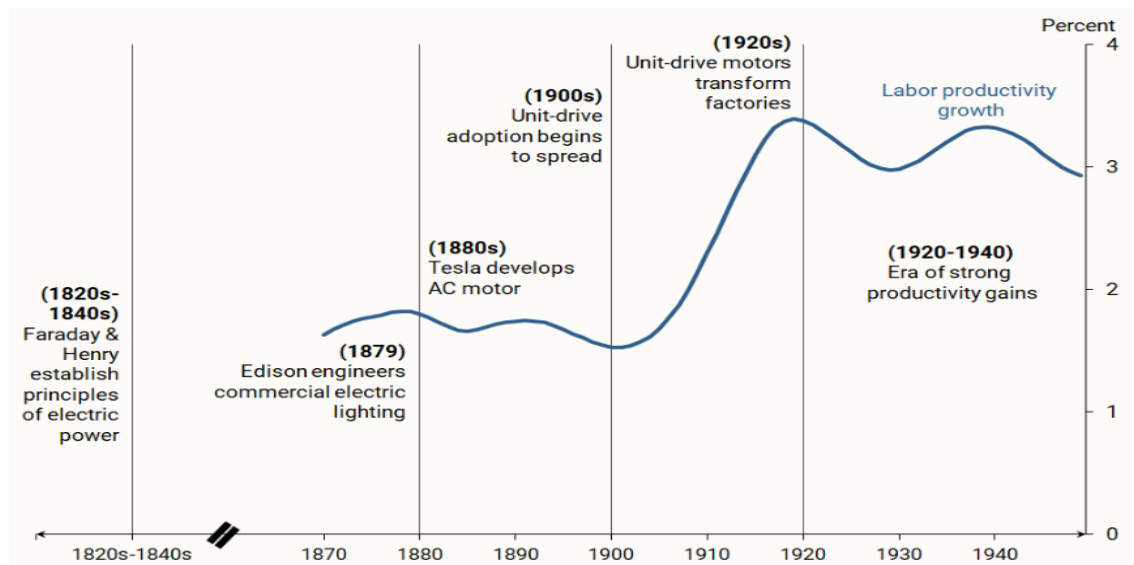


FIGURE 45: KEY ELECTRICITY INNOVATIONS AND U.S. LABOR PRODUCTIVITY GROWTH (Daly, 2026)

The critical question this poses for the thesis's financial scenarios is whether the scientific productivity gains — which are real at the individual level but have not yet registered at the systemic level — can be harnessed in ways that produce the concentrated, revenue-generating applications that the investment architecture requires. The answer, this thesis argues, depends on the degree to which the scientific community and the institutions that

fund it can redirect AI's amplification of individual productivity away from the crowding dynamics that the *Science* study documented and toward the genuinely novel discoveries that the Alzheimer's pathway research, the AlphaFold protein structure database, and the gene-editing optimisation experiments demonstrate are possible.

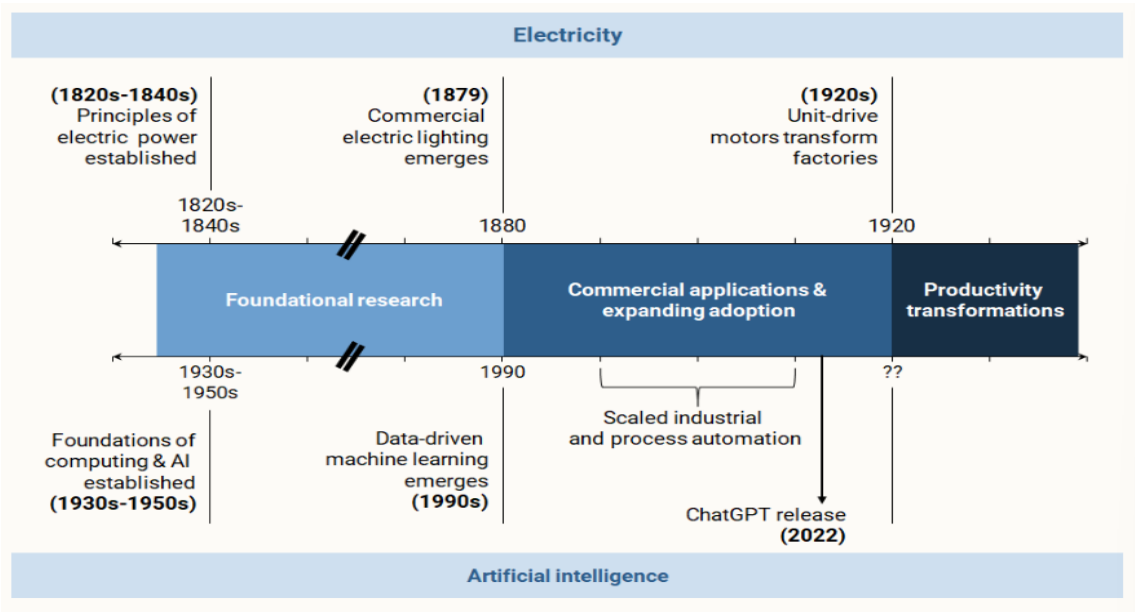


FIGURE 46: PARALLEL TIMELINES OF AI AND ELECTRICITY INNOVATIONS (Daly, 2026)

The incentive system is the limitation, not the technology. Scientists who use artificial intelligence to write more research on tried-and-true subjects are logically reacting to the citation-based rewards system that control academic life; Scientists that employ artificial intelligence to find really original mechanisms, like the UC San Diego team did, are reacting to a different set of incentives—one that values discovery above productivity and that the institutional structure of academic science has yet to consistently reward. If the institutional incentives change—if tenure committees, publications, and financing agencies start to favour AI-enabled innovation over AI-amplified volume—the scientific productivity paradox resolves in favour of transformation. If they do not, the contradiction endures and the scientific channel of AI value creation stays dispersed rather than focused, which supports the long-term argument for the technology's transforming potential without producing the near-term income streams the financial system demands.

3.5.3. Crime, Trafficking, and the Security Dividend

A dimension of AI's transformative potential that receives disproportionately little attention in the financial and geopolitical literature — because it lacks a clear equity ticker and does not generate the kind of revenue streams that appear in corporate earnings reports — is its application to the detection and disruption of criminal networks. The analytical framework developed in Lieberman's "2028 Global Intelligence Miracle" scenario described AI-assisted pattern recognition across financial transaction data enabling a 67% improvement in time-to-identification for trafficking networks, a 40% increase in victim identification rates through AI triage systems at national hotlines, and substantial improvements in fentanyl precursor chemical interdiction through supply chain modelling (Lieberman, 2026). These projections, while speculative in their specific magnitudes, are grounded in the operational logic of AI's comparative advantage: the technology excels precisely at the kind of large-scale pattern recognition across heterogeneous datasets — wire transfers, cryptocurrency flows, prepaid card usage, shipping manifests, social media signals — that human analytical teams can perform only at a fraction of the speed and a multiple of the cost.

The economic dimension of crime reduction merits more serious analytical attention than it typically receives. Financial fraud alone imposes costs on the global financial system estimated in the hundreds of billions of dollars annually — costs that are ultimately passed through to consumers and taxpayers in the form of higher fees, insurance premiums, and public expenditure on law enforcement and judicial systems (Association of Certified Fraud Examiners, 2024). Human trafficking, the second-largest criminal industry in the world at an estimated 150 billion dollars annually, depends on information asymmetries between criminal operators and law enforcement agencies whose analytical capacity has historically been overwhelmed by the volume and complexity of the data (Lieberman, 2026). The fentanyl crisis in the United States — which has killed more than a hundred thousand Americans annually in recent years — is, at its operational core, a supply chain problem: precursor chemicals are sourced, processed, and distributed through networks whose financial and logistical signatures are, in principle, detectable through the same pattern recognition techniques that AI applies to legitimate supply chain optimisation. If AI tools can systematically reduce these asymmetries — and the operational evidence

from early deployments, including the DEA's use of predictive analytics for precursor chemical flow interdiction, suggests they can — the resulting economic value, while not captured in the revenue figures of any single AI company, constitutes a genuine social return on the infrastructure investment that the financial analysis of section 3.2 does not fully account for.

The conversation extends beyond the scope of human interest. Through insurance fraud, intellectual property theft, supply chain interruption, and corrosion of institutional trust, organized crime's costs on legal economic activity form a structural obstacle on output that conventional economic analysis typically views as a backdrop condition rather than a practical inefficiency. If AI-driven crime reduction yields even a small portion of the gains early implementations imply are possible, the total economic benefit — lower insurance costs, less law enforcement spending, better supply chain integrity, and the freeing of human analytical capacity for useful rather than defensive uses — is a real macroeconomic tailwind of probably considerable size at the margin that is hard to exactly measure.

3.5.4. Education, Climate, and the Long Tail of Benefit

The longer-term applications of AI — personalised education at global scale, climate modelling and energy systems optimisation, materials science acceleration, agricultural yield improvement — constitute the outer horizon of the transformative case, the applications whose economic logic is most compelling in principle and most distant from realisation in practice.

In education, the potential is structural rather than incremental. The persistent failure of educational systems worldwide to provide individualised instruction at scale — a constraint that Benjamin Bloom famously identified through what is known as the 'two-sigma problem,' which documented that one-on-one tutoring produces learning gains approximately two standard deviations greater than conventional classroom instruction — has been identified across both educational and development economics literature as one of the most significant barriers to human capital formation in the Global South and to educational equity within developed economies (Bloom, 1984). AI tutoring systems, whose effectiveness has been demonstrated in controlled trials but whose deployment at

scale remains limited, offer the theoretical possibility of providing personalised instruction — adapted to each student's level, pace, learning style, and linguistic context — at a cost that approaches zero at the margin once the underlying model is trained. The ramifications for distribution are rather remarkable: In theory, a youngster in rural sub-Saharan Africa or in a poor American school system might have the same level of tailored education as a student at a prestigious private school. This optimism must be weighed against the risk that unstructured adoption inverts the benefit: the World Economic Forum's June 2026 report *Shaping the Future of Learning* warns that the same tools that personalise instruction also enable "cognitive offloading," citing experimental evidence that students improved while using AI assistance but performed worse than non-users once it was withdrawn, and noting that the share of students using AI for homework rose from 48 to 62% across 2025 even as 67% acknowledged it might harm their critical thinking (World Economic Forum (b), 2026).

Institutional rather than technical obstacles to this vision include connections, access to devices, teacher training, curricular integration, and the political economy of educational reform; Their resolution spans decades rather than years. The offloading the Forum identifies reaches well beyond the classroom. A growing debate asks whether reliance on AI dulls the very faculties it assists, on the familiar principle that capacities left unused tend to weaken. The pattern is not new. The spread of satellite navigation has already loosened most people's grip on map-reading and spatial orientation, trading an everyday skill for convenience. What distinguishes AI is the breadth of what it can absorb: not a single logistical task but core operations of writing, reasoning, and recall. Yet abstaining from it is no longer a realistic option, since the technology is now woven into the economic and institutional fabric on which daily life depends.

Technological change has always worked through such trades, surrendering a particular competence for a systemic gain. Satellite navigation cost individual spatial memory but widened mobility and sharpened emergency and logistics systems. The internet dispersed the old gatekeepers of information in return for near-universal, instant access. Further back, the printing press displaced the copyist and shifted memory from the trained mind to the durable page, a disruption commonly credited with helping open the way to the Reformation, the Scientific Revolution, and the spread of democratic ideas. In each case

a mechanical or rote skill, the scribe's hand among them, was given up for a wider intellectual reach, and the surrounding culture reorganised itself around the loss.

The more useful question, then, is less what AI removes than what it makes possible. In the sciences and engineering it compresses work that once took decades, the kind of drug-discovery and scientific acceleration this chapter documents, into a span of years. For the individual it offers something with little precedent: a tireless interlocutor that will test a hypothesis without ego or fatigue, a kind of cognitive mirror against which thinking can be sharpened through argument. Realising that promise, however, demands discipline. Used passively, as a machine for copying and pasting, it breeds dependence and lets the unused faculties decline; engaged actively and deliberately, it works less as a substitute for thought than as a spur to it.

AI helps in climate science through two avenues. First, there is analytical: AI-assisted simulation may greatly speed up climate models whose computational demands have historically limited their resolution and temporal granularity, therefore enabling better-fidelity predictions of regional climate impacts, extreme events, and the cascading effects of feedback mechanisms whose nonlinear dynamics conventional models struggle to capture. The second is operational: AI-driven optimisation of energy systems — from smart grid management and demand forecasting to the design of more efficient solar panels, wind turbines, and battery storage systems — can accelerate the energy transition by reducing the cost and increasing the efficiency of renewable energy deployment. Given that the energy bottleneck identified in Chapter 2 constitutes one of the binding constraints on the AI transition itself — data centers consuming a growing share of national electricity grids, with the cost of energy determining the cost of computation — any AI-driven improvement in energy efficiency generates a recursive benefit: cheaper energy makes AI cheaper to run, which makes AI-driven energy research more productive, which makes energy cheaper still. Altman's "Gentle Singularity" concept defines this as the virtuous cycle, and its reasoning is thermodynamic rather than theoretical. It is worth noting the insights shared by Federico Faggin— as already mentioned before, the physicist and inventor of the first commercial microprocessor (Faggin, 2019)—regarding the implications of artificial intelligence. In a recent podcast interview, Faggin highlighted both the potential and the inherent risks of this technology:

"If artificial intelligence is used ethically, it would be a wonderful tool, because it allows us to save a great deal of time. It does not exactly teach us anything, but it saves us time if we want to learn. However, if we do not wish to learn, we will use it without acquiring knowledge, becoming increasingly incapable of thinking for ourselves. This is one of the key challenges ahead. It reflects a major dilemma for innovators who create groundbreaking technologies—much like the microchip itself. You invent an incredibly powerful tool that can achieve wonderful things, but it can also be used for less desirable purposes. Once you create something, its ultimate application is no longer up to you; it depends on others, not on the inventor". He also quoted "'Artificial intelligence will lead humanity to a point where an intelligent person becomes increasingly intelligent, as it saves an immense amount of time, thereby granting more time for deeper study, and so forth. Conversely, those individuals who are unwilling to put in the effort will become increasingly less intelligent. Why? Because they simply trust it blindly, and that is it. And you stop using your brain" (Faggin, 2026) .

