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A Comparative Study on the Diffusion Speed and Economic Effects of Artificial Intelligence and Traditional General-Purpose Technologies

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Abstract. In recent years, artificial intelligence (AI) and large language models have rapidly transformed production processes and social structures, whereas traditional general-purpose technologies (GPTs) such as steam power, electricity, and computers have historically had profound effects on productivity and employment. However, current studies provide limited comparisons of AI and traditional GPTs in diffusion, productivity, and employment, and systematic analysis of diffusion bottlenecks, labor adaptation, skill needs, and social costs remains scarce. This study investigates the features and mechanisms of AI and traditional GPTs in diffusion, productivity, and employment, thus examining differences in spatial and industry diffusion, long-term productivity effects, and substitution, compensation, as well as creation impacts on employment. The results reveal that traditional GPTs diffuse slowly with notable regional and industry differences, while AI achieves faster, more synchronized diffusion. Consequently, by driving a shift from scale- to quality-driven productivity growth, GPTs combine substitution, compensation, and creation effects to keep overall employment relatively stable in the short term.

Keywords: General-purpose technologies (GPTs), Artificial intelligence (AI), Technology diffusion, Productivity growth, Employment effects

1. Introduction

In recent years, artificial intelligence (AI) technologies, particularly large language models such as ChatGPT, have rapidly changed production and society, attracting wide attention. Existing studies have mainly explored the technical performance of AI, algorithmic innovations, and its applications in specific industries, while much literature has examined the historical diffusion, productivity, and employment effects of traditional general-purpose technologies (GPTs) like steam power, electricity, and computers. However, several gaps remain in the existing research. Although prior studies have highlighted the link between technology and economic outcomes, the comparisons between AI and traditional GPTs in terms of diffusion speed, cross-industry penetration, productivity contributions, and employment effects remain limited. In addition, the influences of diffusion bottlenecks and the labor, skill, and social challenges of rapid AI growth remain underexplored. This paper compares the characteristics and mechanisms of AI and traditional GPTs in terms of diffusion, productivity, and

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employment. In addition, it examines differences in spatial and industry diffusion patterns and bottlenecks, the long-term impacts of technological evolution on productivity, and the employment impacts of substitution, compensation, and creation. Through an analysis of relevant literature and theoretical frameworks, it examines different GPTs and further extends the discussion to recent developments in AI. The study highlights the mechanisms linking technology diffusion to economic outcomes and provides insights for policy and practice, including forecasting AI trends, assessing employment risks, and planning skill development and labor reallocation.

2. Variation in diffusion speed across regions and industries

2.1. Diffusion characteristics of traditional GPTs and artificial intelligence

With respect to diffusion speed, cross-industry penetration, and spatial distribution, general-purpose GPTs differ considerably. Consequently, traditional GPTs and AI display distinct diffusion patterns, reflecting the intrinsic properties of the technologies themselves and the influence of infrastructure, industry demand, and application environments.

The diffusion of traditional GPTs typically features long lag periods and substantial variations in diffusion speed across regions and industries. For example, steam power followed a core-periphery diffusion pattern, expanding from Britain's industrial heartlands globally. The uptake of electricity mainly followed an "urban-to-rural" diffusion path, gradually reaching rural and remote areas. The diffusion of computers demonstrated marked industry heterogeneity, with capital-intensive sectors adopting them considerably faster than labor-intensive sectors [1]. These characteristics indicate that traditional technology diffusion is largely shaped by structural and infrastructural limits.

In contrast, the spread of AI depends on digital infrastructure and open-source collaboration, thus markedly reducing the lag between technological breakthroughs and cross-sector applications [2]. Spatially, the time gap in AI adoption between developing and developed countries is gradually narrowing. Across industries, AI exhibits enhanced cross-sector penetration synchrony, extending from manufacturing to agriculture. This results in a diffusion pattern for AI that is highly inclusive and synchronous, exceeding that of any previous traditional GPT. Figure 1 presents the diffusion traits of four GPTs, including lag periods, industry heterogeneity, and cross-industry synchrony, serving as a reference for comparing their diffusion patterns.

