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From human capital to asset ownership: AI as rentier asset

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Abstract

Scholars remain divided on AI's implications for the future of work, with debate centred on what AI can do to jobs rather than on the economic regime shaping how it is deployed and who appropriates its returns. This article argues that AI's impact on university-educated labour cannot be understood through technological capability alone, but requires analysing the rentier dynamics of contemporary capitalism. Drawing on political economy and sociology, it develops a framework for understanding AI as a productive rentier asset, one whose returns derive from constructed scarcity and access control rather than commodity exchange. Labour markets for university-educated workers are where the explanatory limits of human capital theory are most consequentially exposed. Credential devaluation, declining returns to educational investment, and oligopolistic capture of productivity gains are intelligible as outcomes of AI-driven assetisation. Addressing AI's labour market effects requires engaging with mechanisms of ownership and access control, not technological capability alone.

Keywords

artificial intelligence, university-educated labour, rentier capitalism, political economy, education

Introduction

The implications of artificial intelligence for the future of work remain deeply contested (Autor et al., 2022; McKinsey, 2025; Suleyman and Bhaskar, 2023). Central questions include whether AI will augment workers' abilities and boost productivity, or whether it will outperform and ultimately replace human workers by performing tasks more effectively or cheaply. While there is widespread consensus that AI will transform work across all skill levels, experts offer divergent predictions about the specific impacts across industries and job types, with little agreement on the magnitude or direction of change.

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University-educated workers employed in finance, technology, law, and other professional sectors face particular uncertainty in this transformation. These workers have historically been distinguished by their complementary relationship with technological change (Tholen, 2017), yet AI is increasingly capable of mastering the advanced skills that many deploy in their work: analysing structured data, natural language processing, and advanced pattern recognition. Creative domains such as graphic design and music composition are also affected (Zhou and Lee, 2024), as are legal research and financial analysis (Nguyen et al., 2024; Tu et al., 2024). Some commentators warn that AI and digital technologies may disproportionately harm university graduates in the workforce (Hinsliff, 2025; Ingraham, 2025), and evidence suggests AI is already transforming labour market demand for university-educated workers (Matchett, 2025). Henseke et al. (2025), using UK worker-reported task data, find that AI exposure increases with occupational skill level, inverting historical patterns of automation.

This article argues that what happens to university-educated labour under AI is determined less by what the technology can do than by the economic regime governing how it is owned and used. For instance, exposure studies assess which jobs face AI disruption based on what the technology can theoretically do (Eloundou et al., 2023; Frey and Osborne, 2024), but they do not capture the broader economic shifts in how and why AI is actually used in workplaces. The deployment of technologies and their effects on labour demand and wages are not exogenous. Beyond firm-specific characteristics (Koepp, 2023), they are shaped critically by the existing balance of power between labour and capital (Acemoglu and Johnson, 2023). This requires examining capitalism as a system of capital extraction and accumulation, specifically, how organisations use, control, and extract value from AI. The article focuses on an emergent form of capitalism, rentier capitalism, that reshapes the value of knowledge and skills of university-educated workers. This accumulation regime, which has gained prominence in contemporary economies (Birch, 2020; Christophers, 2020; Karakilic, 2022; Piketty, 2014; Varoufakis, 2023), conditions not only how AI is deployed in workplaces but also whether education retains its protective function and how productivity and wage gains are distributed. This paper contends that AI is becoming a rentier asset that fundamentally alters the relationship between credentials, skills, and labour market value. The question this paper examines is: through what mechanisms does AI enable rent extraction, and how does this reshape the work of university-educated workers?

The article advances existing literature in two ways. First, it develops a systematic framework for analysing how rentier capitalism's defining characteristics reshape the valuation of graduate knowledge and credentials. Second, it demonstrates that education's capacity to protect workers from AI's negative effects is regime-contingent rather than universal. This challenges the foundational assumption of human capital theory (Becker, 1964; Goldin and Katz, 2008) that educational investment yields consistent returns through enhanced productivity and higher wages. The analysis proceeds in two stages. First, I identify defining characteristics of rentier capitalism through engagement with recent political economy scholarship. Second, I map how these characteristics shape education's function and reward distribution. The evidence demonstrates that under rentier capitalism, the relationship between educational credentials and economic returns has fundamentally changed (Brown et al., 2020). Education no longer functions as a reliable human capital investment because returns predominantly flow to those who control productive assets rather than to those who deploy skills. The conclusion synthesises these strands to assess whether education-led policy responses remain viable across different accumulation regimes.