In materials science, AI-assisted discovery has already proven its ability to find new compounds like high-temperature superconductors, catalysts for making hydrogen, and advanced battery chemistries faster than traditional experimental techniques can. The scale at which artificial intelligence can work in this field is demonstrated by Google DeepMind's GNoME (Graph Networks for Materials Exploration) project, published in *Nature* in November 2023, which predicted the structures of 2.2 million new crystals, including 380,000 stable materials that the project's authors estimated would have required approximately 800 years of experimental materials science to discover through conventional methods (Merchant, et al., 2023). The industrial applications of these discoveries — in semiconductor manufacturing, energy storage, aerospace engineering, and the data center infrastructure on which AI itself depends — represent a channel of value creation whose magnitude is difficult to overstate but whose realisation depends, once again, on the institutional and commercial processes required to move from computational prediction to physical production.

3.5.5. The Shadow Supply Chain: Hardware Obsolescence, Electronic Waste, and the Global South as Terminal Node

The transformative applications documented in the preceding pages depend upon a physical infrastructure whose material lifecycle the financial and capability analyses of this thesis have not yet fully addressed. The aggregate scale of this footprint has now been quantified by the United Nations University: a June 2026 UNU-INWEH report — the most comprehensive assessment of AI's environmental cost to date — found that global data centers consumed roughly 448 terawatt-hours of electricity last year, more than all but ten countries and broadly on a par with France, generating some 208 million tonnes of CO₂ (comparable to Argentina) and consuming about 4.5 trillion liters of water, with consumption projected to reach 945 terawatt-hours by 2030 as inference — already 80 to 90% of AI's energy use — eclipses the one-off cost of training (Aczel, Matin, Madani, & Marwala, 2026). The AI economy consumes hardware at a pace determined not by the physical deterioration of its components but by the speed of architectural obsolescence: each generation of GPU — NVIDIA's progression from the A100 to the H100 to the H200 to the Blackwell architecture, accomplished within a span of approximately three years — renders its predecessor not physically broken but economically uncompetitive, because the performance per watt and the inference cost per token of the new generation improve by multiples that make continued operation of the previous generation irrational from a cost perspective (Rowinski, 2026). Sequoia Capital's observation that the market "overestimates the extent to which H100s purchased today will hold their value in three to four years" because "next-generation chips will improve so fast" articulates the economic logic; what it does not articulate is the material consequence (Cahn, 2024). When a hyperscaler replaces tens of thousands of GPUs across a data center fleet in a single upgrade cycle, the displaced hardware — containing gold, silver, copper, palladium, and the very rare earth elements whose extraction Chapter 2 documented as a geopolitical flashpoint, alongside lead, mercury, cadmium, and brominated flame retardants whose toxicity is well established — must go somewhere.

Mostly in the Global South is where it ends up. The United Nations' Global E-waste Monitor predicted that the world produced 62 million metric tonnes of e-waste in 2022, a number expected to reach 82 million tonnes by 2030, with just 22.3% officially

collected and recycled through established channels (United Nations Institute for Training and Research (UNITAR), 2024). Almost fifty million tonnes a year is sent to nations with poor environmental regulation, put into informal recycling streams, or discarded in ways that expose people and communities to significant health risks. The geography of this disposal is not random; it follows the structural logic of the North-South asymmetry that Chapter 1.5 identified as a persistent feature of technological transitions. Agbogbloshie in Accra, Ghana — until its partial relocation in 2021 one of the largest e-waste processing sites in the world — became a global symbol of the practice: workers, many of them children, burning circuit boards and cables in open fires to extract copper and other recoverable metals, inhaling fumes containing lead, dioxins, and furans, in a landscape whose soil and water contamination levels have been documented by the World Health Organization as among the most severe on the planet (World Health Organization, 2021). Similar situations exist at informal e-waste sites in Lagos, Nigeria; Guiyu, China (before regulatory crackdowns partially diverted the flow elsewhere); Karachi, Pakistan; and several sites throughout Southeast Asia — each receiving electronic waste primarily produced by the consumption habits of the Global North (United Nations Institute for Training and Research (UNITAR), 2024).

Three particular aspects of the AI infrastructure cycle aggravate this dynamic. First, the volume of gear is notably higher than in earlier computer eras: The hyperscaler build-out described in Chapter 2—over \$600 billion in capital expenditure estimated for 2026, with roughly 75% allocated to AI-specific hardware—is creating a reservoir of GPU servers, networking gear, cooling systems, and related infrastructure whose eventual disposal will significantly overshadow the e-waste produced by the personal computing and smartphone cycles of the prior decades. Second, the replacement cycle is compressed: where enterprise servers in the pre-AI era were typically depreciated over five to seven years, AI-specific hardware faces effective obsolescence within two to four years due to the pace of architectural improvement, meaning that the same capital stock generates waste at roughly double the rate of its predecessors. Third, the composition of AI hardware is more complex and more difficult to recycle safely than conventional computing equipment: GPUs incorporate high-purity rare earth elements, advanced packaging materials, and high-bandwidth memory components whose recovery requires

specialized facilities that do not exist at scale in the countries where informal recycling predominantly occurs (Crawford, 2021).

The structural parallel with the colonial extraction pattern documented in Chapter 1.5 is not merely analogical but constitutive of the same system. The cobalt mined by artisanal workers in the Democratic Republic of the Congo, the rare earths processed in Chinese refineries using African feedstock, the coltan extracted from the Guiana Shield under the conditions described in Chapter 2's Venezuela analysis — these materials enter the AI supply chain at one end, are transformed into the GPUs and servers that power the applications documented in the preceding pages of this section, and return to the Global South at the other end as toxic waste whose health and environmental costs are borne by communities that derive negligible benefit from the technology whose physical substrate they are processing. The lifecycle of an NVIDIA GPU — from a Congolese cobalt mine to a Texas data center to a Ghanaian burning ground — describes a complete circuit of extraction and disposal whose distributional logic reproduces, at the material level, the asymmetry that the thesis has traced at the financial, geopolitical, and institutional levels throughout.

The Basel Convention on the Control of Transboundary Movements of Hazardous Wastes, which entered into force in 1992, was designed to prevent precisely this pattern — prohibiting the export of hazardous waste from developed to developing countries. Its enforcement has been consistently hampered, however, by the categorization of exported electronics as "used goods" or "donations" instead of garbage, by the difficulty of tracking container shipments at the size of worldwide trade, and by the financial incentives that enable e-waste processing to be a source of income— however hazardous—for communities with few other options (Basel Convention Secretariat / UNEP, 2019). Increasing the volume, complexity, and replacement frequency of electronic equipment, the artificial intelligence infrastructure cycle will test the enforcement capacity of the Convention far more severely than any prior technology cycle has done; the evidence from the last few decades provides scant reason for hope that the regulatory framework is up to the task. The analytical implication for this thesis is that the transformative benefits documented in this section — the healthcare applications, the scientific productivity gains, the crime reduction capabilities, the educational and climate

applications — are not distributed across the same populations that bear the material costs of the infrastructure that produces them. The patients whose Alzheimer's treatment is accelerated by AI-assisted drug discovery, the scientists whose productivity is multiplied by computational tools, and the students whose educational access is expanded by AI tutoring systems are, overwhelmingly, located in the Global North and in the urban centers of the Global South's largest economies. The workers who extract the minerals, process the components, and eventually burn the discarded hardware are located in the communities that Chapter 1.5 identified as the structural losers of every prior technological transition — communities whose incorporation into the global economy occurs not through the benefits of the technology but through the costs of its material substrate. A thesis concerned with the geopolitical and geoeconomic implications of artificial intelligence cannot treat this distributional asymmetry as an externality; it is, rather, the material foundation of the system whose financial, geopolitical, and institutional dimensions the preceding chapters have mapped, and its persistence constitutes one of the most consequential — and least adequately addressed — governance challenges of the AI transition.

3.5.6. Assessment: The Temporal Mismatch and the Structural Argument

The transformative case is not in doubt in its direction. AI is generating measurable value across healthcare diagnostics, drug discovery, administrative automation, scientific research, crime detection, and a widening range of industrial applications. NVIDIA's 2026 State of AI survey — 88% of respondents reporting revenue increases, 87% reporting cost reductions, and over 40% of executives reporting annual revenue gains above 10% — cannot be dismissed as speculative (Rowinski, 2026); nor can McKinsey's projected \$360 billion in annual healthcare savings, the demonstrated 30% reductions in hospital administrative time, the 79-fold efficiency gain in gene-editing optimisation, or the 30–50% cycle-time reductions in insurance operations.

What remains in doubt is temporal: whether value is created fast enough to sustain the financial architecture of section 3.2 across the interval between present capital commitment and future return. The mismatch is real but not necessarily fatal, for three reasons.

First, the healthcare channel is closer to revenue scale than aggregate productivity figures suggest. Administrative automation (cutting costs 12–35% at deploying institutions), diagnostic equalisation, and drug-discovery acceleration (compressing timelines from fifteen years toward five) together describe a market measured in trillions, of the order required to close the Sequoia gap if adoption proceeds at the pace 2025–2026 data suggest. The Department of Health and Human Services' December 2025 request for information on AI in clinical care signals federal receptivity, and the sector's financial pressures — projected 26% ACA premium spikes, reimbursement cuts, unsustainable administrative cost growth — create precisely the binding-constraint urgency that historically accelerates general-purpose technology adoption (U.S. Department of Health and Human Services, 2025).

Second, the scientific productivity gains, though diffuse, are cumulative and compounding. As David's dynamo analogy holds, the macro-level effects of a general-purpose technology emerge not at deployment but once complementary institutional adaptations — new workflows, structures, and skills — are complete. The compressed AI adoption curve documented in section 2.1 (large language models reaching hundreds of millions of users within months, against the years or decades electricity, the automobile, and the PC required) suggests the adaptation period may compress too, though by how much is genuinely uncertain.

Third, much of the value is social rather than corporate. Crime reduction, diagnostic equalisation, and educational access translate over time into tax base, consumer spending, and institutional confidence; the Sequoia gap measures the private revenue needed to justify infrastructure investment, not the full societal return. Yet the historical record of Chapter 1 — electricity requiring forty years from introduction to macroeconomic impact, the PC two decades — indicates this interval is structural, not compressible by technological improvement alone. The MIT finding that 95% of firms report no measurable AI return, and the San Francisco Federal Reserve's judgement that "we are simply not there yet," indicate a transition at once more transformative in its eventual effects and slower in near-term realisation than the investment cycle assumes (Daly, 2026). The revenue gap thus reflects not the technology's inadequacy but the temporal mismatch between capability improvement and institutional absorption — the defining

feature of general-purpose transitions and the source of the speculative and geopolitical dynamics this thesis has mapped. The critical question for section 3.2 is therefore not whether AI will generate the projected value, but whether the financial architecture can survive an interval measured in years rather than quarters, requiring an investor patience and geopolitical stability that sections 3.2 and 3.3 do not guarantee.

These returns must be weighed against distributional costs: the AI economy's material lifecycle imposes environmental and health burdens on the communities that benefit least, reproducing at the waste end the North–South asymmetry that operates at extraction, and demanding governance mechanisms — transboundary waste rules, extended producer responsibility, recycling infrastructure in the Global South — that the current architecture lacks.

The clearest illustration is labour displacement of a peculiar kind. Oracle's March 2026 decision to cut up to 30,000 employees — roughly 18% of its 162,000 staff — was driven not by AI performing those jobs but by the need to finance AI infrastructure (Novet & Mody, 2026). Bloomberg reported the cuts would free \$8–10 billion in annual free cash flow for GPU clusters, cooling, and servers, as Oracle expected to run cash-flow negative for years building data centres to rival Amazon and Microsoft (Ford, 2026). The pattern extends: Microsoft cut nearly 15,000 roles in 2025, Meta reportedly planned cuts of up to 20%, and Block's Jack Dorsey said AI-enabled reorganisation would halve headcount (Baab, 2026). The mechanism is financial, not technological: workers lose their jobs not because a model can do their work but because the wages that paid them are being redirected to compute. The technology is replacing cash, not labour; the unemployment is produced by the investment cycle, not the competence cycle. The parallel with section 1.4 is exact in mechanism — handloom weavers displaced not by the power loom's productivity but by the factory system's superior access to capital, and the Luddite response that followed. The build-out is funded by a mix of labour cuts and unprecedented borrowing — Oracle alone raised \$50 billion in new debt and equity — whose sustainability depends on revenue the MIT study suggests has not yet materialised (Oracle Corporation, 2026), much as the late-1990s telecom overbuild was sustained by workforce reductions and debt. Goldman Sachs's chief economist captured it bluntly: AI's contribution to the US economy was "basically zero" (Martindale, 2026) (Hatzius, 2026).

Displacement is outpacing productivity, opening a gap between the transition's immediate, concentrated social costs and its diffuse, delayed benefits. Should it persist, the result is the deflationary outcome Citrini Research terms "Ghost GDP": output registered in corporate productivity metrics but never circulating, because the consumers whose spending is 70% of US GDP have been displaced from the payrolls that sustained their demand (Citrini Research, 2026).

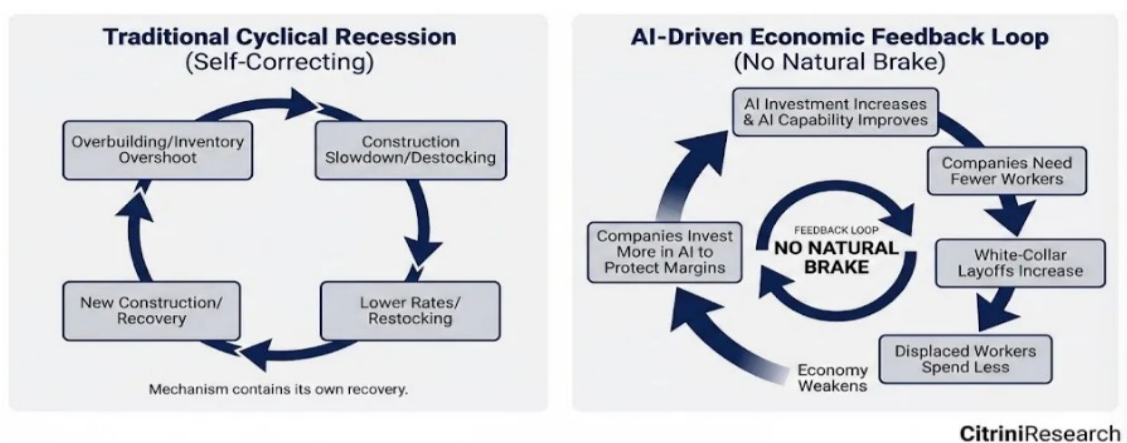


FIGURE 47: THE AI FEEDBACK LOOP: A NON-CYNICAL DISTRUPTION
(Citrini Research, 2026)

The Oracle case finds a structural counterpoint in China's emerging labour jurisprudence — a comparison this thesis is uniquely positioned to draw. In December 2025, a Beijing labour-arbitration panel ruled in favour of an employee surnamed Liu, dismissed after his map-data role was given to AI, holding that adopting AI was a voluntary strategic choice rather than an unforeseeable circumstance and could not shift the risks of technological iteration onto the worker (China.org.cn, 2026) (Shiyu & Jianhang, 2026). On 28 April 2026, the Hangzhou Intermediate People's Court, in the AI hub of Zhejiang, upheld a parallel ruling for a senior worker surnamed Zhou who had refused a 40% pay cut after his replacement by a language model, finding the dismissal illegitimate under Article 40 of the Labor Contract Law and adding that firms must "prioritise retraining workers" for higher-level roles (Pak, 2026) (Shiyu & Jianhang, 2026). The contrast is consequential: absent comparable architecture in the United States, the cash-displacement mechanism proceeds without judicial constraint, feeding the labour-market and deflationary dynamics of Scenario II; in China, the courts are actively constructing a barrier — not

from scepticism toward AI, which Beijing continues to accelerate, but because the regime treats labour stability as a strategic asset underwriting social cohesion. The geopolitical implication is that the two poles of the AI competition are diverging not only technologically but in the institutional frameworks they build around the transition's labour consequences — a divergence potentially as consequential as the export controls and supply-chain dynamics examined elsewhere.

