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Artificial Intelligence and the Limits of Accumulation: Capital, Crisis, and the US Hegemonic Autumn in the World Market

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Abstract: Contemporary capitalism is characterised by persistent overaccumulation, declining profitability, and intensified financialisation under conditions of hegemonic instability. This article argues that the recent surge in artificial intelligence (AI) investment functions less as the basis of a new productive regime than as a crisis response within financialised capitalism. Drawing on Marxian crisis theory, social structures of accumulation, and theories of hegemonic transition, the article shows how unprecedented AI capital expenditure coexists with persistent operating losses, speculative valuations, and fragile revenue models. These patterns indicate a flight toward financial expansion characteristic of hegemonic autumn. By reframing AI as a manifestation of accumulation crisis and hegemonic instability, the article challenges accounts that treat it as an autonomous driver of capitalist renewal.

Keywords: artificial intelligence; financialisation; hegemonic transition; crisis theory; global political economy

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1. Introduction

The contemporary wave of investment in artificial intelligence (AI) is unprecedented in both scale and concentration. By 2025, private AI investment in the United States had reached US$285.9 billion, more than twenty-three times the level recorded in China and nearly fifty times that of the United Kingdom (Stanford HAI 2026). On a global scale, out of the US$344.7 billion in total private AI investment, nearly half (approximately US$163.6 billion) was directed toward generative AI alone, with overall global private funding surging by 127.5 percent in a single year (Stanford HAI 2026). Yet the significance of this investment lies not only in its volume but also in its material form. AI development increasingly depends on vast fixed-capital infrastructures like hyperscale data centres, specialised semiconductor fabrication, dedicated energy systems, and globally integrated computational networks. As of last year, the United States hosted nearly 5,500 operational data centres, far more than any other country,

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underscoring the extreme geographical concentration of the computational infrastructure underpinning contemporary AI production (Stanford HAI 2026). Alongside this infrastructural expansion, frontier AI firms achieved valuations on a scale rarely witnessed in the history of capitalism. OpenAI attained a valuation of US$300 billion following a US$40 billion funding round in 2025, while Anthropic's valuation rose from US$61.5 billion in March 2025 to approximately US$965 billion by mid-2026, propelled by a massive surge in enterprise adoption that pushed its annual recurring revenue to US$47 billion (Reuters 2025a; Reuters 2026a). Taken together, these developments point to both technological innovation as well as the consolidation of an accumulation strategy anchored in computational infrastructure, platform control, and concentrated ownership of productive assets.

However, while this accumulation strategy projects an image of boundless growth, this article argues that AI development should be understood less as the emergence of a new productive regime than as a crisis response within financialised capitalism under conditions of hegemonic instability. Instead of inaugurating a sustained phase of material expansion, AI investment bears the characteristic features of accumulation under strain, including rising capital intensity, weak or uncertain valorisation, speculative valuation detached from current profitability, and growing dependence on credit and equity finance to sustain ongoing losses (Covello and Nathan 2024; Tsui et al. 2026). These dynamics closely resemble the patterns Marx identified in *Capital Volume III* as expressions of overaccumulation and the tendency of the rate of profit to fall, as well as the dynamics Giovanni Arrighi associated with financial expansion during periods of hegemonic transition. In this sense, AI is not separate from contemporary crisis tendencies; it is one of their most advanced expressions.

Situating AI development within critical international political economy requires moving beyond techno-determinist narratives that treat technological innovation as an autonomous driver of growth. Mainstream accounts frequently portray AI as a general-purpose technology capable of revitalising productivity, overcoming stagnation, and restoring profitability across advanced capitalist economies. Such accounts detach technology from the social relations and institutional contexts in which it is developed and deployed. By contrast, this article treats AI as a historically specific form of capital investment shaped by existing accumulation regimes, class relations, and geopolitical hierarchies. At stake, then, is not whether AI is technologically impressive, which is uncontested, but whether its current mode of development can resolve capitalism's structural contradictions.

To address this question, the article synthesises three strands of critical political economy scholarship. First, it draws on Marxian crisis theory, particularly analyses of the rising organic composition of capital, barriers to valorisation, and the proliferation of fictitious capital under conditions of overaccumulation. Second, it engages social structure of accumulation (SSA) theory to examine how institutional configurations shape the profitability and sustainability of new accumulation strategies, highlighting the fragility and incoherence of the regulatory, financial, and geopolitical environments surrounding AI development. Third, it mobilises the theory of hegemonic transition, especially Arrighi's account of systemic cycles of accumulation, to situate AI investment within the broader arc of the hegemonic decline of the United States and the shift from material to financial expansion. Through this synthesis, AI can be read at once as productive investment, speculative asset, and geopolitical instrument.

Empirically, the article documents the capital structure of the AI sector between 2022 and 2025, drawing on corporate disclosures, industry reports, and independent research such as Stanford's AI Index. The evidence reveals a sector marked by rapidly escalating training costs, extreme capital intensity, fragile and contested revenue models, and valuation metrics that price in speculative expectations rather than realised surplus value. Such features point to significant barriers to both valorisation and realisation, raising doubts about AI's capacity to function as a stable accumulation regime. Rather than resolving stagnation, AI development risks intensifying the contradictions of financialised capitalism.

Finally, the article situates AI development within global structures of uneven development and unequal exchange. AI value chains depend on drawing surplus from peripheral labour through data annotation, hardware manufacturing, and the construction of resource-intensive infrastructure, while control over intellectual property, computational capacity, and market access remains concentrated in core-based firms. This configuration reinforces existing core-periphery hierarchies and limits the developmental prospects of peripheral economies, even as AI is rhetorically framed as a universally transformative technology. Understanding AI as a crisis response within the world market thus clarifies both its geopolitical significance and its developmental limits.

2. Theoretical Framework: Accumulation Crisis, Hegemonic Cycles, and Unequal Development

2.1. Marx's Theory of the Falling Rate of Profit and the Digital Commodity Problem

Marx's (1959) analysis in *Capital Volume III* provides one theoretical foundation for understanding AI's economic contradictions. The tendency of the rate of profit to fall is not a deterministic law but a structural dynamic arising from capitalism's internal contradictions. The tendency expresses the effects of technological competition in which individual capitals substitute machinery for labour to gain competitive advantage. The organic composition of capital captures this shift as the rising ratio of constant capital (machinery, infrastructure, raw materials) to variable capital (labour power). Since surplus value originates only in labour power, increases in the organic composition place downward pressure on the rate of profit, defined as surplus value relative to total capital advanced. Individual firms may raise absolute surplus extraction, but the aggregate effect of labour-saving innovation is to intensify capital density whilst eroding the relative basis of surplus value[1].

The structure of AI production is consistent with a rapid rise in capital intensity. Precise magnitudes are difficult to verify given the absence of audited accounts for leading frontier AI firms such as OpenAI, Anthropic, and xAI. Available estimates nevertheless indicate steeply rising training costs across successive model generations. For example, GPT-3 required several million dollars in compute, while GPT-4 is generally estimated at roughly US$50-100 million, a figure not officially disclosed (Brown et al. 2020; Cottier et al. 2024). Industry projections further suggest that frontier model training could reach US$500 million to US$1 billion per run under current scaling trajectories (Henshall 2024). These expenditures primarily reflect compute infrastructure, energy use, and semiconductor inputs, all forms of constant capital, while labour costs, including research engineers and outsourced data annotation workers, remain comparatively small (Noy and Zhang 2023; Perrigo 2023). Additional capital commitments extend to data centre construction, cloud infrastructure, long-term energy procurement, and grid expansion. Senior AI researcher salaries are substantial in absolute terms but marginal against hyperscale fixed investment. AI production thus exhibits a strongly capital-intensive structure consistent with a rising organic composition of capital, though this is an inference rather than a reading of audited firm-level data.

