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The Impact of Artificial Intelligence Applications on Corporate Labor Productivity

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Abstract. In the context of the rapid global development of artificial intelligence (AI), China is also actively advancing the research and application of related technologies. This paper focuses on Chinese A-share listed companies from 2016 to 2023 and explores the impact of corporate AI applications on labor productivity. A model is constructed in which labor productivity is measured by the natural logarithm of revenue per employee. The application indicator is built using the number of AI-related keywords in annual reports, with control variables set accordingly. Empirical results show that AI applications significantly improve labor productivity, with companies that exhibit good growth, strong cash flow, and large scale performing better in terms of productivity. Robustness checks confirm the validity of these conclusions. The study demonstrates that AI holds immense potential in corporate applications, and companies can build industrial ecosystems to promote its widespread use, enhancing labor productivity and contributing to high-quality economic development.

Keywords: artificial intelligence, labor productivity, labor force structure

1. Introduction

In the context of the rapid development of the global economy and digital technologies, artificial intelligence (AI) is entering a phase of fast iteration worldwide, with its application areas continuously expanding. Particularly, in industries such as business, healthcare, education, and finance, significant achievements have been made through in-depth applications. Advances in algorithm optimization and computing power have allowed AI technologies to move beyond simple automation tasks to encompass complex decision support and advanced predictive models. For example, the new generation of generative AI can create high-quality text and image content, widely applied in tasks like intelligent conversation, image segmentation, and 3D reconstruction. These advancements not only drive digital transformation in companies across various countries but also profoundly affect the global labor market.

In China, the development of the AI industry has been characterized by a combination of policy support and technological innovation. Since the release of the "New Generation Artificial Intelligence Development Plan" in 2017, the Chinese government has invested significant resources in AI technology research and industrial application, promoting its widespread use in smart cities, intelligent manufacturing, healthcare, and finance. High-density AI innovation clusters have formed in regions like the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta, with Beijing, Shanghai, and Guangdong emerging as core regions for technological cooperation and innovation. These policies and regional layouts have not only facilitated economic and social transformation but have also positioned China as a key player in the global AI development landscape [1].

At the same time, AI technology is profoundly influencing corporate production methods and the labor market. Research by Acemoglu et al. [2] indicates that the widespread application of AI reduces the demand for basic jobs while simultaneously increasing the need for skill retraining and job optimization. As companies automate processes and adopt intelligent decision-making, there is an increasing need for flexible human-machine collaboration models to maximize the benefits of AI. In this process, the technical understanding and strategic insight of the executive team often determine the effectiveness of AI applications within the company, as top-level decisions directly affect AI implementation and resource allocation. Moreover, companies may encounter a "productivity paradox" in the early stages of AI development, where large investments in AI technologies do not fully result in the expected productivity gains. This phenomenon may be related to the complexity of technology integration, insufficient employee skill adaptation, and the stage of maturity of AI technologies [3]. Therefore, balancing technological innovation with labor demand has become a central issue for policymakers and corporate managers to address.

2. Literature Review and Research Hypotheses

Theoretically, the technological innovation of artificial intelligence (AI) is an innovation that "empowers people" and "replaces human labor." This has implications for multiple aspects of the labor market:

Firstly, it will cause changes in skill demands. The introduction of AI may lead to new demands for labor skills, creating a skill bias, and expanding wage gaps both within skills and job positions through skill premium increases and job polarization [4]. Bessen [5] argues that AI is a labor-enhancing technology; although it may lead to the disappearance of certain jobs, it also creates new employment opportunities, particularly in fields such as AI system development and maintenance, data analysis, and machine learning.

Secondly, it will exacerbate labor market instability. Linhui Wang suggests that the application of robots will intensify the "motherhood penalty," causing structural employment contradictions and affecting the stability of the labor market. Dongmei Chen et al. found that digitization constitutes a potential threat to the labor market, with the emergence of strong individuals leading to increasingly unstable, or even disappearing, employment relationships. Lingzheng Yu et al. [6] compared and concluded that since robots cannot replicate unconventional capabilities to replace workers, the employment share and skill premium for unconventional job positions are continuously rising. Moreover, if skill demands change, this could lead to rising salaries for professionals in certain AI fields, while workers in traditional industries may face wage pressure, further exacerbating income inequality. Acemoglu and Restrepo [7] argue that the advent of automation allows companies to replace tasks previously completed by labor with capital, reducing the cost of labor usage. Although skilled labor still holds a comparative advantage in the face of AI, automation takes jobs away from unskilled workers, leading to increased labor market turbulence and exacerbating social inequality. Furthermore, Arntz et al. [8] studied the impact of AI on wage distribution and found that high-skilled workers are likely to benefit from AI, while low-skilled workers may face greater challenges.

