Economic Contraction From AI-Driven Labor Displacement

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Major technology firms, and universities, such as Anthropic and Stanford University have been doing substantial research and reporting on market trends and what they project may happen soon as Large Language Models (LLM's) and AI continue to advance. This tumult of opinions and differing research results has not led to a consensus on how we should move forward. However, it has brought to light different possibilities about what the future may hold for people who may be directly affected and those who think they are free from the onslaught of this technology. Acemoglu et al. (2022) outlined the differing opinions well when they noted, "Some commentators see this as a harbinger of a jobless future (e.g., Ford 2015; West 2018; Susskind 2020), while others consider the oncoming AI revolution as enriching human productivity and work experience" (p. 2). The vast amount of data available and trends observed are major factors in differing research results.

Advancements and adoption in AI system capabilities pose serious threats to industries and labor markets. The adoption of this technology in businesses has put serious strain on current "white-collar", knowledge-based jobs which has led to mass layoffs and substantial decrease in entry-level employment. Expansion in unemployment will force displaced individuals into labor-based industries, leading to growth of the low-income labor force. A rising lower-class has the potential to hollow out Gross Domestic Product (GDP) as liquidity and spending lessen. Subsequent wealth concentration will occur toward owners of production and capital from these labor shifts. The compounding of these forces has the potential to trigger a Gartner Hype Cycle correction, and without effective governance to induce reintegration, may lead to further financial collapse.

In early 2026 Jack Dorsey, Block CEO, laid off 4,000 workers and said the following on AI systems advancing and taking over roles: “A significantly smaller team, using the tools we’re building, can do more and do it better. And intelligence tool capabilities are compounding faster every week” (Montgomery, 2026, para. 3). The effects of such layoffs have the potential to lead to mass unemployment coming in two forms: layoffs of white-collar knowledge workers and the reduction of hiring for entry-level positions. The effects of this are evident, not only by the example from Block, but also by Massenkoff and McCrory (2026) who outlined the tasks first adopted by AI systems. The coverage of these tasks has almost completely taken over some industry roles, “Programmers are at the top, with 75% coverage, followed by Customer Service Representatives, whose main tasks we increasingly see in first-party API traffic. Finally, Data Entry Keyers… are 67% covered” (Massenkoff & McCrory, 2026, p. 8). Massenkoff and McCrory (2026) further characterized the most displaced worker:

> The more exposed group is 16 percentage points more likely to be female, 11 percentage points more likely to be white, and almost twice as likely to be Asian. They earn 47% more, on average, and have higher levels of education. For example, people with graduate degrees are 4.5% of the unexposed group, but 17.4% of the most exposed group, an almost fourfold difference. (p. 9)

Their data gives a clear outline of the most exposed person, an Asian female with higher levels of education and higher average pay. This report is concerning since it has the potential to undermine the importance of baccalaureate education and graduate education. The path that so clearly led to favorable career outcomes now places individuals at the greatest risk of displacement.

The financial incentive to adopt AI systems is straightforward. By reducing headcount, compensation expenditure will drop significantly, and the one-time costs of implementation will be offset by the compounding operational savings over time. Massenkoff and McCrory (2026) further confirmed this point when their report displayed that “one group of particular concern is young workers. Brynjolfsson et al. report a 6–16% fall in employment in exposed occupations among workers aged 22 to 25. They attribute this decrease primarily to a slowdown in hiring rather than an increase in separations” (*Brynjolfsson et al., as cited in Massenkoff & McCrory, 2026, p. 12).* The result is less access to white-collar income and increasing pressure toward lower wage alternatives.

Reemployment opportunities for displaced workers in similar roles are not being created sufficiently, as Acemoglu et al. (2022) demonstrated, which leaves displaced workers facing constrained labor markets. The occupations least exposed to AI adoption are those requiring physical labor and manual execution such as construction and service roles. As Acemoglu et al. (2022) noted, AI exposure "is very low for service, production, and construction workers, capturing the fact that these occupations involve various manual tasks that cannot currently be performed by algorithms” (p. 15). The surplus of former white-collar workers competing for labor-intensive roles creates wage pressure across those industries, expanding the low-income labor force. Massenkoff and McCrory (2026) confirmed this shift, finding that “occupations with higher observed exposure are projected by the [Bureau of Labor Statistics] BLS to grow less through 2034” (p. 2). The result is an expansion of the low-income workforce, which directly affects aggregate consumption.

In the short run, the effects of unemployment are clear. With fewer people being employed the aggregate demand (AD), the total planned expenditure on all final goods and services produced within an economy, falls as individual liquidity from lower income decreases. Goda et al. (2017) explained that "A fall in the wage share reflects falling unit labor costs and increasing profitability" (p. 9), showing that income shifts away from laborers toward capital owners. Goda et al. (2017) further outlined that "… a rise in inequality in the form of a fall in the share of wages will, other things being equal, suppress domestic consumption since the marginal propensity to consume out of wages is higher than that out of profits" (p. 9).