The centrality of energy and physical infrastructure reinforces this interpretation. The International Energy Agency (2025a, 2025b) projects that data centres will account for more than one-fifth of electricity demand growth in advanced economies by 2030, with major technology firms committing tens of billions of dollars to power generation, transmission upgrades, and long-term energy contracts (Reuters 2026b). This dynamic requires attention to the status of trained models within Marx's categories. Marx distinguishes fixed capital, which participates in multiple production cycles, from circulating capital consumed within a single cycle. Trained AI models function as fixed capital. Once training is complete, they can be deployed repeatedly at near-zero marginal cost. Unlike material commodities, their reproduction cost is effectively negligible as serving additional users requires minimal additional labour or energy expenditure. The non-

[1] Recent scholarship has extended Marx's insights to contemporary conditions. David Harvey (2006) analyses overaccumulation crises requiring geographical expansion and temporal displacement through credit, the proverbial "spatial fixes". Robert Brenner (2002) documents persistent manufacturing overcapacity and declining profitability since the 1970s, arguing that neoliberalism represents crisis displacement as opposed to resolution. Andrew Kliman (2011) defends Marx's falling rate of profit against critiques, demonstrating its empirical validity across advanced capitalist economies. Using data in the internal rate of return on capital stock, a good proxy for the Marxian rate of profit, recent empirical work by Michael Roberts (2020) calculates declining rates across G20 economies from 1950. This is probably the closest one can get to a "world rate". Weighting national profit rates by GDP across 14 countries back to the 19th century, Esteban Maito (2018) identified a clear downward trend in the world rate of profit, though with periods of partial recovery in both core and peripheral countries.

rivalry of AI systems sharpens this problem. AI systems can serve multiple users simultaneously without degradation, generating scale effects irreducible to labour inputs. Value expansion depends on network effects, market position, and data feedback loops rather than on direct labour expenditure. These conditions encourage speculative valuation, in which market price reflects expected future surplus extraction rather than realised labour time, a structural tendency toward disjunction between capital committed and value produced.

AI accumulation thus increasingly depends on large-scale mobilisation of fixed capital and energy infrastructure instead of labour-intensive production, an intensification that ties the valorisation of digital capital directly to physical and energy systems at historically unprecedented scale. AI development resembles earlier industrial phases in which expansion depended on reproducing the means of production at ever-greater scale; it departs from them by shifting the frontier of accumulation toward computational infrastructure, deepening dependence on constant capital investment.

This structure produces a specific problem for value theory. Training embeds socially necessary labour time and represents a determinate moment of value production; post-training distribution does not, however, map onto traditional commodity reproduction costs. Value must be realised through deployment and usage revenue rather than through repeated production. Where realised revenue fails to cover the large upfront capital expenditure, losses concentrate in the initial training investment, a form of realisation risk particular to extreme fixed-cost structures. Valorisation is therefore the binding constraint on AI accumulation. The transformation of large upfront investments into realised surplus value through deployment is not a secondary commercial problem but the primary contradiction of the sector. Where sufficient returns are not achieved, the result is capital devaluation. Marx's theory of crisis locates such breakdowns not in any shortage of use-values but in insufficient valorisation relative to capital advanced. Examined through these frameworks, AI production represents not a departure from capitalist dynamics but their intensification. Put differently, it seems to be an accumulation regime built on large-scale fixed investment and speculative expectations of future surplus value that has yet to demonstrate its capacity to valorise the capital it commands.

2.2. Social Structures of Accumulation and Institutional Crisis

Social Structure of Accumulation (SSA) theory provides a complementary framework by emphasising the role of institutions in shaping accumulation dynamics (Gordon, Edwards, and Reich 1982; Kotz, McDonough, and Reich 1994; McDonough, Reich, and Kotz 2010). Where Marx's theory illuminates capital's internal contradictions, SSA theory explains how institutional arrangements either contain or exacerbate those contradictions. Sustained capital accumulation requires coherent institutional frameworks spanning labour relations, competitive structures, financial systems, and state involvement. When SSAs function effectively, they facilitate profitability and growth. As contradictions accumulate, however, SSAs require reform; otherwise, crisis follows.

The postwar SSA in the United States rested on specific institutional arrangements, including collective bargaining structures that limited wage competition, oligopolistic market regulation that prevented destructive competition, the Bretton Woods monetary system that stabilised international finance, and Keynesian state management that moderated cyclical instability. The breakdown of these arrangements during the 1970s, manifested in declining profitability, stagflation, and the collapse of Bretton Woods, required fundamental restructuring (Kotz 2015). Neoliberalism emerged as the subsequent SSA, characterised by union suppression, deregulation, financialisation, and globalised production (Kotz 2015; Lippit 2010). Yet neoliberalism's contradictions, including growing inequality, financial instability, and environmental crisis, suggest the exhaustion of its institutional foundations. The 2008 financial crisis, incomplete recovery, and political polarisation indicate systemic difficulties comparable to those preceding earlier transitions (Kotz and McDonough 2010).

Neoliberal institutional frameworks constrain state intervention through trade agreements, intellectual property protection, and financial liberalisation (Wade 2003). Technological complexity has intensified, requiring capabilities beyond those necessary for earlier industrialisation. Moreover, core states leverage national security concerns to restrict technology transfers, particularly in advanced semiconductors and AI systems. The securitisation of technology contradicts the hyper-globalisation that characterised neoliberal hegemony, revealing institutional breakdown. Vivek Chibber (2003) is right to criticise much of the developmental state literature for neglecting the class relations that structure state capacities. Business resistance to state direction, working-class political organisation, and international pressures shape states' ability to implement transformative policies. For peripheral economies approaching AI development, these class dynamics intersect with technological constraints, making capability building an explicitly political problem. The question becomes not whether peripheral states can replicate late twentieth-century developmental strategies, but whether AI's capital intensity and geopolitical securitisation preclude such strategies entirely.

Viewed through the SSA lens, AI development represents a technological investment response to institutional crisis. Massive investment amid uncertain profitability signals capital's search for new valorisation opportunities as traditional sectors stagnate, while geopolitical fragmentation around AI governance reveals the breakdown of neoliberal globalization's institutional coherence. In short, existing arrangements are failing to sustain profitability, and capital is responding by seeking new accumulation frontiers.

2.3. Hegemonic Transition within Systemic Cycles of Accumulation

Giovanni Arrighi's (1994) framework of systemic cycles of accumulation situates capitalist development within centuries-long patterns of hegemonic rise and decline. Drawing on Braudel and incorporating Marx's analysis, Arrighi identified recurring cycles in which leading capitalist powers organise world markets through distinct institutional arrangements analogous to SSAs. Each cycle passes through phases of material expansion (productive investment and trade growth) and financial expansion (capital migration toward speculative finance). Financial expansion, Arrighi argued, signals hegemonic autumn because, as productive investment opportunities diminish in the hegemon's core industries, capital seeks returns through financial channels. This shift reflects structural transformation, often culminating in hegemonic crisis and eventual succession. The Dutch cycle (fifteenth to seventeenth centuries), British cycle (eighteenth to nineteenth centuries), and American cycle (twentieth century) each followed this pattern.