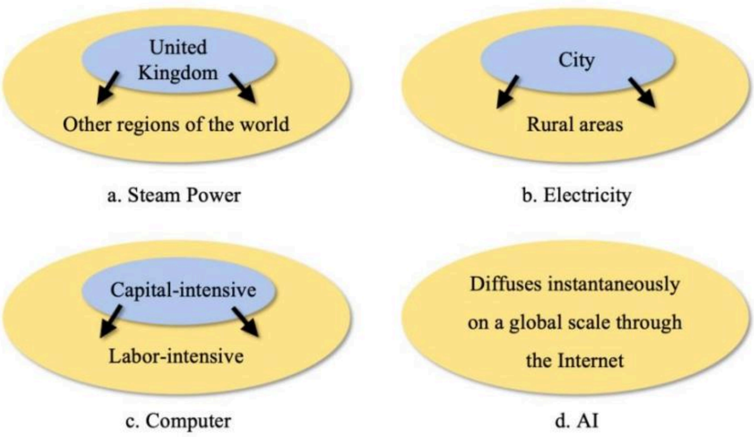

Figure 1. Main diffusion characteristics of different GPTs

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2.2. Diffusion bottlenecks and key limiting factors

The diffusion of GPTs is constrained by various bottlenecks, which differ for traditional GPTs and AI. Based on whether they are physical in nature, these bottlenecks can be categorized as physical or non-physical, as shown in Figure 2. By further considering whether they impact both traditional GPTs and AI, these bottlenecks can be classified into six types, providing insight into the factors that hinder the diffusion of each technology.

For traditional GPTs, physical factors strongly constrain diffusion. Of these, high infrastructure costs represent the most typical bottleneck, substantially limiting the adoption of technologies like steam power and electricity across different regions, corresponding to Region I in Figure 2. Another important bottleneck is the international variation in alternating current (AC) transmission standards, which hampers the establishment of a unified cross-regional coordination mechanism for electricity systems, corresponding to Region II. Besides, a physical constraint shared by both traditional GPTs and AI relates largely to hardware performance. As computers and AI become more reliant on chip performance, the physical limits of Moore's Law poses a major constraint, marked as Region III.

Beyond hardware limitations, non-physical factors also significantly affect technology diffusion. Differences in individual digital literacy constitute a typical bottleneck, as disparities in the ability to employ computers and AI across individuals and regions restrict widespread adoption, denoted Region IV. Moreover, a physical constraint specific to AI is found in neuromorphic computing, as it seeks to achieve more efficient and intelligent computation by simulating the neurons and synaptic structures of the human brain. However, physical limitations in the simulation process, like synaptic plasticity constraints, directly influence the ability of neuromorphic chips to emulate human brain functions, corresponding to Region V.

Furthermore, AI encounters further non-physical diffusion bottlenecks. For instance, AI model training depends on large-scale, high-quality data, yet variations in data ownership and privacy regulations create cross-regional and cross-industry barriers. Meanwhile, the "black-box" nature of algorithms may lead to bias and discrimination, limiting their application in sensitive domains such as healthcare and the judiciary, corresponding to Region VI [3].

