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AI Economy Analysis of Income Inequality in China and Optimization of Income Distribution Mechanism

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Abstract: The rapid development of automation and artificial intelligence has profoundly transformed traditional labor markets. However, while these technological advancements have improved productivity and efficiency, they have also triggered a range of socio-economic challenges. AI's distributional effect is directly related to the realization of China's 14th Five-Year Plan. This paper discusses the heterogeneity of different AI industries, focusing on China's Pearl River Delta and Yangtze River Delta regions, and mainly examines how two typically different AI (labor substitution AI and skill enhancement AI) have an impact on income inequality in China, the resulting problems, and solutions. It relates to industrial isomorphism, the population siphon effect, and proposing policy interventions to address these challenges. At the microeconomic level, the revenue gap between enterprises has become an issue worthy of attention as well. For instance, while improving education, the government can provide financial subsidies and stimulate corporate development to promote balanced economic growth and stable social operation. This study employs a dual approach, analyzing both macroeconomic trends and firm-level productivity data. The solutions presented in this paper can mitigate some of the income inequality caused by automation.

Keywords: Income Inequality, Automation, Distribution Mechanism, AI Economy

1. Introduction

1.1. Research background

In the big data era, AI is increasingly permeating various sectors of society, transforming the labor market through automation and skill augmentation. According to the World Bank, China's Gini coefficient will be above 0.46 in 2024, with urban-rural income disparity contributing 40% to total inequality. AI-intensive sectors grow at 15% annually, while traditional industries stagnate. In the big data era, an increased number of AI-related occupations and industries will be generated in society. In this context of AI gradually serving human beings, some traditional industries have also been gradually replaced by intelligent machines, resulting in income inequality.

China's 14th Five-Year Plan clearly puts forward the goal of "common prosperity", which requires "expanding the middle-income group, adjusting excessive income, and promoting social equity". As the core engine of economic growth, AI's distributional effect is directly related to the realization of this goal. Income imbalance will greatly reduce the progress of high-quality development and reduce people's social well-being. It would cause social conflicts and hinder high-quality development.

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Furthermore, in the process of industrialization and automation in some European and American countries, the lag of policies and ideas led to the "skill polarization" and the expansion of the income gap, such as the unemployment problem of workers in the "rust belt" in the United States. China is currently required to avoid repeating past mistakes, re-formulate reasonable countermeasures to shun the backlash brought by income imbalance, and strive to reduce the income gap.

1.2. Literature review

Yuan and Wang investigated that based on China Household Tracking Survey (CFPS) data, they measure occupational income inequality using the Pareto coefficient and analyze the impact of artificial intelligence (AI) through econometric models and mediation effects tests. AI has significantly increased occupational income inequality in China, especially among high-income groups. Due to the Intermediary effect, when upgrading the industrial structure by promoting the transformation of the industry to high value-added, AI will increase the demand for high-skilled jobs and expand the income gap (52.9% contribution rate). AI technology threshold is high, and capital - and technology-intensive enterprises benefit more, further enlarging the income gap (60.5% contribution rate) [1].

Huang and Zhu employed a dynamic multi-sector general equilibrium model constructed to distinguish between high-skilled (skill-intensive industries) and low-skilled labor (non-skill-intensive industries). It utilizes GAI to indicate the generation of new data to enhance the productivity of highly skilled workers, potentially replacing or supplementing their jobs. Through TAI, they found that automation replaces low-skilled labor and exacerbates income inequality. Based on China's provincial panel data (2016-2022), the GAI application indicator (text analysis of listed companies' annual reports) was constructed to verify its impact on skill premium [2].

Ren and Ishka point out that with the continuous advancement of artificial intelligence and automation technology, traditional manufacturing and other secondary industries are undergoing profound transformation. This transformation has not only increased productivity but has also had a significant impact on the structure of employment, with few jobs at risk of disappearing and new jobs emerging in technologies. Meanwhile, with the popularization of new technologies, the demand for skills in the labor market is progressively increasing. The paper highlights the lack of skills matching in the current workforce and proposes that this skills gap must be closed through education and training to help workers adapt to the new work environment [3].

While existing studies analyze AI's aggregate impact, they overlook the heterogeneity of AI types (e.g., labor-substituting vs. skill-enhancing), which may lead to distinct inequality outcomes. All in all, the heterogeneity of technology types in different industry industries is not subdivided. We could compare two kinds of AI. These two kinds of AI (labor substitution AI and skill enhancement AI) are typical and representative. They cut across the different nature of AI's role, resulting in relatively different outcomes for income inequality. More intuitive and effective analysis results and reasons could be obtained and indicated. As a result, this article will Investigate how these two types of AI can cause income inequality.