Contemporary scholarship has extended Arrighi's analysis to current conditions. William Robinson (2011) assesses Arrighi's framework, noting its power in explaining historical transitions while questioning assumptions about Chinese hegemonic succession. Arrighi himself (2007) suggested that China's developmental path might offer alternatives to Western capitalism's patterns, emphasising cooperative South-South relationships over exploitative imperialism. Critics, however, note that China's global economic integration reproduces capitalist dynamics (Harvey 2003), Chinese corporations engage in exploitative labour practices domestically and internationally (Hung 2009), and state capitalism concentrates power without necessarily distributing benefits equitably (Kiely 2015). Such critiques caution against wishful accounts of a putatively benevolent Chinese hegemony.

Pointing to the enduring structural advantages of American power, Ray Kiely (2015) critiques assumptions about automatic Chinese hegemonic succession. Kiely emphasises US advantages in military dominance, dollar hegemony, and technological leadership; currently, only some of these advantages remain fully intact. China, for its part, faces constraints from environmental limits, demographic pressures, and tensions inherent in authoritarian government. For present purposes, Arrighi's framework enables an examination of AI development within broader hegemonic trajectories. Massive US AI investment combines material expansion characteristics (computational infrastructure and research facilities) with financial expansion features (inflated valuations, speculative orientations, and operational losses). This duality suggests neither confident hegemonic renewal nor clear hegemonic transition, but rather conditions in which AI represents a desperately sought yet structurally problematic accumulation pathway, extending earlier analyses of digital infrastructure and American paramountcy (Timcke 2014; 2017).

2.4. Unequal Exchange and Peripheral Subordination

Dependency theory and unequal exchange scholarship arose to analyse how capitalism structures global inequality through market relations themselves (Emmanuel 2025; Amin 1976; Frank 1966; Wallerstein 1974). Arghiri Emmanuel's core insight, that formally equal market exchanges of commodities embodying unequal labour time create systematic value transfer from periphery to core, challenged liberal trade theory's assumption of mutual benefit. Despite productivity parity, peripheral wages remain systematically lower because of labour immobility, creating unequal exchange. Zak Cope

(2019) demonstrates how wage differentials enable core working classes to benefit from the super-exploitation of peripheral labour. John Smith (2016) argues that globalised production creates "value capture," through which Northern-headquartered corporations appropriate surplus value created by Southern workers through outsourcing and subcontracting arrangements. Jason Hickel and colleagues (2022) seek to quantify the net flow of appropriation from South to North through unequal exchange. Their econometric analysis estimates US$2.2 trillion in annual net appropriation from the Global South to the North, dwarfing official development assistance flows and demonstrating the systematic character of core-periphery exploitation. Contemporary scholars have extended these insights beyond manufacturing to new sectors such as digital labour and knowledge appropriation (Fuchs 2014; Rigi 2014).

For technology development, unequal exchange operates through multiple channels that AI intensifies, including the international division of labour.[2] Hardware manufacturing occurs predominantly in China or peripheral and semi-peripheral economies like Vietnam, Malaysia, or the Philippines, while profit margins concentrate in corporations based in core economies that control intellectual property and market access, often routing revenues through tax havens like Ireland, the Netherlands, Bermuda, and the Cayman Islands to minimise tax obligations and maximise capital accumulation. Software development uses peripheral labour for coding, testing, and maintenance at wage rates far below core equivalents, a differential reflecting not productivity differences but the super-exploitation enabled by imperialism.

Data annotation is another example of extreme unequal exchange. Kenyan annotators earning $1–2 hourly produce training data for models generating billions in value for corporations headquartered in core economies (Tubaro, Casilli, and Coville 2020). The magnitude of this value transfer becomes clear when considering that a data annotator earns approximately $2 per hour. Working conditions in digital labour mediated through platforms feature piece-rate payment that creates income volatility, absence of labour protections, algorithmic management that prevents collective organisation, and geographic isolation that fragments worker solidarity. These conditions enable extreme surplus extraction, with platform intermediaries capturing substantial portions alongside primary AI companies.

3. AI Market Structure

3.1. Primary and Secondary Market Dynamics

AI development divides into two distinct market segments, each with different capital requirements, competitive dynamics, and mechanisms of value creation. The primary

[2] The international division of labour is a dynamic with structural roots in the plantation form of peripheral capitalism, where enclave production and value extraction for metropolitan accumulation established durable patterns that digital capitalism inherits (Fuchs 2016, Timcke 2023b).

market encompasses foundational model developers such as OpenAI, Anthropic, Google DeepMind, xAI, Meta AI, and Mistral. These developers require extensive computational infrastructure and proprietary training data. According to Stanford's 2025 AI Index Report, nearly 90 percent of notable AI models in 2024 came from industry sources, up from 60 percent in 2023 (Stanford HAI 2025), indicating the exclusionary effects of capital intensity on academic participation. The shift from academic to industry dominance marks a qualitative transformation in AI research, driven by capital requirements rather than intellectual capability.

Investment requirements have escalated dramatically. As noted above, training GPT-4 reportedly required roughly US$100 million in compute, and subsequent models are likely to demand far greater expenditures. OpenAI's US$300 billion Oracle computing agreement equals the company's entire market valuation (Metz 2025). This signals either extraordinary confidence in future profitability or systematic overvaluation. The Stanford AI Index (2025) documents that training compute doubles every five months, with datasets doubling every eight months and power consumption doubling annually. Signing bonuses for top AI researchers now reach the nine-figure range, and maintaining competitive research teams is approaching US$1 billion per year. Microsoft, Google, and Meta each committed US$60-100 billion toward AI infrastructure for 2024-2027, with Meta raising its 2025 capital expenditure guidance to US$66–72 billion, up from the previous US$64-72 billion range (Meta Platforms 2025). Capital requirements at this scale exceed the reach of most peripheral governments and many national firms in core economies, even if they sought to pursue a state-led project. A handful of corporations now control the material foundations of future development, effectively creating a near-global oligopoly in AI infrastructure. The question is how sustainable these dynamics are.

Despite massive valuations, primary market companies operate at persistent, substantial losses. OpenAI's reported $12 billion annual recurring revenue (July 2025) corresponds with per-request losses and negative cash flow. xAI reportedly loses $1 billion each month. Anthropic's $61 billion valuation rests on $5 billion annual revenue, a 12x multiple requiring sustained growth to justify. The tension between massive valuations and negative cash flow is a defining feature of the primary AI market. For instance, in-depth financial tracking reveals that while frontrunners like OpenAI and Anthropic dramatically scaled their revenues toward the multi-billion-dollar mark, these gains are consistently offset by the astronomical costs of inference and training compute (Ramzanali 2026).

Three revenue models are currently in use, each facing financial sustainability challenges. The first involves selling computational access to AI models, which provides relatively stable revenue but faces margin compression as competition intensifies. Price wars between providers may drive per-token costs downward while underlying computational expenses remain fixed. The same applies to competition from open-source models. The dynamic mirrors telecommunications infrastructure competition, in which capital intensity meets commoditisation pressures.

The second model, selling AI capabilities to corporate clients through enterprise subscriptions, promises higher margins. This revenue model requires a clearly demonstrated value proposition for those enterprises. McKinsey's 2025 survey indicates that while 92 percent of organisations wish to use AI in at least one business function, enterprise commitment remains experimental, with limited evidence of sustained profitability improvements sufficient to justify current subscription pricing (Mayer et al. 2025). Enterprise adoption also creates switching costs that must be accounted for.

