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Artificial Intelligence and Wealth Distribution: A Unified Framework for Polarisation Within and Between Countries

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Abstract. How Artificial Intelligence reshapes wealth distribution has become a key issue. Existing research is mainly divided into two independent branches: within-country and between-country studies. This paper aims to integrate these two dimensions by constructing a unified analytical framework. Firstly, the three factors affecting the distribution effect of Artificial Intelligence have been identified as the industrial structure, institutional environment and position in the Global Value Chain. Based on the empirical evidence from the United States, China and Latin America, the review shows that the inequality patterns within different countries and regions vary due to institutional and structural differences. At the international level, this paper links forecast data from the International Monetary Fund with potential causal paths to show how Artificial Intelligence is concentrating high-value-added activities in developed countries and driving developing countries into low-skilled and easily replaceable segments, thus widening the North-South divide. By connecting these two perspectives, this review provides a more comprehensive understanding of the uneven distribution of wealth caused by Artificial Intelligence.

Keywords: Artificial Intelligence, Wealth Distribution, Income Inequality

1. Introduction

Wealth distribution is a classic and important topic in economics. Over the past few decades, most scholars have focused on the effects of traditional technological changes and economic globalisation on wealth distribution. However, the rapid development of Artificial Intelligence (AI) has brought more complex challenges to wealth distribution. For example, AI will both replace some jobs and increase the labour productivity of other sectors and skill levels. Differences in countries and institutional backgrounds have further increased the distribution gap. Researchers have recently begun to study this new phenomenon. The key question is how AI will change wealth distribution socially and geographically.

In recent years, the study of the connection between AI and wealth distribution has been divided into two main areas. One strand is on intranational polarisation. Another focuses on divergence between countries. The first is to see how AI changes life for various groups in society. According to these studies, the impact of AI on wages varies by group. For example, Felten et al. developed an Artificial Intelligence Occupation Impact (AIOI) index to show that AI will likely raise wages for high-skilled and high-income workers significantly. AI exacerbates structural income inequality in

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the U.S. domestic labour market [1]. This skill-biased polarisation has been further observed in many emerging economies, including China and Latin America. In China, Cai et al. found that AI has widened the income gap through skill premium and labour transfer. This effect is particularly pronounced in low-income, less educated and rural populations [2]. In Latin America, Ciaschi et al. found the highest AI exposure in the formal sector and among well-educated workers, but their research shows that labour market institutions and the complementarity between human and AI tasks have largely moderated the distributional effects of AI exposure [3]. In contrast, the second strand provides a global perspective. Scholars have explored whether artificial intelligence will expand the North-South Divide. At the macroeconomic level, Cerutti et al. used a multi-regional dynamic general equilibrium model. They predict that AI-driven growth in developed countries could be more than double that in low-income countries [4]. At the micro level, Casilli et al. have studied four countries, finding that AI companies in developed countries outsource tedious data annotation work to the Global South [5].

However, these two empirical studies are usually carried out separately. Few review papers have presented a full analytical framework for within-country and cross-country polarisation, making it difficult to understand how AI can change the overall distribution of global wealth. This fragmentation requires integration.

This paper introduces a unified analysis framework that combines domestic and international dimensions. The rest of the paper is as follows. The second section explores the contextual conditions shaping the distribution effects of AI. The third section focuses on domestic polarisation in the United States, China, and Latin America. The fourth section is global polarisation, exploring the process of widening gaps between developed and developing countries. Finally, section 5 is the summary of the entire text and points out problems for further investigation.

2. Contextual conditions that shape the distributional effect of Artificial Intelligence

Whether AI widens or narrows wealth distribution inequality depends not only on the technology itself. Capraro et al. have pointed out in the discussion of Kranzberg's law that technology itself is neither good nor bad, nor is it neutral. It is the environmental factors at the time of application that determine the direction of changes brought by new technology [6]. Hammerschmidt et al. have also emphasized this situation-dependency. They pointed out that the difference in AI impact lies in the ability to use AI [7]. Therefore, before discussing the specific domestic and international impacts, this review will briefly introduce the following three conditions. They are industry and labour market structure, institutional and policy backgrounds, and position in the international division of labour.

