

Over-accumulating AI. Rationale and fault lines beyond the US AI investment boom

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Over-accumulating AI

Rationale and fault lines beyond the US AI investment boom

Abstract

The stock market valuation of AI-related firms has increased tenfold between 2015 and 2025, while fixed investment in the sector as a whole is so massive that it is the primary driver of US growth in the mid 2020s. This contribution proposes examining the surge in the financial value of AI-related stocks and capital expenditures in AI-related assets through the lens of the crisis theory of overaccumulation and discusses the specificities of this AI rush. After documenting the extent of the AI bubble, we argue that crisis dynamics emerge from a competitive, compulsory drive to invest, which coerces firms' behavior without ensuring the macro conditions needed to sustain the aggregate investment boom. We then distinguish the vulnerabilities arising from the surplus of capital invested in AI relative to valorization opportunities. Following the Anna Karenina principle, we show that only one path leads to sustained expansion of the AI sector (a rosy scenario), but three possibly interacting paths lead to crisis, related to mounting financial fragilities, coordination failures, and labor productivity disappointments. We conclude by discussing the possible fallout from the bubble's bursting.

Keywords

Artificial Intelligence, Bubble, Crisis Theory, Overaccumulation, Productivity

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1. Introduction

Entering the second half of the 2020s, the AI boom is in limbo, undecided. On the one hand, stock market valuations and extraordinary investment plans are echoed in the pervasive adoption of AI in everyday personal and professional life; on the other hand, the hype is wearing off as economic reporters, financial analysts and tech-industry observers are increasingly wary of surging costs, material hurdles, uncertainties over demand, security concerns and, more broadly, the disconnect between financial expectations and effective returns.

What is at stake economically goes beyond the Tech sector. As the BIS cautiously puts it in its annual report, “the AI investment boom raises questions about the sustainability of the current economic expansion” (BIS 2026, 22). Looking at historical episodes of investment booms such as the canal mania of the 1830s, the British railway mania in the 1840s, the electrification exuberance of the late 1920s (roaring 20s) and the dotcom boom of the late 90s, it remarks that “all shared one common trait: a genuine technological breakthrough that attracted capital in excess of what commercial returns could ultimately justify” and that “these episodes ended with an eventual reversal in investment, inducing economy-wide recessions”; considering the resemblance of the current AI investment boom to these precedents, this points to “potential downside risks in the near term”(BIS 2026, 22–23).

This paper examines the crisis potential of the surge in the financial value of AI-related stocks and capital expenditures in AI-related domains through the lens of the Marxist crisis theory of overaccumulation (Clarke 1990; Harvey 2006, chap. 7). More specifically, following the Anna Karenina principle (AKP) based on the opening line of Leo Tolstoy’s *Anna Karenina*, “All happy families are all alike; each unhappy family is unhappy in its own way” (Tolstoy 1994), we hypothesizes that while the rationale supporting the case for a protracted expansion unleashed by the AI investment boom follow one main logical line driven by productivity gains and expanding demand, the lines of AI bust crises are manifold because, as Paul Kedrosky, an investor and financial consultant, remarks, what is striking “is all of these interlocking points of fragility”(Warzel 2026). The aim of this paper is to identify the potential channels and triggers of an AI-driven economic crisis.

This research makes two main contributions. First, to examine the rationale and fragilities behind the surge in AI-related CAPEX, it offers a comprehensive review of the academic literature, which is completed, given the lack of hindsight, by arguments and information taken from the grey literature (consulting, industry, and administrative reports) and the financial press and connects those elements within the framework of the theory of overaccumulation. Second, it presents stylized facts – mostly based on lead US firms’ regulatory filings – for the very recent period (2014-2025) to engage empirically with the relevant mechanisms. All the graphs and data sources are detailed in data companion appendix.

On this basis, our analysis suggests that while it is likely that the current AI investment will not deliver on its promises, the unfolding of the bust could not only follow different paths but could also be contained in ways detrimental to broader socioeconomic outcomes: much like the containment of the fall-out from the 2008 financial crisis prevented a replay of the Great Depression and allowed for a fragile but nonetheless effective reaffirmation of the claims of finance for a decade without providing a socioeconomic safety net for the population affected by the great recession that followed the Krach (Tooze 2018), this time the containment of the fallout of the AI bubble could lead to an entrenchment of Big Tech intellectual monopoly power (Bensussan et al. 2025; Pagano 2014) and nurture techno-feudal trends (Durand 2024).

The second section contextualizes the AI investment boom and provides stylized facts. Section 3 presents our conceptual framework. Section 4 explains the rationale for the furthering of the boom (the rosy scenario). Sections 5, 6, and 7 present the main loci of fragility, namely finance, coordination, and labor. Section 8 discusses our results, putting the stakes in perspective.

2. The AI boom in perspective

The idea of automating human reasoning dates back a very long time, and hardware devices capable of implementing algorithmic thinking have existed for several millennia (Pasquinelli 2023, chap. 1). The term “artificial intelligence” was introduced in 1956 at the Dartmouth Conference, whose goal was to ensure that “machines use language, form abstractions and concepts, solve problems currently reserved for humans, and improve themselves” (McCarthy et al. 2006, 13). For a long time, research focused

primarily on replicating logical reasoning through expert systems. At the same time, techniques known as “machine learning” followed a different path, combining training on multilayer neural networks (deep learning), the use of graphics processing units (GPUs), and big data. Starting in the 2010s, the first approach - symbolic AI - was supplanted by the second - data-centric AI. In the wake of this, advances in algorithm-driven data generation have produced highly realistic images, videos, and text (Pascal et al. 2025, 12–13). These capabilities are associated with the concept of GenAI, which is at the core of the AI investment boom that followed the public release of ChatGPT in November 2022 and the immediate, enthusiastic though uneven adoption by users both in their personal life and in the workplace (Humlum and Vestergaard 2025; Bick et al. 2026).

GenAI systems “produce contextually appropriate artifacts using an open-ended stochastic process that draws from patterns in a dataset. The artifacts may be a variety of things other than text, including computer code, images, music, chemical structures, game environments, mathematical proofs, or dance moves, to name a few » (Baily et al. 2025, 8). Their operation requires a complex stack of advanced electronic chips (mostly provided by NVIDIA) clustered in data centers (provided by firms like Amazon, Google, Oracle, Alibaba, Tencent...) to train the models (created by OpenAI, Anthropic, Google, Deepseek, Mistral...) and run the queries of end users conveyed by their usual interface (Microsoft Windows, Google Android, Mac iOS...) (Kshirsagar 2025).

At the macroeconomic level, the AI investment boom is evident in the surge of investment in AI-related domains, which increased in the US by 1 percentage point of GDP between 2023 and the beginning of 2026 (Figure 1). This evolution takes place on the back of a constant increase in the weight of investment in those various domains since 1980, but unlike the dot.com boom of the late 1990s, this time the investment surge is focused on hardware, mostly chips that are included in the category of computers and equipment (Figure 2).

Figure 1. Total fixed private investment in domains related to AI in the US (Q1 2014 – Q1 2026; BEA and Census Bureau)