AI influence on high-skilled workers

AI reshapes labour markets in uneven ways, benefiting some workers while disadvantaging others. While certain roles allow workers to enhance their skills with AI, others face reduced autonomy and skill use (Brito and Curl, 2020; Korinek and Stiglitz, 2019). AI can exacerbate inequalities by increasing productivity in high-skill jobs while displacing lower-skilled ones (Holm and Lorenz, 2022). Evidence suggests that, unlike previous rounds of technological innovation, high-skilled workers may be particularly vulnerable. Kinder (2024) argue that generative AI marks a major shift from previous ‘skill-biased’ technologies, which primarily replaced routine, low- and mid-wage tasks while complementing high-skilled roles. Unlike past automation, generative AI targets non-routine, cognitive, and interpersonal tasks once thought exclusive to humans: programming, writing, creativity, empathy, and analysis. Higher-paying, degree-intensive sectors such as STEM, finance, law, and architecture now face the greatest exposure.

Numerous studies confirm that high-skill and white-collar jobs are most exposed to AI technologies, while low-skill or manual jobs are less so (Colombo et al., 2024; Department for Education, 2023; Engberg et al., 2024; Fenoaltea et al., 2024; OECD, 2022). Felten et al. (2023) find that the industries most exposed to advances in language modelling are legal services, securities, commodities, and investments. In contrast, manual blue-collar and many low-wage service jobs remain relatively unaffected by current generative AI capabilities. This pattern raises a critical question: if education and cognitive skills no longer protect workers from technological substitution, what does this mean for labour market stratification and returns to human capital investment?

Responses to this question reveal deep analytical divisions rooted in competing theoretical commitments. One strand of literature emphasises complementarity and augmentation. Acemoglu et al. (2022) find that high-skilled jobs show stronger potential for AI complementarity than displacement, while Pizzinelli (2023) stress that impact depends on whether AI augments or replaces human capabilities. Some researchers identify upskilling opportunities as AI handles routine components of professional work (Colombo et al., 2024; Engberg et al., 2024), maintaining faith in skill-technology complementarity and arguing that AI will enhance rather than replace university-educated workers’ capabilities. Bloom et al. (2025) indicate that AI tends to substitute for tasks performed by high-skilled workers more than for those performed by low-skilled workers, a trend that may diminish the wage premium traditionally associated with high-skill occupations.

This optimistic interpretation, however, contradicts mounting evidence of AI’s negative impacts on knowledge workers. Hui et al. (2024) document employment and earnings declines among freelancers in online labour markets following AI adoption. Xue et al. (2022) found that Chinese firms implementing AI reduced demand for college-educated workers by automating tasks that previously required university credentials. Jung and Desikan (2024) estimate that 11% of tasks across UK occupations are currently exposed to generative AI, with this figure potentially reaching 60% over time, suggesting that even if immediate displacement is limited, the cumulative transformation of work may be profound. The divergence between optimistic and pessimistic assessments reflects deeper theoretical differences about capitalism, technology, and work. Complementarity perspectives implicitly assume that labour markets reward productivity-enhancing skills, such that workers who learn to work effectively with AI will capture returns to their enhanced productivity. This reproduces human capital theory’s core assumption that education and skills development provide workers with bargaining power and economic security.

Yet this framework brackets crucial questions about organisational strategy, power relations, and accumulation logics. Exposure studies, by design, ask what AI can do to jobs, treating technological capability as the primary independent variable. This produces analyses that, while methodologically rigorous, function within a framework of technological determinism that obscures the social relations shaping AI deployment (Brown and Tholen, 2025; Stuart et al., 2023). The question of whether AI can automate professional tasks tells us little about whether and how employers will deploy AI to replace, augment, deskill, or intensify work performed by university-educated workers.

Critical scholarship offers an alternative lens by foregrounding power and control. Research on algorithmic management demonstrates how AI enables new forms of workplace surveillance and control that reduce worker autonomy even when tasks are not fully automated (Barati and Ansari, 2022; Jarrahi et al., 2021). Neff et al. (2020) document how AI intensifies work pressures and obscures human contributions, while Korinek and Stiglitz (2019) show how AI can exacerbate inequalities by concentrating productivity gains among already-advantaged workers. These analyses shift attention from AI's technical capabilities to the organisational and economic contexts in which those capabilities are deployed. As Jung and Desikan (2024) acknowledge, exposure generates multiple possible futures; the challenge is understanding which future materialises and why. Brown (2024: 479) captures this well: 'the future of work is never simply a question of the limits of technological possibilities but depends on what "commands a decisive cost or quality advantage" for business'.

