Review Article

COMPARATIVE ANALYSIS OF AI ADOPTION AND ECONOMIC IMPACT VIS-À-VIS EARLIER GENERAL-PURPOSE TECHNOLOGIES

KASHMIR JOURNAL OF SOCIAL SCIENCES
13(1) 101 - 116
ISSN: 0975-6620

https://deanss.uok.edu.in/Files/20ca86b4-9101-4485-98f9-1beb3b33b64b/Journal/059c5de5-983e-4c34-8306-cf5f935ff997.pdf

Sajal Jain*

Abstract
This paper explores how the pace and economic effects of artificial intelligence (AI) adoption differ from previous general-purpose technologies (GPTs) such as steam power, electricity, and computers. While historical GPTs transformed economies through gradual diffusion and physical reinvention, AI's digital, cloud-based nature enables an unprecedented speed of adoption and iteration. By analyzing historical productivity data and current AI diffusion metrics, the study reveals that AI compresses the traditional "Productivity J-Curve," producing earlier and sharper impacts. It amplifies productivity through rapid task automation and predictive efficiency but simultaneously heightens inequality and market concentration due to its cognitive displacement effects and data-driven scalability. Drawing on interdisciplinary insights from economics, sociology, and policy studies, the paper concludes that AI's acceleration demands proactive governance—balancing innovation incentives with safeguards for labor, equity, and competition—to harness its transformative potential without repeating the social dislocations of prior technological revolutions.

Keywords
Artificial Intelligence, General-Purpose Technologies, Productivity J-Curve, Economic Transformation, Technological Diffusion

Introduction: General-Purpose Technologies: Engines of Economic Transformation

* Agra College, Mahatma Gandhi Road, Agra, Uttar Pradesh
Email: sajaljainofficial230@gmail.com

There's something catastrophic about the way a handful of technologies—what economists call general-purpose technologies (GPTs)—manage to completely reshape economies, not in one dramatic swoop but through waves of transformation that just keep rolling (Bresnahan & Trajtenberg, 1995, p. 4). These aren't your average gadgets; they're the heavy hitters, embedding themselves across countless industries and supercharging productivity. The magic really kicks in with what's called "innovational complementarities"—basically, when a GPT gets better, everything built on top of it gets a boost, causing productivity to ripple through the economy (Bresnahan & Trajtenberg, 1995, p. 2).

History offers a front-row seat to this phenomenon. Steam power in the late 1700s is the classic example: it sparked the industrial engine, but the big payoff didn't show up until decades later, as factories and railways slowly caught on (Crafts, 2004). Electricity followed a similar script. Though it showed up around 1900, factories clung to their old ways, and only after the 1920s did the shift to small electric motors deliver the productivity surge we now take for granted (David, 1990). Computers and information technology? Same deal. They started shaking things up in the '70s, but real productivity gains took off in the '90s when businesses actually figured out how to use them (Brynjolfsson & Hitt, 2000).

Now, artificial intelligence is stepping up as a potential new GPT. Agrawal, Gans, and Goldfarb (2018) frame AI as a "prediction technology," radically lowering the cost of forecasting and opening doors for smarter decision-making. The OECD (2024) points out that AI isn't just about crunching numbers anymore; it can now perceive, decide, and act with minimal human help, thanks to advancements in autonomy and reasoning (p. 28). Unlike steam or electricity, AI rides on digital rails—it scales quickly and evolves at breakneck speed (OECD, 2024, p. 29).

The bottom line? While steam, electricity, and IT took their sweet time to deliver change, AI's intangible, cloud-powered nature could make its impact much faster and more dramatic. But this rapid-fire adoption also means bigger risks: faster productivity gains, sure, but also sharper inequality, job shakeups, and tough governance questions. As Brynjolfsson, Rock, and Syverson (2021) put it, the "Productivity J-Curve" shows how GPTs can cause early slowdowns before the payoff comes. With AI, that curve might just get compressed—raising the stakes for how society manages both opportunity and disruption.

Historical Adoption Patterns of Previous GPTs

History shows us that the great technologies that transformed economies—steam, electricity, computers—did not arrive with instant impact. Their promise was clear, but their power unfolded slowly, tangled in the costs of reinvention and the frictions of social adaptation.