Third, consumer applications such as ChatGPT Plus and Claude Pro generate revenue, but they face difficulties involving user acquisition costs, retention challenges, and competition from free alternatives. Pure API provision may also be insufficient. Claude Code reportedly emerged as the fastest-growing enterprise software product in history. It scaled from zero to a US$1 billion annualised run-rate within six months of its public launch and surpassed US$2.5 billion by early 2026 (Reuters 2026c). This suggests that sustainable growth may require vertical integration into user-facing applications. Such integration arguably reflects the market's push to embed AI directly into client-side files and workflows in order to build user lock-in and justify enterprise spending. This revenue base matters because it shows that AI companies face not only short-term losses during market establishment but also potentially permanent barriers to profitability under current capital structures.

Secondary market companies are building specialised user-experience applications atop foundational models. Investor enthusiasm for AI-enabled software has produced extraordinary valuations. Cursor reached a US$10 billion valuation in 2025, Windsurf was valued at roughly US$3 billion, and productivity platform Notion achieved a US$10 billion valuation after its 2021 funding round (Konrad 2021; Temkin 2025; Tong and Hu 2025). These premiums reflect expectations about strategic positioning, user lock-in, and data accumulation. Network effects in secondary markets create winner-take-all dynamics in which early movers accumulate user and data advantages that later entrants struggle to overcome, driving consolidation pressures. The extraordinary market valuations achieved by these applications reflect what economic literature identifies as strategic positioning and the accumulation of workflow data. By capturing user workflows early, they capitalise on network effects that insulate them from underlying API price fluctuations.

Mindful of fragile revenues, some primary market companies could push into the application layer, creating pressures toward vertical integration. Alternatively, they could position themselves as defence contractors or play on modernisation anxieties in the Global South to sell to states seeking to "catch-up" to advanced economies. Such expansion would intensify capital requirements, not resolve them. OpenAI, for example, could either acquire secondary market companies at premium valuations or invest massively in developing competing applications internally. Both strategies would exacerbate capital allocation challenges. Moreover, secondary market dynamics feature network effects and switching costs that favour early movers, further intensifying consolidation pressures. If integration deepens between foundational models and applications, the market structure may evolve toward vertically integrated oligopolies controlling both infrastructure and applications, replicating patterns evident in other digital platform markets. The anticipated endgame would be less a competitive marketplace than market power concentrated to degrees exceeding even current technology monopolies.

3.2. Training Data Constraints and Innovation Plateaus

Advances in large language models between 2022 and 2024 broadly followed OpenAI's scaling laws, which predicted performance improvements through increased computational scale, training-data volume, and model size (Kaplan et al. 2020). However, multiple indicators suggest that approaching these limits could materially affect current valuations. Villalobos et al. (2024) project that language models will exhaust human-generated public text between 2026 and 2032, with high-quality training data depleting even sooner. Synthetic data can certainly provide value for computer vision and image generation. Yet language models require grounding in authentic human communication patterns that synthetic generation struggles to replicate. Training on AI-generated text creates degradation risks as errors and biases compound. Judicial rulings on copyright litigation may also restrict access to substantial portions of high-quality training data, underscoring the intense search for human-generated public text.

GPT-5's August 2025 release was underwhelming relative to expectations set by earlier models. While subsequent improvements occurred, initial reception reinforced concerns about approaching ceilings under current paradigms (Marcus 2025). The constraints suggest that continued performance improvements require either future algorithmic breakthroughs or massive expenditure increases with diminishing returns. Both scenarios challenge assumptions underlying current valuations, indicating that the capital-intensive scaling approach may face hard limits sooner than investors anticipate.

4. AI Development as Manifestation of Falling Rate of Profit

4.1. The Hypothesis of the Rising Organic Composition of Capital in AI Production

Marx analysed how capitalist competition drives a rising organic composition of capital, meaning the ratio of constant capital (means of production) to variable capital (labour power). Technological competition pushes individual capitals toward labour-saving innovations, thereby raising the organic composition. Since only labour power creates surplus value in Marx's framework, a rising organic composition undermines the basis of profit itself. As the share of constant capital rises, the profit rate tends to decline despite increasing absolute surplus extraction. With organic composition rising faster than in traditional manufacturing, AI development takes this dynamic to an extreme.

Consider the capital requirements for training frontier language models, which escalated sharply within three years. In 2020, GPT-3 training cost approximately US$5 million; by 2023, GPT-4 training reportedly cost approximately US$100 million

(Ryabinin and Gusev 2020; Sathish et al. 2024). Projections of training costs for next-generation models range between US$500 million and US$1 billion (Li 2026). Those figures cover only training expenses. They exclude infrastructure development (data centres, custom chips), ongoing operational costs (inference, model serving), personnel expenses (research teams, engineering), data acquisition and curation, and energy consumption demands. The total capital required for competitive primary market participation reaches tens of billions, yet the labour content, which is the source of surplus value in Marx's analysis, represents a small fraction despite high per-worker wages. Even if AI researchers and engineers receive substantial compensation, their numbers remain limited relative to capital deployed.

Scale AI's business model exemplifies this pattern. A $29 billion valuation implied by Meta's June 2025 acquisition of a 49% stake (Sherman, 2025) rests substantially on wage differentials between expensive AI expertise concentrated in core economies and cheap peripheral annotation labour. Yet capital intensity far outweighs even the total labour content across this value chain. AI presents a distinctive feature. The trained model itself constitutes fixed capital for subsequent production rather than commodities directly entering consumption or further production. High capital intensity in training produces outputs requiring further capital-intensive deployment infrastructure, compounding organic composition effects. These figures should accordingly be read as consistent with the hypothesis of rising organic composition across the entire AI stack, not as its empirical proof.

4.2. Barriers to Valorisation and Realisation Problems

Marx distinguished between valorisation (expanding value through production) and realisation (converting commodities into money at profitable prices). AI development faces both challenges simultaneously, creating a double bind that conventional business strategies struggle to resolve. Valorisation barriers emerge from the relationship between capital advanced and surplus value generated. Training a frontier model requires advancing billions of dollars before generating any output. The model then produces "inference" (responses to queries) at marginal costs approaching zero for each additional response. Even so, marginal costs cannot offset the massive sunk costs embodied in the model itself. The profit rate depends on total surplus value generated across the model's lifetime relative to initial capital advanced plus ongoing operational expenses. OpenAI's current pricing cannot cover costs at existing usage levels. Either prices must rise substantially (risking user flight toward competitors), usage must increase dramatically (requiring marketing expenditures and potentially straining computational capacity), or costs must decline significantly (requiring technical breakthroughs whose timing remains uncertain). All three pathways face structural barriers, though novel accumulation and commodification strategies not yet deployed at scale, such as platform advertising or data-licensing, could in principle shift this calculus.

Even if models could theoretically generate surplus value sufficient to justify capital advanced, converting this potential into actual profits requires selling AI services at prices that cover costs. However, several factors prevent this. Competition among primary market players drives pricing toward marginal costs rather than full cost recovery. Secondary market applications capture substantial portions of user-facing value, limiting primary market revenue potential. Granted, Amazon Prime, Netflix, and Disney+ show that willingness to pay for digital subscription services exists. The problem is not categorical consumer resistance but the failure of AI subscription uptake at current price points to offset operational costs. Enterprise clients can also negotiate bulk discounts, further compressing margins. Open-source models provide free alternatives, establishing pricing ceilings that commercial providers cannot exceed without losing users. Realisation problems thus compound valorisation barriers.