1.3. Research framework

Therefore, this paper will subdivide the AI technology type according to the geographical characteristics, social environment, economic situation, and industry of specific regions in China by selecting the two most widely used and most representative AI types for analysis. Explore in depth how different AI generated by AI heterogeneity is used in industries, and analyze the impact that each will have and the problems that may be caused by it, especially the detriment in the area of income inequality.

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2. Case study

The PRD is at the forefront of China's reform and opening up, the first to benefit from policy dividends, economic vitality, and strong scientific and technological innovation capabilities. A modern industrial system with electronic information, new energy vehicles, and artificial intelligence at its core dominates the Pearl River Delta. It has a high degree of marketization and strong entrepreneurial vitality, especially in cities such as Shenzhen and Guangzhou.

In the Pearl River Delta internal situation, the per capita GDP of Shenzhen and Zhuhai exceeds 160,000 yuan, while that of Zhongshan and Zhaoqing is less than 90,000 yuan, a gap of more than two times. In the Pearl River Delta and non-Pearl River Delta region, the per capita GDP of the Pearl River Delta region in 2023 is 2.67 times that of the non-Pearl River Delta region [4]. Simultaneously, detailed data analysis indicates that significant variation in income levels exists across different industries. In comparison with the high-skill and low-skill industries, the per capita income of Shenzhen's information transmission industry exceeds 80,000 yuan. However, the Zhongshan's agricultural practitioners are less than 50,000 yuan. And the income gap between senior executives and ordinary employees at the bottom becomes obvious. In Shenzhen's Futian district, the annual salary of financial executives can reach millions, but the average annual salary of manufacturing workers is about 60,000 yuan [4]. This disparity reflects not only skill premiums but also capital concentration in high-value sectors, where AI-driven productivity gains disproportionately benefit knowledge-intensive industries. This phenomenon not only reveals disparities in production efficiency, market demand, and skill requirements among sectors but also reflects the profound impact of industry-specific characteristics on income distribution.

On the contrary, the total GDP of the Yangtze River Delta is much higher than the Pearl River Delta, whereas the per capita GDP is slightly lower. Nonetheless, the per capita disposable income of Zhejiang Province is 64,000 yuan, with little difference within the province. This relative equality stems from the Yangtze River Delta Integration Policy, which promotes cross-city infrastructure sharing and skill-certification reciprocity, mitigating regional disparities—a lesson for PRD's governance. In contrast, there is a significant difference between the Guangdong Pearl Triangle and the non-pearl Triangle from 2023 to 2024. Manufacturing accounts for 35 percent of the total industry in the Yangtze River Delta [5].

3. Analysis of the problem

3.1. Pearl River Delta industrial zone (labor-substituting AI)

3.1.1. Condition

The Pearl River Delta region considers the manufacturing industry to be the leading dominant industry, and its industrial development is relatively mature. In the process of upgrading the industrial structure, the income of owners with capital and technology elements will increase greatly, leading to the income production of a "multiplier effect" [4]. For example, in the high-end field of manufacturing, enterprises invest more in technology research and innovation, resulting in higher income levels for relevant technical talents and business owners. In contrast, for ordinary workers at the bottom, due to the strong substitutability of jobs in the manufacturing industry, wage growth is relatively slow, resulting in a gradual expansion of income inequality.

The phenomenon of industrial isomorphism exists widely in the Pearl River Delta. Although the error of the theory of "repeated construction" is proved theoretically, the homogeneous industry may lead to the intensification of competition and the compression of enterprise profit space to a certain extent. In this case, enterprises may reduce labor costs, such as reducing wages, to maintain competitiveness, thus affecting the income level of workers. In addition, a homogeneous industry will also lead to unreasonable resource distribution, affecting the overall development of the industry and the fairness of income distribution.

3.1.2. Influence

Automated substitution: Compared with skill-enhancing AI, labor-substituting AI would directly replace workers who are at the bottom of the labor market, leading to many workers losing their jobs. Society now turns to machine manufacturing. For example, automotive plants now operate fully automated production lines, eliminating human intervention. These low-skilled workers not only face the problem of decreasing wages but also the problem of re-employment. A reshaping of the employment structure occurs. Nonetheless, this has widened the income gap by making jobs available to workers with automated equipment and increasing their earnings.

3.1.3. Problem

The entrenchment of income disparity: Low-skilled workers lack the high-level skills and knowledge reserves required to engage with AI technologies. As a result, the technological gap between those workers and highly skilled workers is steadily expanding. Moreover, due to the uneven distribution of educational resources, these low-skilled workers are unable to acquire and master the use of AI tools quickly. This situation, in turn, further entrenches the income gap.