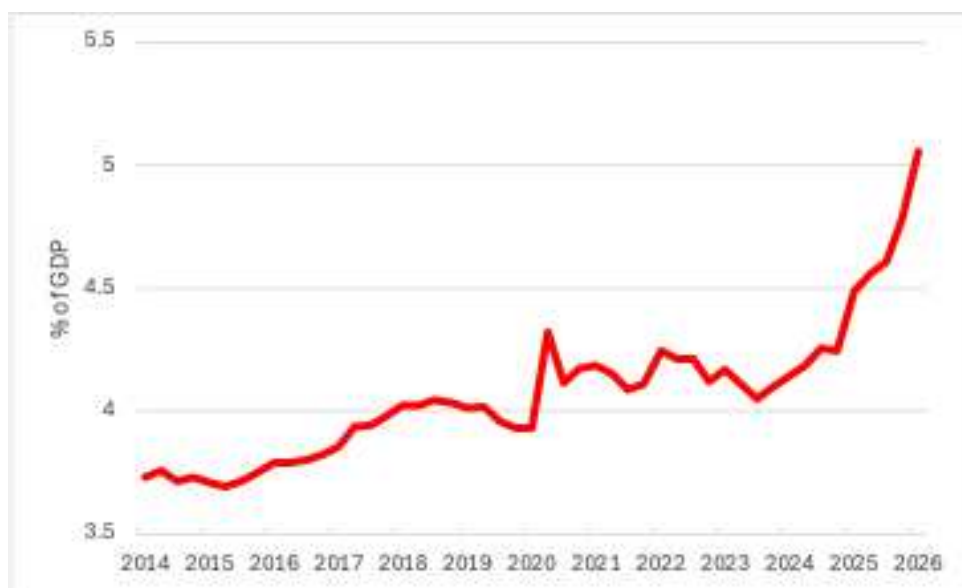
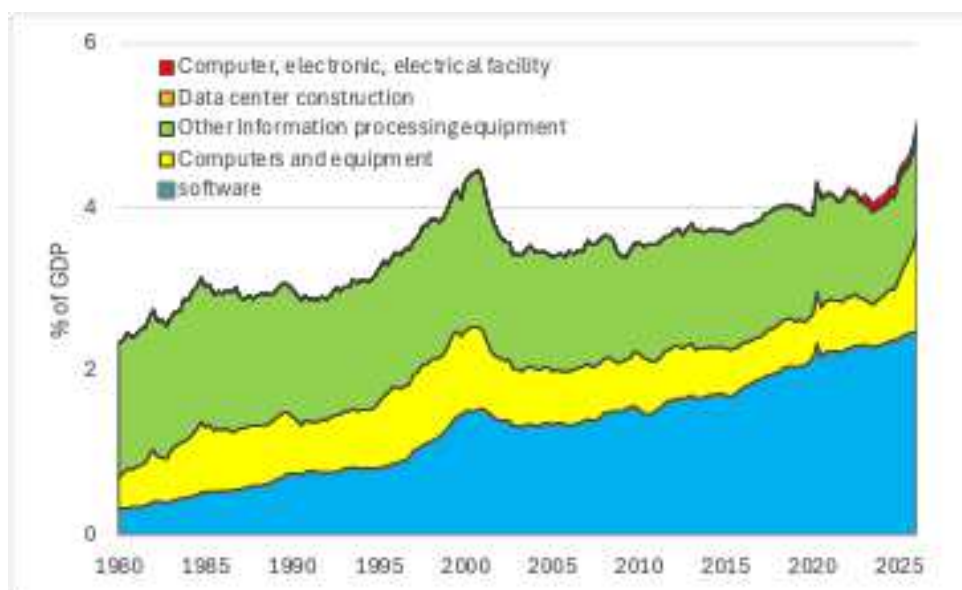


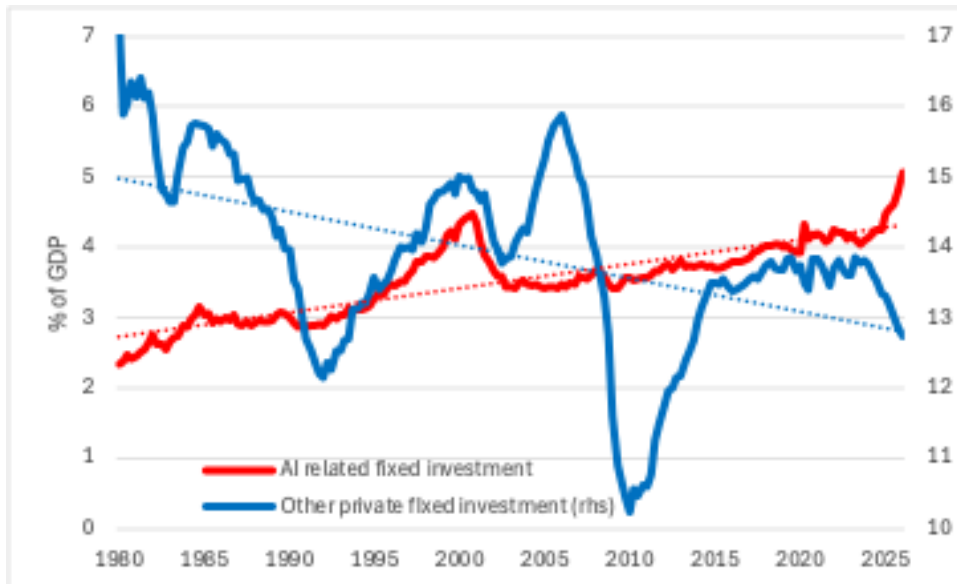
Figure 2. Fixed private investment in domains related to AI in the US (Q1 1980-Q1 2026; BEA and Census Bureau)



Remarkably, this AI-related investment doesn't occur alongside a general surge in investment. In the long run, there is a sharp decline in fixed investment in other domains, as a share of GDP, but what is striking in the current conjuncture is that, contrary to the period of the dot.com bubble, the current AI-related investment boom is not accompanied by an increase in that investment share in other areas; what we observe is

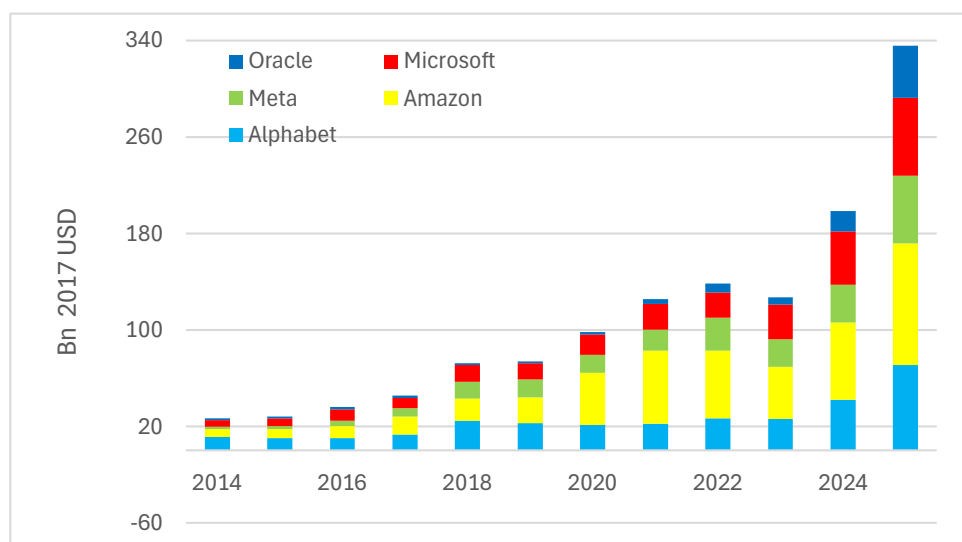
rather a substitution, investment in AI-related domains crowding out other investments (Figure 3).

Figure 3. Fixed private Investment in domains related to AI versus other fixed private investment in the US (Q1 1980-Q1 2026; BEA and Census Bureau)



At the microeconomic level, the surge in the hyperscalers' CAPEX (Figure 4) shows the kernel of the boom. After a prolonged period of sustained growth from 2015, a dramatic acceleration occurred: Since the end of 2023, investment by Meta, Amazon, Alphabet, Microsoft and Oracle has more than tripled, from about 30 billion USD in Q1 2023 to almost 115 billion USD in Q1 2026. Corroborating our observations at the macro level, the business press also remarks that the AI-investment boom goes along with sluggish investment in other sectors, Bloomberg noting that while the 4 hyperscalers (Alphabet, Amazon, Meta, Microsoft) are planning a combined CAPEX of \$ 650 billion in 2026, «By contrast, the largest US-based automakers, construction equipment manufacturers, railroads, defense contractors, wireless carriers, parcel delivery outfits, along with Exxon Mobil Corp., Intel Corp., Walmart Inc. and the spun-off progeny of General Electric — 21 companies — are projected to spend a combined \$180 billion in 2026 » (Day and Bang 2026).

Figure 4: Hyperscalers' CAPEX in 2017 bn USD (Q1 2014-Q4 2025, companies' SEC listings, deflated using BEA GDP deflator)



The AI investment boom in the US is large enough to be relevant at the macroeconomic level and is mostly concentrated in a single product (chips) and a handful of companies, yet it runs alongside a slowdown of CAPEX in the rest of the economy.

3. Conceptual framework: overaccumulation as instability stemming from the compulsion to invest

Rosa Luxemburg remarks that under the whip of competitive forces, firms are compelled “to produce, as cheaply as possible. That is with the highest possible saving of human labour”. This is the core reason why “for capitalism, continuous and ceaseless technical change is a necessity, a vital condition” (Bellofiore 2009, 13). Schumpeter completes by insisting that in capitalist reality what counts the most is “competition which commands a decisive cost or quality advantage and which strikes not at the margins of the profits and the outputs of the existing firms but at their foundations and their very lives” (Schumpeter 1943, 84).