These dynamics mirror the overproduction crises Marx analysed. Capital accumulates in a sector beyond what markets can absorb at profitable prices. The difference is that AI overproduction manifests not as excess physical commodities but as excess computational capacity and trained models relative to the revenue-generating opportunities available for their deployment. Resolution requires either massive destruction of capital value (through bankruptcies and write-downs), fundamental restructuring of market relations (through monopolistic consolidation), or successful displacement of contradictions through new accumulation frontiers (whose location remains unclear).

4.3. Fictitious Capital and Financial Expansion

As opportunities for productive valorisation decline, capital migrates toward financial instruments such as stock valuations, bonds, and derivatives. These instruments, which Marx called “fictitious capital,” are claims on future surplus value. Because such claims stand at a distance from productive investment, they create the conditions for a financial crisis that exposes the gap between expected and realised value. Consider OpenAI’s US$300 billion valuation against US$12 billion in revenue, which implies expectations of 25-fold revenue growth or dramatic margin expansion. Anthropic’s US$61 billion valuation on US$5 billion in revenue reflects similar dynamics. Yet current losses and the difficulty of achieving profitability mean that valuations capitalise profits that must materialise at some indefinite future point. Unlike mature industries, where current profitability provides evidence for extrapolation, AI valuations reflect speculation about eventual profitability, a pattern structurally analogous to the speculative accumulation cycle documented in the NFT market at its peak (Timcke and Rens 2024). Venture capital and corporate investment sustain operational losses while creating dependence on credit and financial fragility. OpenAI, Anthropic, and their competitors sustain negative cash flow through successive funding rounds rather than revenue generation. Eventually, investors require returns, triggering either a successful transition to profitability or financial crisis as valuations correct.

To a degree, the overall pattern resembles previous technology bubbles like the dot-com crash, most obviously. Many pioneering companies failed despite correctly predicting the importance of digital technology. Surviving companies required years of losses before establishing profitable positions. Several important differences set this apart from simple bubble-and-burst scenarios, however. To begin, AI requires substantially higher capital intensity than Internet startups. The sector also faces different regulatory environments emphasising national security, operates amid technology competition that fragments markets along geopolitical lines, and may lack equivalent network effects for winner-take-all outcomes. Given the magnitude of these factors, a prolonged crisis with capital destruction extending beyond the AI sector into the broader financial system cannot be ruled out.

4.4. Counteracting Tendencies and Their Limits

Marx identified several counteracting tendencies that could offset the falling rate of profit. These include increasing exploitation by lengthening the working day or intensifying labour, reducing wages below the value of labour power, cheapening elements of constant capital, using the relative surplus population to depress wages, expanding foreign trade to access cheaper inputs and new markets, and using joint-stock capital to socialise risk while concentrating control. AI development exhibits some of these counteracting tendencies but not others, leaving open whether they can create durable pathways to profitability.

AI companies extract extraordinary surplus value from highly paid researchers and engineers through long hours, intense work cultures, and equity compensation that defers immediate payment. More significantly, AI development relies on vast global data annotation workforces experiencing extreme exploitation. The global labour arbitrage involved represents classic unequal exchange dynamics. AI development already maximises global value-chain participation. Improvements in computational efficiency, algorithmic innovations that reduce training costs, and hardware advances could lower organic composition, yet competition drives adoption of efficiency gains for scaling rather than cost reduction. Capitalism's competitive logic prioritises relative advantage over collective efficiency. This postpones the reckoning without resolving the underlying barriers to profitability.

The limits of these counter-actions suggest that AI's current trajectory is unsustainable. Absent dramatic technical breakthroughs or business model innovations that generate substantial new revenue, the industry faces inevitable consolidation, corrections, or transformation. The timing remains uncertain, but the structural dynamics point toward crisis. Whether it takes the form of gradual consolidation through acquisitions, sudden valuation corrections triggering broader financial instability, or transformation into utility-like infrastructure with regulated returns remains open, but all scenarios involve substantial capital destruction and restructuring.

5. AI Development and Hegemonic Transition

5.1. Financial Expansion as Signal of Hegemonic Autumn

Arrighi's framework positions financial expansion as characteristic of hegemonic decline. When productive opportunities for profit diminish in a hegemon's core industries, capital migrates toward speculative financial activities. This transition reflects not merely cyclical downturn but fundamental structural transformation, often culminating in hegemonic crisis. The British hegemonic cycle illustrates the dynamic clearly. Britain's industrial supremacy during the mid-19th century rested on manufacturing dominance in textiles, iron, and machinery. As German and American competition intensified, British capital increasingly flowed toward financial services, international lending, and colonial investment rather than domestic industry. London's position as global financial centre persisted even as Britain's industrial leadership eroded. The interwar period witnessed British hegemonic decline alongside financial instability, culminating in American succession.

American hegemony followed a parallel evolution over the late twentieth century. Postwar industrial dominance in manufacturing, aerospace, electronics, and chemicals provided the material basis for American leadership. From the 1970s onward, however, profitability in manufacturing declined (Brenner 2002). Capital shifted toward finance, real estate, and services. Financialisation intensified, and profits from this sector rose from 10 percent to 40 percent of total corporate profits between 1980 and 2006 (Crotty 2009). The 2008 financial crisis exposed contradictions in this finance-led accumulation model.

This mixture of material and financial expansion in AI development occurs amid this broader trajectory. Hundreds of billions flow into tangible productive assets like data centres, computational capacity, research facilities, and technical personnel. This material expansion promises transformation of production processes across economic sectors. It could even be mistaken for an attribute of hegemonic vitality. Yet the divergence between valuations and profitability, plus the willingness to sustain indefinite operational losses, resembles financial expansion more than productive accumulation. Recent warnings about potential AI investment bubbles lend weight to the interpretation stressing financial expansion. The fallout would be significant if AI fails to deliver enough economic value to justify the investment. This ambiguity reflects AI's position within hegemonic transition rather than confusion about its character.

American hegemony faces challenges from multiple directions, including China's economic rise, the relative decline of US manufacturing capacity, and the self-sabotage of multilateral institutions and military alliances. AI development represents an attempt to establish technological supremacy that might extend American hegemony into a new paradigm. Yet the unsustainable character of current investment patterns suggests that this attempt may fail, contributing instead to financial instability that further facilitates hegemonic decline.

5.2. Geopolitical Competition and Technology Securitisation

US AI development operates within an explicit national security framing. The 2022 CHIPS Act restricted semiconductor exports to China; executive orders in 2023 limited AI technology transfers. This securitisation turns AI into an instrument of geopolitical competition. Historically, hegemonic transitions involve contests over technology transfer whose outcomes shape subsequent power distributions. British attempts to prevent industrial technology exports failed to stop American industrialisation. Current US restrictions on China reflect similar tensions, attempting to maintain American technological advantages while China pursues national innovation.

AI differs from prior industrial technologies in ways that affect this contest's dynamics and outcomes. AI development requires capabilities beyond those necessary for earlier industrialisation. Semiconductor manufacturing, advanced algorithm development, massive computational infrastructure, and specialised expertise create higher barriers to autonomous development. As AI applications span military and civilian domains, export controls must distinguish between legitimate commercial activities and potential military threats. Regulatory oversight faces pressures from the rapid pace of AI advancement, with corporate desires for immediate deployment setting aside questions about long-term implications. The pace, scale, and scope of these changes leave little room for gradual institutional adaptation.