2.1. Task structure and sectoral exposure

The breadth and depth of AI's impact on wealth distribution are deeply influenced by the industrial structure and composition of the labour market. According to the study by Cerutti et al., AI exposure is defined as the degree of relatedness between AI applications and the abilities needed in a given occupation, thus reflecting the scale of AI's potential influence [4]. AI exposure itself does not show the direction of the effect. That direction depends on the nature of the tasks involved. Li and Nichols divide them into "routine tasks" (which are susceptible to automation) and "non-routine cognitive tasks" (which are more likely to be augmented by AI). As AI expands, some routine tasks are taken over by AI through substitution effects, exerting downward pressure on low-skilled wages, whereas non-routine cognitive tasks appreciate through complementarity, raising high-skilled wages [8]. The

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high exposure sector contains both types of tasks. Therefore, the high exposure score only indicates that the income distribution of the sector is more significantly affected, without predetermining the direction of this redistribution effect.

2.2. Institutional buffers and amplifiers

The institutional environment shapes the distribution of AI benefits among different groups through various channels. 1) Tax system : many developed countries tax labour more heavily than technology, resulting in a lower share of labour income and a higher share of capital investment [6]. 2) Labour system : strong labour unions can increase the cost of labour displacement, slow down automation, and protect existing workers [9]. 3) Education policy : subsidies for skills acquisition encourage more workers to invest in advanced training [8]. Countries with these institutional supports are less prone to extreme polarisation of within-country distribution when AI arrives. At the international level, better-prepared countries can more effectively transform AI into productivity growth under equal AI exposure.

2.3. Global Value Chain (GVC) location and AI-induced marginalization

A country's position in the Global Value Chain profoundly shapes whether it can gain more or fall behind from the AI-driven economic transformation. Zheng et al. proved through empirical research that AI's enabling effect is more pronounced in countries with higher positions in GVCs [10]. This shows that a country's existing role in the global division of labour determines whether it can convert AI-driven productivity gains into a greater share of value.

3. Domestic polarisation: evidence from 3 regions

3.1. The United States

Existing research has not yet provided direct empirical evidence to quantify the impact of AI on the Gini coefficient. Yet it has amassed many indicative signs that AI will exacerbate wealth inequality within the U.S.

According to the U.S. Bureau of Labor Statistics, the share of labour income decreased from 67.8% to 58.4% between 1987 and 2019 [9]. Acemoglu's macroeconomic model estimates that the spread of AI could further increase the share of capital by about 0.31%, which means a corresponding decline in the share of labour income and the transfer of wealth from workers to capital owners [9]. AI-driven productivity growth rarely benefits workers. This trend is closely related to the institutional structure of the United States. Unlike European countries, the U.S. has a weak collective bargaining system and declining union coverage [11]. Although most developed economies use collective bargaining, in which unions or employer associations negotiate wages, the United States is known for its highly decentralized wage-setting structure, in which individual companies and workers determine wages in the vast majority of cases [12]. In this institutional context, the efficiency gains from AI are more likely to flow to capital returns rather than labour returns, because workers replaced by AI lack institutional channels to share productivity gains and are forced to engage in low-wage service work, while capital owners gain excess profits.

Applying the task-based framework proposed by Li and Nichols to the U.S. labour market, Eloundou et al. found that about one-fifth of U.S. workers are employed in occupations where more than half of their tasks are exposed to AI, with a heavy concentration among mid- to high-wage

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cognitive occupations [13]. Among these exposed jobs, routine tasks are affected by the substitution effects that suppress the wages of workers engaged in these jobs, while non-routine cognitive tasks benefit from complementarity, thereby increasing the income of participants [8]. This pattern is consistent with the service-oriented industrial structure of the U.S. economy. The financial, information services and professional sectors employ a large number of cognitive workers, making wage polarisation a structural feature of AI's impact on the U.S. labour market. Some displaced workers in these middle-and-high-wage cognitive roles may be forced to work in low-paid, low-AI exposure service jobs. Although these jobs are not easily replaced directly by AI, the increase in labour supply will further lower their wages.

In summary, the above literature shows that AI affects the distribution of wealth in the United States mainly through two channels. Firstly, it changes the proportion of wealth allocated between capital and labour. Secondly, it promotes wage disparity among the workers themselves.

3.2. China

Different from the research in the United States, China's research on AI has focused more on regional and urban-rural disparities rather than the capital-labour model used in the United States. This difference does not deny the importance of China's capital-labour relations or regional inequality in the U.S., but reflects different national conditions and priorities.