Those two forces are compounded in the current AI boom. From the perspective of capitalist firms, the possibility of massive labour automation (Anthropic research 2026; McKinsey 2023; Goldman Sachs 2023) appears as an irresistible opportunity to reap extra profits. And the discourse about a near-coming singularity (Booth et al. 2025) – although strongly rebutted by specialists (Hammond 2025a; Werner 2026) – dramatizes the stakes:

under the hypothesis of an elasticity of substitution of informational capital to labour >1 (which can be considered as arbitrary), this would lead to a definitive marginalization of labour, capital tendentially reaping all the income (Nordhaus 2021). For the investors buying the argument, the mere plausibility means that discarding that business line is not an option. This context exerts pervasive pressure across various levels of the AI chain - from chip providers to model developers, hyperscalers, and business customers - to engage with and develop the technology. Echoing Rosa Luxemburg, Hemant Taneja, a venture capitalist, states that this is a matter of compulsion rather than choice: «AI is a transformative force (...). Organisations that have the culture and courage to transform themselves will be strengthened by AI; organisations that don't will be left behind» (Hammond 2025b).

Yet, the rationale fueling the boom cannot be separated from the building up of fragilities. This issue is all over the business press in 2026; Bloomberg, for instance, observes that big tech corporations are, at the same time, “struggling to meet customers’ demand for computing power and facing increasingly tough questions about whether all that spending will pay off » (Ford and Day 2026). In the meantime, worries are mounting about the sustainability of the huge financial bets made as “big tech firms began issuing tens of billions of dollars in debt as they scrambled to ramp up investing in AI capacity” while “new businesses such as OpenAI and Anthropic [...] have each raised billions of dollars in funding from venture capital investors”(Arroyo and Barbuscia 2026). In a nutshell, the question is: Will all that financial and fixed capital invested in AI really pay off?

Crisis dynamics emerge from the compulsion to invest, entangled in the process of capitalist competition. This is a general principle labeled by David Harvey as the overaccumulation and devaluation of capital:

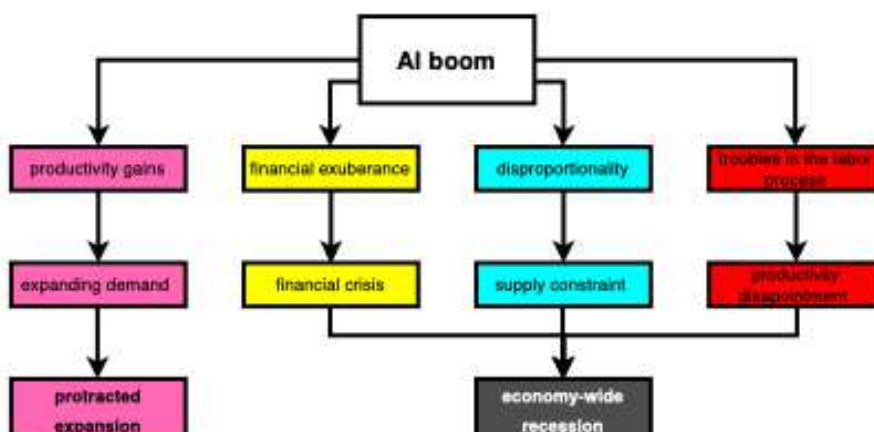
“the capitalists’ necessary passion for surplus-value-producing technological change, (...) produces a surplus of capital relative to opportunities to employ that capital. Such a state of over-production of capital is called the ‘overaccumulation of capital’.

If the amount of capital in circulation is to remain in balance with the limited capacity to realize that capital through production and exchange (...), then a portion of total capital must be eliminated. If equilibrium is to be re-established, then the tendency towards overaccumulation must be counterbalanced by processes that eliminate the surplus capital from circulation. These processes can be examined under the heading ‘the devaluation of capital’” (Harvey 2006, 196–97).

Overaccumulation crises and the subsequent capital devaluation can, for Harvey, materialize in different “forms of appearance” (Harvey 2006, 195). The unfolding of an accumulation crisis is therefore context-specific and depends on the concrete interlocking of contradictions.

Recent articles have analyzed how the current AI overaccumulation crisis reflects broader contemporary capitalist dynamics, such as financialization or hegemony transition (Timcke 2026). In this paper, we approach the AI crisis through its concrete manifestations by distinguishing among the apparent contradictions that threaten the sector's stability and could spill over into the macroeconomy. In other words, we want to understand how overaccumulation occurs in this case and what the specific venue for devaluation could be. The rest of the paper will be structured along the various paths we identify after the AI boom (Figure 5). In line with the principle of Anna Karenin, while there is only one way toward expansion, through a virtuous dynamic of productivity gains and expanding demand, we explore three paths to crisis that would necessarily overlap and interact: one related to financial instability, one resulting from disproportionality arising from market coordination failure, and one touching at the core the labor automation AI promise.

Figure 5: One path of expansion and three paths to crisis after the AI boom



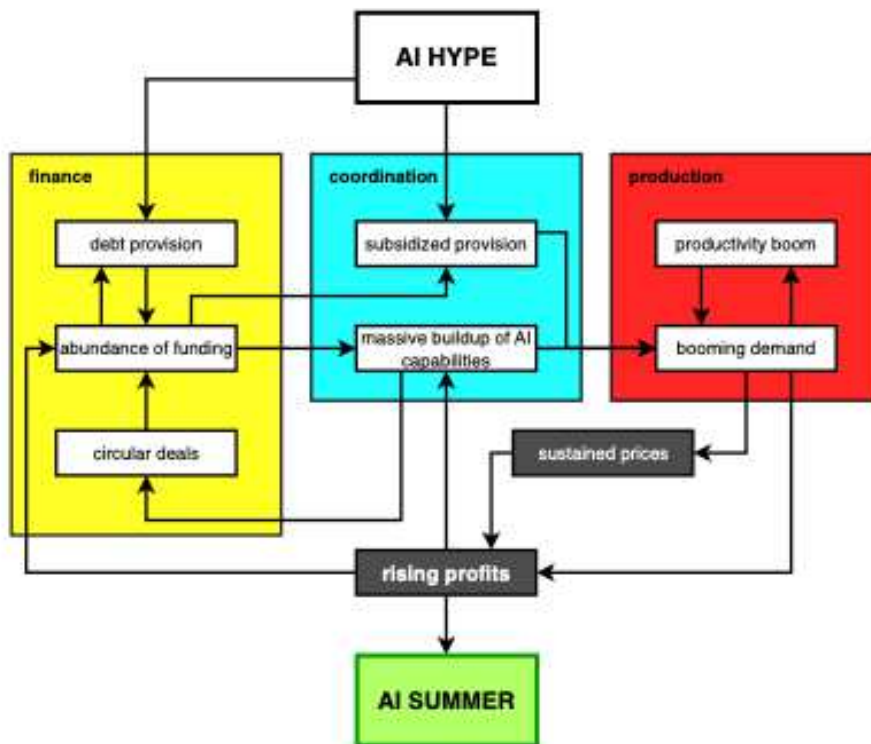
4. The rosy scenario of an AI summer

The point of departure for the boom is AI hype resulting from the combination of the initial viral adoption of ChatGPT (Bick et al. 2026) and the impressive, rapidly improving performance of models in many domains such as coding, mathematics, and writing (Epoch AI 2026a), including complex cognitive tasks related to scientific discovery (Wang et al. 2023; Tang et al. 2026). The rationale is that, at the technical level, powerful AI is just around the corner, which means, as Anthropic's Dario Amodei puts it, a “country of geniuses in a datacenter” will become ubiquitously available (Amodei 2024). At the economic level, such technical wonders open up a huge opportunity for prosperity, with a total addressable market (TAM) in the trillions of US dollars (UNCTAD 2025; Morgan Stanley 2025; Barrett 2024).

As summarized in Figure 6, such a perspective paves the way for a rosy scenario in which the main difficulty is the timing of investment, considering the lag between the surge of demand and the build-up of infrastructure. Abundant financing (Goldfarb 2026) and rising demand are supported by circular deals that combine equity investment and purchase commitments, acting “like a flywheel” to drive the simultaneous expansion of chip production, model development, and cloud capabilities necessary to advance AI (Sam et al. 2026). The model segment of the AI value chains is incurring losses as product availability is subsidized to favor widespread adoption, but users and income are rapidly rising (Jin 2026; Elder and Hammond 2026).

The combination of widespread adoption and increasing performance creates the market. Although evaluation varies in the extent of AI-related automation and productivity gains, these are expected to be substantial enough (Hammond 2025b; Anthropic research 2026; Baily et al. 2025; McElheran et al. 2025) to support a highly dynamic and sustained demand. Although some competition is expected, the case is that in the key segments of the AI value chains (chip making, models, cloud capacities) it will be imperfect competition à la Cournot where “a small number of players [...] independently behaving rationally”(Patel 2026) will be able to capture enough profits to justify the boom of investment and to further the upward trend.