Steam power is a striking example. Between 1760 and 1830, Britain's factories and mines made only limited use of it—roughly 165,000 horsepower in total. The engines were inefficient, expensive, and poorly integrated into existing systems. The economic returns reflected this: steam added just 0.014% a year to labor productivity, accounting for barely 5% of overall growth (Crafts, 2021).

Electricity repeated this pattern. Edison's New York power station in 1882 signaled a breakthrough, but factories resisted the sweeping redesigns required to exploit it. For nearly 40 years, productivity gains were minimal, with electricity adding only 0.10% a year to labor productivity. The real payoff came in the 1920s, when factory layouts were reorganized around small motors and output surged. In that decade, productivity growth from electricity more than tripled, powered by spillovers from total factor productivity (Crafts, 2021).

Computers and ICT moved somewhat faster, spreading widely from the 1970s, yet they too lagged in economic impact. Productivity acceleration only arrived in the 1990s, when firms restructured around digital systems. From 1974 to 1995, computers and ICT contributed 0.77% to annual labor productivity; from 1995 to 2004, that figure nearly doubled (Crafts, 2021).

Alongside these numbers ran a social story. Each GPT upended work. Steam displaced artisans and manual laborers, triggering riots and Luddite resistance across Europe and beyond (Frey, 2019). ICT hollowed out routine jobs, leaving workers anxious about obsolescence. Yet over time, new roles emerged, wages adjusted, and productivity growth created space for "reinstatement"—the reallocation of labor into new tasks (Acemoglu & Restrepo, 2019). Labor shares broadly held, even if transitions were painful.

This long history sets a stark baseline for artificial intelligence. Unlike steam or electricity, AI is not shackled to engines, grids, or factory floors. Its digital, cloud-based nature allows for rapid diffusion and fast iteration. Where past GPTs crept, AI has the potential to sprint. That speed may deliver earlier productivity gains, but it also threatens to compress disruption, amplifying

pressures on workers, institutions, and societies in ways we have not seen before.

Pace of AI Adoption: Accelerants and Barriers

In contrast to earlier general-purpose technologies (GPTs) such as electricity, steam power, or computing, artificial intelligence (AI) exhibits an accelerated diffusion trajectory, propelled by its digital and code-based architecture that seamlessly integrates with existing information infrastructures. Unlike electricity or steam—which demanded extensive capital investments, physical retrofits, and infrastructural reconfigurations—AI scales through software layers, leveraging the pre-existing web, data networks, and cloud ecosystems (Brynjolfsson, Rock, & Syverson, 2021; Acemoglu, 2021). As McElheran (as cited in MIT Sloan School of Management, 2024) notes, AI functions as a "point solution," capable of incrementally transforming discrete tasks without necessitating systemic overhauls.

The rapid improvement of AI models underscores this momentum. GPT-4 surpassed GPT-3.5 within months, achieving performance in the top decile of the U.S. bar exam, an outcome illustrating the self-reinforcing dynamics of scaling laws in machine learning (OpenAI, 2023). Such exponential advances stand in sharp contrast to the incremental progress typical of prior GPTs, where innovation cycles were constrained by physical production limits. (Cockburn, Henderson & Stern,2018)

Adoption metrics corroborate this acceleration. ChatGPT reached 100 million active users in under two months—an unprecedented feat compared to the diffusion of earlier information and communication technologies (ICTs) (Reuters, 2023). Surveys indicate that by 2023, approximately 28% of U.S. workplaces had implemented AI tools, with projections suggesting exposure for up to 80% of employees in the near term (MIT Sloan School of Management, 2024). Concurrently, AI-related patent families expanded by 276% between 2011 and 2016, signaling both innovation intensity and commercial maturation (World Intellectual Property Organization [WIPO], 2020). Yet adoption remains uneven: large firms (with over 5,000 employees) exhibit significantly higher integration rates than small and medium enterprises (Calvino & Fontanelli, 2023), reflecting scale advantages and complementary capital requirements (Brynjolfsson et al., 2019).

