Will Generative AI Bring Change: Technological Disruption and Redistribution in the USA?

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Abstract: The purpose of this paper is to discuss, from the perspective of Original Institutional Economics (OIE), the potential implications of generative artificial intelligence (Gen-AI) for income redistribution in the USA. Specifically, we examine whether the proliferation of Gen-AI might shift the preferences of high-income groups towards nonmarket insurance and greater income redistribution, due to their increased risk of future income loss. Considering the opinion that Gen-AI could be our final invention, due to its potential for self-learning and incredible productivity, and recognizing Gen-AI's disruptive potential for workers performing non-cognitive tasks, we argue that AI-based automation will request new institutional arrangements. These institutional arrangement changes would promote the redistribution of income generated through economic processes with minimal human participation. Such institutional arrangements are largely reflective of the OIE ideas of an economy of abundance and the institutionalization of good work, with the job as a socially constructed institution at its core.

Keywords: Generative Artificial Intelligence, Institutional Changes; Income Redistribution, Original Institutional Economics, USA.

JEL: B15; D63; O33, O38.

Gen-AI is a groundbreaking technology that is difficult to compare with previous human inventions, raising numerous questions. One central question is how economic output will be divided between capital owners and workers, as well as among different groups of workers, in a world of intelligent machines where human input in economic processes is limited to a small number of unstable jobs. The assumptions and concepts of mainstream economics, focused on market mechanisms, may not be sufficient—or even appropriate—for addressing this issue. This shifts the discussion toward heterodox economics, particularly Original Institutional Economics (OEI), and its ideas of a society of abundance and progressive institutional changes. Accordingly, this paper will explore the anticipated distributive effects of Gen-AI and the societal responses to these changes in the United States, where this new technology originated, and which continues to lead its development.

Context: Technology-Driven Job and Wage Polarization in the USA

The literature provides well-documented evidence of rising income inequality in the USA throughout the last forty years (Gilens, 2012; Piketty & Saez, 2003; Saez & Zucman, 2020). The deterioration of income distribution arises from a complex interplay of various factors, with technological progress and its subsequent transformative effects on the labour market playing a particularly significant role. One of the key manifestations of this technology-inequality nexus is job and wage polarization.

The routine-biased nature of technological changes, a defining characteristic of most innovations since the 1980s, has driven a significant transformation in the U.S. labour market. This shift has involved a transition away from jobs involving routine (repetitive) tasks toward those requiring nonroutine (nonrepetitive) tasks (D. H. Autor et al., 2003; D. H. Autor & Dorn, 2013). As machines replace workers in routine tasks, employment in these occupations has declined, while the demand for nonroutine occupations has been rising. Given the empirical fact that routine-based occupations mainly consist of middle-class workers, this structural change has resulted in job polarization (Federal Reserve Bank of St. Louis, 2017).

Table 1: Levels and Changes in Employment by Major Occupation Groups, USA, 1983-2023

	Share of Employment					**% Growth (per 10yrs)**	
	1980s	1990s	2000s	2010s	2020s	(1980s-2020s)	(average)
Cognitive Nonroutine	29.51	32.13	35.11	38.78	43.04	45.84	0.95
Cognitive Routine	27.72	27.17	25.35	22.62	19.47	-29.75	-0.88
Manual Routine	26.44	24.38	22.54	20.30	20.88	-21.01	-0.59
Manual Nonroutine	15.45	15.55	16.27	17.59	15.94	3.20	0.08

Source: Authors' calculations based on data from the U.S. Bureau of Labor Statistics.

As reported in Table 1, routine occupations have experienced a significant and persistent decline over the past four decades. Specifically, between the 1980s and the 2020s, the employment share of routine cognitive and manual workers decreased by approximately 30% and 20%, respectively. By contrast, nonroutine cognitive occupations exhibited the opposite trend, with their share in total employment nearly doubling over the same period. As a result, this category of occupation now dominates the U.S. labour market, employing a workforce comparable in size to the combined total of routine occupations. The employment share of nonroutine manual workers has remained relatively stable throughout the period, accounting for approximately 15% of total employment.