Figure 6: From hype to profits: the rosy scenario



5. An AI financial crash

In his classic *Short History of Financial Euphoria*, John Kenneth Galbraith identifies three recurring features in the various episodes of financial mania: first, “There is the thought that there is something new in the world”; second, investments in the bubble are fueled by leveraging assets to the point where “debt (..) has become dangerously out of scale in relation to the underlying means of payment”; after the inevitable crash “anger and recrimination” are all-over the place, but there is no open discussion of “speculation itself” because it is widely accepted that “the market is neutral and accurate reflection of external influences; it is not supposed to be subject to an inherent and internal dynamic of error” (Galbraith 1994, chap. 2). If it is too early to assess if the third step will take place after the AI boom, the two first elements are already clearly identifiable. Alongside the narrative of radical novelty that justifies the optimism outlined in the

previous section, there is considerable financial exuberance that sustains the investment boom well beyond the cash flow currently generated by the sector.

The BIS has modeled the current surge of risk in the financial system related to the AI boom. Echoing the overaccumulation framework without naming it, they begin by stressing that excessive investment is due to the dynamic of competition: since “most of the reward goes to a small number of contest winners rather than being shared proportionately [...], each coalition invests heavily to outcompete its rivals and improve its chance of capturing the reward” and “the sector as a whole becomes prone to excessive investment relative to the socially optimal level”(Rungcharoenkitkul 2026, 2). What is especially relevant here is the role of circular deals that accelerate the boom in an unusually endogenous fashion, since circular equity stakes and lease contracts could serve as collateral to facilitate further debt leveraging. When things go wrong, the flywheel effect reverses, accelerating retrenchment forces. As Bloomberg notes, “if revenue from AI products does not grow as much or as fast as expected”, some companies “might find itself staring at untenable bills for data center capacity and hardware” then, any other company involved in a circular deal loses twice since: on the one hand, the company in difficulty stops buying its products and, on the other hand, its stake in that company tumbles (Sam et al. 2026). The BIS remarks that this high level of concentration of financial and investment operations is a key idiosyncratic characteristic of the AI financial mania, stressing that “Real and financial exuberance are thus bound together: the competition that over-builds the boom is also what selects the fragile financing that turns it into a bust” (Rungcharoenkitkul 2026, 4).

Considering the network structure of that process, close interlinkages also mean that a shock to a firm could propagate through the whole sector and, given their centrality in the US current accumulation regime and the centrality of the US financial system in the world economy, trigger a systemic crisis.

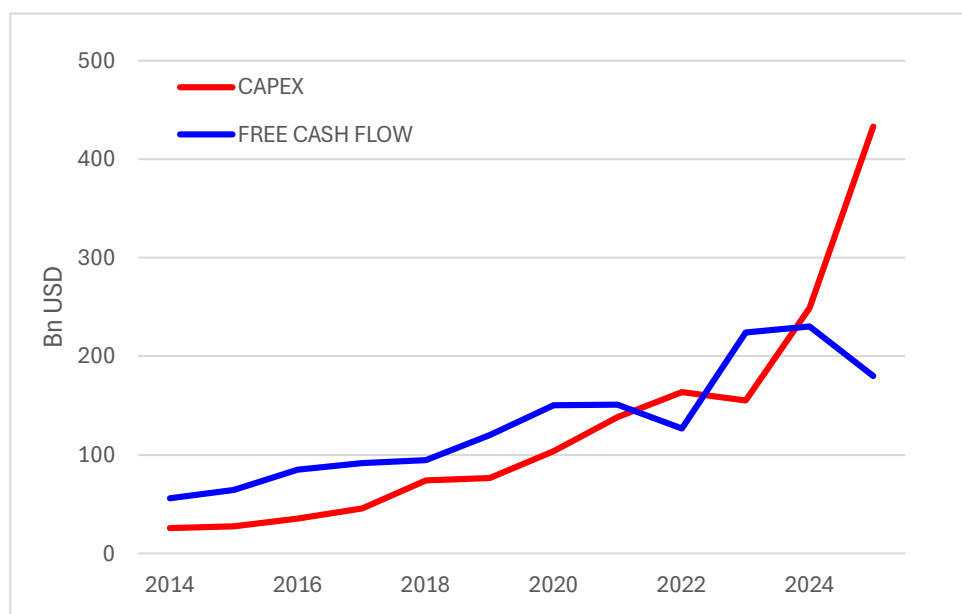
One complementary aspect is the role of relatively opaque, less-regulated private credit. A meaningful and growing share of debt is indeed provided by private capital firms (Grafteo 2026), bridging the gap with long-term investors such as insurers. An example can clarify the dynamic at stake. The October 2025 23.6 bln USD ‘Hyperion’ corporate bond sale shows both enthusiasm on the bond-buying side and intriguing sophistication on the part of META, the main beneficiary of this financing round dedicated to building a

gigantic datacenter in Louisiana (Wigglesworth 2025). The datacenter is owned by Beignet Investor LLC, a joint venture between Mark Zuckerberg's Meta and Blue Owl, a private capital firm. However, neither Blue Owl clients nor Meta will provide the bulk of the financing, which will come from a vast pool of bondholders. Meta is primarily committing to a long-term lease to use the facility. The point is that Meta is ready to pay about a 1-percentage-point higher interest rate to finance Hyperion off its balance sheet, thereby transferring a risk it doesn't want to bear to lenders that investment bankers convince to assume it, though they probably do not fully understand it.

Since 2023, analysts have grown increasingly concerned about hyperscalers' free cash flow, which has declined following the steep increase in CAPEX (Figure 7), a phenomenon pervasive for all the companies considered here, with the exception of Microsoft where the pattern is less clear (See Appendices 1-5). The trend is likely to continue, as analysts forecast a sustained drop in FCF towards the end of 2026, with CAPEX rising to almost 2 trillion USD at the same time (Rosner-Uddin, McMorow, et al. 2026). The drop in hyperscalers' FCF illustrates a broader shift: rather than financing AI investments with internal funds, hyperscalers are increasingly relying on debt and equity. In June 2026, Google raised a "record" equity to USD 85 billion in equity to finance its AI investments (Wells et al. 2026). Moreover, the combined debt of Alphabet, Amazon, Meta, Microsoft and Oracle amounted to USD 541.2 billion in 2025, almost double that of 2020, which was USD 294.3 billion (Day and King 2026). A sustained reliance on external funds is not specific to hyperscalers, as shown by SpaceX's IPO in June 2026 and OpenAI and Anthropic's announced public listings (Lipschultz 2026; Ludlow 2026).

As "as a measure of the cash companies have left to service debt or return to shareholders after covering their operating costs and capital spending", FCF is "closely watched" by investors; its decline therefore sparked anxieties about hyperscalers' capacities to sustain the boom (Rosner-Uddin, McMorow, et al. 2026). The decline feeds into a broader debate on the productive model of US AI, which extends beyond its financing to the profitability of the underlying infrastructure.

Figure 7: Combined free cash flow of five hyperscalers (Alphabet, Amazon, Meta, Microsoft and Oracle) (Q1 2014- Q4 2025, companies' SEC filings)