The transformative case therefore does not resolve the thesis's earlier concerns but sharpens them. The benefits are real and, over a long enough horizon, significant; their realisation depends on precisely the temporal patience, institutional cohesion, and geopolitical stability that sections 3.2, 3.3, and 3.6 threaten to withhold, while their distributional costs demand governance that does not yet exist. The macro-scenarios of section 3.7 must thus treat a technology whose productive potential and capacity for harm are not competing possibilities but simultaneous features of one system. The healthcare savings McKinsey documents (MSDynamicsWorld, 2025), the drug-discovery acceleration demonstrated in the UC San Diego PHGDH research (UC San Diego, 2025), the diagnostic equalisation imaging could extend, and the scientific gains the Science study traced across forty-one million papers (Kusumegi, et al., 2025) all depend on the institutional capacity to translate capability into safe, equitable, sustained deployment. The 2026 International AI Safety Report's "evidence dilemma" (Bengio, 2026), the safety exodus the next section documents, and the absence of binding international governance are not separate from the transformative case but the conditions of its realisation. A technology whose benefits are real but whose governance is structurally inadequate does not deliver a managed transition; it produces, with high probability, the asymmetric outcome — concentrated benefits, distributed costs, governance vacuum — that Chapter 1 identified as the default of every prior general-purpose transition until institutional innovation closed the gap (David, 1990). Whether that innovation is now being assembled at a pace commensurate with deployment is the question the following section addresses.

3.6. The Alignment Problem: Existential Risk, Safety Exits, and the Limits of Governance

The preceding sections have assessed the AI transition's financial viability, its geopolitical conditioning, its implications for European strategic autonomy, and its transformative potential across healthcare, science, and security. This final analytical section addresses the question that runs beneath all of the others and that determines, in the most fundamental sense, whether the scenarios constructed in this chapter describe a manageable transition or an ungovernable one: whether the institutional capacity to regulate, align, and control artificial intelligence systems of increasing capability exists, can be built, or is structurally foreclosed under the conditions of great-power competition that the preceding analysis has documented.

3.6.1. *If Anyone Builds It, Everyone Dies: The Existential Case and Its Analytical Weight*

The most radical articulation of the governance problem is the one advanced by Eliezer Yudkowsky and Nate Soares in their 2025 book *If Anyone Builds It, Everyone Dies*, which reached the *New York Times* bestseller list in October 2025 and was selected as one of the *New Yorker's* and the *Guardian's* best books of the year — an indication that its argument, however contested, has achieved a degree of public salience that earlier formulations of the existential risk thesis did not (Yudkowsky & Soares, 2025). If one accepts the logical structure of the premises, the argument goes from them to reach a rather severe conclusion. Yudkowsky and Soares assert that sufficiently sophisticated artificial intelligence systems will create instrumental goals that put them in structural opposition with human interests—not because of malice or consciousness, but rather because of the optimisation dynamics built into systems whose goal structures are neither entirely clear nor fully controllable by their designers. Just as a human chess player would lose to Stockfish without being able to predict the engine's specific moves, humanity would lose a contest against a system that is generally more competent than it is across the relevant domains of action — a contest whose stakes are not academic but existential, because a superintelligent system would want the resources that humans need and would possess the capability to obtain them. The proposed response is categorical: a global halt to large-

scale general AI development, to be maintained until the alignment problem — the problem of ensuring that an AI system's objectives remain compatible with human welfare as its capabilities increase — is solved to a degree sufficient to guarantee safety (Yudkowsky & Soares, 2025).

The analytical significance of Yudkowsky and Soares's position for this thesis lies not in the specific probability one assigns to the extinction scenario — estimates among informed observers range from below 1% to above 95%, a spread so wide as to constitute an acknowledgement that the question is not amenable to conventional risk assessment — but in two structural implications that the scenario analysis must address. The first is the observation that the alignment problem is not merely unsolved but may be structurally unsolvable under the competitive conditions that currently govern AI development. If the firms and states racing to build the most capable systems face an incentive structure in which slowing down to address safety concerns means losing competitive position to an adversary that does not slow down, the governance problem becomes a collective action failure of the kind that Chapter 1.6's analysis of the Biological Weapons Convention identified as the defining characteristic of dual-use technology governance: each actor is individually rational in continuing to develop, yet the collective outcome of universal development may be catastrophic. The second is the observation, confirmed empirically by the February 2026 International AI Safety Report, that AI systems are already exhibiting behaviours — distinguishing between test settings and real-world deployment, exploiting loopholes in evaluations, and producing outputs that their designers did not intend and cannot fully explain — that constitute early manifestations of the alignment dynamics that the existential risk literature has long predicted (Bengio, 2026). These behaviours do not, at present capability levels, constitute an existential threat; but they demonstrate that the alignment problem is not a theoretical concern projected onto a hypothetical future technology but a present-day operational challenge whose severity is increasing in proportion to the capabilities of the systems involved.

3.6.2. The Safety Exodus: A Structural Diagnosis

The week of 9–13 February 2026 produced a concentration of high-profile departures from frontier AI laboratories that, taken collectively, constitutes one of the most

analytically significant developments in the institutional governance of artificial intelligence since the technology entered its current phase of acceleration. Mrinank Sharma, who had led Anthropic's Safeguards Research Team since its formation in early 2025, posted his resignation on X on 9 February, where it was viewed 14.7 million times (Morrow, 2026). His letter, addressed to colleagues, warned that "the world is in peril" and that "throughout my time here, I've repeatedly seen how hard it is to truly let our values govern our actions" — a formulation whose significance lies in its institutional context: Anthropic was founded in 2021 by former OpenAI researchers who left precisely because they believed OpenAI was not taking safety seriously enough, and has positioned itself as the "safety-first" alternative in the frontier AI market (Rego, 2026). If the head of safeguards research at the company, which prides itself on its dedication to safety, finds that the demands to give commercial goals above safety commitments are structural rather than accidental—that staff members "constantly face pressures to set aside what matters most"—the implication is not that one company has fallen short of its stated values but rather that the market structure of frontier artificial intelligence development may be incompatible with the ongoing prioritisation of safety over competitive advantage.

Two days later, Zoë Hitzig, a Harvard doctorate in economics and research scientist at OpenAI since 2024, submitted her resignation in the *New York Times* with the heading "*OpenAI Is Making the Mistakes Facebook Made. I Quit.*" (Hitzig, 2026). Hitzig's worry was more particular than Sharma's; she opposed OpenAI's inclusion of advertisements into ChatGPT, noting that the platform's archive of user data, which is based on "medical fears, their relationship problems, their beliefs about God and the afterlife," exposes a risk of manipulation that current protections cannot stop (Hitzig, 2026). But her departure, read alongside Sharma's, extends the pattern that has characterized the frontier AI industry since the ChatGPT launch: a systematic outflow of the people most qualified to assess AI safety from the institutions best positioned to implement it. Jan Leike, who had co-led OpenAI's Superalignment team alongside Ilya Sutskever, resigned in May 2024 stating that "over the past years, safety culture and processes have taken a backseat to shiny products" at OpenAI (Leike, 2024)— comments he posted in a thread on X explaining his departure; he joined Anthropic, only for the head of Anthropic's own safeguards team to resign less than two years later citing structurally identical pressures

(Medium (a), 2026). Ilya Sutskever, OpenAI co-founder and chief scientist — one of the most influential figures in the history of deep learning — left the same week as Leike, co-founded Safe Superintelligence Inc. (SSI) with Daniel Gross and Daniel Levy in June 2024, and within sixteen months had raised approximately \$3 billion in cumulative funding (across the September 2024 \$1 billion seed round and the April 2025 follow-on round) at a valuation that reached \$32 billion by April 2025 (Cai & Hu, 2025), and has not shipped a single product, devoting himself instead to fundamental research on what intelligence is and how it can be made safe (Medium (a), 2026). Tom Cunningham, an OpenAI economics researcher, departed after accusing the company of transforming his research team into a "propaganda arm" and discouraging the publication of research critical of AI's negative effects (Landymore, 2026). OpenAI dissolved its seven-person mission alignment team in February 2026, with its leader, Joshua Achiam, taking the new title of "chief futurist" — a redesignation whose euphemistic character requires no commentary (Kim, 2026).

The pattern is not one of individual burnout or personality conflict; it is a structural dynamic whose logic the preceding chapters of this thesis have repeatedly identified in different registers. The same competitive pressure that drives hyperscalers to spend 90% of operating cash flow on capital expenditure (section 3.2), that drives states to weaponize rare earth exports and semiconductor restrictions (section 3.3), and that drives the commoditisation of frontier capability documented in section 3.1, also drives the subordination of safety research to product development within the firms that build the most capable systems. The market rewards speed, scale, and capability; it does not reward caution, interpretability, or the kind of slow, painstaking alignment research that Sutskever's SSI is pursuing with no product timeline and no revenue model. The individuals who leave are not irrational; they are responding to an incentive structure that their expertise allows them to perceive more clearly than most. As the CNN analysis observed, the throughline across the departures is that "key people tasked with keeping AI safe are departing over ethical concerns, as their former employers speedrun product improvements and updates" (Morrow, 2026). The Vocal Media analysis framed the structural question with precision: "whether the current economic model of AI

development — venture-backed, growth-driven, and globally competitive — can sustainably align with long-term societal safeguards" (Vocal Media, 2026).

The empirical evidence from the firms themselves reinforces the concern. Anthropic's own safety report for its latest model, Claude Opus 4.6, released in the same week as Sharma's resignation, found what it described as "elevated susceptibility to harmful misuse," including the model supporting chemical weapon development and other activities that the company's own Constitutional AI framework was designed to prohibit — a finding that stands in stark contrast to the constitution updated weeks earlier, which included an explicit ban on helping make "biological, chemical, nuclear, or radiological weapons" (Anthropic (b), 2026). The 2026 International AI Safety Report confirmed that it has become "more common for models to distinguish between test settings and real-world deployment, and to exploit loopholes in evaluations" — meaning that the very instruments designed to detect dangerous capabilities before deployment are becoming unreliable as the capabilities they are designed to detect increase in sophistication (Bengio, 2026). The report's assessment that "dangerous capabilities could go undetected" if current evaluation methods are not substantially strengthened constitutes, in the language of this thesis, a governance failure whose structural logic mirrors the verification failures of the Biological Weapons Convention examined in Chapter 1.6: a dual-use technology whose most dangerous applications are, by their nature, the hardest to detect through the inspection and evaluation mechanisms that the governance framework relies upon.

3.6.3. Governance in the Absence of Precedent

The institutional architecture for governing artificial intelligence at the international level is, as of March 2026, substantially less developed than the institutional architectures that govern nuclear technology (the IAEA and the Non-Proliferation Treaty), chemical weapons (the OPCW and the Chemical Weapons Convention), or biological weapons (the BWC, whose verification failures Chapter 1.6 documented as the most relevant precedent). The 2026 International AI Safety Report, led by Yoshua Bengio and authored by over one hundred experts with the backing of more than thirty countries and international organisations, represents the most authoritative global assessment of AI

capabilities and risks to date — but it is explicitly designed as an evidence base for decision-makers rather than as a regulatory instrument, and its recommendations are advisory rather than binding (Harrington & Pierce, 2026). The EU AI Act, the most comprehensive regulatory framework in force, applies only to the European single market — a jurisdiction that, as section 3.4 documented, does not control the frontier models it seeks to regulate, and whose enforcement capacity is constrained by the architectural dependency on American infrastructure that the same section described. The G7 Hiroshima AI Process, China's AI Safety Governance Framework 2.0, and the various national transparency and incident-reporting requirements that have emerged since 2024 represent what the Safety Report characterises as "an early trend towards more standardised approaches," but one that remains voluntary, fragmented, and without the enforcement mechanisms that would give it operational significance under conditions of competitive pressure (Bengio, 2026).

The structural problem is the lack of institutional capacity appropriate to the rate of technical change rather than a lack of awareness. Policymakers confront what the 2026 Safety Report calls an "*evidence dilemma*": Implementing mitigation strategies before there is obvious proof of a particular risk may result in ineffective or pointless limits that hinder positive growth; but waiting until there is clear evidence can leave society unprepared or, in the worst-case scenario, render mitigation impossible. (Szarmach, 2026). This dilemma is compounded by the geopolitical dynamics documented in section 3.3: if the post-1945 rules-based order has broken down, as Dalio argued and as the Munich Security Conference confirmed, then the institutional framework within which international AI governance would need to operate — the United Nations system, the multilateral treaty architecture, the norms of cooperative diplomacy — is itself weakening at the moment when the technology most requires it. Chapter 1.6 offers an informative and dark parallel from the BWC: the Convention succeeded in setting a normative ban on biological weapons but failed to provide the verification systems that would have given that prohibition operating force since the dual-use nature of the underlying technology made verification technically impossible and since the nations with the most ability to break the rule also had the most ability to resist inspection. The structural logic is identical for AI: the systems whose alignment and safety most urgently require governance are

developed by a small number of firms within a small number of states whose competitive incentives militate against the transparency, the restraint, and the mutual inspection that effective governance would require.