Displaced laborers will be affected by such shifts in a 3-step process. First, shrinking income and savings, second, exhaustion of savings to cover basic needs, and third taking on debt and interest to cover necessities. The deterioration of funds and accumulation of debt further reduces their consumption, compounding the initial decrease in demand. As Gusella and Variato (2025) demonstrated, "the value of financial assets and the presence of capital gains favors the process of inequality. Basically, the portfolio choices of those who belong to the bottom deciles of the distribution of wealth are qualitatively different from the ones of those who belong to the top decile" (p. 9). Goda et al. (2017) further explored this using the 2008 housing crisis, where rising demand for debt securities among a wealthier class led to the creation of collateralized debt obligations (CDOs), leading to financial assets concentrated upwards, while working-class households suffered the burdens of defaulting loans.

In the long run, the advancements of AI systems drastically improve the productivity of outputs, and cost of inputs are significantly less. Ajuzieogu (2025) examined how,

> The development of foundation models requires substantial upfront investment in research, data acquisition, and training compute, often ranging from tens to hundreds of millions of dollars for frontier models. However, once trained, the marginal cost of serving an additional inference request approaches zero, particularly for text-based models. (p. 5)

Ajuzieogu (2025) further argued the high costs of initial training from companies provides substantial opportunity to draw upon economies of scale, which is the decreasing long-run average cost as output increases. Not only will the company that produced these models benefit from economies of scale, other firms that can replace white-collar knowledge workers with AI systems will also benefit. Furthermore, decreasing average costs will lead to a rightward shift in long run aggregate supply (LRAS), which is the total output of an economy when all factors of production are fully employed. However, in the case of AI system adoption, this will not lead to increased economic growth as workers replaced by these models will have decreased individual liquidity. Growiec (2024) confirmed that "some outcome measures, such as global GDP and people's aggregate consumption, which have been correlated in a world where economic growth serves the needs of people, may cease to be correlated in a world overseen by superhuman general AI" (p. 20).

The opposition will note that as AI system production and job displacement increases, new labor markets will evolve. The new labor market associated with AI system production will be managerial and cognitive type roles to control and oversee the use of these tools. Acemoglu et al. (2022) outlined this possibility noting that:

> AI-exposed establishments may see an increase in (non-AI) hiring if either AI directly complements workers in some tasks, increasing their productivity and encouraging more hiring, or AI substitutes for workers in some tasks but increases total factor productivity sufficiently to raise demand in nonautomated tasks via a productivity effect. (p. 4)

The displaced workers being forced to work in more labor-intensive industries may be able to leverage previous experience and knowledge they had to oversee the use of these tools. Zhang (2026) confirmed that "Firms adopting agent workflows will show rapid declines in job postings for entry-level roles while continuing to post supervisory/AI-ops roles" (p. 8). Acemoglu et al. (2022) further observed that "the possibility that AI will complement workers engaged in exposed tasks…This type of human-complementary AI may increase labor demand because algorithms raise human productivity in exactly the tasks in which AI is being adopted" (p. 10). These two views work together so long as the effectiveness of these models and capabilities are below what humans can supervise. However, Growiec (2024) noted that "AI tended to increase employment in sectors exposed to it (Albanesi et al., 2023); this trend will probably reverse as AI algorithms become more advanced and more broadly adopted in the economy" (p. 5). Acemoglu et al. (2022) additionally noted that "any positive productivity and complementarity effects from AI are at present small compared with its displacement consequences" (p. 4).

The displacement of labor income does not disappear, rather, it is distributed to owners of production, widening the gap in income inequality. Goda et al. (2017) noted that "between 1986 and 2012 HNWIs' wealth increased 6.6-fold — from US$7.2 trillion to US$46.2 trillion — and billionaires' wealth more than 15-fold. In the US, 'the top one percent received 38 percent of the total growth in net worth... the upper quintile got it all" (p. 13). Gusella and Variato (2025)

additionally observed “that those who hold financial assets become wealthier during the growth process with respect to those who have no financial wealth” (p. 17), a situation which generates increasing income inequality.