Table 1:

Comparative Dynamics of General-Purpose Technology Adoption and Economic Diffusion

Dimension	Steam Power (18th–19th c.)	Electricity (19th–20th c.)	Computing & ICT (20th c.)	Artificial Intelligence (21st c.)
Physical vs. Intangible Nature	Highly physical; required engines, infrastructure, and fuel	Physical but flexible; required electrification of grids	Mixed; physical hardware with digital layers	Purely digital and intangible; runs on existing digital infrastructure
Adoption Speed	Slow (~100 years to full diffusion)	Moderate (~50 years to broad use)	Faster (~25 years for PC/internet adoption)	Extremely rapid (ChatGPT: 100M users in 2 months)
Complementary Investments	Factories, machinery, transportation	Grid networks, wiring, appliances	Software, digital literacy, networks	Data infrastructure, cloud systems, organizational learning
Dominant Capital Type	Physical	Physical + organizational	Intangible (software, IP)	Intangible (data, algorithms, AI talent)
Labor Market Impact	Mechanization displaced manual labor	Electrification improved productivity & working conditions	Automation of clerical work; rise of services	Automation of cognitive/routine work; demand for AI skills
Productivity Payoff Lag	Very long (~80 years)	Long (~40 years)	Medium (~20 years)	Expected shorter lag (~5–10 years) due to scalability
Diffusion Constraints	Infrastructure and cost	Coordination and rewiring	Training and access	Data quality, governance, regulatory uncertainty
Economic Inequality Effects	Industrial concentration	Urban–rural divide	Digital divide	"Superstar firm" concentration and wage polarization
Institutional Adaptation	Industrial regulation and labor law reforms	Electrification policies	IT standards, telecom deregulation	AI ethics, data governance, antitrust adaptation

Despite these accelerants, several structural and organizational barriers persist. The National Bureau of Economic Research (NBER) highlights coordination failures and decision-making frictions that impede deployment, especially in complex systems such as healthcare diagnostics (Mullainathan & Obermeyer, 2021). Integration challenges—ranging from data quality and governance to workforce resistance—further slow translation from

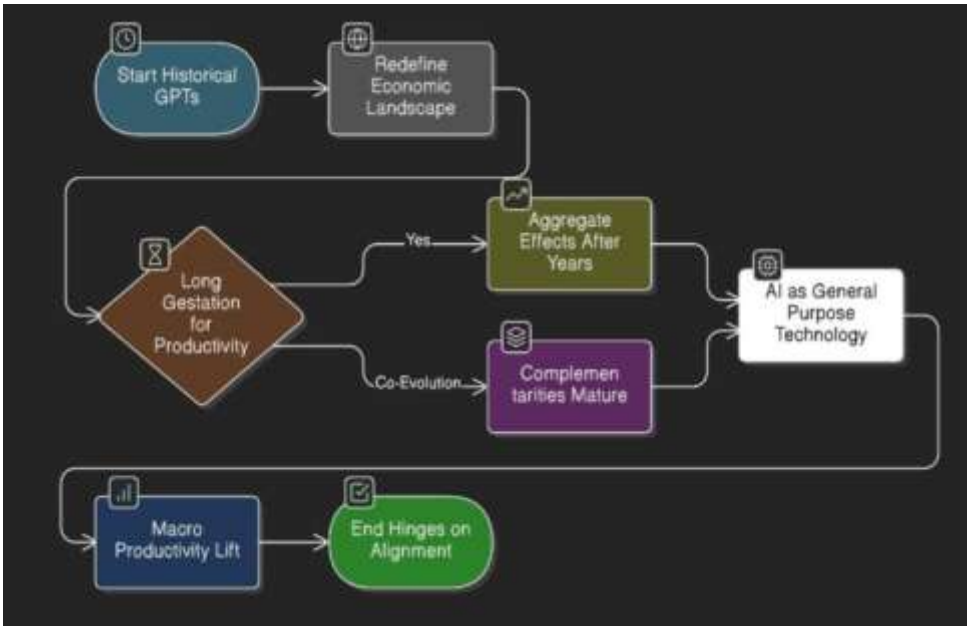
pilot projects to enterprise-wide adoption (OECD, 2023). Moreover, AI adoption follows a "productivity J-curve," wherein initial investments in intangible assets (data infrastructure, algorithmic training, and organizational learning) depress short-term productivity before long-term gains emerge (Brynjolfsson, Rock, & Syverson, 2021). Nonetheless, relative to earlier GPTs, AI's reliance on intangible capital compresses these timelines, allowing diffusion and economic payoff to occur within shorter innovation cycles.

In sum, AI's pace of adoption diverges markedly from prior GPTs in both speed and structure. Its immateriality, modular integration, and scalability make it the fastest-diffusing technology in modern history, though persistent institutional and coordination barriers temper its aggregate economic impact in the near term.