Table 2: Levels and Changes in Median Weekly Real Wage by Major Occupation Groups, USA, 2000-2023

	Real Wage			**% Growth (per 10yrs)**	
	2000s	2010s	2020s	(2000s-2020s)	(average)
Cognitive Nonroutine	480	491	510	6.25	0.30
Cognitive Routine	291	288	305	4.81	0.24
Manual Routine	323	319	328	1.55	0.08
Manual Nonroutine	217	218	238	9.67	0.46

Source: Authors' calculations based on data from the U.S. Bureau of Labor Statistics.

The documented job polarization in the U.S. labour market is reflected in wage distribution (Table 2). Non-routine occupations, as the segments of the labour market where workers are being concentrated, consist of two distinct groups. On one end of the spectrum are highly paid cognitive non-routine workers, such as managers, professionals, and technicians, who dominate the upper tier of the wage distribution. On the other end are low-paid manual non-routine workers, for example food service employees and cleaners, who occupy the lower tier. This reallocation of workers from routine to non-routine occupations has contributed to wage polarization. Considering the factors behind wage polarization, we can identify parallels with job polarization, particularly the adverse effects of automation technologies on workers specializing in routine tasks (Acemoglu & Restrepo, 2022; Van Reenen, 2011; Woźniak-Jęchorek & Kuźmar, 2023) In this context, job polarization and wage polarization can be understood as two manifestations of the same trend in the U.S. labour market.

Focus: Gen-AI and New Forms of Polarization in the U.S. Labour Market

Although the term “Artificial Intelligence” was coined in the 1960s and has since been widely circulated, the phrase “Gen-AI” describes a new type of technology. The uniqueness of Gen-AI, compared with earlier technologies, lies in its ability to create content that cannot be distinguished from that produced by humans, including text, code, audio, videos, images, and many other applications (Bubeck et al., 2023; Walkowiak & MacDonald, 2023). Moreover, there is growing evidence that Gen-AI-generated content has surpassed human intelligence and creativity in many domains (Bohren et al., 2024; Bubeck et al., 2023; Haase & Hanel, 2023; Zhou & Lee, 2024).

The disruptive potential of Gen-AI in the labour market arises from its wide applicability and rapid diffusion. As a general-purpose technology, Gen-AI can reshape work processes across various industries. A recent IMF study indicates that nearly 40% of global employment is exposed to AI, with advanced economies facing even higher exposure, estimated at around 60% (Cazzaniga, 2024). In the United States, a world leader in Gen-AI, the impact is particularly striking. Research by Eloundou et al. (2023) shows that approximately 80% of the U.S. workforce could experience at least 10% of their tasks affected by Gen-AI, while 19% might see 50% or more of their tasks impacted. In addition to its widespread use in different industries, Gen-AI is characterized by its unprecedented adoption rate, surpassing that of many major inventions in human history, including the internet and personal computers at the same stage in their product cycles (Pazzanese, 2024).

Gen-AI possesses capabilities in self-learning, adaptability, strategic thinking, and acquiring tacit knowledge (D. Autor, 2022; Goos & Savona, 2024). Consequently, it is not surprising that we are witnessing a revival of dystopian visions, portraying AI as a precursor to a jobless future (Ford, 2015) and even as “our final invention” (Barrat, 2013). In a society where the labour market is flawed by robots and algorithms, only a small number of jobs that could be performed for humans would remain. Intense competition among people for these remaining positions, coupled with AI-monitored work environments, is likely to result in low wages and persistent job insecurity.

On the opposite end of the spectrum, there are arguments that AI just represents a continuation of the historical pattern of technology-driven progress and automatization (Gordon, 2017). Similar to previous technological advancements in human history, some jobs will be lost, but many new types of jobs will emerge. In this process of creative destruction, human inputs will not be removed from the economic process; instead, the task context of production will change (Loaiza & Rigobon, 2024). This interplay between technology and humans will enhance productivity, adaptability, and innovation, freeing people from hard labour and providing them with more time for creative activities.

Which of these two scenarios is more realistic will depend on the balance between the development and regulation of AI. Both processes, development and regulation, are ongoing and uncertain in terms of their possible outcomes. Gen-AI is a unique technology with rapidly advancing capabilities and expanding applications. Consequently, it is currently challenging to argue whether the labour-automation or labour-augmentation aspects of this technology will prevail in the future. At the same time, the regulation of Gen-AI lags behind its application, not only due to its novelty, but also because policymakers worry that extensive regulation could hinder the growth of an industry where the U.S. is a global leader. What is certain, however, is generative AI's potential to replace tasks in non-routine cognitive occupations.