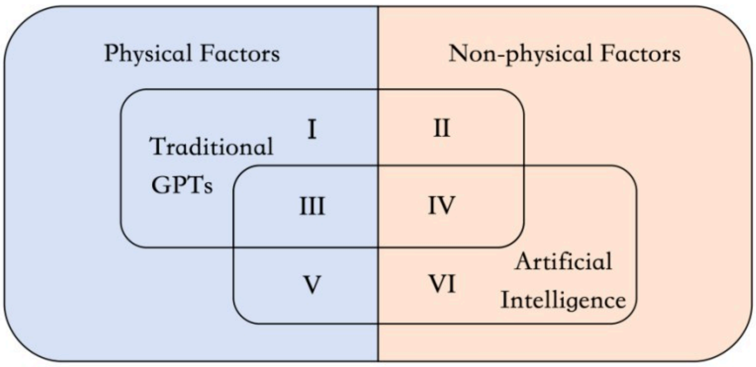

Figure 2. Diffusion bottlenecks of different GPTs

3. Technological evolution and its impact on productivity

3.1. Short-term effects of GPTs and the Solow Paradox

In the early stages of technological development, both traditional GPTs and AI exhibit the so-called "Solow Paradox." Specifically, despite rapid technological progress, productivity gains are often

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limited or may even decline. This phenomenon primarily arises from the substantial complementary investments required for effective technology adoption. According to Brynjolfsson et al., process reengineering, business model innovation, and human capital accumulation constitute investments that are largely intangible and thus not fully captured in national economic accounts [4]. As a result, short-term productivity is often underestimated.

The reasons behind short-term inefficiency can be analyzed from several perspectives. First, the adoption of new technologies often requires firms to restructure their production processes, and the time needed for organizational adjustments delays the realization of their benefits. Second, the use of AI and new GPTs imposes greater skill requirements on employees, and the time needed for training and talent development delays the full realization of the technology’s potential. In addition, the effective use of new technologies often depends on supporting hardware, software, and energy infrastructure, which demand substantial upfront investment and yield limited short-term returns. As a result,even when technological breakthroughs occur rapidly, productivity may not increase correspondingly in the early stages, giving rise to the Solow Paradox. This phenomenon highlights the lag between technology diffusion and actual economic gains, as well as the structural constraints faced during the initial adoption of new technologies.

3.2. Technological evolution and productivity enhancement

In the long run, GPTs can notably improve productivity, following an evolutionary logic that shifts from “physically driven” to “intelligently information-driven” mechanisms. The four representative technologies, steam power, electricity, computers, and artificial intelligence, sequentially overcome different bottlenecks in production efficiency, forming a layered technological chain in which each generation builds upon and upgrades the previous one.

By stabilizing energy supply and mechanizing production tools, steam power reduced reliance on human labor, animals, water, and wind, thus laying the foundation for industrial production. On this basis, electricity further boosted energy efficiency, enabled long-distance transmission and flexible energy distribution, and powered subsequent technologies like computers. Through the digitization and automation of information processing, computers bypassed manual processing limits, enabling AI data and algorithm operations. By analyzing and utilizing data, AI overcomes human cognitive and decision-making limits, improving efficiency in production planning and innovation [5].

This technological evolution shows that each generation of technology builds on the previous one and exceeds it in functionality and efficiency, enabling a shift from scale-driven productivity growth to quality improvements. Thus, the influence of these four GPTs on productivity presents a pyramidal structure, where foundational technologies establish the base capabilities and subsequent technologies further optimize efficiency and intelligence, as illustrated in Figure 3.

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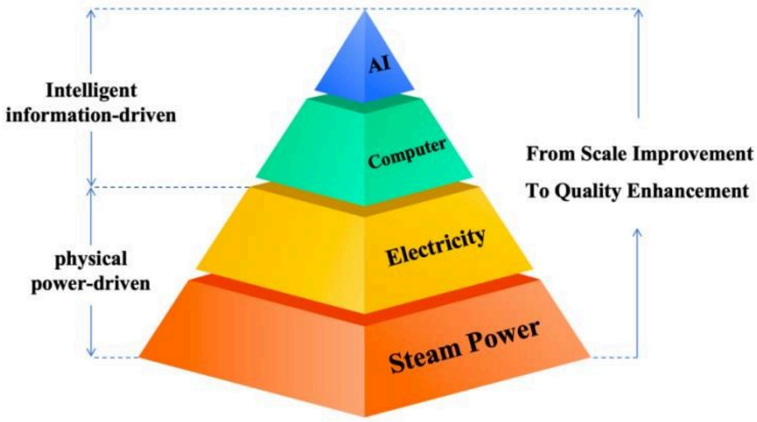

Figure 3. Relationship of the impact of different GPTs on productivity

4. Employment impacts and the substitution, compensation, and creation effects

The impact of GPTs on employment, whether from AI or traditional GPTs, can be understood via three effects: substitution, compensation, and creation, as shown in Figure 4. These effects interact to determine the short- and long-term consequences of technological expansion on the labor market.