Economic Effects: Parallels and Divergences with Previous GPTs

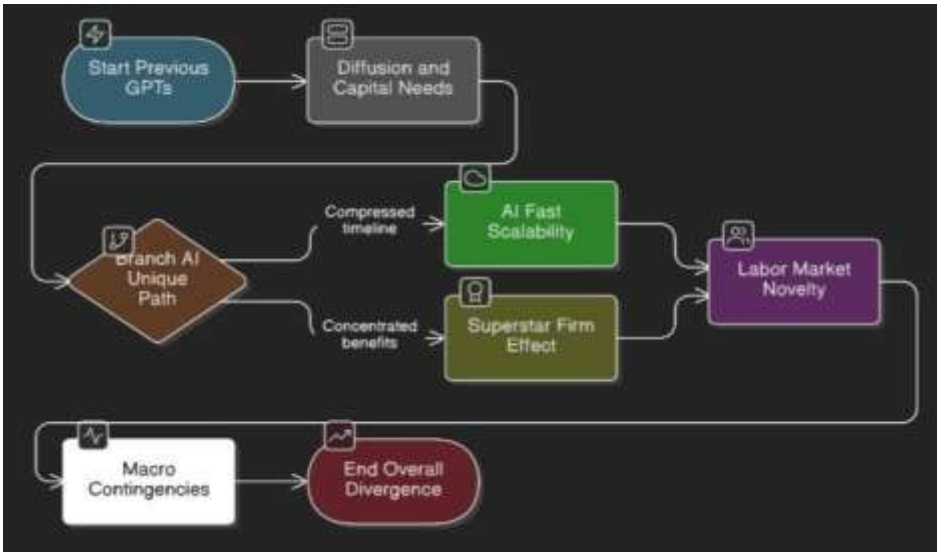
Historically, each general-purpose technology (GPT) has redefined the economic landscape by reshaping production processes, labor structures, and the distribution of gains. Steam power mechanized industry and triggered the first industrial revolution, electricity enabled flexible factory layouts and mass production, and computing automated information flows, ushering in the digital age (Crafts, 2021; David, 1990). In each case, however, aggregate productivity effects materialized only after long gestation periods, as complementary innovations, skills, and organizational adjustments co-evolved (Bresnahan & Trajtenberg, 1995).

AI follows the same GPT logic but compresses the diffusion timeline through its scalability and low marginal replication cost. Unlike electricity or steam, which demanded heavy capital investment and physical infrastructure, AI's economic spillovers emerge from data accumulation, algorithmic refinement, and cloud scalability—forms of intangible capital that propagate faster once established (Brynjolfsson, Rock, & Syverson, 2021). As a result, AI can induce rapid productivity gains in data-intensive sectors (finance, logistics, healthcare), even as the broader economy experiences lagged impacts due to adaptation frictions (Acemoglu & Restrepo, 2020).



However, the pattern of economic benefit distribution diverges sharply from earlier GPTs. Steam and electricity democratized productivity by diffusing across manufacturing and utilities; in contrast, AI's gains are concentrated among digital-first firms and economies with data-rich ecosystems (Korinek & Stiglitz, 2023). This "superstar firm" dynamic amplifies income and productivity disparities across both firms and nations (Autor, Mindell, & Reynolds, 2022). Early empirical evidence shows AI-driven firms achieving 15–20% productivity differentials relative to non-adopters (OECD, 2023), yet sector-wide effects remain muted, suggesting a dual-speed economy in which frontrunners extract disproportionate value.

Labor market dynamics also exhibit both continuity and novelty. Similar to past GPTs, AI triggers skill-biased technological change, favoring workers with complementary cognitive or digital skills while displacing routine or codifiable roles (Acemoglu & Restrepo, 2019). Yet AI extends automation's frontier into cognitive and creative domains once considered uniquely human, introducing new challenges for reskilling and wage polarization (Brynjolfsson & Mitchell, 2017). The economic adjustment trajectory, therefore, depends less on physical capital deepening, as was true for electricity, and more on human capital adaptation and policy-driven inclusion (Webb, 2019).