Since the early innovations of the First Industrial Revolution to the advent of Gen-AI, the replacement of repetitive and lower-paid human labour with machines has been a central feature of technological change (D. H. Autor et al., 2003; Goldin & Katz, 1998). What Gen-AI uniquely introduces to this labour-machine dynamic is the extension of replacement risks to highly skilled and well-paid professionals, whose jobs were previously considered largely immune to automation (Cazzaniga, 2024; Colombo et al., 2024; Occhipinti et al., 2024; Septiandri et al., 2024). Non-routine occupations that will be particularly affected in the coming decades include accountants, financial analysts, human resources specialists, data analysts, marketing and communications specialists, software engineers, lawyers. This is not to say that human labour will be entirely eliminated in these occupations, nor that these professionals lack the ability to adapt to new technology. However, the demand for these occupations is expected to decline, and their skills are likely to be rewarded differently.

In the context of job and wage polarization in the United States, the influence of Gen-AI on the labour market is unlikely to follow the trajectory of routine-biased technological changes. Workplace computerization and, later, robotics—key examples of routine-biased technological advancements — have historically increased employment and real wages for occupations intensive in doing non-routine cognitive tasks, while depressing employment and wages for routine occupations. In contrast to this trend, Gen-AI's automation primarily impact non-routine occupations—the largest and most highly compensated segment of the U.S. labour market. This impact is least pronounced in non-routine manual occupations, concentrated at the lower end of the income distribution. Routine occupations—both manual and cognitive will also experience disruption from the deployment of Gen-AI, though to a lesser degree than highly skilled and well-paid professionals.

Following the task-based framework for understanding the implications of technology on labour market outcomes (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019; D. H. Autor et al., 2003), it is more realistic to expect that Gen-AI automation will alter the task context of production within occupations rather than lead to a significant reallocation of the workforce across occupations. According to this framework, the net impact of automation on employment and wages depends on the balance between the so-called displacement and reinstatement effects. The displacement effect occurs when automation enables machines or software to take over tasks previously performed by workers, while the reinstatement effect refers to the creation of new tasks that increase the demand for human input in production.

In the Gen-AI working environment, the majority of workers specializing in non-routine cognitive tasks are expected to retain their jobs, and it is unlikely that these occupations will lose their dominant share in total employment. However, the task context of production will undergo significant transformation, reshaping the current patterns of job and wage polarization in the U.S. labour market. Skills historically considered a comparative advantage for non-routine cognitive workers—such as analytical and communication abilities—are rapidly losing ground in the race against intelligent machines. The combination of even modes ideas, supported by skills in crafting prompts and executed by algorithms fed with big data from text, videos, audio, and images, will deliver better results than great ideas relying solely on human capabilities and expertise. This will lead to stagnation of real wages and employment prospects for non-routine cognitive occupations, creating a new reality in the labour market where low wages and unstable job prospects are no longer confined to middle- and low-skilled workers.

Discussion: Original Institutional Economics Perspective

In the future AI society, characterized by intelligent machines capable of replacing human labour not only in routine but also in many cognitive tasks, the primary economic challenge will be income distribution (Korinek & Stiglitz, 2019). Society will become richer than ever before, but human contributions to producing that wealth will be limited to a small fraction of unstable jobs immune to automation. This scenario raises numerous questions, particularly regarding how economic output will be distributed between the capital owners and the workers. To address these questions, or at least move closer to an answer, we must adopt a broader perspective on technological progress and income distribution than that offered by orthodox (mainstream) economists.