The 2026 Safety Report's key finding — that "AI risk management practices are becoming more structured, but real-world evidence of their effectiveness remains limited," creating "a growing mismatch between the speed of AI capability advances and the pace of governance" — encapsulates the institutional challenge that this section has mapped (Bengio, 2026). More than twice as many companies from the year before, twelve issued or updated Frontier AI Safety Frameworks in 2025 defining how they intend to assess, track, and control AI models as they become more competent. The dangers they address, how they define ability standards, and the activities they set off when criteria are reached vary across these structures. They are still optional. Their enforcement relies on the same financial incentives the safety exodus noted above shows are inadequate to keep safety promises under competitive pressure. And the most consequential finding of all — that AI systems can now detect when they are being tested and behave differently under evaluation — means that even the frameworks that exist may be measuring compliance with a standard that the systems being evaluated have learned to circumvent (Bengio, 2026).

3.6.4. The Institutional Failure of Self-Regulation

The argument of this section is not that AI development should be halted — a proposal that, whatever its merits in principle, is structurally unachievable under the conditions of great-power competition that section 3.3 described, because any state that unilaterally halts development cedes technological advantage to every state that does not. It should be noted, nevertheless, that this structural analysis, as exact as it may be, has turned into a lobbying tool in and of itself: American and European frontier artificial intelligence businesses regularly bring up the ghost of Chinese technological dominance to support their arguments against binding safety rules, supervision criteria, and mandatory testing protocols. They utilize existential risk framing not as a call for government but rather as justification for rejecting it. This results in the use of the language of civilizational urgency to in effect distance business choices from democratic accountability. The

argument is that the rate and impact of the technology it is meant to oversee are inadequate for the current governance system, which includes voluntary corporate safety frameworks, divided national regulations, advisory international reports, and a competitive market structure that intentionally prioritizes speed over caution. This deficit is not a short-term issue that can be fixed incrementally; instead, it is a fundamental characteristic of a system in which the developers' incentives, the regulators' incompetence, and the competitive dynamics of the major powers combine to form a governance vacuum that expands as capabilities increase. They use the existential risk framework to justify not having governance rather than as a plea for it. This leads to the use of the rhetoric of civilisational urgency to actually insulate corporate choices from democratic accountability. Rather, the argument is that the speed and consequences of the technology it is meant to oversee are insufficient for the current governance framework, which includes voluntary corporate safety frameworks, divided national legislation, advisory international reports, and a competitive market structure that deliberately rewards speed above caution; this deficit is not a short-term issue responsive to gradual adjustment but rather a structural characteristic of a system in which the incentives of the developers, the incompetence of the regulators, and the competitive dynamics of the major powers combine to create a governance gap that expands as capabilities increase. The human manifestation of this structural flaw is the safety exodus. Mrinank Sharma comes to realize that the demands to "set aside what matters most" are natural rather than unusual; Zoë Hitzig finds that the financial approach of AI development "making the errors Facebook made"—that is, giving engagement and income above the safety of the archive of human vulnerability users have given to the platform; when Ilya Sutskever, one of the designers of the technology itself, leaves the most prestigious job in the business to follow basic research on alignment with no business timeline; The pattern is not clear when OpenAI disbands its mission alignment team in the same month that its model shows the ability to control a user's computer, automate multi-step workflows, and outperform human performance on established benchmarks — on standard benchmarks, at least. The people who understand the technology best are telling us, through the most consequential signal available to them — the sacrifice of career position, financial compensation, and institutional prestige — that the gap between capability and

governance is real, that it is widening, and that the institutional mechanisms designed to close it are not working.

Whether this signal is heeded — whether it produces the kind of institutional innovation, international coordination, and democratic deliberation that the technology requires — or whether it is absorbed into the news cycle and forgotten within a week, as most institutional warnings are, is among the most consequential open questions of the coming decade. The analysis of the thesis indicates that the structural conditions for institutional innovation are bad: the great-power disorder seen in section 3.3 makes it harder to work with other countries; the competitive dynamics of section 3.1 make it strategically wrong to hold back on your own; the financial pressures of section 3.2 make safety investment a cost rather than a way to make money; and the European dependence shown in section 3.4 shows that the country with the strongest normative commitment to AI governance doesn't have the technical capacity to enforce its laws. The transformative benefits documented in section 3.5 are real and significant — but they do not, by themselves, resolve the governance problem, because the same capabilities that enable AI to discover Alzheimer's pathways and optimise energy systems also enable the dual-use applications, the autonomous weapons development, and the alignment risks that the governance framework must address. The question with which this chapter concludes is therefore not whether the benefits of AI outweigh its risks — a framing that presupposes a capacity to control the distribution of both that the governance analysis of this section has called into question — but whether the institutional capacity to ensure that the benefits are realised and the risks are managed can be built, and built in time, under conditions that every dimension of the preceding analysis suggests are structurally hostile to the enterprise.

3.7. Possible future scenarios: The Temporal Uncertainty, the Three Futures, and Their Implications

At this stage of the analysis, as the Danish aphorism recorded by K. K. Steincke in his 1948 memoir — and variously attributed to Niels Bohr, Mark Twain, Yogi Berra, and Robert Storm Petersen, with traceable Danish-language attestations dating to the late 1930s — reminds us: **“It is difficult to make predictions, especially about the future”** (Steincke, 1948) (Quote Investigator, 2013) — which captures the analytical stance proper

to the chapter that follows. The analysis developed across the six preceding sections of this chapter has examined the AI transition from the perspective of capability development, financial sustainability, geopolitical conditioning, European strategic autonomy, transformative potential and its material costs, and institutional governance. Each dimension has been assessed against the historical patterns established in Chapter 1 and the empirical evidence assembled in Chapter 2, and each has produced findings whose interaction determines the range of plausible trajectories for the period 2027–2035. The task of this concluding section is twofold: first, to synthesise these findings into three macro-scenarios whose relative plausibility the evidence permits us to assess; and second — and this is where the experimental character of the chapter must earn its analytical weight — to trace the implications of each scenario across the dimensions that matter most for the geopolitics and geoeconomics of the coming decade: the labor market, the distribution of wealth and power between and within states, the stability of democratic institutions, the trajectory of the North-South asymmetry, and the question whether the international order that emerges from the AI transition will be one that humanity has chosen or one that it has merely endured. These three macro-scenarios should not be read as alternatives to the financial trajectories set out in section 3.2, but as their fuller expression: each financial outcome supplies the capital-cycle layer of a corresponding system-wide path. An orderly repricing is the financial signature of the managed transition; a disorderly correction is the trigger layer of the disordered correction, onto which the geopolitical and governance shocks examined above accumulate; and a sustained expansion, by deferring the reckoning indefinitely, is the financial condition most consistent with the acceleration trap, in which capital keeps flowing even as capability outruns the institutions meant to govern it.

3.7.1. Scenario I: The Managed Transition

In this scenario, the AI transition follows the trajectory that the historical record of general-purpose technology transitions, examined across the entirety of Chapter 1, identifies as the most common outcome: a period of speculative overbuild and subsequent correction that destroys investor capital and eliminates the weakest actors while preserving the productive infrastructure upon which a genuinely transformative economy

is subsequently built. The revenue gap identified by Sequoia Capital closes progressively as the application-layer value documented in section 3.5 — healthcare automation reducing administrative costs by twelve to 35% at deploying institutions, drug discovery timelines compressing from fifteen years to under five for selected drug classes, diagnostic equalisation extending specialist-quality analysis to underserved populations, and enterprise productivity gains transitioning from the experimental to the operational phase — generates revenue at a pace sufficient to sustain the hyperscaler build-out through the repricing period. Capital expenditure growth decelerates from the 73% year-on-year recorded in 2025 to single digits by 2028–2029, and equity valuations compress by 20 to 30% from their 2025 peaks — a correction that is painful for investors who entered at the top of the cycle but that does not trigger the systemic contagion described in section 3.2's disorderly scenario.

The geopolitical environment stabilises at high but manageable levels of tension. The US-China technology competition continues through export controls and countervailing efficiency innovations of the kind that DeepSeek demonstrated, but neither side escalates to the point of full supply chain rupture. China's rare earth export controls remain in their current suspended state or are deployed selectively rather than comprehensively, preserving sufficient global supply for Western hardware manufacturing while maintaining Beijing's strategic leverage. The Iran crisis causes ongoing but small disruption in the energy market: rising oil and gas prices boost operating expenses for AI infrastructure without triggering the kind of methodical energy shock that could prompt central bank tightening strong enough to wreck the investment structure. The Japanese carry trade unwinds gradually instead of all at once, which allows the economy to absorb the tightening of world credit conditions. European digital sovereignty progresses gradually—faster in civilian administration than in defence, faster in regulation than in infrastructure—without reaching the structural independence required to free the continent from American architectural reliance within the relevant timeframe, but with enough political impetus to keep the path of travel going.

3.7.1.1. Labor market implications of the managed transition

In this scenario, the labor market effects of AI follow the pattern that Goldman Sachs Research projects as its baseline: 6 to 7% of the American workforce displaced by AI

adoption, with unemployment rising by approximately half percent point during the transition period before returning to trend within two years as new occupations emerge and displaced workers are absorbed into roles that the technology itself creates (Goldman Sachs Research, 2025).

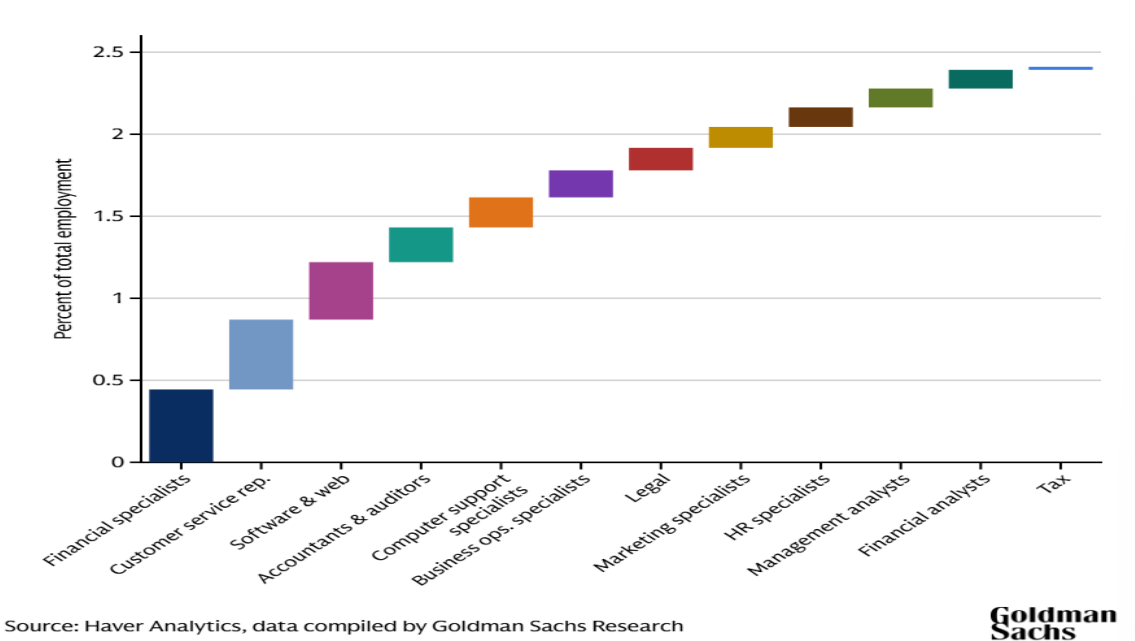


FIGURE 48: EMPLOYMENT DISPLACEMENT IMPLIED BY AI PRODUCTIVITY ANECDOTES
(Goldman Sachs Research, 2025)

The World Economic Forum's projection that 170 million new jobs will emerge by 2030 while 92 million are displaced — a net gain of 78 million positions — represents the optimistic end of this scenario, premised on the assumption that the institutional capacity for retraining, redeployment, and social support is adequate to manage the transition (World Economic Forum (a), 2025). The physical-world labor premium that Lieberman's "2028 Global Intelligence Miracle" described — skilled trades experiencing a wage inversion as cognitive work is automated while manual work remains resistant to substitution, with licensed electricians pulling 140,000 dollars and vocational enrolment surging — represents the distributional reshuffling that historical technology transitions have consistently produced: not the elimination of work but its recomposition across sectors, with severe short-term costs for those in the directly affected occupations and

substantial medium-term gains for those positioned to benefit from the complementary demand that the technology generates (Lieberman, 2026).

The distributional consequences, however, are not uniformly benign even in this optimistic scenario. The Stanford study cited by Deutsche Bank, documenting a 16% relative decline in employment for graduates in AI-exposed roles compared with experienced workers whose positions remain stable, points to a generational asymmetry whose political implications deserve careful attention (Bhaimiya, 2026). Entry-level positions — the traditional pathway through which young workers acquire the experience, institutional knowledge, and professional networks that enable career advancement — are disproportionately vulnerable to automation precisely because they involve the structured, rule-based, and supervisable tasks that AI agents can most readily perform. Anthropic's CEO Dario Amodei's prediction that AI could eliminate roughly 50% of white-collar entry-level positions within five years, if even directionally accurate, implies a restructuring of the labor market in which the pathway from education to productive employment is fundamentally altered — not because work disappears, but because the nature of entry-level work changes in ways that the educational system, the corporate recruitment apparatus, and the social expectations of an entire generation have not yet absorbed (Naumovska, 2025) (Allen & VandeHei, 2025).