Thirdly, AI will lead to structural changes in the labor market. Research has shown that while AI facilitates capital substitution for labor, it also increases labor productivity and creates new jobs [9]. Despite the overall stability of employment due to the opposing effects of substitution and suppression, structural shocks are inevitable [10]. Changes in labor demand will lead to structural shifts, resulting in uncertainty regarding the direction of AI's impact on industrial structure transformation and the share of labor income [11]. Yongqin Wang and Wen Dong argue that the structural impact of AI is targeted at labor demand with different skill structures. While robots replace some jobs that can be automated, they will also further increase the demand for labor in non-automated positions and roles that complement robotic skills. Hong Cheng et al. [12] used the Chinese Enterprise-Labor Matching Survey Database to test and found that the overall substitution effect of robots on China’s labor market is 0.3%, and the effects on different skill levels of labor are asymmetrical. Linhui Wang et al., based on CLDS data, calculated that AI technology has a job substitution effect, with 19.05% of labor employment in China facing high job substitution risks at present.

Overall, the impact of AI development on the labor market is complex, potentially bringing both opportunities and challenges.

Existing literature suggests that the application of AI in companies will have both substitution and complementary effects on labor, both of which will lead to improvements in corporate labor productivity. On one hand, AI can replace some manual labor in high-frequency, repetitive, and rule-based production activities, thus increasing corporate labor productivity. On the other hand, with the accumulation of capital and the improvement of intelligence, AI could create more new job positions, which would allow AI technologies to be better applied in corporate production and business activities, thereby enhancing corporate labor productivity. However, some literature points out that although AI technology has been rapidly popularized and developed in many industries, productivity has not seen significant improvements, leading to the "AI productivity paradox," a phenomenon similar to the "Solow paradox" observed during the information technology revolution in the 1980s. In light of this, this paper will investigate whether the current stage of AI development in China and its application by companies has led to improvements in corporate labor productivity.

H1: Corporate AI applications can enhance corporate labor productivity.

3. Research Design

3.1. Data Sources

This study uses A-share listed companies in China's Shanghai and Shenzhen stock markets as the research subject, with the sample period spanning from 2016 to 2023. The reason for selecting 2016 as the starting point is twofold: First, 2016 marked the rapid development phase of artificial intelligence (AI), such as the victory of Google's DeepMind AlphaGo program over Go master Lee Sedol, which ignited China's attention to AI technology and spurred companies to increase their investment in AI. Second, 2016 is considered a key milestone for AI development in China, primarily because the government began to emphasize the strategic importance of AI. The "New Generation Artificial Intelligence Development Plan" (AIDP) released in 2017 formally set the goal for China to become a global leader in AI, with preparations for this plan starting as early as 2016, which facilitated the data collection for AI indicators in this study. The annual report information of listed companies used in this study comes from the Sina Finance website, while labor and financial data of companies are sourced from the Guotai An Database (CSMAR). To ensure data quality, the sample was processed as follows: (1) samples of companies classified as ST or *ST in the given year were excluded; (2) companies in the financial industry were excluded; (3) samples with missing data were excluded. The final sample consisted of 18,588 observations. To mitigate the influence of extreme values, the study applied tail trimming to continuous variables at the 1% level.

3.2. Model Specification

$$LP_{i,t} = \alpha + \beta * AI_{i,t} + \gamma * Controls_{i,t} + year + ind + pro + \varepsilon_{i,t} \quad (1)$$

Where i and t represent the company and year, respectively. LP denotes labor productivity, and AI represents the application of artificial intelligence by the company. ε is the random error term, while year, ind, and pro represent year fixed effects, industry fixed effects, and province fixed effects, respectively. Controls refers to the control variables.

3.3. Variable Explanation

3.3.1. Corporate Labor Productivity

The dependent variable in this study is corporate labor productivity (LP), an important indicator of a company's production efficiency, reflecting the output level produced by unit labor input over a certain period. Previous literature typically uses metrics like "company employee salary/employee number" and "company operating income/employee number" to represent labor productivity. Following previous methods, this study uses the natural logarithm of per capita operating income to measure corporate labor productivity.

3.3.2. Corporate AI Application

The core explanatory variable in this study is corporate AI application (AI). Drawing from the AI indicator construction methods of Yao Jiaquan [13] et al., an AI dictionary was created, and the number of AI-related terms in the annual reports of listed companies was counted. The AI indicator is represented by the natural logarithm of the number of AI keywords in the annual report plus one.

3.3.3. Control Variables

This study adopts control variables based on the work of Jianyu Zhao and Zhengfei Lu (2018), Kangtao Ye and Weihang Sun (2019), among others. The following control variables are selected: company age (Age), growth potential (Growth), board size (Board), cash flow status (Cashflow), independent director proportion (Indep), leverage ratio (Lev), company size (Size), and the shareholding ratio of the top five shareholders (Top5). The definitions of the variables are shown in Table 1.