Cai et al. have found that AI has further widened the income gap in China, and the effect is more severe in the central and western regions than in the east [2]. This regional disparity reflects the difference of industrial structures. The area in the east has an established industrial base and diversified structures. Therefore, it can offer other jobs for the displaced workers. In contrast, the weaker industrial structures in the central and western regions are unable to absorb the displaced labour force effectively, and thus AI will exacerbate income disparities.

In terms of urban and rural areas, there are also two important findings. Cai et al.'s research shows that the impact of AI on expanding inequality in rural areas is much stronger than that in cities [2]. The above can be explained by different abilities of rural workers to respond to technological shocks. Rural labourers with higher education and digital skills can use AI to make production decisions and expand markets in order to increase their income. On the contrary, low-skilled labour is under price pressures and market contraction, so its productivity and income have been stagnant. At the same time, due to the lack of non-agricultural industries and vocational training resources in rural areas, labour redistribution to other sectors is limited, intensifying rural polarisation.

Zhang and Han have confirmed that AI promotes urban employment, but the effect on the countryside will be relatively small [14]. This difference reflects two factors. Cities with advanced industries have created more jobs that complement AI, and the rural areas are still dominated by agriculture and low-skilled services. In terms of human resources, rural workers lack access to educational resources for skills upgrading and are unable to secure new jobs created by AI [14].The above reasons have collectively disadvantaged rural areas in the AI-driven industrial transformation and widened the income gap between urban and rural areas.

Liu et al. have further found that although AI has reduced the pay gap between executives and employees, it has increased wage polarisation at the task level (e.g., lowering wages for conventional financial staff and raising wages for non-conventional salespeople) and at the industry level (e.g., the gap between high-tech and traditional industries is widening) [15] . Therefore, the distribution effects of AI in China are multifaceted.

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Overall, the distribution effect of AI in China is uneven at both the regional and sectoral levels. Cai et al. found an inverted U-shaped relationship between AI and income inequality, but 87.3% of Chinese cities still lie on the upper left of the curve [2]. It can be seen that although most areas are still in the stage where AI increases inequality, there is still policy space for helping more areas pass this turning point.

3.3. Latin America

Latin America provides another study perspective. Based on household survey data from 14 Latin American countries, Ciaschi et al.'s study found that AI-related risks are systematically higher among women, younger workers, and formal-sector workers [3]. Sectors such as banking, finance, the public sector, and customer service face the highest risk of AI automation, where the proportion of women is relatively high. Young people in the early stages of their careers have not yet developed specialized skills that complement AI, so they are still more likely to be replaced. Meanwhile, due to the high cost of adopting AI, informal employees are less exposed to AI, and thus less affected than formal employees [3]. This means that in Latin America, the threat posed by AI does not simply fall linearly on the most disadvantaged groups. Instead, it is concentrated among salaried workers in the formal sector, who are relatively highly educated but lack irreplaceable professional expertise. When formal workers lose their jobs to AI, some may turn to the informal economy, although they usually accept lower wages [3]. At the same time, due to the lack of capital, primitive technology and small scale, these workers generate far less productivity [16].

Another key feature of the AI distribution effect in Latin America is the significant gap between "exposure" and "benefit". Research from ILO and World Bank shows that 8% to 14% of jobs in the region could theoretically increase productivity improvements from generative AI, but nearly half of them cannot achieve this improvement due to the lack of computer and Internet access. For example, in Mexico, the top fifth of the population is 5.6 times more likely to have jobs that benefit from AI and involve computer use than the poorest one-fifth. This digital divide suggests that AI may not only widen income inequality, but also strengthen and deepen existing class barriers [16].

In short, what distinguishes the distributional effects of AI in Latin America is the reinforcing relationship between high exposure in the formal sector and low productivity in the informal economy. In the absence of adequate digital infrastructure, this interaction makes technological shocks more likely to deepen existing class divisions, rather than mitigate them.