Additionally, AI development relies on globally distributed supply chains for hardware manufacturing, talent recruitment, and data collection. Fragmenting these chains through security restrictions imposes costs on all parties. If peripheral economies were forced to choose between competing systems, this fragmentation would mark a departure from the hyper-globalisation that characterised the neoliberal SSA.

China's trajectory in AI development warrants specific attention given its implications for potential hegemonic transition. China has pursued aggressive AI investment through state coordination, massive funding, and domestic market advantages. Firms such as Baidu, Alibaba, Tencent, and ByteDance have developed competitive AI capabilities. State support includes industrial policy, infrastructure investment, and initiatives to expand technical talent. However, China faces constraints that limit its ability to achieve AI supremacy. Advanced chip manufacturing remains concentrated in Taiwan (TSMC) and South Korea (Samsung), while design capabilities are concentrated in the United States (Nvidia, AMD, Intel). US export controls specifically target Chinese access to cutting-edge semiconductors, creating bottlenecks for AI development. Although China has developed strong algorithmic capabilities, frontier research continues to concentrate in American institutions and corporations. Whether Chinese firms can achieve sustained innovation leadership remains uncertain, in part because they face restrictions in Western markets on security and regulatory grounds, limiting their ability to achieve global scale comparable to American competitors. There is also some conjecture that the Chinese state's insistence on ideologically sanitising training data and restricting cross-border research pipelines creates an unavoidable systemic drag on its domestic AI capabilities (see Kendall-Taylor and Kalathil 2021; Schmidt and Huttenlocher 2024).

Against both dismissive and optimistic assessments, a more precisely calibrated position is warranted. Whether technological leadership constitutes a necessary condition for hegemony is not obvious. Farrell Gregory and Samuel Hammond (2026) show that China's AI strategy prioritises national orchestration and provincial competition, targeting diffusion of AI across manufacturing, administration, and infrastructure rather than frontier model performance. The Fifteenth Five-Year Plan sets a target of 90 percent AI integration across key economic areas by 2030. Hegemonic capacity, on this view, is built through depth of adoption as much as through frontier superiority, a strategic logic Kai-Fu Lee anticipated in AI Superpowers (2018) through his argument that China's advantage lies in data integration across payments, healthcare, and logistics rather than algorithmic novelty. That frontier performance is also within reach was demonstrated by DeepSeek's release in January 2025, which prompted a reassessment of AI capital expenditure assumptions across emerging markets (Timcke 2025). Chip dependency is real but contingent. Chinese firms have achieved competitive outputs with less advanced semiconductors than those targeted by export controls, and domestic development at SMIC continues to advance, if slowly.

Furthermore, the Chinese state has operationalised Lee's diffusion thesis at scale through layered national coordination and subnational competition. Computing-power vouchers, now issued by Beijing, Shanghai, Shenzhen, Hangzhou, and other municipalities, subsidise 30 to 60 percent of AI training costs, a productive subsidy with no American equivalent. The "Eastern Data, Western Computing" initiative routes compute demand from coastal economic centres to energy-rich inland provinces through planned national computing hubs, combining energy, land, and infrastructure planning at a scale that US institutional fragmentation currently prohibits (see Gregory and Hammond 2026). The strategic logic is explicit. AI's economic benefits accrue through deep sectoral integration rather than frontier model competition. However, Xi Jinping's 2025 warning to provincial cadres that not every province needs to develop AI, computing power, and new energy vehicles simultaneously signals that subnational competition risks reproducing the overcapacity and debt pathologies that characterised earlier Chinese industrial rounds in solar panels and electric vehicles. The mechanism that generates competitive discipline simultaneously generates provincial debt accumulation.

In *Trade Wars Are Class Wars*, Matthew Klein and Michael Pettis (2020) identify a structural constraint of a different kind. China's export-led growth model suppresses domestic wages to subsidise manufacturing, flooding global markets and inducing tariff responses that ultimately constrain the demand-side expansion on which sustained hegemony depends. Whatever its short-term successes, the model limits hegemonic reach unless China transitions to domestic demand-led growth, a transition repeatedly announced by the party-state and not yet achieved. The AI sector is not exempt. Chinese firms' difficulty penetrating Western consumer markets reflects not only security barriers but also the demand-side consequences of the domestic wage compression Klein and Pettis diagnose.

Mercantilism is structurally ambivalent for hegemonic prospects in a more precise sense than Klein and Pettis foreground. Export surpluses fund state-directed AI investment. In this respect, wage suppression is instrumentally useful for accumulating the material base of power competition. But hegemony requires the capacity to organise global demand, not merely to supply global markets. The United States achieved this through dollar hegemony, running persistent deficits while remaining the indispensable source of global demand. A hegemony built on compressed domestic wages lacks this demand-side instrument. Chinese AI firms face the constraint directly. The consumer market depth that generates network effects comparable to American platforms is foreclosed not only by security policy but by the domestic wage structure itself.

Ho-fung Hung's account in *The China Boom* (2015) grounds Chinese hegemonic limits in its structural dependence on US Treasury purchases that enabled Chinese export surpluses, constraining foreign policy assertiveness and preventing the decoupling from dollar hegemony that genuine succession would require. Yuan-denominated trade with selected partners after 2020 has partially addressed the constraint without dissolving it. Dollar hegemony remains largely intact, and Chinese reserves depend heavily on dollar-denominated assets. The trajectory is one of slow and contested erosion of dollar dominance, not the clean succession that Arrighi's framework models. The AI parallel is direct. Chip dependence on TSMC mirrors Hung's broader pattern of genuine productive capacity coupled with structural exposure to a rival. DeepSeek demonstrated frontier-adjacent performance under semiconductor constraint, but constraint is the operative word, not independence. SMIC's domestic fabrication remains multiple process generations behind TSMC's leading nodes, and post-2020 Chinese investment in semiconductor self-sufficiency has absorbed substantial state capital with limited returns at the frontier.

On balance, Chinese hegemonic succession appears structurally improbable in the medium term, though Chinese great-power status is not in question. This assessment differs from Arrighi's (2007) "noble hegemon" thesis in *Adam Smith in Beijing*. China's peripheral engagement through extractive resource arrangements and the debt dynamics of Belt and Road financing reproduces core-periphery exploitation under altered arrangements rather than transcending it. Hegemony in Arrighi's sense requires productive superiority as well as the capacity to organise the world economy around one's own institutional arrangements, financial architecture, standards, and demand generation. That capacity does not yet exist. What Chinese state power has demonstrated is the ability to accumulate within a system still organised around American arrangements.

That said, considering the aforementioned vectors together, Chinese hegemonic succession is neither inevitable nor impossible. Both confident predictions are unwarranted. Demographic pressure, environmental costs of the existing growth model, chip dependency, and the tensions between authoritarian governance and open research environments do constitute constraints. State-directed investment, the depth of data integration across the economy, manufacturing scale, and the capacity to mobilise capital through provincial competition are genuine advantages that simple dismissal ignores. What the current conjuncture most probably produces is a prolonged interregnum of multipolar instability rather than clean succession, consistent with Arrighi's framework but under conditions of a declining hegemon still in structural crisis and a rising challenger whose consolidation remains incomplete.