Table 1. Variable Definitions

Variable Name	Variable Symbol	Variable Description
Labor Productivity	LP	Labor productivity, measured by the natural logarithm of per capi operating income
Corporate AI Level	AI	Natural logarithm of the number of AI keywords in the annual report plus 1
Company Age	Age	Company age, represented by the natural logarithm of the company’s age
Growth Potential	Growth	Sales revenue growth rate, represented by the natural logarithm
Board Size	Board	Number of board members, represented by the natural logarithm
Cash Flow Status	Cashflow	Ratio of net operating cash flow to the net value of fixed assets at the beginning of the period
Independent Director Proportion	Indep	Ratio of independent directors to total board members
Leverage Ratio	Lev	Ratio of total liabilities to total assets at year-end
Company Size	Size	Total assets at year-end, represented by the natural logarithm
Top 5 Shareholders' Shareholding Ratio	Top5	Proportion of shares held by the top five shareholders

4. Empirical Analysis

4.1. The Impact of Corporate Artificial Intelligence Application on Labor Productivity

Table 2. Summary Statistics

VarName	Obs	Mean	SD	Min	Median	Max
LP	18588	8.454	1.024	6.455	8.328	11.199
AI	18588	1.056	1.183	0.000	0.693	4.143
Age	18588	2.270	0.686	1.099	2.303	3.401
Growth	18588	0.157	0.338	-0.486	0.106	1.907
Board	18588	2.106	0.196	1.609	2.197	2.639
Cashflow	18588	0.054	0.064	-0.124	0.051	0.242
Indep	18588	37.867	5.410	33.330	36.360	57.140
Lev	18588	0.410	0.191	0.065	0.405	0.867
Size	18588	22.393	1.299	20.166	22.176	26.360
Top5	18588	0.532	0.151	0.200	0.529	0.887

The descriptive statistics of the variables are shown in Table 2. Table 3 reports the overall test results for the impact of corporate AI application on labor productivity. Column (1) in Table 3 presents the regression results when only the core explanatory variable is included. It can be seen that corporate AI application has a significantly positive impact on labor productivity. Column (2) presents the regression results after adding control variables. It can be observed that corporate AI application significantly increases labor productivity at the 1% confidence level. Among the control variables, companies with higher growth, better cash flow, and larger size tend to perform better in terms of labor productivity.

Table 3. Empirical Results

	(1)	(2)	(3)
	LP	LP	LP
AI	0.110*** (0.005)	0.012** (0.005)	
MD&A_AI			0.008* (0.005)
age		-0.131*** (0.027)	-0.125*** (0.027)
Growth		0.263*** (0.010)	0.267*** (0.010)
Board		-0.002 (0.039)	-0.018 (0.038)
Cashflow		0.769*** (0.055)	0.772*** (0.055)
Indep		-0.000 (0.001)	-0.000 (0.001)
Lev		-0.141*** (0.051)	-0.165*** (0.050)
Size		0.565*** (0.017)	0.561*** (0.016)
Top5		-0.133 (0.086)	-0.090 (0.082)
_cons	8.241*** (0.017)	-4.055*** (0.372)	-4.247*** (0.386)
N	18588	18588	18588
R2		0.544	0.557
year		Yes	Yes
pro		Yes	Yes
ind		Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2. Robustness Check

To test the robustness of the results, an alternative AI indicator was used. Specifically, the frequency of AI-related terms in the MD&A (Management Discussion and Analysis) section of the company's annual report was used to re-measure the AI application indicator. The regression results are shown in Column (3) of Table 3. After adding the control variables, the coefficient of MD&A_AI is 0.008, which is significantly positive. This result confirms that the conclusions of this study remain valid.

5. Research Conclusions and Policy Implications

China's rapid development of artificial intelligence (AI) technology, increasing data and computational resources, and expanding application scenarios are leading companies to actively explore new models and pathways for AI development, promoting high-quality economic growth through advanced AI applications. At the same time, the application of AI by companies is also affecting the labor market within enterprises. However, there has been no clear conclusion on the impact of corporate AI applications on labor productivity during the early stages of AI development in China.

This study collected annual report data from A-share listed companies in China between 2016 and 2023, constructing corporate AI indicators based on the method of Yao Jiaquan et al. Through descriptive statistics and empirical research, the study concludes that the application of AI by companies can significantly enhance labor productivity. This indicates that AI technology has tremendous potential and practical value in enterprise applications. Through automation and intelligent processing, a large number of repetitive and routine tasks can be completed quickly and accurately, thereby saving labor and time costs and improving overall production efficiency.

To better harness the potential of AI applications in improving labor productivity, it is recommended that companies establish an industrial ecosystem. By building collaborative innovation platforms for AI, supporting small and medium-sized enterprises in adopting AI technology, and lowering the application threshold for AI across various industries, the widespread application of AI in enterprises can be promoted.

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