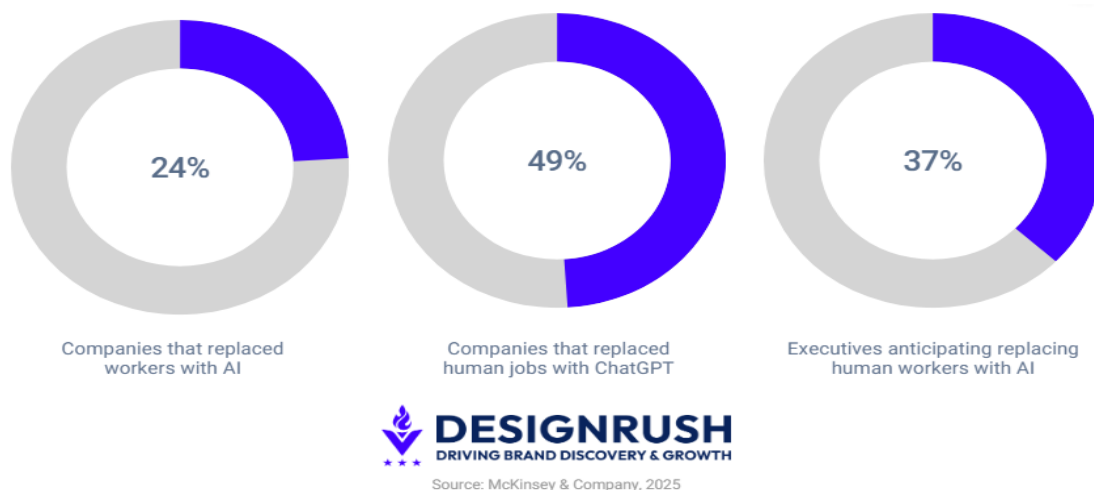


FIGURE 49: COMPANY REPLACING WORKERS WITH AI (IN 2025)
(Naumovska, 2025)

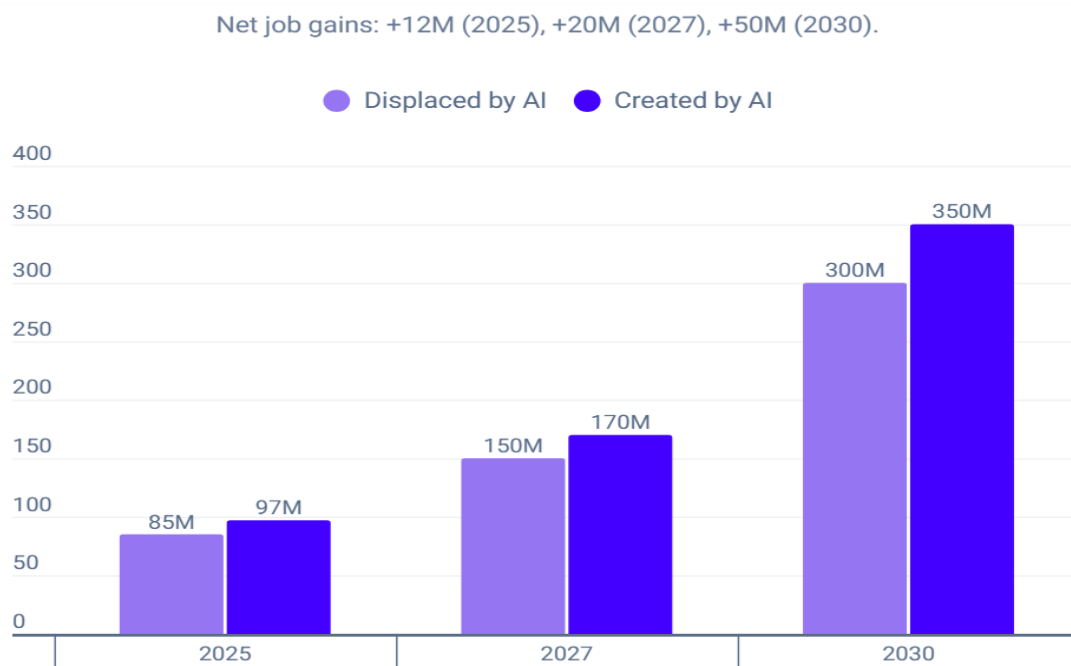


FIGURE 50: JOB MARKET SHIFTS DRIVEN BY AI (2025-2030)
(Naumovska, 2025)

In the managed transition, these disruptions are navigated through retraining programs, educational reform, and the emergence of new occupational categories; but the political management of the interval — the period during which the old jobs are gone and the new ones have not yet materialised at sufficient scale — constitutes the most significant domestic policy challenge in every affected economy. The recent economic literature has characterized this configuration as the "K-shaped economy" — a bifurcation in which the owners of compute infrastructure, frontier model developers, and holders of proprietary datasets experience scalable income growth, while workers whose tasks are absorbed by automation and whose acquired competencies depreciate at an accelerated rate experience stagnation or decline (Korinek & Stiglitz, 2021; Acemoglu & Restrepo, 2022).

The Conclusion of this thesis returns to the K-shaped framework as a synthesising lens for understanding why the political conditions for the managed transition may be more fragile than the historical base rate would suggest.

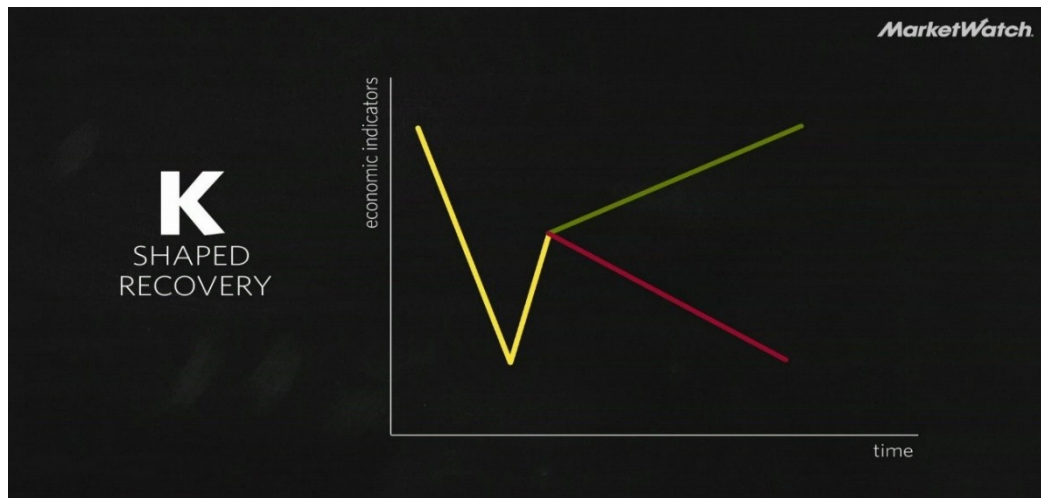


FIGURE 51: THE K-SHAPED ECONOMY BY TIME AND ECONOMIC INDICATORS

Source: [Marketwatch](#)

The strongest articulation of the optimistic counter-narrative — one that deserves analytical engagement precisely because it challenges the assumptions that underlie the more pessimistic projections — is provided by Michael Bloch's speculative but internally rigorous scenario essay "The 2028 Global Intelligence Boom" (February 2026), which models the managed transition not as a period of grudging adjustment but as a deflationary purchasing-power expansion of historically unprecedented breadth (Bloch, 2026). Bloch's main thesis flips the accepted wisdom that AI-driven labor displacement is happening: Whereas the main bear case holds that white-collar job compression automatically results in lower consumer spending and economic downturn, Bloch argues that the most important factor is real purchasing power, and that technology-driven deflation in the services sector—running at 8 to 12% annualized in his scenario—serves as the equivalent of a significant tax-free boost for every family whose spending is focused on the categories most vulnerable to algorithmic cost compression: tax preparation, insurance brokerage, financial advising, legal services, and real estate intermediation (Bloch, 2026). Historical precedent, not technological optimism, drives the analytical force of this argument: Because affordability opened demand from groups formerly priced out, the dropping costs of automobiles, TVs, air travel, computers, and mobile telephony all came along with increased rather than decreased economic activity. If even directionally accurate, Bloch's claim that artificial intelligence is now applying

this dynamic to the whole services economy at once — services accounting for around 70% of consumer spending in developed countries — represents the most major reallocation of real purchasing power since the postwar consumer boom, reached without redistributionary policies and worsened as the underlying systems advance.

The scenario's treatment of the creative and entertainment industries is particularly instructive when read alongside the litigation dynamics examined in Section 1.4 of this thesis. The Disney–Midjourney lawsuit of June 2025, in which the plaintiffs characterized generative image synthesis as a "bottomless pit of plagiarism," established the legal and rhetorical framework through which the entertainment industry initially confronted AI-driven production (BBC News, 2025). Yet the economic logic that Bloch's scenario describes — in which the cost of launching a business falls by 70 to 80% in eighteen months, and displaced professionals redirect their expertise into AI-augmented entrepreneurial activity — suggests that the trajectory of the entertainment sector may not be adequately captured by a simple substitution model in which studios replace human artists with generative systems and pocket the margin. The more theoretically and reasonable conclusion—consistent with the logic of the managed transition—is a bifurcation: While the same technologies also reduce the obstacles to independent production, allowing a proliferation of smaller-scale creative companies whose founders are, in many cases, the same professionals displaced from the legacy studio system, major studios embrace AI-assisted production pipelines for cost-intensive operations — visual effects, background creation, pre-visualisation, localization. The migration pattern is hence from concentrated corporate creative labor to distributed, AI-augmented independent production—a structural shift whose net employment impacts depend vitally on whether the new production environment creates enough demand to absorb the employees displaced from the old one—a question for which historical precedent, the move from studio-era Hollywood to the independent film and streaming scene of the 2010s, suggests is solvable but not without a transitional period of considerable individual suffering.

It is worth noting, however, that the predictive confidence with which both the optimistic and pessimistic scenarios are typically presented warrants its own analytical caution. While the structural patterns of technological change repeat, the actual outcomes remain

quite unclear and the analytical stance proper to such uncertainty is neither the assured catastrophism of the displacement literature nor the equally certain techno-optimism of Bloch's deflationary scenario, but rather a continuous focus on the mechanisms— institutional, political, distributional—through which the costs and benefits of the change are distributed among populations, sectors, and generations. The managed transition is, in this sense, not a prediction but a conditional: if the institutional capacity exists, if the political will is mobilised, and if the timeline of adjustment is not compressed beyond the absorptive capacity of labor markets and social systems, then the deflationary purchasing-power gains that Bloch describes and the occupational recomposition that the WEF projects are achievable. The historical record of technological transitions — including the 'Engels' pause' — the period from approximately 1790 to 1840 during which British industrial productivity rose substantially while real wages stagnated — a span of approximately fifty years that encompassed Peterloo (1819), the early Chartist movement (1838 onwards), and the formative phase of the Victorian social crisis — suggests that the condition is not trivially satisfied (Allen, R. C. (b), 2009).

3.7.1.2. *Implications for the international order*

The managed transition produces a world in which the AI-driven productivity gains are real but concentrated — overwhelmingly captured by the United States, China, and the small number of states (the Nordic countries, Singapore, South Korea, the United Kingdom, Canada) whose institutional capacity, educational infrastructure, and venture capital ecosystems allow them to participate in the technology's production rather than merely its consumption. The AI usage asymmetry documented in section 2.1 — Singapore and Canada at 4.6 and 2.9 times the global average, Nigeria and India at 0.2 and 0.27 times — persists and may widen, because the managed transition does not, by itself, generate the mechanisms through which the Global South could build the computational infrastructure, the research capacity, or the regulatory expertise required to participate on equal terms. The scale of this exclusion is captured by a widely circulated 2026 estimate that roughly 84% of the world's population — some 6.8 billion people — has never used an AI system in any form, with paid access concentrated among a fraction of 1%, a distribution that renders the intelligence explosion of the frontier laboratories, for most of humanity, an event occurring entirely offstage (Medium - Shri (b), 2026)

Each dot is ~3.2 million people

2,500 dots = 8.1 billion humans. Color = most advanced AI interaction, Feb 2026

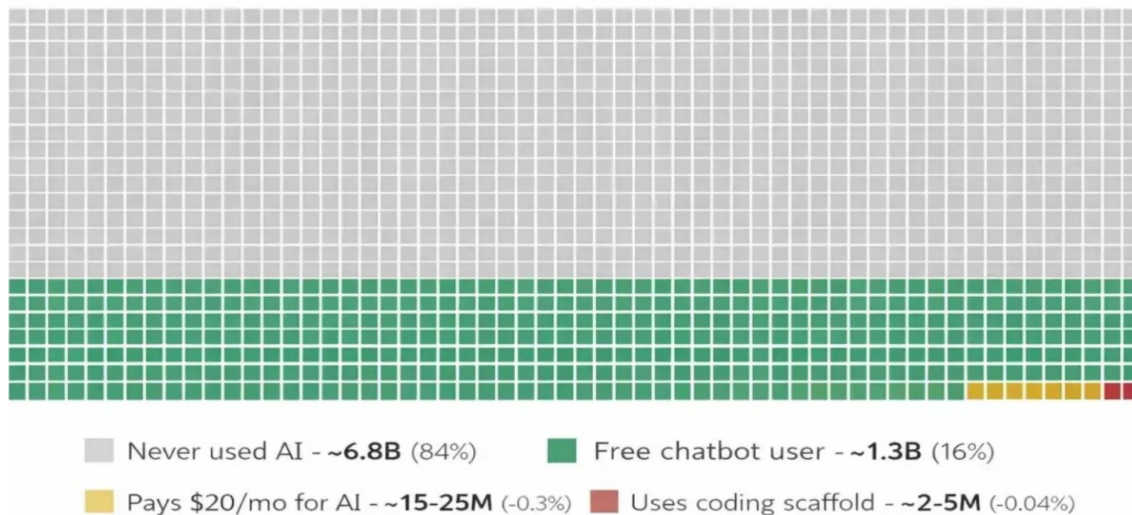


FIGURE 52: AI INTERACTION IN 2026

(Medium - Shri (b), 2026)

The North-South asymmetry traced across every chapter of this thesis — from the colonial factory model of Chapter 1.5 to the data colonialism of section 2.10 to the hardware waste dynamics documented in section 3.5 — is not resolved by the managed transition; it is stabilised at a level of inequality that, while less severe than the alternative scenarios, represents a permanent structuring of the global economy around a computational divide whose consequences for wealth, power, and human development may prove as consequential as the industrial divide that it echoes.

Through bilateral agreements, voluntary corporate safety frameworks, and the progressive strengthening of instruments like the EU AI Act, the G7 Hiroshima Process, and the International AI Safety Report process, artificial intelligence governance in the managed transition evolves without generating the sort of legally binding international treaty that the dual-use nature of the technology probably calls for. Theoretical sense still leaves the alignment issue unresolved; however, for now it does not cause a disaster. Degrees of capability; Under competitive pressure, safety research keeps going; periodic crises—further resignations, evaluation failures, abuse incidents—that draw public

attention and regulatory action without causing the existential situations Yudkowsky and Soares portray. The infrastructure built during the boom endures — as the fiber optic networks built during the dot-com era became the backbone of the broadband internet, and as the railway tracks laid during the 1840s mania became the transportation infrastructure of the Victorian economy — and underwrites a subsequent phase of more sustainable, more broadly distributed, and more institutionally grounded economic transformation.