Would Chinese AI supremacy substantially alter the position of peripheral economies? If China merely replaces American hegemony while maintaining capitalist relations, unequal exchange and core-periphery exploitation would persist under different SSA arrangements. Alternatively, if China's rise facilitates genuinely multipolar competition, peripheral economies might gain leverage through playing competing powers against each other. Current evidence suggests that while multipolarity creates some opportunities, fundamental structural constraints on peripheral development persist regardless of hegemonic succession.

5.3. Unequal Exchange and Peripheral Economies in AI Development

AI development participates in and intensifies globalised production's exploitative dynamics through value chains that systematically transfer surplus from peripheral to core economies. While primary AI companies concentrate in the US and China, their operations depend on globally distributed supply chains for hardware manufacturing, data labelling, and computational infrastructure.

Semiconductor production exemplifies the complexity of global value chains. Design occurs primarily in the United States (Nvidia, AMD, Qualcomm). Manufacturing concentrates in Taiwan (TSMC) and South Korea (Samsung), with assembly occurring across Southeast Asia. Raw material extraction occurs predominantly in Africa and Latin America under conditions often approaching super-exploitation. The value distribution across this chain reflects unequal exchange dynamics in ways that quantification might capture. Assembly workers in Vietnam or Malaysia earn wages enabling subsistence but not wealth accumulation, despite producing commodities sold at massive markups. Mining communities in Congo or Chile experience environmental devastation and health impacts without corresponding compensation. This extractive geography and its implications for African development have been documented in more detail elsewhere (Timcke 2024).

Human-generated content constitutes an essential input to AI, yet economic returns from AI systems trained on this data accrue overwhelmingly to corporations headquartered in core economies. This pattern represents classic unequal exchange. Peripheral labour inputs (content creation) exchange for core outputs (AI services) on systematically disadvantageous terms whose magnitude becomes clear through linguistic diversity analysis. While English dominates training datasets (approximately 60–70% of training data), millions of hours of unpaid human labour producing content in Swahili, Zulu, Yoruba, Amharic, and hundreds of other languages contribute to model capabilities. When these models serve commercial applications such as translation services, content moderation value flows from peripheral linguistic communities to core technology corporations without compensation. Even accounting for infrastructure costs, research investments, and computational expenses, the surplus appropriated through this and similar exchange substantially exceeds conventional commodity production's exploitation rates.

This unequal exchange operates through multiple mechanisms simultaneously, compounding rather than offsetting each other. Training data extracted from websites, social media platforms, and digitised materials occurs without creator compensation. While some publishers negotiate licensing agreements, most training data derives from uncompensated content. AI-generated content displaces human creators in content production, translation, and creative work, enabling a form of secondary appropriation. As AI capabilities improve, content creators face downward wage pressure or unemployment while AI companies capture economic gains from automation. Indigenous knowledge, traditional practices, and cultural expressions embedded in training data become commodified through AI systems without community consent or benefit-sharing. Digital enclosure is the apt term as common resources are privatised for capitalist accumulation (Timcke 2021)[3].

6. Rethinking Development Strategy in the AI Era

6.1. The Envelope of Strategic Responses

Peripheral economies face constrained options for participating in AI development. Competing with US or Chinese AI investment exceeds most peripheral economies' capacities. However, alternative approaches may succeed through selective capability development as opposed to comprehensive competition. Focusing on specific capabilities aligned with local strengths requires substantially less investment while building genuine expertise. Fine-tuning existing open-source models for specific applications, for example, requires substantially less investment than training frontier models. The approach would enable participation without direct primary market competition, though it would reproduce dependency on models developed in core economies. African Union initiatives, regional economic communities, or multilateral partnerships might pool resources for shared computational infrastructure, joint research programs, or collaborative dataset development.

Regulatory frameworks merit careful calibration. Premature restrictions might stifle local innovation while failing to constrain platforms operating transnationally from core-economy bases. Regulatory absence, by contrast, invites external dependencies and potential exploitation. Optimal approaches likely involve coordination with other peripheral economies to establish common standards that could influence global regulatory evolution. Recent policy experiments offer instructive examples. India, Brazil, and South Africa have implemented or proposed data-localisation rules requiring domestic data storage. While these protect citizen privacy and create infrastructure development incentives, they also risk retaliatory trade measures. Several African countries are

[3] Caner Kerimoglu (2026) provides a narrower instance of cognitive enclosure in service of AI capital accumulation. They show shows how AI deployment in academic writing reproduces the logic of profit-driven publishing monopolies. Herein measurable, rapidly circulatable outputs are rewarded while critical depth is marginalised.

pushing to implement digital-services taxes targeting multinational technology corporations. Such taxes generate modest revenue at the cost of opposition from core economies threatening trade sanctions. Some communities assert collective rights over cultural knowledge and traditional practices. These initiatives challenge dominant intellectual-property frameworks but face entrenched interests.

6.2. Dependency Reproduction or Development Opportunity?

The fundamental question is whether AI development offers development pathways for peripheral economies or reproduces dependency in new technological forms. The answer turns on political organisation, not technological determinism. Historical precedents suggest cautious pessimism. Earlier technology cycles, including mainframe computing, personal computers, and the Internet, promised development opportunities. These cycles ultimately reinforced core-periphery hierarchies. While peripheral economies participated as manufacturers, assemblers, and users, high-value activities remained concentrated in core economies. African Internet penetration increased dramatically without corresponding local value capture. Social media platforms extract behavioural data from African users while revenue flows to Silicon Valley.

Even so, this is not a one-sided affair. Specific features of AI development create dynamics that differ from earlier cycles in ways that might enable different outcomes. Unlike hardware manufacturing or software, effective AI applications require deep contextual knowledge. Western companies struggle to develop products serving African users effectively due to insufficient understanding of local languages, cultural practices, and institutional environments. The difficulty creates competitive advantages for African developers. While foundational model development concentrates in core economies, building specialised applications atop these models requires less capital. Local developers can create educational tools, healthcare diagnostics, agricultural extension services, or financial inclusion platforms for underserved populations. Peripheral economies collectively possess substantial data resources that core AI companies require for model improvement and market expansion. Coordinated data governance frameworks might enable better negotiating positions, extracting technology transfer, revenue sharing, or infrastructure investment as conditions for data access.

These opportunities remain constrained by structural features of global capitalism, including capital mobility, unequal exchange, and institutional power asymmetries. Realistically, AI development in peripheral economies will likely reproduce dependencies while leaving limited spaces for local capability building and value capture. Whether these spaces expand or contract depends substantially on political organisation, both domestically within peripheral economies and through international coordination among them. Whether AI offers development opportunities or deepens dependency thus remains politically contingent rather than technologically determined.

6.3. Institutional Requirements and State Capacity

Traditional development strategies emphasised industrialisation through manufacturing-led growth, export orientation, and integration into global value chains. Historically, industrialisation absorbed rural surplus labour into urban manufacturing, enabling productivity gains and wage growth. If AI enables automated manufacturing before peripheral economies complete industrialisation, this pathway may close.[4] The same is true for service sector work conducive to even partial automation. Education and skill development traditionally offered social mobility pathways, yet AI capabilities increasingly span routine cognitive work traditionally requiring education. The skill premium may shift toward uniquely human capabilities (creativity, emotional intelligence, complex problem-solving) that current educational systems inadequately develop. These transformations suggest that imitating core economy development pathways may prove impossible for peripheral economies approaching industrialisation.