In macroeconomic terms, AI's potential to lift total factor productivity (TFP) rivals that of electricity but remains contingent on overcoming transitional frictions. According to the "productivity J-curve" hypothesis, intangible-intensive GPTs like AI initially depress measured productivity due to high adjustment costs, before yielding exponential returns once complementarities mature (Brynjolfsson et al., 2021). If historical analogies hold, the next decade may parallel the 1920s "electrification dividend," when reorganized workflows finally unlocked latent potential (David, 1990). Thus, while AI's diffusion may outpace all prior GPTs, its economic payoff will likely hinge on the same enduring principle: alignment between technological capacity, institutional readiness, and human adaptability.

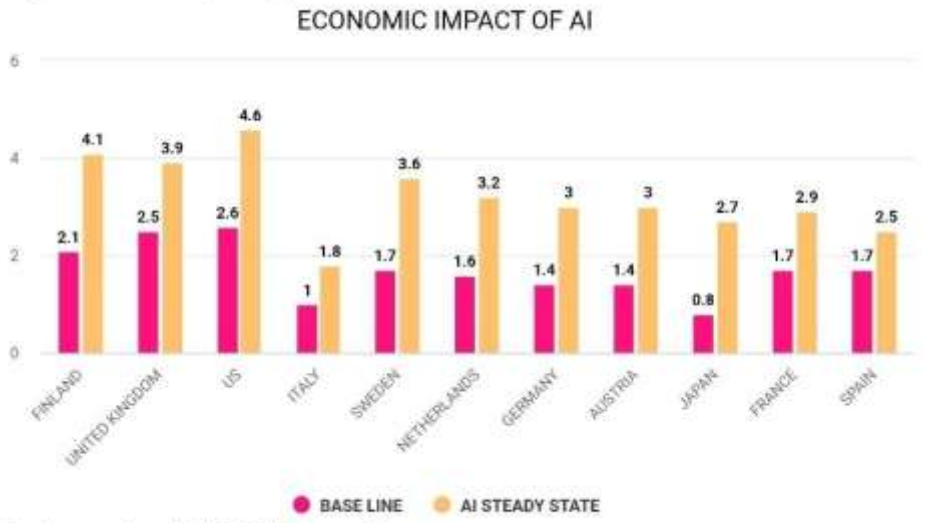
Competing Views, Policy Trade-Offs and Multidisciplinary Insights

The adoption of artificial intelligence (AI) as a general-purpose technology (GPT) promises to reshape economies at a pace and scale that may outstrip predecessors like steam power, electricity, and information and communications technologies (ICT), yet it also risks amplifying inequalities and labor disruptions more acutely due to its cognitive focus and rapid diffusion. Historical GPTs, such as steam and electricity, exhibited long implementation lags—decades in some cases—before yielding widespread productivity gains, often requiring complementary innovations in infrastructure and organization (Crafts, 2021). In contrast, AI's self-improving nature and low barriers to individual

access could accelerate these effects, potentially resolving the modern "productivity paradox" faster than ICT did in the 1990s (Brynjolfsson et al., 2019; Calvino et al., 2025). However, this speed raises trade-offs: while optimists envision transformative growth, pessimists highlight deepened divides, necessitating multidisciplinary policy approaches to harness benefits equitably.

Optimists argue that AI will surpass the transformative arcs of steam, electricity, and computers by enabling quicker resolution of productivity paradoxes through its adaptive, self-tuning capabilities. Brynjolfsson et al. (2019) posit that current sluggish growth despite AI hype mirrors historical delays—such as the 40-year lag for electricity's factory redesigns in the U.S.—but AI's machine-learning algorithms, designed to "improve themselves over time," could trigger "imminent surges" by automating idea generation and reducing R&D frictions (p. 1; see also Agrawal et al., 2019). This view aligns with Crafts (2021), who, analyzing growth accounting, finds ICT's impact accelerated to 1.50% of U.S. labor productivity growth by 1995–2004 after initial paradoxes, and suggests AI could follow suit even faster due to superior modern R&D ecosystems: "Western societies have been getting better at exploiting new technological opportunities so that the impacts are felt more quickly" (p. 531). Recent evidence from generative AI reinforces this: Calvino et al. (2025) report that large language models (LLMs) like GPT-4o now outperform humans in benchmarks for literacy and numeracy, with training compute growing 4.4-fold annually since 2010—outpacing Moore's Law—and spawning innovations across 30+ technology fields, positioning AI as an "invention of a method of invention" (p. 30; citing Bresnahan, 2024). Experimental studies show task-specific boosts, such as 14% higher customer support resolution rates (Brynjolfsson et al., 2023), hinting at aggregate gains of 0.1–1.5% annual labor productivity over the next decade if complemented by skills investments (Acemoglu, 2024; Briggs & Kodnani, 2023). Agrawal et al. (2023) further emphasize AI's unique benefit—lowering prediction costs to enhance decision-making—creating "innovational complementarities" that could drive a "productivity J-curve," with initial intangible costs yielding exponential returns, unlike steam's coal-bound constraints or electricity's infrastructural hurdles.