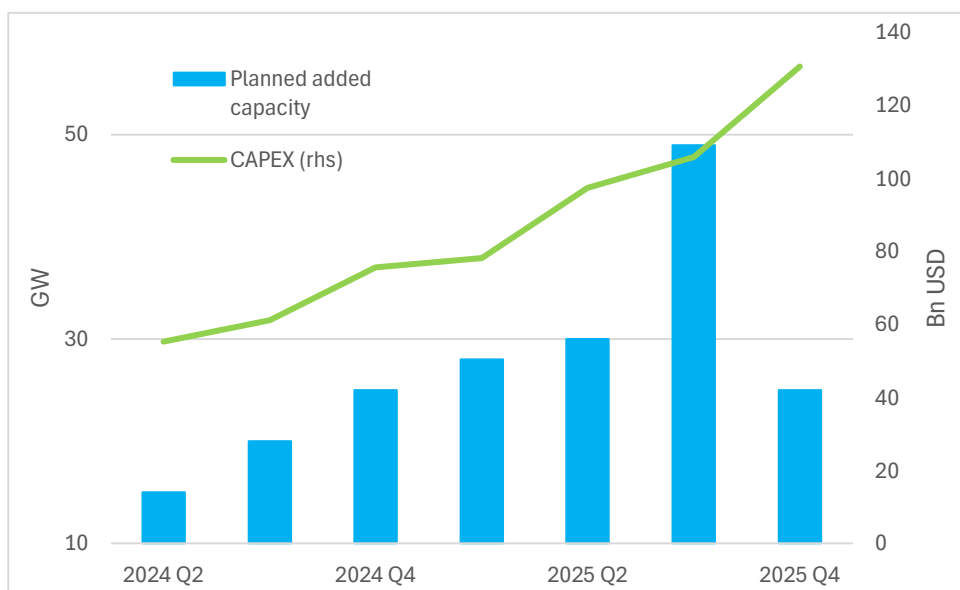
6. Coordination challenges

Raising capital does not mean achieving productive capacities, and economic vulnerabilities of the AI industry are not confined to the financial sphere. From producing chips to building data centers and selling AI products, the US AI value chain shows several challenges that threaten the creation and realization of value. Three specific coordination issues appear particularly critical. First, increasing socio-political and material barriers to advancing AI infrastructure result in a growing disconnect between the financial resources mobilized for CAPEX and the actual buildup of AI productive capacities. Second, given that chips account for the bulk of CAPEX in AI spending, the relatively rapid pace of their obsolescence, combined with demand uncertainties, makes smooth deployment of the infrastructure unlikely and calls into question the possibility of sustaining it. Finally, and relatedly, uncertainties abound regarding competitive dynamics, the quality, quantity, and price elasticity of demand for AI services, calling into question the income projection dynamics used to inform investment decisions.

6.1. Socio-political and material barriers to AI infrastructure build-up

The last quarter of 2025 and early 2026 revealed the many bottlenecks facing the construction of datacenters: “[...] even as the piles of capital secured have grown ever larger, the ability to deploy it in the artificial-intelligence race has become less certain. Supply-chain backlogs, permitting fights and availability of power supplies are among the issues that have caused the construction of data centers to fall behind targeted timelines [...]” (Blunt 2026). This tendency will likely continue in the years ahead: in April 2026, the Financial Times reported that almost 40% of 2026 data center projects were delayed (Rosner-Uddin, Muir, et al. 2026). Figure 8 illustrates the decoupling between CAPEX spending trends and planned US data center capacity additions. It underscores the disconnect between the boom in capital expenditure and AI firms’ capacity to realize those investments.

Figure 8: Planned added US data centers’ capacities versus hyperscalers’ CAPEX (Q2 2024- Q4 2025, Kedrosky (2026) and Companies’ SEC filings)



The challenge that US AI firms face in materializing CAPEX and continuing to build data centers at a sustained pace reflects the interlocking contradictions in AI production. An immediate and visible cause of delay is political backfiring in the US. In August 2026, 25 of 50 US states were either implementing or considering restrictions on data centers construction within their jurisdictions, while only 8 were not discussing such a possibility

(Datacenterbans 2026). Political contestation is a worldwide phenomenon, as multiple elements of the AI value chain affect energy prices, environmental resources and workers' conditions across continents (Muldoon et al. 2026).

Data centers require massive amounts of energy for cooling, which constitutes a material limitation on AI development (Epoch AI 2026b). Data centers' electricity demand is predicted to double by 2030 (International Energy Agency 2026). Ensuring supply is, and will be, a major challenge for US hyperscalers as exemplified by the reopening of a nuclear reactor to supply Microsoft (Luscombe 2024; Kearney 2026). Google also acknowledged this limitation by announcing research on solar-powered TPU-carrying satellites that would ensure the path to a "future spaced-based, highly scalable AI infrastructure system design" (Google Research 2026), while SpaceX announced plans to deploy A first orbital datacenter already in 2027 (Bott and John 2026).

The difficulty of providing enough energy to run the data centers comes on top of other material challenges in hardware supply. Among them, some are related to global geopolitical instability as became more apparent with the 2023–2025 naval blockade imposed by Yemen in the Red Sea (Kumar 2026) and during the US-Israeli war in Iran. The blockade of the Strait of Hormuz threatened Taiwan's fossil fuel supply, thus sparking fears for the production of advanced semi-conductors by Taiwan Semiconductor Manufacturing Company (TSMC), which controlled over 90 percent of the market. A similar mechanism could affect Samsung Electronics and SK Hynix, both major players of high-bandwidth memory market based in Korea (Parikh 2026). Chip manufacturing also requires other critical materials such as Sulphur, helium and bromine whose provision vulnerable to be caused bottlenecks by the war and maritime blockade (Storm 2026).

Beyond political resistance and immediate material bottlenecks, the US path toward AI development, largely based on brute computing power, is not environmentally sustainable. The surge in energy consumption increases CO₂ emissions, accelerating climate change (S. Chen 2025), while the structural problem of cooling data centers (Chamayou 2026) requires a rapidly surging amount of water (de Vries-Gao 2025), pressuring already strained water provision systems. More broadly, estimate of the AI-

related mineral extraction and amount of e-waste (de Vries-Gao 2026; Guegant et al. 2025) also point to unsustainable trajectories.

From direct political opposition to land, water, and energy pressures related to data centers to material hurdles to capacity build-up, vulnerabilities in global supply chains, and ecological degradation, it becomes increasingly apparent that, beyond financial constraints on the AI boom, socio-political backlash, material constraints and ecological limits could impede the effective buildup of AI capabilities.

6.2. The conundrum of vulnerable fixed capital and volatile demand

The very nature of AI fixed capital and uncertainty about demand dynamics pose major coordination challenges.

While the current AI investment boom is comparable in size to preceding technological booms, unlike the fiber cables, production lines, or railways deployed in the past, GPUS – along with other chips, data storage, racks, and servers – that amount to 70% of data center costs have a relatively short lifespan. Cables and rail can be used for decades after their investment, representing a lasting material legacy and, at least potentially, a long-term economic value; by contrast, AI chips become obsolete after 2 to 6 years, depending on the estimates (de Vries-Gao 2026, 2), and must then be discarded. The implication of that technical aspect is that the window of opportunity to valorize investment in chips is much shorter than in previous industrial booms and that smoothing potential difficulty in the valorization process by extending the period of use is not straightforward. Correlatively, this means that AI investment is a recurring cost necessary to maintain the medium- and long-term ecosystem of AI services. In other words, if, for any reason, CAPEX scale-back outweighs cost reductions from improvements in AI processes, the computing power available for AI queries may decline, with wide-ranging economic implications.

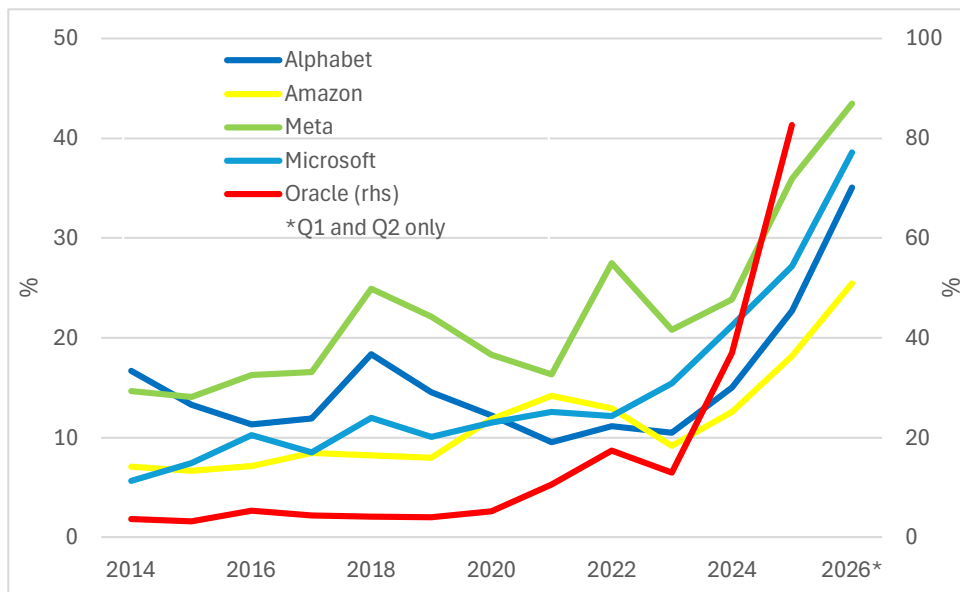
The coordination imperative for maintaining a rapidly wearing-out AI infrastructure is complicated by the dynamics of economic obsolescence. Fast-moving technology quickly loses value. Precisely, the performance of AI chips themselves, as well as transformations in the way models are trained, deployed, and used, imply that the price of computing power is very hard to predict and could plummet either due to the deployment of cheaper options or the collapse of solvable demand (Chan et al. 2026). In particular, it is doubtful that there will be enough demand to support the most computing-intensive, most expensive, and best-performing models while cheaper alternatives flourish (Hammond 2026a). This also has the potential to trigger abrupt asset devaluation and major disruptions along the financial chains involved.