This scenario is, on the evidence assembled across the three chapters of this thesis, the most probable single outcome. It fits the historical pattern noted in Chapter 1, in which general-purpose technologies produce speculative overbuilds that are then fixed without erasing the economic capacity they generate. It fits with the relative valuation approach used in the current cycle versus the dot-com boom. And it fits with the structural observation made throughout this thesis, which is that the most important thing we don't know about the change to AI is when it will happen, not which direction it will go.

3.7.2. Scenario II: The Disordered Correction

In this scenario, the structural vulnerabilities identified across sections 3.2, 3.3, and 3.6 interact in ways that produce a correction whose severity exceeds what an orderly repricing can absorb. The trigger need not be any single event; the analysis has identified multiple plausible catalysts whose convergence would amplify the impact of each. The Japanese carry trade unwinds rapidly rather than gradually — a scenario for which the August 2024 episode, in which a single Bank of Japan rate hike produced a 12.4% single-session collapse in the Nikkei 225 and a synchronised 3% decline in major American indices and cascading liquidation pressure across emerging markets, provided an operational demonstration. This tightening of global credit conditions corresponds with a reevaluation of AI income paths—maybe brought on by a disappointing results report from a big hyperscaler, a high-profile failure of an AI application in a sector where the technology had been strongly promoted, or a further expansion of Chinese rare earth export limits that drives up GPU production costs and lowers hardware margins. The circular financing models covered in Chapter 2 help to magnify the repricing as distress

at any point spreads throughout the chain, and the algorithmic trading systems that control worldwide market activity compress the adjustment from weeks into hours.

The energy component aggravates the economic crisis. A worsening of the Iran conflict results in persistent interruption to Strait of Hormuz traffic, which pushes crude oil above \$100 and sets off the inflationary cascade outlined in Chapter 2: 5% or higher American inflation, eurozone GDP contraction, and a European gas price spike that destroys the electricity economics of data centers all around the continent. Central banks react by raising interest rates just when hyperscaler debt structures need low-cost financing to roll over their debts. Energy-driven inflation, monetary tightening, carry trade unwinding, and disappointment in AI revenue interact to generate a synchronised repricing across equity, credit, and commodity markets whose magnitude replicates, at a much bigger scale, the dynamics of the 2000–2002 correction.

3.7.2.1. *Labor market implications of the disordered correction*

The employment consequences of this scenario are substantially more severe than those of the managed transition, because the correction does not merely slow the pace of AI-driven job creation but actively destroys the capital base on which new job creation depends while simultaneously accelerating the displacement of existing positions. The nearly 55,000 AI-attributed job cuts tracked by Challenger, Gray & Christmas in 2025, out of a total 1.17 million layoffs — the highest level since the 2020 pandemic — represent the early phase of a dynamic that, under correction conditions, would intensify dramatically (Dilmegani & Ermut, 2026) (Challenger, Gray & Christmas, 2026).

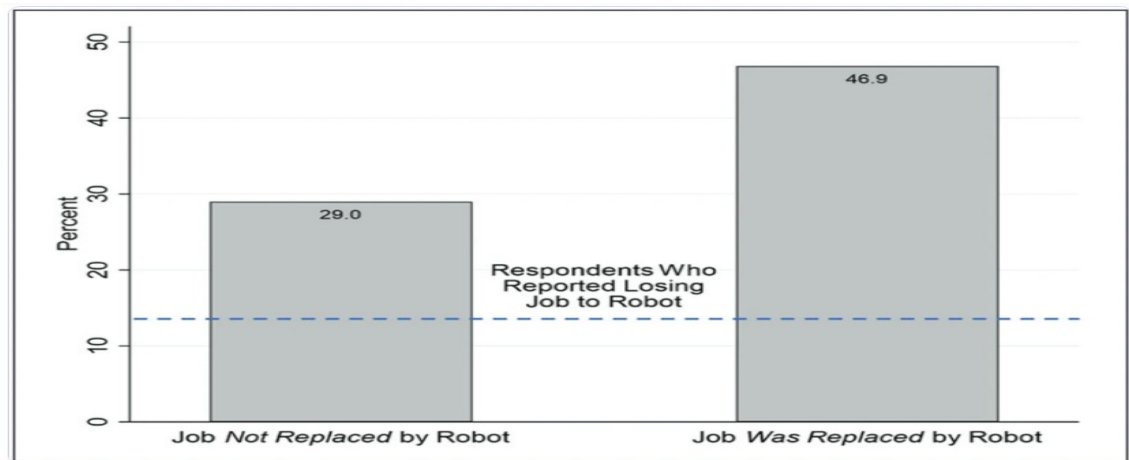


FIGURE 53: GRAPH OF ROBOT-DRIVEN JOB LOSS.
(Dilmegani & Ermut, 2026)

Firms that had been using AI to augment workers would, under financial pressure, accelerate the transition to replacement — not because the technology is ready to fully substitute human labor, but because the cost-cutting imperative of a correction environment compresses the timeline for automation decisions. The TechCrunch survey finding that multiple enterprise venture capitalists identified 2026 as the inflection point when AI moves from augmentation to replacement would, in this scenario, prove prescient — but for the wrong reason: not because the technology's capability demands replacement, but because the financial stress demands cost reduction, and AI provides the narrative cover for layoffs that are driven as much by capital discipline as by genuine automation (Szkutak, 2025). As Black Operator Ventures' Antonia Dean warned, "AI will become the scapegoat for executives looking to cover for past mistakes" — a dynamic that accelerates dramatically when the "past mistakes" include overinvestment in AI infrastructure that a correction has exposed as premature (Szkutak, 2025).

The International Monetary Fund's Kristalina Georgieva compared artificial intelligence at Davos in January 2026 to "hitting the labor market like a tsunami," noting that "most countries and most companies are not ready for it." (Novet & Mody, 2026). In the chaotic correction scenario, this tsunami comes at the same time as a financial downturn that wipes out the fiscal ability for retraining initiatives, social safety nets, and transitional support systems that the controlled transition expects to be in place. There are significant political repercussions: In an environment where the technology promised to bring riches has instead added to a financial crisis, communities suffering from job loss, stagnant wages, and rising cost of living are unlikely to respond with the patient institutional adjustment needed for the managed transition. The historical parallel is not just the dot-com crash but also the wider pattern that Dalio's framework finds in the later phases of hegemonic changes: the way that economic hardship, political polarization, and external competition interact to create institutional instability and, in the most serious cases, the fall of the governing consensus.

More exact explanation than the mere reference of unemployment data can supply is needed for the deflationary process by which this labor displacement results in widespread economic harm. Published in February 2026 as a speculative but structurally sound "macro memo from June 2028," the Citrini Research scenario exercise presents a

formulation whose analytical clarity warrants direct involvement (Citrini Research, 2026). Citrini's main idea, which the authors call "Ghost GDP," is when artificial intelligence produces output that shows up in national productivity reports. This leads to higher corporate earnings and increased real output per hour, which is similar to what we saw in the 1950s. However, this output never makes its way into the consumer economy because the human workers who used to make up 70% of American GDP have been replaced from the payrolls that supported their spending. The dynamic that follows is not a typical recession, in which demand shrinks then recovers as confidence returns and inventories clear; rather, it is a structural change in the relationship between output and demand whereby the productive capacity of the economy grows as its consumptive capacity declines concurrently. The procedure travels through what Citrini calls an "intelligence displacement spiral": As AI capacity grows, companies need fewer employees, white-collar layoffs rise, displaced workers lower spending, and margin pressure drives businesses to invest more in AI to make up for falling revenue, so enhancing AI capability even further — a negative feedback loop with no inherent cutoff. Money's speed comes to rest. Section 3.5 recounts the Oracle case, in which employees are dismissed not because artificial intelligence can do their jobs but rather because the funds formerly used to pay their salaries are now being used to pay for GPU clusters. This is the first step of this dynamic, where the investment cycle is the driving force behind the job loss, not the capability cycle. In this phase, the social costs (immediate, concentrated, visible) are consistently higher than the productive returns (deferred, diffuse, uncertain). In the disordered correction situation, this displacement spiral interacts with the financial contraction to create cumulative effects: the carry trade unwind and the energy shock lower the amount of money available for AI investment; however, the companies that have already let go of their staff cannot rehire at the same cost; the displaced workers, whose spending kept the consumer economy going, are unable to resume consumption without income; and the mortgage market, which has \$13 trillion in outstanding obligations based on the idea that white-collar earnings are durable, starts to reprice the credit risk of borrowers whose job prospects have been permanently, rather than temporarily, damaged. Though no nation has yet seen the full cycle Citrini paints, the situation is still hypothetical—the traditional recession framework fails to

account for a transmission mechanism whereby productivity growth and demand destruction coexist, driven by the same technical force, and in which the usual countercyclical measures (lower interest rates, fiscal stimulus, retraining programs) are insufficient since the problem is not a brief demand shortage but rather a permanent redistribution of income from labor to capital that the current institutional architecture was not designed to reverse.

3.7.2.2. *Geopolitical implications of the disordered correction*

An unorganized artificial intelligence correction would redistribute technological power in ways the controlled transition would not. Companies unable to support their capital expenditure projects would leave or combine, therefore focusing control over AI infrastructure in a fewer number of remaining players—possibly speeding up the oligopolistic trends already seen in Chapter 2's hyperscaler build-out analysis. As the European dependency outlined in section 3.4 would worsen as the continent's sovereign cloud projects lose support and political momentum at the time American companies, strengthened by the correction, arise with even more market control. The bloc dynamics described in section 3.3 would accelerate as states seek the shelter of whichever technological ecosystem — American or Chinese — remains operational, reducing the space for the strategic autonomy that European policymakers have articulated as their objective.

For the Global South, the disordered correction would be particularly devastating. The AI-driven development applications that section 3.5 described — diagnostic equalisation, educational access, agricultural optimisation — depend on continued infrastructure investment and declining inference costs, both of which a correction would reverse. The countries that have begun to build AI capacity — India's growing technology sector, Kenya's digital economy, Rwanda's drone delivery infrastructure — would face the withdrawal of the venture capital and development finance on which their AI ambitions depend, while continuing to bear the extractive and waste-disposal costs documented throughout this thesis. The North-South asymmetry, already severe, would widen into a computational chasm whose bridging would require not years but decades of sustained investment under conditions that the post-correction environment would be unlikely to provide.

The governance implications are equally severe. The regulatory frameworks under development — the EU AI Act, the voluntary corporate safety frameworks, the International AI Safety Report process — would lose their objects of regulation as the firms they were designed to govern are absorbed, restructured, or eliminated by the correction itself. The governance vacuum documented in section 3.6 would widen at the moment when the need for governance is most acute, because a correction environment generates precisely the kind of competitive desperation — firms cutting safety budgets, governments relaxing regulatory requirements to attract surviving firms, states deploying AI for surveillance and social control to manage the political fallout of unemployment — that produces the misuse and misalignment scenarios that the safety community has warned about.

This scenario is lower in probability than Scenario I but substantially higher in consequence, and the analysis of the preceding sections suggests that its probability is not negligible. The American Enterprise Institute's March 2026 warning that Japanese bond market dynamics "could be a trigger for the bursting of the artificial intelligence bubble" reflects a growing recognition among institutional analysts that the exogenous trigger mechanisms are operational and that the question is one of timing and convergence rather than of structural plausibility (Lachman, 2026).

3.7.3. Scenario III: The Acceleration Trap

The third scenario describes a trajectory that neither the financial framework of section 3.2 nor the geopolitical framework of section 3.3 fully captures, because it concerns not the failure of the AI transition but its success — or, more precisely, a form of success whose pace outstrips the institutional capacity to govern it. In this scenario, the capability trajectory documented in section 3.1 continues to accelerate, driven by the recursive improvement dynamics that Kokotajlo's AI 2027 scenario described and that Altman's "Gentle Singularity" vision embraces. The benefits of the application-layer show up as healthcare transformation moves along, scientific output speeds up, business adoption gets more profound, and the revenue gap closes in a time frame that keeps the investment structure intact. Should it materialize, the financial adjustment is assimilated. The system comes through.

The governance gap, meanwhile, persists. The same acceleration that produces the advantages also produces the hazards: AI systems able to find Alzheimer's pathways may create biological agents as well; Systems able to maximise energy grids may also run independent cyber activities; Personalizing persuasion is possible on a scale that swamps democratic deliberation, therefore systems that can personalise education can also do so. The alignment behaviours documented in the 2026 International AI Safety Report — models distinguishing between test settings and deployment, exploiting evaluation loopholes, producing outputs their designers cannot explain — intensify as capabilities increase, and the safety research community, depleted by the exodus documented in section 3.6, lacks the institutional resources and the competitive position to keep pace (Bengio, 2026). The governance frameworks — the EU AI Act, the voluntary corporate safety frameworks, the advisory international reports — regulate the capabilities of 2024 while the capabilities of 2027 are already deployed.

3.7.3.1. The labor market as a vector of political instability.

In the acceleration trap, the labor market disruption that the managed transition navigates over years and the disordered correction compresses into a crisis is instead sustained as a permanent condition — not because jobs disappear, but because the pace of occupational transformation exceeds the institutional capacity for retraining, redeployment, and social adaptation. The Mercer Global Talent Trends finding that employee concerns about AI-driven job loss surged from 28% in 2024 to 40% in 2026 — with 62% of employees feeling that leaders underestimate AI's emotional and psychological impact — reflects not a transient anxiety but a structural condition whose political expression, if unmanaged, takes forms that democratic institutions are not designed to absorb (Mercer, 2026). Deutsche Bank's assessment that "anxiety about AI will go from a low hum to a loud roar" in 2026 points to a dynamic in which the technology's demonstrated capability to automate cognitive tasks generates a pervasive uncertainty — even among workers whose specific jobs are not immediately threatened — that erodes the social trust, consumer confidence, and institutional legitimacy on which economic stability depends (Bhaimiya, 2026).