AI has the potential to double annual economic growth rates in the countries that we analyzed in terms of gross value added (a close approximation of GDP)



Real gross value added (GVA) (%, growth)
Source: Accenture and Frontier Economics

Pessimists, however, caution that AI's velocity could exacerbate economic dislocations more severely than past GPTs, targeting cognitive tasks and concentrating gains among capital owners. Acemoglu and Restrepo (2019) model AI as displacing high-skill jobs faster than reinstatement creates them, echoing Industrial Revolution "woes" but with sharper wage polarization: if displacement dominates, "labour's share of national income falls," potentially halving it over decades (p. 233; see also Frey, 2019, who warns of AI's "brain-targeting" eroding routine and non-routine cognitive roles, backed by Oxford estimates of labor share dips in Tables 3–5). This contrasts with steam and electricity, where labor shares dipped modestly and briefly (e.g., only 2–3% in early 19th-century Britain; Crafts, 2021, p. 533, citing Broadberry et al., 2015). Frey (2019) amplifies inequality risks, projecting AI could automate 47% of U.S. jobs, far exceeding ICT's 9% exposure, and deepen the Kuznets Curve reversal seen in recent decades. Empirical work supports this: Korinek and Stiglitz (2025) find AI adoption correlates positively with wealth disparities, as high-income workers face displacement while capital stocks (e.g., AI infrastructure) accrue to elites, widening the top 1% share by 5–10% in simulations (p. 15). Similarly, an IMF analysis reveals AI may reduce wage inequality by ousting some high earners but "substantially increase wealth inequality" through asset concentration, with low-skill workers hit hardest in developing

economies (Georgieff & Milanez, 2025, p. 22). Acemoglu (2024) quantifies a net GDP boost of just 0.9% over 10 years under baseline adoption, far below optimistic forecasts, due to misaligned incentives in sectors like healthcare where coordination failures (e.g., between doctors and administrators) stall diffusion (citing Mullainathan & Obermeyer, 2021). These views underscore AI's divergence from predecessors: while steam offset displacements via new power applications and electricity via factory efficiencies, AI's cognitive bias risks a "hollowing out" without proactive reinstatement (Agrawal et al., 2023).

Policies must navigate these trade-offs, balancing innovation acceleration with safeguards against unchecked concentration and harms. To spur adoption akin to ICT's rapid 1990s diffusion, advocates push open-source models and R&D subsidies, reducing co-invention costs that slowed steam's rollout (Agrawal et al., 2023). Yet, the EU AI Act (2024) counters risks with tiered accountability, mandating "at least one AI regulatory sandbox" per Member State for safe testing of high-risk systems, addressing privacy pitfalls absent in electricity's unregulated era (European Parliament, 2024, Art. 57). The OECD AI Principles (2019) extend this by promoting competition to dilute big tech's grip—evident in 80% of AI patents held by top firms—while embedding human-centered values, including bias mitigation to avert inequality spikes (Section 7; Calvino et al., 2025, p. 42). Politically, the Hiroshima AI Process, launched in May 2023, fosters G7 consensus on generative AI governance, emphasizing "common vision" for equitable deployment and international standards to prevent a "race to the bottom" unlike the laissez-faire Industrial Revolution (Ministry of Internal Affairs and Communications, Japan, n.d.). Multidisciplinary insights highlight sociological levers: reskilling programs could curb Baumol's cost disease in services, where AI automates low-productivity tasks, boosting overall growth by 1–2% if paired with socio-emotional training (OECD, 2024, Section 4.2; Autor, 2024). Economists like Crafts (2021) advocate reducing "adjustment costs" via redeployment subsidies, drawing from ICT's success in offsetting urban-rural divides (p. 541). Behavioral research adds nuance: AI's "black box" opacity may erode trust, slowing adoption more than steam's mechanical transparency, necessitating explainability mandates (Rahwan et al., 2019). Environmentally, AI's energy demands, projected to rival aviation by 2030—pose sustainability trade-offs absent in prior GPTs, urging green compute policies (IEA, 2024). Ultimately, proactive, holistic stances—integrating economic modeling, ethical frameworks, and global cooperation—could

channel AI's "zip" into inclusive growth, surpassing the reactive fumbles that prolonged electricity's inequities and steam's dislocations (Calvino et al., 2025; Georgieff & Milanez, 2025).