At the heart of this debate lies a paradox While AI demonstrably targets the cognitive, non-routine tasks that define work performed by university-educated workers, the implications for workers remain deeply contested. This uncertainty reflects not merely gaps in our empirical knowledge but fundamental disagreements about the mechanisms through which technology shapes employment. Addressing this paradox requires moving beyond both technological determinism and firm-level analysis to examine the broader political-economic regime shaping AI deployment. While rentier capitalism has been identified as a defining feature of contemporary digital economies, its implications for understanding AI's impact on university-educated labour remain under-explored. Yet this framework proves essential, because technological capability answers only one of two distinct questions. It can tell us which tasks and jobs are exposed to AI, but not who captures the resulting gains, and it is the second question that determines the consequences for university-educated workers. Two mechanisms, which capability-based accounts tend to conflate or ignore, govern that outcome. The first is substitutability. The bargaining power of credentialised workers has historically rested on the scarcity of what they know; once that capability is available to employers as a cheap and ownable asset, the worker's fallback position erodes regardless of which provider supplies the tool. The proliferation of competing, interchangeable models intensifies rather than softens this effect, since abundant and low-cost AI is more readily substitutable for credentialised labour. The second is enclosure. While the application layer at which workers choose between models is competitive and substitutable, the infrastructure layer beneath it, the cloud platforms, proprietary models, and hardware on which those tools depend, is concentrated and costly to exit. It is there, through access pricing, API dependency, and ecosystem lock-in, that productivity gains are appropriated upward as rent rather than competed away or passed to those who deploy the technology. Analysing AI as a productive rentier asset therefore reveals how educational investment and economic returns are decoupling, reshaped by the logic of ownership and access control rather than by technological capability alone. The infrastructure rentier does not extract value from credentialised workers directly. Rather, by enclosing the capability and capturing the gains from its deployment at the point of access, it forecloses the diffusion of those gains through the wider economy, the diffusion through which labour might otherwise have secured a share. What weakens the worker's position is therefore not a transfer of wages upward but the removal of the conditions, scarce expertise and viable alternatives, on which bargaining power depended. The following sections develop this argument.

Rentier capitalism: A theoretical framework

Rentier capitalism is characterised by wealth generation through asset ownership and control rather than through the production and sale of goods and services. Christophers (2020: xxvi) defines rent as ‘income derived from the ownership, possession or control of scarce assets under conditions of limited or no competition.’ Building on this, Birch and Ward (2023) define economic rents as value extracted from the socio-natural world as a result of relations of ownership and control of particular assets or resources, primarily because of their constructed degree of scarcity or quality, that is, scarcity that is actively produced and maintained through legal, technical, and organisational mechanisms rather than arising from natural limitation alone. This asset-centred conception of rent is contested. Within the classical Marxian tradition, Maher and Aquanno (2026) argue that defining rent as any return on the ownership of scarce assets severs it from its proper foundation in the equalisation of the profit rate, thereby rendering rent and profit indistinguishable and making monopoly appear everywhere. On their account, genuine rent must rest on barriers to capital mobility and must show up empirically as returns persistently above the social average, a threshold they argue even leading technology firms do not clear. The framework adopted here does not contest that claim on its own terms. It uses rent in the asset-centred sense developed by Christophers (2020) and Birch and Cochrane (2022), and its argument concerns the mechanism through which income is generated, the ownership and control of an enclosed productive asset, and the consequences of that mechanism for credentialised labour. It does not rest on a claim that AI firms earn persistently supernormal profits, and so is not adjudicated by the profit-rate test. What is at stake is not whether returns exceed a Marxian average, but how the assetisation of cognitive capability reshapes the relationship between credentials and economic security.

The rentier capitalism framework is not without its critics. Three objections are most relevant. First, Post-Keynesian and heterodox economists have long questioned the productive/unproductive boundary that rentier capitalism implicitly invokes, all capital ownership involves some degree of passive income, and the line between innovative and rentier firms is analytically difficult to draw (Aspromourgos, 2018; Lavoie, 2014). Second, it is a legitimate and unresolved question in political economy whether rentier capitalism constitutes a genuinely new form of capitalism or an intensification of tendencies always present within it; this paper does not seek to adjudicate that debate. Third, the concept risks conflating analytically distinct forms of market power, land rents, financial rents, intellectual property rents, and platform rents, which function through different mechanisms and have different distributional consequences. These are legitimate objections that this paper cannot fully resolve. This paper responds to these objections in two ways: by grounding the analysis in the observable mechanisms of constructed scarcity identified by Birch and Ward (2023) rather than adjudicating deeper theoretical disputes; and by distinguishing between fixed passive assets and productive rentier assets, as elaborated below. The concept is deployed here for its descriptive and explanatory value rather than whether rentier capitalism represents a fundamentally new form of capitalism.