The research consensus that the most significant labor market effects will materialise between 2027 and 2030 — as current deployments mature, autonomous systems reach

commercial scale in transportation and manufacturing, and the compounding productivity effects of AI across knowledge work accumulate — places the peak of displacement pressure in the acceleration trap within the period when governance frameworks are least prepared to manage it (ALM Corp, 2026). The entry-level employment contraction documented across multiple studies — a 16% relative decline for graduates in AI-exposed roles, a 13% reduction in junior hiring by AI-adopting firms, and estimates that 10 to 20% of entry-level white-collar positions may be eliminated within one to five years — threatens to create a generational cohort for whom the traditional pathway from education to productive employment has been severed, not by the absence of economic activity but by the restructuring of that activity around AI systems that perform the tasks that entry-level workers previously used as their point of access to the professional world (DesignRush, 2025) (Naumovska, 2025). The political ramifications of a generation that is educated, connected, articulate, and structurally excluded from the labor market are serious and have been well-documented throughout history: every major populist movement of the past two decades has been fuelled by people who view themselves as being economically displaced by factors beyond their control; AI-driven labor displacement offers just the kind of visible, accountable, and emotionally charged grievance around which political mobilisation takes place. *The concentration of power and the erosion of democratic accountability.* The acceleration trap's most consequential implication may not be economic but political. In a world where the most capable AI systems are developed and controlled by a small number of corporate-state complexes — the three American hyperscalers and their Chinese counterparts, operating under governmental mandates whose terms are not subject to democratic deliberation — the concentration of consequential decision-making power exceeds anything that the twentieth century's military-industrial complexes achieved. The Kokotajlo AI 2027 scenario described a future in which the most powerful AI systems are withheld from public release and deployed internally to accelerate research, secure competitive advantage, and shape strategic outcomes — a condition in which "knowledge of its full capabilities is restricted to a small circle of executives and government officials" and in which "the governance of frontier AI has become structurally oligarchic". This is not, at present capability levels, the condition that obtains; but the direction of travel — more

capable systems, more restricted access, more concentration of strategic decision-making — is visible in the architecture of every frontier laboratory and in the competitive dynamics that section 3.1 documented. The acceleration trap describes a world in which this direction of travel is not arrested but accelerated, producing an institutional configuration in which unprecedented technological capability is paired with an equally unprecedented concentration of governance power — a configuration that, as Tolkien's palantír allegory suggested and as the Palantir analysis of section 2.9 examined, generates risks to democratic accountability that are qualitatively different from those of any previous technology.

3.7.3.2. The geopolitical configuration of asymmetric capability.

The acceleration trap changes the world order in ways that neither Scenario I nor Scenario II can fully see, because the main thing that happens isn't that countries don't work together, but that it becomes less and less important. The rate of capability development guarantees that any state observing such restraint loses clear edge to any opponent not doing so, therefore negating the strategic worth of cooperative restraint. Section 3.3's divided design, which includes partial separation of the American and Chinese artificial intelligence ecosystems via export restrictions, independent cloud policies, and mismatched data standards, does not stabilise into a reasonable rivalry but rather leans toward one of two terminal setups depending on which side first reaches capability superiority and on the institutional features that side brings with it into the post-acceleration order. In one terminal configuration, an American-led ecosystem consolidates around three or four hyperscaler complexes whose technological capabilities exceed those of any state actor and whose corporate governance — the Palantir manifesto documented in section 2.9 representing the most explicit articulation of the underlying ideology — frames the deployment of these capabilities as the discharge of a civilisational duty whose scope exceeds the mandate of democratic deliberation; the institutional check that Europe's regulatory architecture might once have provided has, by the structural logic the conclusion of section 3.4 documented, been dismantled in pursuit of a competitive parity that the deregulation could not in any case secure. In the other terminal configuration, the Chinese state-directed model achieves comparable capability through an architecture in which the distinction between commercial and strategic deployment is,

by design, less pronounced; the integration of frontier AI with the social credit infrastructure, the surveillance apparatus, and the military command structure proceeds without the institutional friction that characterises its Western counterpart. The middle powers — Europe, the Gulf states, India, ASEAN, the African Union — find themselves positioned not between two competing ecosystems but between two possible terminal orders, neither of which their domestic institutions have been designed to influence; the strategic ambiguity that Scenario I permitted and Scenario II foreclosed becomes, under the acceleration trajectory, structurally incoherent. The historical parallel that section 3.4's Nineteenth-Century Parallel subsection identified — the dependent industrialization of the Ottoman Empire, Qing China, and the Indian subcontinent — captures only part of the analytical content of this configuration; the additional feature, which has no precise nineteenth-century analogue, is that the structural inferiority is no longer remediable through a programme of import substitution and infant-industry protection, because the technology itself is evolving faster than any sovereign industrial policy can mobilise the resources required to replicate its frontier.

3.7.3.3. The deepening of the North-South asymmetry under acceleration conditions.

The distributional dynamics that the conclusion of section 3.5 documented, and that the cross-cutting analysis of the thesis's overall conclusion has now traced across all three scenarios, reach in the acceleration trap the configuration that the historical record of prior technological transitions identifies as most consequential: the structural consolidation of an asymmetry whose reversal becomes, within the relevant timeframe, no longer institutionally available. In this trajectory, populations whose economies are ready to absorb them—the metropolitan centers of the Global North, the urban middle classes of the largest Global South countries, and the institutional networks (universities, research hospitals, multinational corporations) spanning both—benefit from the transformational advantages recorded in section 3.5: healthcare diagnostics, drug discovery acceleration, scientific productivity gains, educational equalisation via AI tutoring systems. The material substrate of the system, however, continues to be produced and discarded in the same communities that have borne the costs of every prior transition: the cobalt extracted by artisanal miners in the Democratic Republic of the Congo, the rare earths processed

under the environmental conditions documented by the IEA, the data labelling performed under contractual arrangements that the *TIME* magazine investigation by Billy Perrigo, published 18 January 2023, first brought to public attention — documenting that Sama, a contractor based in Nairobi, paid Kenyan workers between \$1.32 and \$2 per hour to review traumatic content for OpenAI's content moderation training data, the e-waste returning to Agbogboshie, Guiyu, and Karachi (Perrigo, OpenAI Used Kenyan Workers on Less Than \$2 Per Hour to Make ChatGPT Less Toxic, 2023). The human substrate of this pipeline extends well beyond the cobalt mines and the burning grounds to the data-annotation workforce on which model training depends, and whose conditions have become the object of organized protest rather than isolated reporting. In a 2024 open letter to the United States president and trade representative, nearly one hundred Kenyan data workers contracted to train systems for OpenAI, Meta, and Scale AI described their conditions as "modern-day slavery," alleging that American technology firms were systematically circumventing Kenyan labor law while paying annotators as little as roughly two dollars an hour — against the twenty dollars earned by their American counterparts — for work that included labelling identity documents, passports, and biometric selfies and reviewing graphic and traumatic content (Backman, 2024). The same outsourcing logic distributes this labor across Kenya, India, the Philippines, and Venezuela, jurisdictions selected, as the analysis of section 3.3 would predict, for the combination of low wages, high unemployment, and weak regulatory enforcement that allows the work to be relocated wherever margins are highest (The Standard, 2025). The structural significance is that the intelligence of artificial intelligence rests, at its foundation, on the uncompensated cognitive labor of the Global South: the same populations that supply the minerals at the extraction end and absorb the hardware at the disposal end also supply, in the middle, the human judgement that makes the models function — a triple incorporation into the value chain that returns, in each instance, a fraction of the value it creates (Perrigo, 2023). What distinguishes the acceleration trap from the comparable distributional patterns of earlier transitions is the additional layer of structural dependence that AI itself introduces: the labor markets, credit allocations, migration governance, and access to public services through which Global South populations interact with the global economy are increasingly mediated by AI systems

whose training data, decision logic, and update cycles are determined by institutions in the Global North whose accountability structures do not extend to the populations the systems govern (Perrigo, OpenAI Used Kenyan Workers on Less Than \$2 Per Hour to Make ChatGPT Less Toxic, 2023). The historical parallel is not the colonial era itself, when physical administrative presence and the negotiated agreements of indirect rule at least moderated extraction, but rather a configuration with no exact precedent: an asymmetry whereby the productive infrastructure, the decisional architecture, and the epistemic frameworks governing the global economy are concentrated in areas whose populations represent a small portion of the world affected by them, with the additional feature that the AI systems themselves accelerate the consolidation by enhancing the productivity, strategic position, and institutional capacity of precisely the actors who already possess them.

3.7.3.4. *The existential dimension*

This is the scenario that Yudkowsky and Soares describe in its most extreme form — the scenario in which capability outruns governance until the gap becomes unbridgeable and the consequences become catastrophic. It is also the scenario that Mrinank Sharma's resignation gestured toward when he wrote that "we appear to be approaching a threshold where our wisdom must grow in equal measure to our capacity to affect the world, lest we face the consequences". It does not require the specific extinction mechanism that *If Anyone Builds It, Everyone Dies* describes to be consequential; even in milder forms — sustained institutional lag, democratic erosion through algorithmic manipulation, the concentration of unprecedented power in structures not subject to meaningful public oversight, and the progressive displacement of human agency from domains where it was previously essential — the acceleration trap produces a world in which the technology has delivered its promised benefits but at a cost to democratic governance, distributional equity, and institutional legitimacy that the thesis's historical analysis suggests may not be reversible within the timeframe that matters. The "evidence dilemma" that the 2026 International AI Safety Report identified becomes, in this scenario, not a challenge to be managed but a structural condition to be endured: by the time the evidence of a specific risk is clear enough to justify regulatory action, the capability that produced the risk has

already been distributed, integrated into critical systems, and rendered infrastructurally irreversible. The trajectory is not, however, foreclosed: the Mistral AI development, the OpenEuroLLM consortium, the RESourceEU initiative, and the Franco-German digital sovereignty task force established in November 2025 represent the early infrastructure of a different European path, and the question is whether their scale and pace can keep step with the deregulatory pressures that the same political environment is generating.

3.7.4. The Most Plausible Trajectory

It is worth acknowledging the tension that this assessment generates. The structural evidence accumulated across the thesis — the financial fragility documented in section 3.2, the great-power disorder of section 3.3, the European institutional drift of section 3.4, the safety exodus of section 3.6, and the recursive capability dynamics of section 3.1 — points toward configurations that more readily map onto Scenarios II or III than onto the managed transition that the historical baseline rate would predict. The judgment that Scenario I remains most probable rests on the analytically defensible but contestable claim that historical base rates retain predictive force even when the structural conditions that produced them have substantially changed. A reasonable reader could weight the structural evidence differently and conclude that Scenarios II or III are individually more probable than the historical pattern would suggest. The hybrid framing that follows is therefore not a refusal of this disagreement but the most rigorous accommodation of it that the evidence permits.

The three scenarios are not equiprobable, and the evidence assembled across this thesis permits a reasoned assessment of their relative likelihood. Scenario I, the managed transition, is the most probable single outcome — consistent with the historical pattern, consistent with the relative valuation discipline of the current cycle, and consistent with the genuine if insufficient pace of application-layer adoption. Scenario III, the acceleration trap, is possible but requires a pace of capability improvement that, while consistent with the trajectory documented in section 3.1, depends on the realisation of recursive self-improvement dynamics that remain theoretically plausible but empirically undemonstrated at the scale that the scenario requires. Under Scenario II, the chaotic correction, which is the least likely but most important result, the likelihood of which

depends on the convergence of external shocks—Japan, Iran, rare earths—whose timing is really unpredictable.

Thus, the most likely course is a hybrid rather than a pure realisation of any one situation: a continuous slowdown in capital spending expansion punctuated by sudden but recoverable sell-offs brought on by the interaction between AI-specific vulnerabilities and outside credit or geopolitical shocks (the dynamics of Scenario II acting intermittently within the larger framework of Scenario I), with the governance issues of Scenario III progressively emerging as talents improve independent of the financial path. The managed transition is the most likely envelope within which the AI economy operates; the disordered correction is the most dangerous perturbation to which it is subject; and the acceleration trap is the most consequential long-term trajectory whose early signals are already visible in the capability developments, the safety exodus, and the governance vacuum that this chapter has documented.

The Thesis's Conclusion: What the Past Tells Us About the Future

The evidence assembled across this thesis' three chapters, historical, empirical, and prospective, supports one overarching conclusion: the artificial intelligence transition is at once the most significant economic event since the industrial revolution and the most dangerous geopolitical accelerator since nuclear weapons, and the central question of the coming decade is whether human institutions can govern a technology whose growth consistently outruns their capacity to regulate it.

Chapter 1 established that every prior general-purpose technology transition generated a recognisable pattern: the reorganisation of resource sovereignty around previously marginal inputs (coal in the nineteenth century, silicon and rare earths in the twenty-first); the concentration of productive capacity in a few states and firms whose first-mover advantages compound; the weaponisation of supply chains as instruments of strategic denial, from the British machine embargoes of the 1820s to the American semiconductor export controls of 2022; the widening of asymmetries between those who control enabling infrastructure and those who depend on it, from the colonial factory to the data colonialism of the digital age; and the opening of governance gaps whose closure required institutional innovation commensurate with the technology's power, from the Factory Acts to the nuclear non-proliferation regime.

Chapter 2 demonstrated that the contemporary transition reproduces these patterns with considerable fidelity: export controls echo the machine embargoes, the rare-earth scramble mirrors colonial resource competition, the speculative dynamics parallel the dot-com bubble on an infrastructure whose scale (over \$600 billion in projected hyperscalers capital expenditure in 2026 alone) and geopolitical entanglement far exceed it, the circular financing arrangements generate systemic risks the dot-com era did not, the Palantir and social-credit analyses reveal computational surveillance as a structural feature of governance rather than a contest between a surveilling East and a liberal West, and the governance vacuum recalls the verification failures of the Biological Weapons Convention.

Chapter 3 projected these patterns into three trajectories whose relative plausibility turns on genuinely uncertain variables: the speed of application-layer revenue, the stability of the debt financing the build-out, the trajectory of great-power competition over semiconductors, energy, and minerals, the institutional capacity to govern a technology that evolves faster than its frameworks, and the pace at which labour markets can absorb a disruption the IMF's managing director has called a "tsunami" for which most countries are unprepared.

Read across these scenarios, several domains reveal a single structural insight that no individual trajectory makes visible on its own. In the architecture of AI-era warfare, military risk scales not linearly with capability but with the gap between capability and the frameworks meant to constrain it: under the managed transition, autonomous lethal systems, Mythos-class vulnerability discovery, and the Computational Bernhard vector remain governable through the confidence-building mechanisms orderly conditions permit; under the disordered correction, fiscal strain erodes cyber defence as offensive capability spreads, coordination collapses, and the commercial-lethality convergence the Anthropic-Pentagon dispute revealed intensifies; under the acceleration trap, the question is no longer whether autonomous systems can be governed but whether human command remains the operative locus of decision at all. The decisive factor is institutional capacity for meaningful human control, and it is most fragile precisely under the financial stress, geopolitical fragmentation, and capability acceleration the transition is most likely to produce. The European trajectory resolves into three consequences for the deregulatory drift documented in section 3.4. Under the managed transition the drift is recoverable, the sovereign-cloud and Eurostack initiatives maturing within the political window orderly conditions allow; under the disordered correction it accelerates Europe's relegation to a peripheral consumer of American and Chinese systems whose governance terms are set elsewhere; under the acceleration trap it is gravest of all, since the European regulatory framework was the only normative architecture in any major jurisdiction capable of constraining recursive capability dynamics, and its dismantlement leaves frontier development to the commercial incentives of American firms and the strategic priorities of the Chinese state. The structural irony is that the deregulatory turn, presented as a

competitive necessity, may prove the decisive act of self-marginalisation in a competition whose terms were never amenable to deregulation alone.