6.3. Lasting discrepancy between capex and income

These latent vulnerabilities are apparent in the difficulty of generating income from increasing CAPEX. Figure 9 shows that the AI boom significantly increased the hyperscaler ratio of CAPEX to revenue, which almost doubled for most of the firms between 2022 and 2025 and, in the extreme case of Oracle, resulted in a situation where CAPEX exceeds revenue, a very unusual situation for an established firm. Analysts forecast this trend to continue at least through 2028 (Rosner-Uddin, McMorow, et al. 2026), which casts doubt on hyperscalers' future profitability. The consulting firm Panmure Liberum calculated that current CAPEX and revenue forecasts through 2030 imply a negative internal rate of return on invested capital for Alphabet, Meta, Microsoft, and Oracle. The problem, consultants argue, is that revenue does not follow the trends in capital expenditure, which leaves the firms with two choices to ensure investors' returns:

“Either, hyperscalers significantly reduce their capex to levels that generate a reasonable ROIC based on the projected revenue. This would be bad for the entire AI boom because it would imply large revenue downgrades for the entire value chain, from hardware manufacturers selling GPUs, memory chips and other components to the software providers that rent compute time for their LLMs in data centers. Or, hyperscalers find billions of additional revenue above and beyond what is currently projected by analysts to lift the implied ROIC for the planned capex” (Klement and Reis 2026, 24).

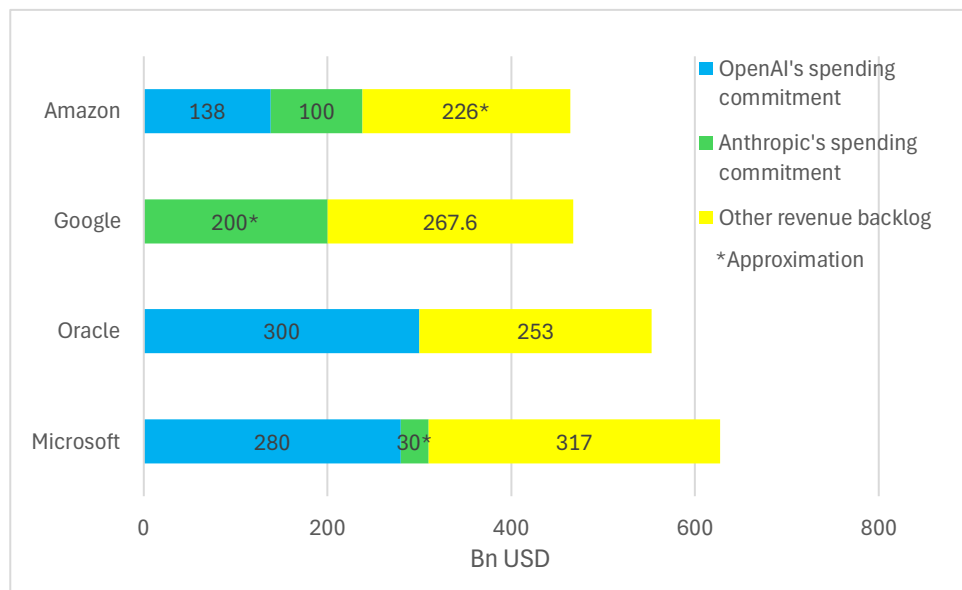
Figure 9 Hyperscalers' CAPEX to revenue ratio (Q1 2014-Q1 2026, companies' filings)



Part of hyperscalers' future revenue is covered by backlogs from signed contracts whose revenue has not yet been recognized (Muppidi et al. 2026; Zitron 2026a). They mostly cover cloud expenses. Figure 10 shows that, on average, 49% of the backlog revenue of Amazon, Google, Oracle, and Microsoft is committed by OpenAI and Anthropic. This interdependence mirrors the circular claims mentioned in section 5 and brings into focus the fragilities of the financials of the two AI startups.

Cloud payments, which are a source of revenue for hyperscalers, indeed represent a cost for the two AI startups. It contributes to concerns repeatedly raised by the financial press and investors regarding the future operational costs of OpenAI and Anthropic (Timcke 2026). Leaked financial statements, analyzed by author Ed Zitron and the Financial Times, have led analysts to conclude that OpenAI's net loss increased in 2025 to USD 38.5 billion, up from USD 5.09 billion in 2024 (Elder and Hammond 2026; Zitron 2026b). As with hyperscalers, the viability of AI startups' investments ultimately depends on their ability to generate significantly higher revenue over the coming years, and therefore on future demand for AI products. This is clear from Sam Altman's speech at the 2026 BlackRock Infrastructure Summit in Washington: "Fundamentally our business and I think the business of every other model provider is going to look like selling tokens [...] We see a future where intelligence is a utility like electricity or water and people buy it from us on a meter and use it for whatever they want to use it for [...]" (Spirlet 2026).

Figure 10: Hyperscalers' revenue backlog in March 2026 (data from Zitron (2026) based on Muppidi et al. (2026))



Altman's quote also hints at the shift in billing methods that happened in the first quarter of 2026. The revenues of AI firms such as Anthropic and OpenAI can be generated via two alternative pricing methods: consumer and firms' flat-rate subscriptions to applications, or usage-based billing, which charges according to the user's consumption of tokens (Timcke 2026). Following an established Big Tech business strategy, the provision of generative AI was initially subsidized by AI firms, which offered either free access or flat-rate subscriptions to incentivize customers to use their products (Rikap 2024). Yet, this price model is designed to be temporary, as it does not cover operational costs. Therefore, in early 2026, several AI firms, including OpenAI and Anthropic, extended token-based billing (John 2026).

The consequences of this shift for corporate clients quickly became apparent, as major firms faced surging AI costs and limits on their established AI use. Uber's Chief Operating Officer announced in late May 2026 that the company had already consumed its entire token budget for the year (Angelo 2026; John 2026). Amazon also indirectly acknowledged the rising costs of intensive AI adoption by removing an internal usage-score ranking dashboard that had incentivized employees to maximize token consumption and, in turn,

costs (Rosner-Uddin 2026b). Usage-based billing therefore challenges the ability of US AI firms to find sufficient demand and fuels doubts about future revenues.

Token-based billing also intensifies price competition between model providers. In July 2026, the Silicon Data LLM Token Expenditure Index indicated that the price users paid for AI tokens was nearly 20% lower than its peak in May 2026 (Barnert and Msika 2026). In addition, other models, in particular Chinese models such as DeepSeek and Minimax offer cheaper per-token rates. In July 2026, DeepSeek V4 Pro (Max) costs USD 0.04 for an index of tasks, against USD 0.48 for GPT-5.4 mini (xhigh) and USD 3.25 for Claude Fable 5 (Artificial Analysis 2026). US firms such as OpenAI and Anthropic are therefore caught between, on the one hand, growing concern about their ability to cover operational costs and, on the other hand, the need to withstand price competition.

Ultimately, the profitability of the token-based business model depends on whether returns for customer firms will offset token costs in the medium run, as explained by Amy Hood, Microsoft's Chief Financial Officer, in the firm's 2026 Q3 Earnings Call: "You'll just bill for usage, if that usage has great value to customers ... then you'll keep spinning [the meter], and they'll keep using those agents if they're adding direct value or growth to your business" (Millward 2026). The viability of AI firms is therefore still highly uncertain, as it depends on generating substantial productivity gains through the implementation of AI in work processes.

7. Obstacles to labor productivity improvement

Tech firms and AI investors promise that large-scale AI implementation will enable labor-saving automation of entire work processes. In February 2026, Sebastian Duesterhoeft, partner at the venture capital firm Lightspeed, explained: "AI is not an 'enterprise' software in the traditional sense of going after IT budgets: it captures labour spend, at some point you're taking over human workflows end to end" (Hammond 2026b). Based on technical efficiency, financial markets anticipate a significant contraction in the workforce, which would threaten entire economic sectors (Erin Lang 2026).

However, as Acemoglu and Johnson have argued, the macroeconomic effects of efficiency-increasing technological change depend on the institutional context (Acemoglu and Johnson 2023). Efficient technologies are not employed if they are unprofitable, and wasteful ones can be diffuse if they allow capital to capture gains. The global impact of AI on jobs and productivity remains uncertain, as its implementation depends on the ongoing development of regulatory and profit-making strategies at the firm level (Suss and O'Connor 2026).