Instead of pursuing comprehensive integration into global value chains, peripheral economies need industrial policy capacity to identify sectors where local advantages exist, coordinate investment, and manage external dependencies. If AI limits traditional employment pathways, development may require emphasising social reproduction (healthcare, education, housing) over employment generation. This shifts development logic from market-mediated welfare toward direct provision. Any future development project in peripheral economies would have to address extensive unemployment. Development itself may have to be reconceptualised.

Implementing alternative AI development strategies requires substantial state capacities whose absence in many peripheral economies constitutes a major barrier. Evans's (1995) embedded autonomy framework suggests successful developmental states combine policy independence and bureaucratic competence with close business cooperation. Applied to AI, effective governance requires technical expertise spanning computer science, economics, law, and social science. Building such expertise demands sustained investment in education and institution-building, recruiting technical talent into public service, and maintaining bureaucratic quality against corruption pressures.

AI development intersects multiple policy domains. Telecommunications, education, industrial policy, labour regulation, and intellectual property are only the beginning of a longer list. Coordination across bureaucratic silos demands institutional capabilities often weak in peripheral economies. Engaging with multinational AI corporations, negotiating technology-transfer agreements, and participating in international standard-

[4] This situation is reminiscent of what Dani Rodrik (2016) termed "premature deindustrialisation". He meant that peripheral economies losing manufacturing employment share at income levels far below those at which advanced economies underwent the same transition. AI-enabled automation compounds the threat, foreclosing the manufacturing pathway before peripheral economies have extracted the productivity and wage gains that industrialisation historically delivered.

setting require specialised negotiating capabilities. Corporations based in core economies possess vast legal and technical resources; peripheral-economy negotiators must match these capabilities as far as possible. Compelling compliance from powerful transnational corporations requires legal frameworks, technical monitoring capabilities, and political will to impose penalties, recognising that any one of these capacities may invite corporate regulatory arbitrage with other peripheral economies. Hence the need for solidarity among peripheral economies.

Decades of neoliberal restructuring have created formidable obstacles. Structural adjustment programmes hollowed out state capacities across much of Africa and Latin America. Neoliberal ideological hegemony delegitimised state intervention. Fiscal constraints limit public investment. Brain drain draws talented personnel toward the private sector or emigration. International agreements constrain policy autonomy. Overcoming these obstacles requires political transformation alongside technical capacity-building. Developmental states historically emerged from specific political coalitions, including business-state alliances in East Asia, nationalist movements in postcolonial contexts, and revolutionary transformations in China and Vietnam. Contemporary peripheral economies must forge comparable coalitions around technology sovereignty as a development imperative (Timcke 2024)

Individual peripheral economies lack the resources for comprehensive AI development. Regional coordination, which offers scale economies and bargaining leverage, may be not merely advantageous but necessary. Pooling resources for computational infrastructure, research facilities, and training programmes achieves capabilities beyond individual national capacities. The African Union's Digital Transformation Strategy and regional economic community initiatives provide frameworks for such cooperation, though implementation remains limited. Coordinating data governance frameworks, interoperability requirements, and ethical guidelines creates larger unified markets attractive to AI companies while maintaining policy autonomy. However, achieving regional consensus faces challenges from divergent national interests and limited institutional capacity.

Alternative trajectories also deserve attention, beyond American hegemonic renewal or Chinese succession. Neither the US nor China may achieve decisive AI dominance. They may produce regional technological blocs with different standards, platforms, and governance frameworks. European Union AI regulation, American national security restrictions, Chinese innovation policies, and emerging economy initiatives may create overlapping but incompatible systems. This scenario offers peripheral economies potential advantages through strategic engagement with multiple technological systems, yet fragmentation also risks marginalisation from multiple markets simultaneously. Maintaining competency across incompatible systems requires substantial resources. Moreover, regional blocs might enforce exclusivity requirements, pressuring peripheral economies to choose alignment over autonomy.

The most likely trajectory may combine elements from multiple scenarios. There may be partial American hegemonic renewal in specific technological domains, Chinese advances in others, regional fragmentation around competing standards, and periodic crises as speculative bubbles burst. Such complex multipolar instability differs from both the stable American hegemony of the postwar era and the clean hegemonic transitions Arrighi analysed historically. Managing this ambiguous environment requires strategic analysis and institutional flexibility from all actors, but especially from peripheral economies lacking the resources to withstand sustained turbulence.

7. Conclusion

The preceding analysis has examined AI development through political economy frameworks emphasising capital accumulation dynamics, hegemonic transition, and unequal exchange, thereby attending to patterns that conventional approaches miss or misinterpret. AI investment bears characteristics Marx identified in *Capital* Volume III's analysis of the falling rate of profit, especially the rising organic composition of capital, barriers to valorisation, and the proliferation of fictitious capital as productive accumulation opportunities stagnate. The divergence between massive capital expenditure and operational losses indicates that AI development represents a crisis response within financialised capitalism rather than a sustainable accumulation strategy.

Placing AI within Arrighi's framework of systemic cycles of accumulation reveals these patterns as symptoms of potential hegemonic transition. AI development combines material expansion features, including infrastructure investment and productive capacity-building, with financial expansion characteristics, including speculative valuations, operational losses, and dependence on credit, typical of hegemonic autumn. Whether AI consolidates American hegemonic renewal, facilitates Chinese succession, produces multipolar fragmentation, or triggers systemic crisis remains uncertain, but current dynamics suggest instability rather than stable hegemonic reproduction.

AI development reproduces and intensifies the unequal exchange characteristic of contemporary imperialism through mechanisms spanning hardware manufacturing, the exploitation of data annotation labour, and the appropriation of training data. Global value chains transfer surplus value from peripheral to core economies through market mechanisms. While AI creates constrained opportunities for peripheral economy participation, structural features of global capitalism ensure that value capture concentrates in corporations based in core economies that control intellectual property, market access, and computational infrastructure.

Whether AI market concentration trends toward monopoly or stable oligopoly bears directly on the crisis argument. Marxist political economy identifies a general tendency toward monopoly as competition destroys weaker capitals, yet platform markets have historically produced stable oligopolies before monopolisation or crisis. AI pulls in both directions at once. Extreme capital requirements create barriers to entry that consolidate the field. OpenAI, Anthropic, Google DeepMind, Meta AI, and xAI form a recognisable oligopoly, with Microsoft's OpenAI partnership conferring quasi-participant status. Yet the high fixed-cost structure simultaneously incentivises aggressive market-share competition through below-cost pricing, compressing margins for all participants and accelerating instead of deferring the valorisation crisis. The probable trajectory is a transitional oligopoly intensifying consolidation pressures, resolving into either one or two dominant integrated platforms, as occurred in search and social media, or a capital destruction crisis that resets market structure. Which outcome materialises depends on regulatory intervention, technical developments, and geopolitical dynamics.

For peripheral economies in Africa, these dynamics create profound challenges whose resolution depends on political organisation transcending current configurations. Participation without replicating unsustainable models requires strategy, substantial state capacity, and the political organisation to pursue them. Alternatives like technological exclusion, dependent integration, or perpetual marginalisation offer little promise.

Ultimately, meaningful AI development requires confronting capitalism's fundamental contradictions. These include the social character of production against the private character of appropriation, use value against exchange value, and humanity's collective capabilities against their subordination to profit imperatives. Technology alone cannot resolve these contradictions. Only political transformation that reconstitutes social relations can create conditions in which AI capabilities serve human flourishing rather than capital accumulation. That transformation exceeds this article's scope but remains the horizon toward which critical scholarship should be oriented.

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