Rentier assets are not homogeneous, and a key analytical distinction within the framework concerns their relationship to the production process. Fixed passive assets, financial instruments, land, and real estate generate returns through ownership and appreciation but are largely inert in the production process itself. Their value derives from scarcity, exclusivity, and the ability to charge for access, but they do not actively transform or displace labour. Productive rentier assets, by contrast, are both rent-generating and actively constitutive of the production process; proprietary platforms, data infrastructure, and AI systems are the clearest examples. They generate income through ownership while simultaneously restructuring how work is performed and organised. This distinction addresses a central objection that the dynamics described are simply capitalism under a new name. Previous accumulation regimes invested in costly means of production and deskilled workforces, but they did so within competitive markets and primarily targeted physical and routine labour. Critics in the Marxist tradition note that asset ownership that generates returns at the expense of labour defines capitalism, not rentier capitalism specifically (Karakilic, 2022). What sets productive rentier assets apart is that they generate income by enclosing and charging for access to a scarce asset, not by outcompeting rivals on cost or quality, and that they penetrate the labour process itself rather than sitting alongside it.

A defining feature of contemporary rentier capitalism is the shift from commodification to assetisation, the transformation of resources, ideas, and infrastructures into capitalised property valued for their ability to generate future income streams rather than for their immediate exchange value (Birch and Muniesa, 2020). This shift privileges long-term value extraction over productive exchange, typically enforced through legal protections that limit competition and increase exclusivity. Digital platforms exemplify this logic. Dominated by tech giants including Amazon, Alphabet, Meta, Apple, and Microsoft, these ecosystems mediate interactions between users and providers, extracting and monetising data through network effects and algorithmic optimisation (Sadowski, 2019; Srnicek, 2016; Zuboff, 2019). Network effects and aggressive competitive strategies reinforce market dominance, producing winner-takes-all dynamics; Google Search, with over 85% market share, exemplifies this tendency. Birch and Cochrane (2022: 46) define digital rentiership as the construction and extraction of value through the techno-economic extension of ownership and control over assets, often resulting from artificial or natural scarcity, quality, or productivity. Importantly, Birch et al. (2021) clarify that in the case of Big Tech platforms, it is users rather than data that constitute the pivotal asset. The relationship with users generates the ongoing returns from which rents are extracted.

The empirical consequences of rentier dynamics for labour are observable and well-documented. The labour share of total income has declined dramatically since the early 1970s, falling from nearly 70% to 55% (Christophers, 2020: 37). Wealth generated from assets has grown far faster than both the overall economy and wages (Adkins et al., 2020; Piketty, 2014). In rentier systems, returns flow increasingly to those who own and control productive assets rather than to those who deploy skills and labour. The distinctiveness lies not in the fact that owners capture returns, which is true of capitalism generally, but in the mechanism: income is secured through constructed scarcity and access control rather than through competitive productive contribution.

This is not to claim that rentier firms contribute nothing to production, many combine substantial R&D investment with rent-extracting strategies, but rather that the mechanisms through which income is secured are increasingly those of constructed scarcity and access control rather than competitive efficiency or productivity enhancement. In the digital economy, in particular, value is created and preserved not by outperforming competitors on price or quality, but by restricting access to key technologies and infrastructure (Birch and Cochrane, 2022; Sadowski, 2020).

These rentier dynamics take a specifically consequential form in the case of artificial intelligence. AI infrastructure belongs firmly in the category of productive rentier assets: it is prohibitively expensive to develop, concentrated in the hands of a small number of firms, and generates returns through access-based extraction rather than commodity sale. But unlike passive financial assets, AI actively performs cognitive labour, absorbs and codifies existing expertise, and restructures the conditions under which human workers contribute. This makes AI a distinctively powerful form of rentier asset for credentialised labour markets; it does not merely extract a toll alongside production, as land or finance does, but penetrates the cognitive labour process itself, appropriating and potentially displacing the human capital that credentialised workers were previously protected by. The following section develops this argument by examining the three mechanisms through which AI functions as a rentier asset and their consequences for the employment of university-educated workers.