Existing research suggests that, even if generative AI automation increases the efficiency of certain tasks when considered in isolation, scaling up productivity gains to long-term replacement of entire work processes and tangible benefits for firms is far from being automatic. Moreover, a growing body of evidence points toward AI's increasingly visible disruptions of the labor process –including quality failures and potential detrimental impacts on workers' skills and workplace coordination.

7.1. The gap between technical possibilities for task automation and actual economic gains

Randomized experiments and studies using firm-level data conclude that generative AI substantially increases productivity in specific tasks. The use of gen AI is found to reduce time spent and increase the quality of writing (Noy and Zhang 2023), coding (Cui et al. 2026; Peng et al. 2023), providing customer assistance (Brynjolfsson et al. 2025), and even some complex tasks within the consulting industry (Dell'Acqua et al. 2023). However, the possibility of scaling up the gains remains highly uncertain (Acemoglu 2025). Tasks that show the potential for important gains from automation in controlled settings are harder to automate in firms' complex organizational environments (Agrawal et al. 2024; Baily et al. 2025; Dell'Acqua et al. 2023).

An explanation for this gap is the weak link model, which considers single-task automation within the broader chain of tasks necessary to produce finished products (Jones 2026). Productive gains from automation are constrained by the presence of “weak links”: other tasks that are not automated and slow down the whole process (Demirer et al. 2026; Jones 2026). A 2026 study found that coding agents significantly

increase coding output of GitHub developers up to 180% cumulative effect, but gains from actual releases are far smaller (30%). According to the authors, “human bottlenecks” in later-stage tasks necessary for releases, such as pull request review and app launching, are responsible for this limitation (Demirer et al. 2026, 2).

Optimistic scenarios, however, postulate that such a gap might close over time. The productivity J-curve model, for example, explains the initial gap between the technological potential of non-specialized, diffusing, and improving technologies – usually called general-purpose technologies (GPTs) – and actual productivity gains. The model builds on the idea that “realizing the potential” of such technologies “requires large intangible investments, and a fundamental rethinking of the organization of production itself. Firms must create new business processes, develop managerial experience, train workers, patch software and build other intangibles.” (Brynjolfsson et al. 2021, 333). These intangible investments explain the potentially long-lasting drop in productivity following a technological invention, while acknowledging that this initial period is followed by important gains. In this scenario, if generative AI qualifies as a GPT, it will likely follow this trajectory, leading to important future productivity gains (Baily et al. 2025).

The J-curve scenario assumes that these technologies have positive effects on individual tasks that will eventually materialize at the organizational level as work processes are adapted. In the case of generative AI, however, substantial evidence points to disruptive effects on labor processes, calling this assumption into question.

7.2. Disruptions of the labor process

A growing body of research suggests that AI implementation not only fails to automatically yield productivity gains but may also negatively affect the quality of labor. The main reason is that, in many instances, AI use shifts critical-thinking effort from task execution to stewardship, as cognitive workers are increasingly required to guide, integrate, and monitor the quality of AI output, rather than exerting their own creative and critical cognitive capabilities through information gathering and problem-solving. Such a major disruption of the labor process poses a serious danger to workers’ capabilities, in

both their individual and collective dimensions, and to the quality of output, with the potential for negative productivity outcomes.

Dilution of learning through petty managerialization of knowledge work

Generative AI frequently produces mistakes that are difficult to detect. The 2026 International AI Safety Report flags five types of issues: hallucinations, basic reasoning failures, out-of-distribution failures, tool-use failures such as privacy breaches, and multi-agent system failures that lead to miscoordination and conflicts (Bengio et al. 2026, 72). According to the same report, “despite significant research efforts, no combination of methods ensures the high reliability required in critical domains. New training methods and giving AI systems access to tools can make failures less likely but usually do not eliminate them completely” (Bengio et al. 2026, 71). Beyond failures in critical domains such as medicine or law, individual examples of firms undergoing such problems are already visible. In 2026, Amazon, which had previously laid off 10,000 employees on the grounds of LLM integration, underwent a series of outages related to the use AI tools in coding (Rosner-Uddin, Georgiadis, et al. 2026; Rosner-Uddin 2026a). Management is now more cautious about AI, and less experienced engineers need approval from senior employees to implement AI-suggested changes (Rosner-Uddin 2026a).

Not only do these failures lead to costly mistakes and outages, but the mere possibility of AI-related errors also requires employees to spend more time verifying AI outputs (Becker et al. 2025). Because generative AI can produce high-quality content, it is difficult for workers to understand its errors and limits. Dell’Acqua and colleagues call point to this phenomenon the “jagged productivity frontier” of AI (2023), meaning that the tasks in which it obtains better results are similar to those where mistakes are frequent. Accordingly, since tasks in which AI programs perform best are the ones usually attributed to junior professionals and since supervision by senior is still necessary, “people will stop delegating work inside the frontier to junior workers, creating long-term training deficits” (Dell’Acqua et al. 2023, 202).

In sum, automating tasks within the range of generative AI’s best performance destroys the crucial space for learning by doing (Anzai and Simon 1979), depriving the younger generation of the opportunity to acquire the competences necessary to recognize AI’s

errors and limitations. The petty-managerialization of AI thus allows for increasing output while progressively eroding the ability to monitor the quality of that output.

Deskilling, demotivation and exhaustion of individuals

At the individual level, there is mounting evidence that AI leads to widespread skill degradation and demoralizing effects. A growing body of research points to erosion of cognitive and critical thinking capabilities associated with AI use (Bastani et al. 2025; Strömberg et al. 2026; Kosmyna et al. 2025; Lee et al. 2025; Tian and Zhang 2025). The ability to attain an acceptable result with low effort has been linked to a “mediocrity trap”, where workers lose work engagement and motivation to strive for better results (Y. Chen et al. 2025). Some studies also indicate that in some contexts, AI use can contribute to various forms of fatigue, as ceaseless changes in the organization of work, the increasing turnover of tools, the abundance of AI-generated input, and frequent multitasking could result in cognitive strain, attention depletion, and information overload (Han 2027; Shalu et al. 2026; Savolainen et al. 2026; Ranganathan and Ye 2026)

Deterioration of the labor collective and the risk of a general knowledge collapse

Beyond individual capabilities, Generative AI can also affect the labor process at the collective level. The first negative channel could be the deterioration of workers’ cooperation. The surge in AI-produced output of mediocre quality (“workslop”) creates a downstream surplus of work, resulting in mounting defiance and frustration among people on the receiving end, thereby decreasing trust among colleagues and weakening teamwork and cooperation (Niederhoffer et al. 2025). The second one proceeds through a theoretical vicious feedback loop: improving the quality of agentic AI could lead to better local performance but could also result in AI substituting for human effort to produce general knowledge, ultimately diminishing the quality of agentic AI itself and risking general knowledge collapse (Acemoglu et al. 2026). A complementary mechanism suggests that as access to the original diversity of human knowledge is increasingly mediated by a narrow subset of views, common beliefs will gain preeminence while more marginal views will be discarded, cumulatively restricting the space of learning and discovery (Peterson 2025).

The cooperative dimension of the labor process and the production of general knowledge are intimately related, as noted by Matteo Pasquinelli, who advances that AI is « implicitly sociomorphic – aiming to encode the forms of social cooperation and collective intelligence in order to control them.» (Pasquinelli 2023, 160). In such a perspective, the lack of engagement in cooperation manifests in the surge of AI slop and the potential collapse of general knowledge are the two sides of the same phenomenon.

An AI productivity inverted J-curve?

Dilution of learning processes, demoralization, and deterioration of the collective forces of labour are cumulative and affect the quality of work (Table 1). Therefore, even if generative AI improves significantly efficiency on tasks measured at the individual level, such technical prowess, measured in isolation, does not necessarily translate into economic gains for firms whose performance relies on complex cooperative labor processes.