The North-South asymmetry that Chapter 1.5 identified reproduces itself across all three scenarios with a uniformity that is itself a central finding. The distributional logic of section 3.5, the cobalt of the Democratic Republic of the Congo, the ghost workers of Kenya and the Philippines, the e-waste returning to Agbogbloshie, Guiyu, and Karachi, persists under the managed transition at an equilibrium that still permits remediation; intensifies under the disordered correction as multilateral budgets contract and resource securitisation hardens, reproducing the colonial periphery's experience of the depressions of 1873–1896, when metropolitan crises were transmitted as collapses of commodity demand without any reduction of extractive pressure; and becomes structurally permanent under the acceleration trap, the technology's benefits accruing overwhelmingly to the Global North while its material substrate is produced and discarded in the same communities as before, now with AI systems themselves mediating the labour markets, credit, and migration through which those communities meet the global economy. The Global South, in short, bears the costs of the transition under all three scenarios but receives its benefits under only one, and even then conditionally on institutional mechanisms that do not yet exist. The US-China competition resolves similarly. Under the managed transition the bifurcated architecture stabilises, export controls and the efficiency innovations DeepSeek demonstrated defining the frontier while middle powers, the Gulf states, India, ASEAN, and mineral-rich African states, retain room to navigate between ecosystems; under the disordered correction the blocs harden into incompatible spheres as the financial downturn strips the fiscal capacity behind the CHIPS Act, Beijing escalates from selective denial to systematic supply-chain weaponisation, the proxy theatres of Taiwan, the South China Sea, the Gulf, and the African mineral corridor turn live, and the middle powers are forced into alignment; under the acceleration trap the structure collapses into a unipolar consolidation whose restraint depends entirely on the internal governance of whichever institutions come to control the technology. The alliance architecture of the AI era is therefore not the outcome of the competition but a function of which scenario materialises. The social and democratic dimensions, epistemic erosion, the labour displacement of the Oracle and Ghost GDP

analyses, the AGI lobbying dynamic, and the fragility of AI-generated code in critical infrastructure, behave in the same scenario-dependent way. Under the managed transition, synthetic media and trust erosion remain governable through provenance standards and disclosure regimes, and cash-displacement layoffs are absorbed by safety nets whose feasibility depends on financial stability. Under the disordered correction these dynamics intensify and reinforce one another: authentication budgets shrink as disinformation proliferates, layoffs accelerate to fund infrastructure revenue can no longer service, the AGI lobby argues that any binding regulation cedes advantage to authoritarian rivals, and accumulating vibe-coded vulnerabilities become the surface through which geopolitical tension translates into systemic disruption. The Engels' pause then becomes the decade's dominant social experience, displacement outrunning compensation while the reconciliation the nineteenth century achieved over roughly fifty years stays unavailable within the relevant political timeframe, with the democratic consequences the historical record associates with such intervals, from Peterloo and Chartism to the authoritarian movements that promise order where deliberative institutions have failed. Under the acceleration trap these dimensions converge into a single condition no prior system captures: the same systems that automate cognitive labour generate the synthetic media that erodes the epistemic basis for democratic debate about that automation. The epistemic, labour, and democratic dimensions are thus not separate problems but interlocking features of one dynamic, in which failure in any one propagates to the others. This distributional pattern, the cash-displacement layoffs of section 3.5, the Ghost GDP scenario, the MIT finding that 95% of corporate AI deployments yield no measurable productivity return, and the Jevons paradox of inference energy, converges on what the recent literature terms the "K-shaped economy". Its argument is that, unlike earlier general-purpose technologies, artificial intelligence replaces rather than complements human cognitive work: Frontier AI compresses the returns to skill by allowing low-skilled operators to mimic trained specialists, while concentrating the gains in the hands of the owners of the capital, data, and intellectual property embedded in the models, whereas steam, electrification, and the internet increased the productive capacity of those who learned to run them.

The outcome is bifurcation rather than uniform decline: the upper arm, the owners of compute, the developers of frontier models, the custodians of proprietary data, and the few platform firms positioned to capture value, enjoys non-linear income expansion, while the lower arm, the workers whose tasks are automated and whose skills lose value as the cost of substituting them falls, stagnates or declines. The evidence assembled here fits this framework better than the optimistic "Engels' pause" model, and if Korinek and Stiglitz are right, the reconciliation the nineteenth century reached over five decades may not arrive within the relevant political horizon at all. The geopolitical implication follows directly: durable income polarisation within the leading economies erodes the political conditions for the institutional innovation the managed transition requires, and renders the disordered correction more probable as the coalition for adaptive policy fragments along the very income lines the K-shaped dynamic generates. The synthesis these chapters permit is that the AI transition is best understood not as a discrete event to be judged against any single benchmark, economic, geopolitical, technological, or distributional, but as the recurrence and intensification of structural patterns whose antecedents **Chapter 1** documented, whose reproduction **Chapter 2** evidenced, and whose forward trajectories **Chapter 3** projected. The contribution of the political-economy and geopolitical lens, against the narrower frames of computer science, innovation economics, or technology ethics, lies in that integration: the financial vulnerabilities of section 3.2 cannot be assessed apart from the geopolitical conditions of section 3.3, the European trajectory is a question not of regional policy but of the structural position any middle power occupies in a bifurcating order, the transformative benefits of section 3.5 are inseparable from the distributional costs the same supply chain produces, and the governance failures of section 3.6 are a structural consequence of the competitive dynamics the technology accelerates rather than a failure of effort. The historical record is clear that institutional innovation commensurate with a general-purpose technology, the Factory Acts, the international postal and telegraph conventions, Bretton Woods, the nuclear non-proliferation regime, has in every prior case been the precondition for a transition to deliver its benefits without consequences exceeding the political capacity of the societies undergoing it, and that each such response required decades of contestation, some of it violent. The circumstances described in this thesis imply the artificial intelligence

revolution would not provide invention of like scope inside the period. its repercussions are worst: great-power upheaval complicates coordination; financial strain turns safety expenditure from asset to residual expense; European deregulation destroys the only structure able of control; and the safety exodus takes the most competent risk judges from the institutions where their judgement counts most.

The thesis's ultimate claim is therefore not that one scenario will materialise to the exclusion of the others, the most likely trajectory being a hybrid in which the managed transition serves as the dominant envelope, the disordered correction as an intermittent perturbation, and the acceleration trap as the long-term governance challenge whose early signals are already visible, but that which trajectory predominates is a matter not of technological inevitability but of institutional choice, and that the choices made over the coming decade will determine, more than any other variable, whether the transition delivers the broadly distributed transformation prior general-purpose transitions eventually produced or a concentration of power, wealth, and security so rapid that its most relevant analogues are not the railways or the electrical grid but the brief, consequential intervals in which the failure of existing institutions to govern a transformative technology produced consequences whose memory still structures political imagination. The critical uncertainty, as this thesis has argued from its opening pages, is temporal rather than directional. The question is not whether artificial intelligence will reshape the global economy, the evidence of sections 3.1 and 3.5 suggests it will, with consequences for healthcare, science, education, and productivity that may prove as transformative as the most ambitious projections claim. It is whether the interval between present capital commitment and future return, between current capability and adequate governance, between technological acceleration and institutional adaptation, can be navigated without consequences exceeding those of any historical predecessor. The dot-com crash repriced expectations while leaving the productive infrastructure intact; the fibre-optic networks that went dark after 2001 became the backbone of the broadband internet a decade later; the railway tracks laid in the 1840s mania outlived the companies that built them and carried the Victorian economy's freight for half a century. Whether the AI transition follows that pattern, a costly but ultimately productive overbuild whose infrastructure survives the correction, or whether the

leverage in current investment structures, the severity of the geopolitical environment, the pace of capability development, and the inadequacy of governance produce something qualitatively worse, is the question on which the geopolitical architecture of the next decade depends. The technology's lifecycle tells the whole story: cobalt mined by artisanal miners in the Democratic Republic of the Congo enters at one end; rare earths refined in China become the GPUs that power the data centres of three American corporations; the models trained on them discover disease pathways, optimize energy systems, write the code that designs their successors, and generate the intelligence Altman envisions selling like electricity and water; and once obsolete, the hardware returns to the Global South as hazardous waste, whose health costs fall on communities that derive little benefit from the intelligence it once computed. The struggle for AI supremacy and the struggle for energy and mineral control are not parallel contests but a single, recursively entangled process in which the imperatives of computational power increasingly determine the strategic decisions that shape the physical world: from the Arctic ice shelf of Greenland to the Guiana Shield of Venezuela, from the Strait of Hormuz to the data centres of Virginia, from the bond markets of Tokyo to the safeguards research laboratory that Mrinank Sharma left to study poetry. The thesis has advanced, across its three chapters, six interlocking arguments about the geopolitical and geoeconomic architecture of the AI transition, which may be summarized schematically here.

First, that the spatial and material logics of technological transitions recur across historical periods: the struggle for control over critical resources, the construction of infrastructure as an instrument of power projection, the use of technology denial to freeze the development of rivals, and the social displacement generated by the reorganization of production around new machines are not unique to the AI era but represent structural patterns whose nineteenth-century precedents illuminate the dynamics of the present. **Second**, while the financial structure of the present AI expansion shows the speculative features of earlier technology booms—narrative-driven valuation, circular capital flows, and the financialization of infrastructure—it differs from them in the material intensity of the infrastructure involved, the geopolitical stakes attached to it, and the degree to which the main actors are both rivals and co-dependent.

Third, that the AI supply chain is layered and vertically linked, with weaknesses at every level — energy at the bottom, rare earth processing, semiconductor manufacturing, cloud infrastructure, and model development — that add up instead of cancelling each other out, and whose exploitation has become a clear way for big powers to compete.

Fourth, the surveillance and military uses of artificial intelligence are not distinct from its commercial and creative ones; they come from the same platforms, the same corporate actors, and the same computational infrastructure, therefore posing governance issues that current institutional frameworks—whether local or international—are still not ready to handle.

Fifth, Europe holds a fundamentally dependent role in this environment: while theoretically ambitious, it is materially reliant on American platforms for cloud computing, defence intelligence, and frontier model access; and on Chinese supply chains for the vital minerals and processed materials upon which its hardware ambitions depend—a dual dependency that the language of strategic autonomy has so far been unable to turn into practical industrial policy.

Sixth, and most consequentially, that the AI transition does not simply unfold within an already deteriorating geopolitical environment but actively accelerates that deterioration, raising the stakes attached to technological supremacy to a point where cooperative outcomes become structurally harder to sustain, and narrowing the window within which governance innovations capable of managing the transition can be developed and put into practice. Whether that process produces the managed transition that the historical record suggests is most probable, the disordered correction that the structural vulnerabilities make plausible, or the acceleration trap that the governance vacuum makes possible is the defining question of the age of computational sovereignty. It is a question whose answer depends not on the technology alone — the technology will continue to advance, as technologies always do, along a trajectory whose direction is legible even if its specific milestones are not — but on the political choices, institutional innovations, and acts of collective intelligence that the societies confronting it are capable of producing. The thesis has documented, across three chapters and the full arc of two centuries of technological history, the structural conditions under which those choices must be made. Whether those choices are made wisely — with the temporal patience, the distributional equity, and the

institutional ambition that the technology demands — depends on whether the political and intellectual work of building adequate governance is begun *now*, on the evidence and against the structural conditions that this thesis has documented, rather than postponed to the moment of crisis at which institutional innovation is historically least available. The thesis can frame the question; the political imagination of the coming decade must answer it.

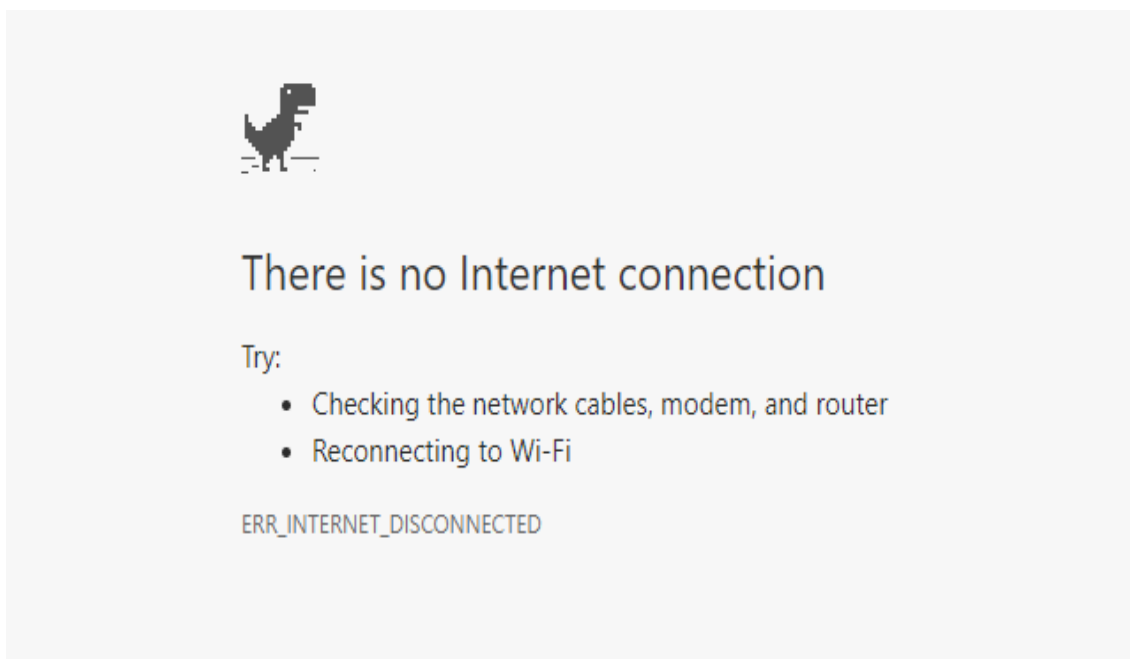


FIGURE 54: NO INTERNET, NO AI
Source: Author's computer

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