How AI functions as a rentier asset

Technologies are increasingly used as assets to generate revenue over time, controlled through property rights, exclusivity agreements, and licensing (Birch and Muniesa, 2020). AI is a key example. AI functions as a distinctively powerful rentier asset through what Birch (2020) identifies as the assetisation process: transforming infrastructure, data, and computational capabilities into capitalised property, generating ongoing returns through ownership and control rights rather than through commodity exchange. This assetisation process transforms how value is extracted from work, but through a mechanism distinct from classical deskilling accounts. Braverman (1974, see also Thompson, 1983) documented the degradation of craft knowledge under industrial capitalism. Until recently, credentialised cognitive labour remained a relatively protected space. AI infrastructure is different in that the question is not only how work is reorganised and controlled within the firm, but who captures the returns from the cognitive capabilities that AI absorbs, and through what mechanisms of ownership and access control. What makes this income rent rather than competitive profit is its source: control of scarce, enclosed assets under conditions of limited competition, rather than productive contribution in a competitive market. Three interconnected characteristics establish AI's rentier nature, each corresponding to mechanisms identified in technoscience rent literature (Birch, 2020).

First, prohibitive capital barriers prevent competitive entry. AI models require massive computing resources and vast proprietary datasets that only a handful of firms can provide at scale. Google, Microsoft, Amazon, Meta, and Nvidia control the dominant share of the hardware, cloud infrastructure, and data necessary to train and deploy frontier models, with Nvidia alone producing over 80% of high-performance AI chips (Cosgrove, 2025). Winner-takes-all dynamics (Kampmann, 2025) entrench this concentration, with venture capital flowing predominantly to firms already backed by tech giants, making independent competition structurally prohibitive (Hammond, 2023; Lehdonvirta, 2022). Those best positioned to benefit, including investors, tech executives, and senior AI engineers, will see their returns soar accordingly (Isaac et al., 2025). This barrier is structural, not merely temporary. Even as costs potentially decline, the competitive advantage lies with those who already control resources at scale. Only a few tech companies can afford the billions required to train foundational models, thereby reinforcing and extending scarcity through proprietary control beyond what technical constraints alone would dictate (van der Vlist et al., 2024). This concentration forces enterprises to access AI capabilities through expensive API subscriptions and custom deployments, with global corporate AI investment reaching $252.3 billion in 2024, representing a 44.5% year-over-year increase since 2014 (Stanford HAI, 2025).

It is important to note that many leading AI application firms are currently loss-making, a point Srnicek (2025) uses to complicate simple rentier readings of AI. However, this does not undermine the assetisation argument. As Christophers (2020) makes clear, rentiership is a strategy of asset construction and enclosure, not merely passive income extraction. Current losses by firms such as OpenAI and Anthropic reflect the capital investment phase of assetisation, while the rent extraction mechanism, access-based pricing, API dependency, and ecosystem lock-in, is already structurally in place even if full profitability has not yet materialised. Nvidia controls a scarce resource the rest of the sector depends on. What matters is not how much it earns but that nearly everyone building AI must go through it.

The cloud providers who own and operate AI infrastructure, and chip manufacturers like Nvidia whose proprietary ecosystems create significant switching costs, are already closer to classic rentier extraction in that their returns derive primarily from ownership and control of scarce assets rather than from productive services rendered. Application firms such as OpenAI and Anthropic occupy a more ambiguous position: they simultaneously extract rent from their users through subscription and API pricing, while themselves paying rent to the infrastructure layer below them. They are both rentiers and rent-payers depending on where they are positioned in the value chain.

Second, AI generates income primarily through access-based extraction rather than commodity exchange. Once AI companies establish monopolistic positions, they pursue what Verdegem (2022: 732) identifies as an enclosure strategy: restricting access to their data and creating barriers that prevent users from migrating to competitors, progressively expanding their private control over digital resources. Tech companies do not sell AI as a product but rent access through API calls, cloud computing services, and subscription-based licensing (Pandl et al., 2021; Syed et al., 2025). AI technology enables what Birch and Cochrane (2022) define as enclave rents by enclosing users within proprietary ecosystems controlled through APIs, models, and interfaces. Birch and Ward (2023: 1433) identify 'gatekeeping through digital infrastructures' as a distinct form of rent extraction within the broader critical rentiership literature. Providers enforce technical standards and architectural specifications while setting usage policies, rate limits, and access tiers that restrict portability across platforms. This control extends to both training data and user interactions, creating dependency on ecosystem-specific capabilities. Workers and firms become captive populations locked into particular AI infrastructures, unable to migrate without significant costs, while their engagement generates valuable data that providers monetise through tiered access models and third-party integrations.