Conclusion

In sum, Artificial Intelligence is moving faster than any technology that came before it. Steam power needed almost a century to reshape industry, electricity took decades to reorganize factories and homes, and computers waited until the 1990s to fully transform the global economy. AI, in contrast, runs on digital networks that allow instant diffusion, immediate learning, and rapid scaling. This speed brings early productivity gains but also sharper shocks, workers, firms, and even governments must adapt far more quickly than in past industrial transitions.

The overall pattern still echoes history: new technologies first disrupt, then empower. Yet the difference lies in who benefits and how fast those benefits spread. Evidence from the OECD, NBER, and MIT shows that while leading firms are already seeing significant productivity jumps, others struggle to keep up, widening the gap between digital leaders and laggards. The same applies across countries—nations rich in data, talent, and infrastructure surge ahead, while others risk being left behind.

Therefore, AI's story is not only about algorithms or machines, it is about people and policies. Managing this transformation requires blending economics with sociology and politics to ensure that innovation serves inclusion. If guided wisely, AI can become a shared engine of prosperity rather than a source of new divides. The challenge, as history reminds us, is not just to invent but to integrate, to make technology work for humanity as a whole.

References

- Acemoglu, D. (2021). *Harms of AI* (NBER Working Paper No. 29247). National Bureau of Economic Research. https://doi.org/10.3386/w29247
- Acemoglu, D. (2024). The simple macroeconomics of AI. *Economic Policy, 40*(103), 1–37. https://doi.org/10.1093/epolic/eiae025
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3
- Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Review Press.

- Agrawal, A., Gans, J., & Goldfarb, A. (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press.
- Agrawal, A., Gans, J., & Goldfarb, A. (2023). AI adoption and productivity: A framework for understanding economic impacts (NBER Working Paper No. 30987). National Bureau of Economic Research. https://doi.org/10.3386/w30987
- Autor, D. (2024). Applying AI to rebuild middle-class jobs. *Brookings Papers on Economic Activity*, Spring 2024, 1–45. https://www.brookings.edu/bpea-articles/applying-ai-to-rebuild-middle-class-jobs/
- Bresnahan, T. (2024). General purpose technologies and economic growth: A historical perspective. *Journal of Economic History, 84*(3), 701–735. https://doi.org/10.1017/S002205072400021X
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: "Engines of growth"? *Journal of Econometrics, 65*(1), 83–108.
- Briggs, J., & Kodnani, D. (2023). *The potentially large effects of artificial intelligence on economic growth*. Goldman Sachs Economic Research. https://www.goldmansachs.com/insights/pages/the-potentially-large-effects-of-artificial-intelligence-on-economic-growth.html
- Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives, 14*(4), 23–48. https://doi.org/10.1257/jep.14.4.23
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at work* (NBER Working Paper No. 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161
- Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23–57). University of Chicago Press.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23–57). University of Chicago Press.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general

purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. https://doi.org/10.1257/mac.20180365