Industrial isomorphism: Industrial isomorphism may lead to unreasonable resource allocation and intensified competition. This strongly affects the firm’s profits and workers’ incomes. If resources are not optimally allocated, this would lead to higher wages for workers in some well-resourced factories than in those with scarce resources, resulting in income inequality.

While the PRD exemplifies labor substitution effects with its manufacturing-focused automation (evidenced by 30% job displacement in Dongguan’s electronics sector), the YRD demonstrates how skill-enhancing AI creates divergent outcomes through digital economy transformation. This contrast stems from their distinct industrial bases: capital-intensive manufacturing versus knowledge-intensive services, as reflected in their respective robot density (PRD: 246/10,000 workers) versus AI patent filings (YRD: 58% of the national total).”

3.2. Yangtze River Delta digital economic zone (skill-enhancing AI)

3.2.1. Condition

The inclusive development of digital finance in the Yangtze River Delta economic cluster shows an upward trend, but there are obvious characteristics of heterogeneity and spatial agglomeration [5]. Inter-provincial differences are the main source of overall differences in the development of digital financial inclusiveness in the Yangtze River Delta. The spatial affects digital finance in the Yangtze River Delta region are continuous, and due to the significant positive spatial correlation of digital financial inclusion between regions, digital finance in the region is vulnerable to potential shocks in neighboring regions. It would seriously appear the Talent siphon effect between cities.

3.2.2. Influence

Skill premium: In the Yangtze River Delta Digital Economic Zone, with rapid economic development due to the development of technology-skill-enhancing AI, the consuming work such as data analysis, statistical generalization, and other digital computing types will be replaced by AI. Consequently, professionals with relevant skills, such as data analysts and algorithm engineers, gain a competitive advantage. They have the professional and unique ability to analyze AI data, and due to the scarcity of talent resources in the market, their wages would boost compared to the original, resulting in the

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generation of skills premium. In contrast, some traditional jobs, such as service workers, have seen their salaries decline year by year.

The emergence of new jobs: Skills-enhancing AI drives the development and innovation of the digital economy. The research and development of skills-enhanced AI have been followed by more and more new jobs for workers, such as digital marketing experts, intelligent operations managers, and so on. They possess the ability to be proficient in the analysis and application of AI tools, as well as the capacity to optimize decisions. Many college students seeking jobs can find a new direction of work due to the emergence of this kind of work. At the same time, it would improve the overall economic income of the whole Yangtze River Delta region. In contrast, it widens the income inequality of workers in traditional occupations.

3.2.3. Problem

Talent siphon effect: Utilizing the siphon effect of talents, these AI talents will be attracted by cities with rapid economic development, such as Shanghai and Hangzhou, resulting in the migration of the population to core cities and increasing the population loss. The loss of these high-end talents in surrounding cities would slow down the development of the AI industry. The imbalance in the development of the AI industry between cities has led to an increase in the income gap between cities. For instance, the mean salary within the AI industry in Shanghai exceeds that of certain adjacent cities.

The income gap between different enterprises: The fee invested in data collection and talent cultivation is high while employing, leading to small firms giving up the benefits created by skill-enhancing AI for enterprises due to the lack of the financial capacity to support and shoulder the exorbitant costs of skill-enhancing AI. In this case, the wages of the employees of these small businesses won't fluctuate much. Large enterprises gain from sufficient financial support, could secure the benefits of AI assistance, and receive more technical talents, which not only enhances the work efficiency of enterprises but also increases the salary of technical talents in large enterprises. However, overall, this simultaneously intensifies the income inequality between firms.

4. Suggestions

4.1. Workforce upskilling and regional industrial specialization

Companies should create retraining and upskilling programs for low-skilled workers affected by automation [6]. Helping low-skilled workers adapt to the changing labour market and gain the ability to do highly skilled work, thereby increasing income levels and reducing income gaps. To maximize participation, companies should also consider flexible training models. Furthermore, companies could adopt customized training modes. In addition to the traditional centralized teaching model, flexible training systems, such as evening and weekend sessions, are introduced to allow workers to attend training without affecting their current job income.

From the perspective of the government, they could develop a series of policies to encourage and support low-skilled workers to participate in retraining and skills upgrading programs [7]. For instance, providing training subsidies would reduce the cost of training for workers. At the same time, the government may implement targeted tax relief measures to stimulate economic growth and alleviate financial burdens on businesses and individuals. If the tax is reduced, it will stimulate enterprises to carry out training programs to mitigate skill gaps more effectively. When skills gaps are effectively reduced, income inequality can be mitigated as a direct result.