Third, scarcity is reinforced and extended through proprietary control mechanisms beyond what inherent technical limitations alone would produce. The largest AI models remain proprietary rather than open-sourced. Training datasets are hoarded behind corporate walls. Infrastructure for deploying AI is monopolised by a small number of cloud providers. Intellectual property regimes prevent competitive development. Two forms of monopoly are at work here. Property-rights based monopolies, as in pharmaceuticals or proprietary software, derive exclusivity from legal protections such as patents and licensing regimes. Platform monopolies derive dominance from network effects that make competition structurally prohibitive even without direct legal exclusion. AI infrastructure combines both. Proprietary model weights and training data are protected through IP regimes, while network effects create switching costs that reinforce exclusivity independently of legal protection.

Capital barriers construct scarcity by making competitive entry prohibitive; access-based extraction constructs scarcity through proprietary ecosystems and API lock-in; and proprietary control through IP regimes and data hoarding restricts competitive development directly. All three mechanisms map onto what Birch and Ward (2023) describe as the transformation of social relations into capitalised, excludable property from which private actors can extract value (see also Christophers, 2020). Together they establish AI infrastructure as a productive rentier asset whose consequences for credentialised labour markets the following sections examine.

Evidence from labour markets for the university-educated

Labour markets for university-educated workers are where the limits of human capital theory, the assumption that educational investment reliably yields returns through enhanced productivity, are most consequentially exposed. While education has historically served as a worker's protection against technological disruption (Arntz et al., 2016; Goldin and Katz, 2008), this protective function has increasingly come into question (Brown et al., 2020). The rentier capitalism framework allows us to make sense of patterns that human capital theory cannot explain: credential devaluation, declining returns to educational investment, and oligopolistic capture of productivity gains are intelligible as outcomes of AI-driven assetisation in ways that technological capability alone cannot account for. The following sections examine three interconnected ways in which this operates.

Credential devaluation. First, rentier capitalism undermines the credentials' signalling value. Whereas knowledge capitalism has advanced skills developed in Higher Education (HE) portrayed as an essential prerequisite for economic success, this has become less obvious in recent decades. Although the status of elite HE credentials continues to matter, the value of degrees is highly uncertain. Despite the graduate premia, on average upholding the value of education investment, once disaggregated, the premia seem to be primarily found in specific sectors and high-earning occupations (Holmes and Mayhew, 2012). The wages of the bottom 60% of US graduates in 2019 were even lower than in 2000 (Gould, 2019).

The context of this issue is a university-educated labour market where overqualification is a persistent problem (Erdsiek, 2021; OECD, 2024; Rose, 2017), and the concept of learning to earn has faced challenges due to the varied labour market outcomes among graduates. Evidence shows employers increasingly find educational credentials less helpful in sorting candidates. Brown and Souto-Otero (2020) found that educational credentials lost importance in UK recruitment advertisements; instead, employers emphasise 'job readiness' and specialised skills rather than broader qualifications. The authors argue that the digital labour market is reshaping the relationship between education and employment by challenging the traditional importance of educational credentials in job competition and labour market outcomes. They suggest that while credentials have long been seen as key indicators of abilities, digital platforms and data-driven hiring processes may alter this dynamic. Digital labour markets create alternative forms of assessment and credentialing, including direct observation of skills through online tests and simulations, social media-based personality profiling, peer endorsements and online reputation metrics. Education credentials remain important in regulated professions and elite roles, but digital technologies enable employers to reconfigure or bypass educational hierarchies more easily (Souto-Otero and Brown, 2024). This decline is supported by other research. Between April 2021 and April 2024, there was a 14.2% increase in UK job postings not requiring university degrees (Feist, 2024). A survey of nearly 15,000 professionals and employers found 45% of UK employers stated degrees are unimportant when considering applicants. Additionally, 73% of employers believe willingness to learn matters more than existing skill sets, highlighting a trend towards valuing soft skills and adaptability over formal qualifications (Hays, 2023). A US study found that between January 2019 and 2024, job postings requiring college degrees decreased from 20.4% to 17.8%, with formal requirements declining in 87% of occupations (Stahle, 2024). Many American companies, including Walmart, American Airlines, and Dell, have removed educational qualifications for knowledge workers (Dodd, 2023). IBM eliminated bachelor's degree requirements for over half its US openings, with degree requirements dropping from 93% in 2017 to 77% in 2021. Similar trends appear in the UK (Tobin, 2025). This shift reflects the platform-mediated hiring process, where algorithmic assessment tools can evaluate competencies directly, rendering credentials redundant as screening mechanisms. This is a trend that AI is now measurably accelerating. AI does not simply extend this digital reconfiguration of hiring. Where digital platforms changed how credentials are screened, AI changes what credentialised workers are for: by absorbing and codifying the cognitive tasks that degrees certified, it erodes the productive basis of the credential's value rather than merely bypassing it as a signal. An analysis of US job postings finds that highly AI-exposed entry-level roles declined by over 40% between January 2023 and mid-2025 (Simon, 2025). Brynjolfsson et al. (2025) also find this decline using payroll data. An analysis of UK job postings by Klein Teeselink (2025) shows that entry-level roles have experienced the steepest decline since generative AI entered the mainstream. Crucially, the employment effects are concentrated almost entirely in higher-wage, higher-skill segments, with the sharpest hiring declines in software engineering, QA testing, data analysis, design and IT roles. Beane (2024) argues that AI and automation risk eroding the traditional pathways to expertise, as mastery requires challenge, complexity, and connection.