3.4. Comparative summary

In these three cases, there is a common feature: AI exposure is concentrated in cognitive-intensive, middle-income occupations. These jobs are concentrated in the fields of data processing, finance, public administration, etc., which are the sectors where wage polarisation is most likely to occur. However, this shared exposure pattern does not mean that the distribution results of countries are the same. On the contrary, each country shows different characteristics shaped by its institutional background and industrial structure. In the U.S., a service-oriented industrial structure focused on finance and IT, coupled with a lack of wage coordination mechanisms, has translated AI's capital bias into a continued decline in the share of labour income. In China, the uneven industrial base and AI policy across regions have widened the urban-rural and regional gaps. In Latin America, the employment exposed to AI is concentrated in the formal service industry, reflecting a highly dual labour market. The distribution effect of AI does not follow a single trajectory, but is shaped by the institutional background and industrial structure at the time of technology implementation.

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4. Global polarisation: the North-South divide in the age of Artificial Intelligence

4.1. Macro evidence: quantitative analysis of the International Monetary Fund (IMF)

Cerutti et al. used the IMF's global model to simulate the productivity impact of AI on the global economy and found that the growth gains in developed economies may be more than twice as high as those in low-income countries [4]. According to the IMF, three factors explaining this gap are AI exposure (as discussed in Section 2.1), the AI Preparedness Index (AIPI), and the access to advanced technologies [4]. In terms of exposure, developed economies (concentrated in finance, information, and professional services, etc.) have higher exposure than emerging market and low-income countries. Preparedness involves digital infrastructure, human capital, innovation, and regulation, where developed countries also lead. In terms of access to cutting-edge technology, many low-income countries are constrained by geopolitics and export controls, resulting in a significant gap compared to leading countries.

The combination of the above three factors amplifies the productivity impact of AI in rich countries, while the impact is gradually decreasing in poor countries. Cerutti et al. predict that in the context of high Total Factor Productivity (TFP) growth, global GDP would grow by nearly 4% in 10 years, reaching 5.4% in the United States alone, while low-income countries will only grow by 2.7%. This shows that AI not only reflects existing inequalities, but also strengthens them.

4.2. Behind the scenes: the North-South divide in production and application

While the IMF's data shows the unequal distribution of AI benefits, the following research can help explain why. Casilli et al. have discovered global labour division inequalities in the AI production chain [5]. AI companies in developed countries have advantages in capital, R&D, and talent. They can utilize the data and computing resources to design algorithms and train models. In contrast, developing countries do not have these resources and abilities. As a result, most of their workforce is restricted to low-wage, easily replaceable work such as data annotation and content moderation in the global AI production chain [5]. This division of labour further concentrates profits in developed countries and keeps developing countries as low-skilled labour suppliers, worsening the existing global North-South resource gap.

Regarding the application of AI, Koch pointed out that AI can help core economies internalize high-value activities, which also provides a rational basis for the IMF's research results [17]. Before the AI era, core enterprises in developed countries moved production to developing countries with lower labour costs, enabling these regions to enter GVCs. Due to the high costs of remote coordination, core enterprises had to have some design, predictive maintenance and quality control work done by on-site staff. Therefore, the production knowledge and technology were inevitably transferred to the local workers, and developing countries gradually built up their own capabilities and moved towards innovation through participation. However, the development of AI has made many production decisions automatic, greatly reducing the cost of remote control of high-value-added activities. Core enterprises no longer need to transfer this knowledge to local factories, thereby reducing knowledge spillover to developing countries [17]. Although developing countries are still part of GVCs, most are limited to low-end and easily replaceable segments, cutting off the path to upgrading through practical learning in production.

5. Conclusions

This paper shows that the impact of AI on wealth distribution is heavily influenced by the structure of industry and labour market, institutional contexts, and the division of labour in GVCs. At the domestic level, AI's impact on wealth distribution differs by country, depending on local circumstances. Internationally, AI has intensified the North-South divide by increasing the asymmetry in global AI production labour division and shifting high-value-added segments in GVCs. The distributional effects of AI are not determined by the technology itself. Relying solely on technology diffusion cannot achieve a fair result, but may deepen inequality.

This review combines domestic and international polarisation in a single analytical framework to address the deficiency in prior research that often separates these two dimensions. It offers researchers, policymakers, and international organisations a systematic perspective to help understand the distribution effect of AI and avoid biased conclusions. Future research could further examine how institutions influence AI's distributional effects in the long term, providing more quantitative evidence for policy design. Additionally, it could also explore how international cooperation mechanisms might help to alleviate the North-South gap.

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