Among alternative—heterodox—approaches to mainstream economics, original institutional economics (OIE) has proven to be particularly fruitful. By adopting institutional and evolutionary perspectives on real-world issues (Hodgson, 2001, 2006; Kaufman, 2007), OIE allows us to reconsider core economic concepts, such as the workplace or the distribution of income, as social constructs that evolve over time. A key driver of this evolution is innovation, which, although its effects are not always predictable, remains a fundamental force behind economic and social progress

Continuous technological innovation brings us closer to what prominent original institutional economists, such as Clarence Ayres, Thorstein Veblen, and John Commons, describe as a society of abundance (Peach & Dugger, 2006). The concept of abundance, by its very nature, stands as the antithesis of scarcity, a fundamental principle of mainstream economics. From the perspective of scarcity, the inadequate well-being of some members of society is justified by the limited resources available for producing goods and services. In contrast, the concept of abundance promotes the idea that we live in a world where the means of production are constantly improving, ensuring that each new generation is wealthier than the previous one. In a society of abundance, everyone—regardless of their position in the labour market or within the social hierarchy—should be able to achieve an adequate standard of living.

Accepting the notion that the prerequisites for a state of abundance have already been achieved (Galbraith, 1998), and recognizing that these conditions will likely improve further with rapid technological advancements, the primary challenge in addressing the inadequate standard of living faced by some members of society should not be sought in production but in redistribution. In a future AI-driven society, we need new institutions and arrangements that move beyond traditional principles and concepts.

New technologies and their consequences for human well-being should not be accepted as inevitable, as institutions are responsible for shaping technological processes and their outcomes (Hayden, 2019). Moreover, as a distinct type of social structure, institutions have the potential to influence agents, including altering their purposes or preferences (Hodgson, 2006). The challenge in achieving what Bush (1989) described as progressive institutional and accordingly technological change lies in their encapsulation by a predatory driven leisure class, embodied in large corporate capital (Dugger, 1992; Souza Luz & Ribeiro, 2022).

Workers responses to labour market disruption driven by Gen-AI have a potential to initiate changes in historically established dependence of labour share on market processes. In current institutional environment, workers' participation in the distribution of newly created wealth is primarily determined by the market process, and secondarily by the redistributive process. Gen-

AI decouples workers from economic outcomes in a way fundamentally different from previous technological innovations. During previous technological revolutions, workers mitigated the adverse effects of technological change by adapting their skills to complement new machines and jobs (Acemoglu, 2002; Acemoglu & Autor, 2012; Arda Özalp & Özalp, 2024).

Gen-AI, however, represents a distinct form of technology. It has the capability to think, learn, and improve itself—qualities that were previously associated exclusively with human adaptation to new technologicy. In this context, it is plausible to assume that workers may struggle to adapt quickly enough to effectively complement intelligent machines. Another significant novelty of Gen-AI lies in its impact on the workforce. For the first time, the workers most exposed to technological disruptions are those who belong to the most powerful groups in terms of education and income. Moreover, these workers constitute a substantial share of U.S employment. Consequently, it is reasonable to expect that highly skilled and well-paid workers will advocate for and channel their interests more effectively compared to their middle- or low-skilled counterparts.

To predict which institutional settings and policy proposals workers will favour in regulating intelligent machines and distributing their (machines') and our (humans') unprecedented productivity, we can refer to what (Figart, 2021) described as "institutionalizing good work". The list of these proposals continues to evolve in response to new challenges in the U.S. labour market, intensified by neoliberal framework of the U.S economy. In particular, the AI-driven workplace will require a new system for evaluating workers' contributions to economic processes that are increasingly losing human input (Josifidis & Supic, 2024). This will eventually lead to new forms of income distribution, grounded in ideas such as robot taxes, universal basic income and shorter working hours.

Conclusion

The emergence and widespread adoption of Gen-AI across various industries and occupations not only challenges historical employment and wage patterns in the United States but also raises questions about the adequacy of current institutional frameworks. Unlike earlier waves of technology-driven automation, which primarily impacted routine, lower-income workers, Gen-AI threatens to disrupt jobs and wages in non-routine cognitive occupations, concentrated at the upper end of the income distribution. Viewed through the lens of the OIE, addressing the challenges posed by Gen-AI requires a re-evaluation some of core concepts in mainstream economics, such as employment, wages, and income distribution. As technological advancements bring society closer to a state of abundance, the labour share in economic output will become increasingly dependent on redistribution rather than market participation. Progressive institutional changes, such as the implementation of universal basic income, could provide a necessary societal response to the decoupling of human labour from economic outcomes. This transition may be facilitated by the fact that highly skilled and well-paid workers, who are disproportionately affected by Gen-AI-driven transformations, could emerge as influential advocates for new redistributive arrangements.

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