They warn that novices are becoming increasingly removed from the daily tasks of experts. Even if entry-level jobs remain, companies may underinvest in training and mentorship, assuming those roles are short-term, leaving workers unprepared for senior positions (Roose, 2025). In addition, there is evidence to suggest that some employers are relying on AI automation to reduce costs, putting entry-level white-collar jobs at risk. One US study revealed that recent graduates faced higher unemployment rates primarily in technical fields such as finance and computer science, where AI advancements have progressed more rapidly, suggesting that 'entry-level positions are being displaced by artificial intelligence at higher rates' (Oxford Economics, 2025: 1, see also Gent, 2025).

Asset ownership versus human capital. Second, rentier capitalism fundamentally alters how education translates into economic returns, shifting wealth generation from human capital development to asset ownership. Two distinct claims are at work in what follows. Rentier capitalism in general weakens the link between education and reward, since much rent-generating activity does not depend on credentialised skill; the distinctive case arises where the rent-generating asset is AI itself, built from the very cognitive capacity that credentials once certified. Whereas knowledge-based capitalism rewarded credentialised labour with a wage premium, on the assumption that scarce, certified skills command a return in the labour market, rentier capitalism loosens that link. Earning capacity is increasingly tied to the ownership of rent-generating assets rather than to the skills that credentials certify. Many forms of rentierism do not require advanced levels of education, including HE degrees. The relationship between education and accumulation is limited as the payoff of assets is indirectly related to the skills developed in HE. In rentier capitalism, earning opportunities are linked to the control or possession of assets that generate rent-based income. In rentier systems, owning assets does not require qualifications. The emphasis of rentier capitalism is on making passive returns on investments rather than on the productive parts of the economy, driven by labour power. For that reason, rentier capitalism does not hinge on education to support the extraction of value.

Yet rentier firms can automate processes and extract rents with fewer high-skilled employees than were common in successful tech firms during the knowledge capitalism era, such as IBM, Nokia, or AT&T. In economies characterised by strong rentier dynamics, inherited advantages such as family wealth and asset ownership can supersede professional competence or knowledge (Pfeffer and Killewald, 2018). The share of employment earnings is declining, with wealth increasingly tied to intellectual property, equity, tokens, or infrastructure (Koh et al., 2020). Education becomes less relevant to economic success if access to capital is the primary gatekeeper. However, education still plays a crucial role in accessing elite circles, as it helps reproduce wealth. Elite education (e.g., Ivy League schools, Oxbridge) remains crucial for gaining access to influential networks in finance, politics, and technology (Eaton and Gibadullina, 2025; Rivera, 2015; Vuković, 2024). Yet rentier capitalism privileges asset ownership over credentials. Rewards flow to asset owners, not necessarily workers. This privileging of asset ownership over credentials becomes particularly consequential when AI infrastructure itself becomes the key asset, concentrated in the hands of oligopolies who determine access terms. This shift reflects the growing dominance of access-control mechanisms over competitive skill-based exchange as the basis for economic returns in AI-intensive labour markets. This is not to claim that asset ownership generating returns at the expense of labour is itself new. What is specific to AI-driven rentier capitalism is that the productive asset is built from absorbing and codifying the cognitive capacity it then displaces, structurally subordinating returns to credentialised knowledge work to returns to infrastructure ownership in a manner specific to this form of technological change.

Concentration and monopoly control of AI and productivity gains. The concentration of AI capabilities within tech oligopolies intensifies existing rentier dynamics in ways specifically consequential for university-educated workers. Christophers (2020) documents how rentier logics contribute to wage stagnation and labour market insecurity, with returns accruing to asset owners rather than to the workers whose labour generates them, while reinvestment in wages is minimised unless it directly serves rentier income (Christophers, 2020: 45). AI infrastructure extends and deepens this pattern. As a productive rentier asset, it actively restructures the conditions under which credentialised workers contribute, redirecting returns that might once have flowed to knowledge work.