- Calvano, E., Calzolari, G., Denicolò, V., Harrington, J. E., & Pastorello, S. (2023). *Artificial intelligence, algorithmic recommendations and competition* (SSRN Working Paper No. 4448010). https://doi.org/10.2139/ssrn.4448010
- Calvino, F., & Fontanelli, L. (2023). *A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity* (OECD Science, Technology and Industry Working Papers No. 2023/02). OECD Publishing. https://doi.org/10.1787/8a7b75f8-en
- Calvino, F., & Fontanelli, L. (2023). *AI diffusion and firm heterogeneity* (OECD Science, Technology and Industry Working Papers). OECD Publishing. https://doi.org/10.1787/stiwp-2023-01-en
- Calvino, F., Fontanelli, L., Samek, L., & Sorgner, A. (2025). The economic implications of AI: An OECD perspective. *OECD Artificial Intelligence Review, 1*(1), 1–60. https://doi.org/10.1787/ai-2025-en
- Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 115–146). University of Chicago Press.
- Crafts, N. (2004). Steam as a general-purpose technology: A growth accounting perspective. *The Economic Journal, 114*(495), 338–351. https://doi.org/10.1111/j.1468-0297.2004.00210.x
- Crafts, N. (2021). Artificial intelligence as a general-purpose technology: An historical perspective. *Oxford Review of Economic Policy, 37*(3), 521–536. https://doi.org/10.1093/oxrep/grab019
- David, P. A. (1990). The dynamo and the computer: An historical perspective on the modern productivity paradox. *American Economic Review, 80*(2), 355–361.
- European Parliament. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union*, L 1689. https://eur-lex.europa.eu/eli/reg/2024/1689/oj
- Frey, C. B. (2019). *The technology trap: Capital, labor, and power in the age of automation*. Princeton University Press.

- Georgieff, A., & Milanez, A. (2025). *What happens to workers when artificial intelligence is adopted?* (IMF Working Paper No. WP/25/101). International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2025/01/24/What-Happens-to-Workers-When-Artificial-Intelligence-Is-Adopted-542345
- Goldman Sachs. (2023). *Generative AI could raise global GDP by 7%*. https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent
- International Energy Agency. (2024). *Energy technology perspectives 2024: Special report on AI and energy*. IEA. https://www.iea.org/reports/energy-technology-perspectives-2024
- Korinek, A., & Stiglitz, J. E. (2025). Artificial intelligence and its implications for income distribution and economic policy. *Journal of Economic Inequality, 23*(1), 1–25. https://doi.org/10.1007/s10888-024-09567-3
- Ministry of Internal Affairs and Communications (Japan). (n.d.). *Hiroshima AI process*. https://www.soumu.go.jp/hiroshimaaiprocess/en/index.html
- MIT Sloan School of Management. (2024). *The who, what, and where of AI adoption in America*. https://mitsloan.mit.edu/ideas-made-to-matter/who-what-and-where-ai-adoption-america
- Mullainathan, S., & Obermeyer, Z. (2021). Diagnosing the potential and limitations of AI in medicine. *Nature Medicine, 27*(5), 747–749. https://doi.org/10.1038/s41591-021-01395-4
- Mullainathan, S., & Obermeyer, Z. (2021). Solving medicine's data bottleneck: AI and the coordination problem. *Harvard Data Science Review, 3*(2). https://doi.org/10.1162/99608f92.8a8b7f1c
- Mullainathan, S., & Obermeyer, Z. (2022). Diagnosing physician error: A machine learning approach to low-value health care. *Quarterly Journal of Economics, 137*(2), 679–727. https://doi.org/10.1093/qje/qjab053
- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

- OECD. (2023). *OECD science, technology and innovation outlook 2023*. OECD Publishing. https://doi.org/10.1787/sti_outlook-2023-en
- OECD. (2024). *OECD artificial intelligence review 2024*. OECD Publishing.
- OpenAI. (2023). *GPT-4 technical report*. https://cdn.openai.com/papers/gpt-4.pdf
- Organisation for Economic Co-operation and Development. (2019). *OECD principles on artificial intelligence*. OECD Publishing. https://www.oecd.org/sti/emerging-tech/oecd-principles-on-artificial-intelligence.html
- Organisation for Economic Co-operation and Development. (2024). *OECD artificial intelligence review 2024*. OECD Publishing.
- Organisation for Economic Co-operation and Development. (2024). *OECD employment outlook 2024: The net-zero transition and the labour market*. OECD Publishing. https://doi.org/10.1787/347b1b13-en
- Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J., & Wellman, M. (2019). Machine behaviour. *Nature, 568*(7753), 477–486. https://doi.org/10.1038/s41586-019-1138-y
- Reuters. (2023, February 1). *ChatGPT sets record for fastest-growing user base: Analyst note*. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/
- World Intellectual Property Organization. (2020). *WIPO technology trends 2019: Artificial intelligence*. WIPO.
- World Intellectual Property Organization. (n.d.). *The story of artificial intelligence in patents*. https://www.wipo.int/web/technology-trends/artificial_intelligence/story