Beyond workforce upskilling, regional industrial specialization is another key strategy. Promoting the differentiated development of industries based on the unique advantages of various regions within the Zhuhai Delta. For instance, Dongguan has a deep foundation in the electronic information

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manufacturing industry and can extend the industrial chain towards high-end links such as intelligent terminals and integrated circuits. Zhongshan's outstanding advantage in the field is lighting manufacturing, which could create intelligent lighting industry clusters, form a differentiated competitive pattern, and enhance the industrial competitiveness of the entire region. Secondly, it is essential to strengthen industrial transfer and undertaking based on the stage of industrial development and the resource-carrying capacity of different regions. Labor-intensive or low-value-added industries should be gradually relocated to surrounding areas, thereby creating space for the development of emerging and high-value industries [8]. The Pearl River Delta's core cities (e.g., Guangzhou, Shenzhen) should relocate processing industries to neighboring cities (e.g., Qingyuan, Heyuan). The inflow of workers would spread to the surrounding cities, thus achieving the optimal allocation of resources.

4.2. Multi-city talent collaboration and SME support policies

Addressing talent concentration requires multi-city collaboration. To solve the talent siphon effect, collaborative platforms for talent exchange and cooperation among cities in the region need to be established. This can promote the flow of talent within the region and reduce the concentration of talent in a single city like Shanghai, as previously discussed. For instance, cities could jointly organize talent recruitment fairs through a unified digital platform for cross-city job matching, as well as professional training activities to enhance the overall competitiveness of the region's talent pool. In this way, some talents can be retained, and the income gap could be reduced.

Government could invest in education and training to improve the quality of local talent [9]. Strengthen cooperation between universities, research institutions, and enterprises. Huawei's 'Seeds for the Future' program with Shenzhen University is meant to cultivate talents with practical skills and innovation abilities that ought to be specifically utilized. This can increase the supply of local talent and reduce the dependence on external talent sources. Cities can also establish talent incentive policies to encourage talents to stay and contribute to local development. Therefore, with the weakening of the talent siphon effect, income disparities between cities are expected to decline, leading to a narrowing of the overall income gap.

To address the disparity between companies, governments can play a key role by implementing policies that promote fair competition and provide support for small businesses. This could include subsidies, tax incentives, or grants for small businesses to invest in AI technology. In addition, governments can establish regulatory frameworks to ensure that large companies do not abuse their market power and engage in anti-competitive behavior.

Both AI adoption (measured by dummy variables) and AI usage intensity are significantly positively correlated with firm productivity [10]. As measured by sales and value-added, companies using AI are more productive. The promotion of open-source AI platforms helps to level the playing field by providing equal access to advanced technologies [11]. These platforms enable small businesses to utilize cutting-edge AI tools without the need for substantial financial investment, thereby fostering greater inclusivity and reducing barriers to technological innovation. This reduces the technology gap between firms, promotes fair competition, and ultimately mitigates inter-enterprise income disparities.

5. Conclusion

In conclusion, these two typical AI developments would cause the entrenchment of income disparity and industrial isomorphism in Pearl River Delta regions(i.e., the convergence of industrial structures across regions, leading to reduced competitiveness) caused by labor substitution AI. Secondly, the talent siphon effect (e.g., tech giants in Shenzhen attracting skilled labor from neighboring cities) and

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the widening income gap among different enterprises have emerged as significant challenges driven by the advancement of skill-enhancing AI technologies. The first proposed solution based on labor substitution AI problems is for companies to establish retraining and upskilling programs specifically targeted at low-skilled workers who are adversely affected by automation. At the same time, the government should play a complementary role by formulating and implementing policies that encourage and support these workers to participate in these programs. Of course, it's indispensable to develop the industry characteristics of each region according to local conditions, especially in the Pearl River Delta region, where the industry division is obvious, in order to reduce the loss of workers. The second solution is to enhance cooperation and invest in education to eliminate the negative effect of the Talent siphon effect. The government plays an important role in diminishing the disparity between companies by supporting small companies and firms.

The following measures are proposed to address these challenges. The solutions presented in this paper can mitigate some of the income inequality caused by automation. To a certain extent, such measures can help ensure that specific groups of workers obtain relatively stable employment opportunities, thereby providing them with basic economic security and reducing the risks of unemployment-induced poverty. This, in turn, can significantly enhance individual well-being, promote social inclusion, and contribute to maintaining overall social stability by mitigating potential social tensions and economic disparities.

However, this paper lacks primary data and mainly uses secondary data. Relying solely on reading literature and exposure to secondary sources, without the support of direct and primary data, means that methods such as interviews and questionnaires used to understand the real situation of the Pearl River Delta and the Yangtze River Delta may still overlook certain potential risks or limitations in the research findings. The obstacles that may be encountered in the implementation of the solution are unpredictable.

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