Wage inequality has, of course, increased in most Western countries over the last four decades (Alvaredo et al, 2018). Income growth has been disproportionately concentrated among top earners (Francis-Devine, 2021; Horowitz et al., 2020). The majority of workers in both the UK and the US have seen little to no real growth in earnings over recent decades (Cribb et al, 2023; Mishel and Kandra, 2021). These trends are part of a larger trend characterised by a significant uncoupling of wages, productivity, and economic concentration, particularly in Anglo-Saxon countries. In recent decades, wealth generated from assets has grown much faster than both the overall economy and wages (Piketty, 2014). In the US, productivity increased by 86% between 1979 and 2025 while hourly pay rises by only 32% (EPI, 2025). A similar divergence is evident in the UK, though less pronounced: from 1981 to 2019 labour productivity increased by 87% while median wages rose by 62% (ONS, 2024; Teichgräber and Van Reenen, 2021; Whittaker, 2019), a gap that widened further following the 2008 financial crisis. In both cases, the decoupling reflects rising inequality, with mean wages growing faster than median wages as top earners captured a disproportionate share of productivity gains. Instead of benefiting most workers, rising productivity has primarily fuelled higher executive salaries and corporate profits (Bivens et al, 2024; Brill et al, 2017; Machin, 2025). This shift has contributed to wage inequality and a decreasing share of income allocated to labour. Rentier sectors have consistently generated returns substantially above the broader economy while labour shares decline (Christophers, 2020; Schwartz, 2022); AI infrastructure concentration extends that dynamic into the professional labour markets that have historically offered university-educated workers relative security.

Concluding discussion

Capitalism has always involved rent extraction alongside productive activity, and this article makes no claim that rentier capitalism is historically unprecedented. What is analytically distinctive is not the existence of rentiership but its growing dominance and its specific extension into cognitive labour through AI assetisation. AI's impact on university-educated labour cannot be understood through exposure studies alone but requires analysing how rentier capitalism shapes education's protective function and reward distribution.

The proliferation of AI use throughout the economy may improve job quality, enhance expertise, and increase remuneration for some university-educated workers. For others, however, rentier capitalism fundamentally restructures the sources of worker bargaining power. Treating AI as a rentier asset has observable implications. Economic returns should accrue to those who control access rather than to the workers who apply them, educational credentials should lose their protective function, and productivity gains should concentrate among infrastructure owners rather than be distributed to workers.

These observed patterns reflect three interconnected mechanisms through which rentier capitalism erodes the position of many university-educated workers. They are not separate problems but mutually reinforcing dynamics: infrastructure concentration enables rent extraction, which devalues credentials by shifting returns from human capital to asset ownership, which further entrenches infrastructure owners' power. Crucially, it is not AI's capabilities alone that determine how work performed by university-educated workers is reshaped, but the broader capitalist forces that structure the value of skills, credentials, and labour market outcomes.

Several critical implications emerge. First, the findings challenge prevailing policy assumptions that educational investment will continue to protect workers from technological disruption. Policymakers have long treated higher education as the primary solution to labour market disruption from technological change (Arntz et al., 2016). Yet supply-side skills policies fail to address the fundamental shift from human capital to asset ownership as the basis for economic returns. While schools, colleges and universities may eventually embed AI skills development across their provision, this does little to alter the power dynamics governing AI deployment or the concentration of infrastructure ownership, especially in Anglo-Saxon countries where supply-side approaches have dominated.

Second, the actual deployment of AI is shaped by the imperatives of capital accumulation within specific economic regimes, not by technological capabilities alone. Policy interventions focused solely on 'preparing workers for AI' prove insufficient when they ignore underlying power dynamics. As Bivens (2024) observes, 'Efforts to blame inequality and unemployment on bloodless, apolitical forces like "technology" constitute a convenient alibi for those social forces supporting the concrete policy changes that actually drove these outcomes. This technology alibi has been extraordinarily effective in distracting attention away from the major causes of rising inequality and anemic wage growth.' Framing AI's impact as inevitable technological disruption obscures the institutional and economic forces that determine how AI is implemented and who benefits.

Under rentier conditions, individual strategies based on human capital accumulation are structurally insufficient: the mechanisms governing AI deployment operate at the level of ownership and access control rather than at the level of individual skill or credential. The challenge facing university-educated workers is thus not simply adapting to AI, but contesting the rentier logics that increasingly determine whether technological change enhances or erodes their autonomy, economic security, and collective power.

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