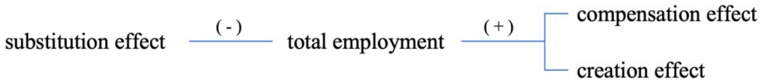

Figure 4. Relationship of the impact of different effects on the total employment

More specifically, the substitution effect occurs when the capital components of GPTs replace the labor components of non-GPTs, directly leading to the disappearance of certain jobs [6]. For instance, according to Acemoglu and Restrepo, an additional robot per 1,000 workers leads to a 0.18%~0.34% decline in the employment share in the U.S. labor market [7]. This effect shows that technological progress may initially exert pressure on traditional jobs. Besides, the compensation effect refers to the expansion of related industries driven by productivity gains from GPTs, which offsets the reduction in jobs per unit of output [8]. As industries expand, labor demand is partially replenished, mitigating the adverse impact of substitution. Moreover, the creation effect emphasizes that GPTs foster new forms of employment [9]. For example, the rapid expansion of generative AI has endowed models with powerful content-generation capabilities, though output quality remains highly dependent on user-provided prompts. This demand has directly resulted in the emergence of a new profession called “prompt engineer.” This exhibits that technological innovation can displace existing jobs and create new employment opportunities. As such, the expansion of AI exhibits both negative substitution effects and positive compensation and creation effects. Under the combined influence of these opposing forces, total employment remains relatively stable in the short term, and the extreme scenario of complete replacement of workers by AI is unlikely to occur.

In addition, different GPTs exhibit distinct characteristics in terms of substitution, compensation, and creation effects. First, the evolutionary process from steam power to AI shows a gradual shift of impacts from physical labor to cognitive labor. Second, AI-driven substitution, compensation, and creation processes occur at a higher speed. For example, certain occupations can be replaced within a short period simply through the deployment and operation of software systems, without relying on long-term infrastructure projects as required by traditional GPTs. Third, the ease of employment

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transitions differs across GPTs. In the eras of steam power, electricity, and computers, workers only needed to adapt physically or receive basic training to obtain new jobs. In contrast, the AI era imposes higher skill requirements on labor. Large-scale reallocation of labor is difficult to achieve without friction and often incurs substantial social costs.

5. Conclusion

This study analyzes the diffusion, productivity enhancement, and employment impacts of traditional GPTs and AI, indicating that traditional GPTs exhibit long lag periods and significant regional and cross-industry differences, while AI, relying on digital infrastructure and open-source collaboration, exhibits high synchrony, inclusiveness, and rapid cross-sector penetration. Regarding productivity, GPTs evolve from physical to intelligent information-driven mechanisms, building on steam power and electricity, with computers overcoming information-processing limits and AI exceeding human cognitive and decision limits, thus driving a shift from scale- to quality-driven productivity growth. In terms of employment, GPTs exhibit overlapping substitution, compensation, and creation effects, with AI-driven processes occurring at higher speed and imposing greater skill requirements, making large-scale labor shifts difficult and costly, yet overall employment remains relatively stable in the short term. However, the study mainly relies on literature and macro data, lacks detailed micro-level analysis of heterogeneity, social costs, and labor adaptation, and faces uncertainty regarding AI and emerging GPTs. Future studies could conduct cross-country and cross-industry micro-level analyses, explore policies to improve skills and labor reallocation, and measure GPTs' long-term effects on productivity, innovation, and employment to guide decision-making.

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