Table 1: Main mechanisms related to AI use detrimental to labor productivity

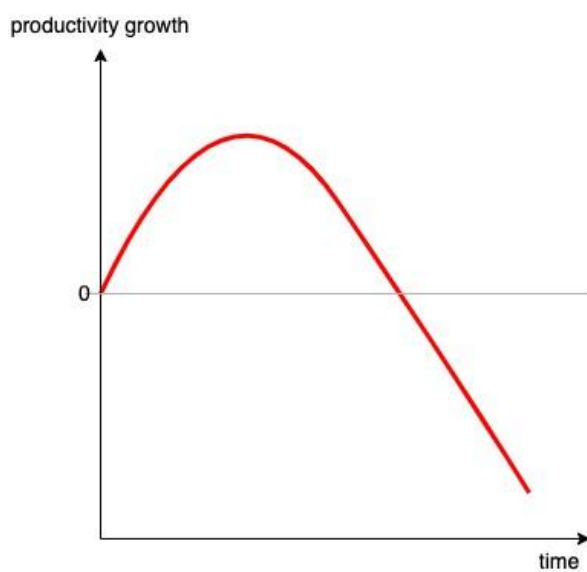
OBSTACLES TO PRODUCTIVITY	
Dilution of learning processes	Automation destroys learning-by-doing opportunities for junior professionals, resulting on the lack of reproduction of senior capabilities to supervise automated process
Demoralization of labour	Individual worker effective investment in labor is debilitated by loss of skills, demotivation, and emotional exhaustion
Deterioration of the collective forces of labor	Workslop deteriorate the quality of cooperation while diminishing quantity of individual contribution and reduced diversity deplete general knowledge

Standard productivity J-curve models posit an adaptation to disruptive technological change driven by individual firms’ intangible investments. However, given the depth and the multiple paths through which GenAI’s negatively affects labor at the individual and collective level, another hypothesis is worth considering, according to which the impact is too disintegrative to be compensated by adjustments of production processes within individual businesses. If significant, AI’s multifold negative impact could imply an

inverted-J-curve scenario, in which short-term productivity gains would be offset by a general deterioration in work quality in the medium run (Figure 11).

The inverted J-curve hypothesis highlights two sides of capitalist automation. On the one hand, it is a serious threat to workers' well-being, motivation, and collective mastery of working processes. On the other hand, automation could also be self-defeating for capitalists due to rising costs associated with the erosion of labor-process quality.

Figure 11: The possibility of a productivity inverted J-curve



8. Conclusive discussion: AI Winter or AI Gloom?

Figure 12 proposes a stylized summary of the three interlocked paths to crisis that we distinguished in the previous sections. Fueled by optimistic beliefs about future returns (the AI hype), the boom is supported by abundant funding driven by circular deals that enable the expansion of subsidized provision and the rapid buildup of capabilities. However, the rosy scenario of an AI summer described in section 4 could be derailed if

sophisticated financial engineering and coordination challenges result in financial strain and higher costs, leading directly or indirectly – i.e., via slowing supply and /or demand and/or increased competition – to mounting losses and bankruptcies. On the production side, AI use could also disappoint if disruptions to the labor process prevent the realization of the expected productivity gains that motivate firms to adopt AI in the first place, thereby slowing the final demand for AI services and preventing the materialization of income projections that justify the surge in upstream CAPEX.

An upward trend in interest rates amid rising febrility in the debt market, fueled by the AI boom itself, could be a crisis-triggering factor, but a failed IPO, real mismatches along the value chain, surging competition, or a lack of demand could also play that role. One of these scenarios is currently expected by many analysts, the general sentiment being that the boom is not sustainable. However, the discussion regarding the shape, extent, and distribution of the losses of an AI crisis is only beginning.

In that regard, Figure 12 suggests two potential types of outcomes. AI winter indicates that devalorisation of capital along the AI value chain will ultimately lead to a substantial contraction of AI capabilities and, accordingly, a retreat of the availability and uses of AI services. In that perspective, AI would not become a General Purpose Technology, but rather a costly tool whose lasting deployment would be limited to some corner of the economy. By contrast, AI gloom points to a scenario in which, while productivity gains expected from AI fail to materialize, there will not be a general retreat of AI use. Due to the lasting technological lock-in effect of the current subsidized deployment of AI across the corporate landscape, the cost of scaling back AI would be prohibitive, hooking most organizations on AI.

In such a configuration, some devaluation could hurt segments of the AI value chain, for instance, highly leveraged model developers such as OpenAI and Anthropic, but that would not lead to bankruptcies or major losses for US Big Tech firms, nor to a general retreat in AI use. The central positioning of Amazon, Meta, Google, and Microsoft in global knowledge and innovation networks would persist, along with their unique combined capabilities to secure profits, including via partnerships and strategic alliances that enable them to spread innovation costs and capture customers (Rikap 2026). Hyperscalers' cloud services are necessary for developing AI products and allowing inferences for their use. Therefore, even intensified competition at the segment level

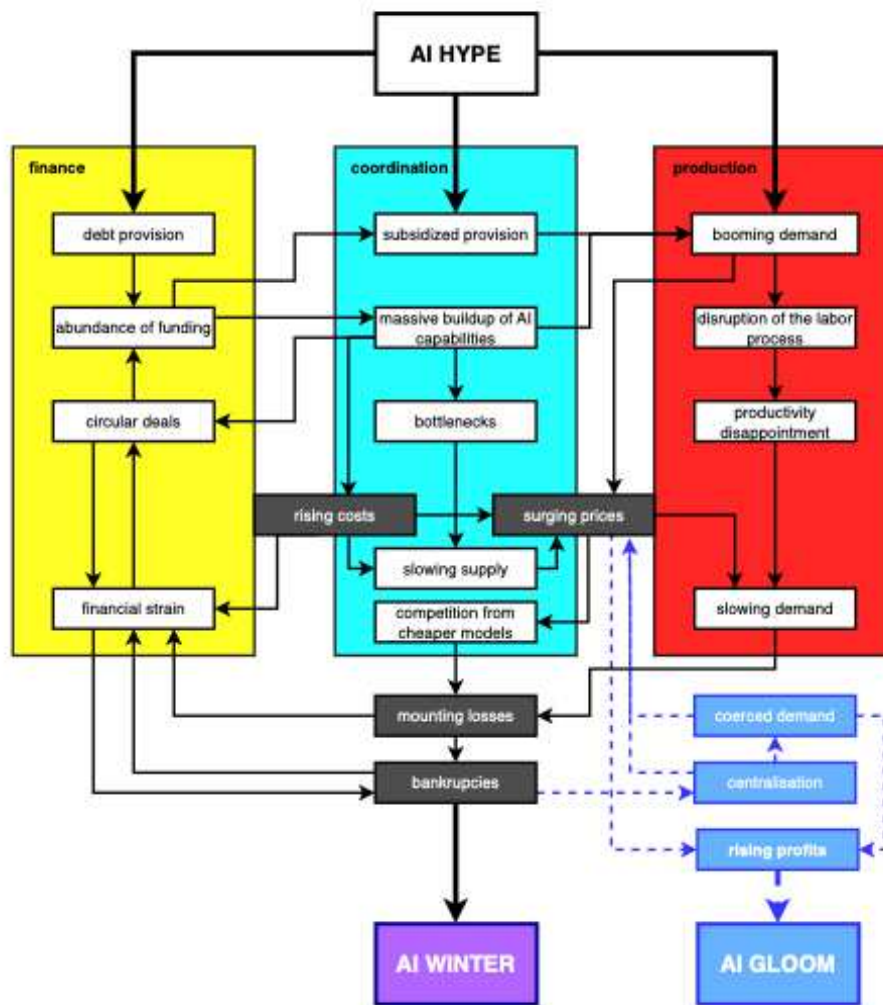
would not necessarily hurt these firms' revenue, as they provide the general digital infrastructure necessary for contemporary large-scale digital services.

Moreover, with the *Mission Genesis* (US Executive Order 2025) on the domestic front and *Pax Silica* (US Department of State 2026) at the international level, the US government made clear its commitment to support the US-led AI ecosystem financially and to deploy a supportive regulatory and security framework to counter Chinese competition (Morozov 2026). The intent to secure the state as a backup option is a general trend across the AI industry. A striking example is the proposal by OpenAI executives, disclosed in July 2026, that each major US AI firm could give the US government a 5% stake (Criddle and Hammond 2026). Tech firms are also increasingly turning to defense contracts to offset lower-than-expected revenue from business subscriptions (Saad-Filho and Taggart 2026).

Even if an AI crisis spills over into the broader macroeconomy, provoking a severe recession, coerced demand and state backing could help Big Tech strengthen its position by increasing concentration. Depending on the dynamic of state support, socialization of the losses could also insert AI in a broader pattern where the US state hands over public assets and governmental capabilities to Big Tech, extending their structural power (Mann 1984; Fourcade and Healy 2016) and reinforcing their hybrid political and economic status of actors championing the advent of a technofeudal social order (Durand 2024).

This contribution focuses primarily on the US AI development path and overlooks many crucial dimensions of AI's future. Most importantly, what is lacking is a comparative outlook on the Chinese AI development path and its broader implications for competitive regimes, class relations, and other countries' developmental space. We leave those crucial issues for future research.

Figure 12: From AI hype to winter and gloom: the unfolding of overaccumulation dynamics



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