The Gartner Hype Cycle examines the “progression of an emerging technology from overenthusiasm through a period of disillusionment to an eventual understanding of the technology's relevance and role in a market or domain” (Linden & Fenn, 2003, p. 1). The rise portion of this cycle displays emerging products, and the research and development costs associated with them. Ajuzieogu (2025) previously mentioned the high cost associated with training these models; this is precisely what occurs in the rise of the cycle. Advancements are currently at the peak of the cycle with the high number of firms providing these models and seeing potential shifts in how they are used alongside human labor. Linden and Fenn (2003) explained the trough, or falling portion, of the cycle as disillusionment from lower expectations. Rather, the trough of the cycle is not due to lower expectations but from major shifts in labor markets resulting in wealth concentration. Climbing the slope and plateau of this cycle is where firms better understand the application of this technology and can use it for their benefit. The plateau “… represents the beginning of mainstream adoption, when real world benefits of the technology are demonstrated and accepted” (Linden & Fenn, 2003, p. 9). Integrating these models will drive the major shifts in labor markets, and high displacement of white-collar workers into labor-intensive markets. One major difference between the AI revolution from previous revolutions, such as the industrial, and internet, is the plateau does not reabsorb displaced labor. Previous revolutions allowed for sufficient scaling to create new job positions in a mixture of management and engineering roles. However, the narrow nature of AI operation

roles is not sufficient to offset the volume of displaced workers. Therefore, the plateau does not represent a new equilibrium, rather it is the accumulation of economic consequences converging: decreased aggregate consumption, wealth concentration, and labor force restructuring. Growiec (2024) examined that,

> …markets are notoriously bad at pricing latent risks that rarely materialize... as the bubble burst in mortgage markets causing the Global Financial Crisis of 2007–09, along came the late realization that financial development created mounting latent risk which was not adequately priced. A similar mechanism is observed with AI system development — as long as the existential risk does not materialize, its effects are highly beneficial for economic productivity and its risks are severely underpriced. (p. 18)

As established above, displaced workers increasingly rely on debt to maintain necessities and consumption. Goda et al. (2017) identified this pattern as unstable, noting that debt driven by growth "[relies] on increasing accumulation of debt" (p. 8). At the same time wealth concentration accelerates the accumulation of financial assets among owners of production and capital, creating conditions Gusella and Variato (2025) described as the Minsky cycle; "the process of Minsky's instability characterizes the process of growth, simultaneously fueling increasing inequality in the functional distribution of income" (p. 27). When consumption depends on debt and assets are concentrated toward upper percentiles, the financial system becomes vulnerable to demand-side shock. Without governing mechanisms to reintegrate displaced workers and relocate gains from increased productivity, the deficits and aggregate demand have potential to escalate beyond the economy's ability to self-correct, raising systemic financial instability.

The structural risks outlined above are not predetermined, they are the product of policy choices, or the absence of them. Gusella and Variato (2025) proposed that correction,

> …can be controlled by the state through a process of the taxation of capital gains and the regulation of finance processes. It is necessary to understand how to stabilize or control financial fluctuations to avoid significant and negative repercussions on the rest of the economy. (p. 29)

Research points to three areas where policy can have an impact. First, taxation of capital gains brought by AI-driven productivity and redistributing a portion of those gains back into the labor market through retraining programs or wage subsidies. Second, regulating financial instruments that concentrate AI-generated wealth upward preventing the debt-driven demand substitution Goda et al. (2017) mentioned. Third, labor market intervention by investing in infrastructure that prepares displaced workers for supervisory and AI-operations roles that may emerge, rather than allowing displaced workers into low-wage industries. Without intervention, these pressures will build faster than the economy can absorb them.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics, 40*(S1), S293–S340. https://doi.org/10.1086/718327

Ajuzieogu, U. C. (2025, May). *Pricing models for AI inference: Economic efficiency and market equilibria*. SAAGEX Research.

Goda, T., Onaran, Ö., & Stockhammer, E. (2017). Income inequality and wealth concentration in the recent crisis. *Development and Change, 48*(1), 3–27. https://doi.org/10.1111/dech.12280

Growiec, J. (2024). Existential risk from transformative AI: An economic perspective. *Technological and Economic Development of Economy, 30*(6), 1682–1708. https://doi.org/10.3846/tede.2024.21525

Gusella, F., & Variato, A. M. (2025). Financial instability and income inequality: Why the Minsky–Piketty connection matters for macroeconomics. *Review of Political Economy, 37*(1), 108–141. https://doi.org/10.1080/09538259.2022.2117982

Linden, A., & Fenn, J. (2003, May 30). *Understanding Gartner's hype cycles* (Report No. R-20-1971). Gartner, Inc.

Massenkoff, M., & McCrory, P. (2026, March 5). *Labor market impacts of AI: A new measure and early evidence*. Anthropic. https://www.anthropic.com/research/labor-market-impacts

Montgomery, B. (2026, March 3). What was really behind Jack Dorsey laying off nearly half of Block's staff? *The Guardian*. https://www.theguardian.com/technology/2026/mar/03/jack-dorsey-block-ai-worker-jobs

Zhang, S. (2026). *AI zero-cost multiplier effect on white-collar labor: An economic analysis* [Preprint]. SSRN. https://doi.org/10.2139/ssrn.6147972