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*Original Paper*

# The Impact of Artificial Intelligence on the Income Gap between Labor and Capital—Empirical Analysis Based on A-share Listed Companies

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***Abstract***
*Against the backdrop of artificial intelligence reshaping the income distribution pattern of enterprises, the widening gap between labor and capital income shares has raised concerns about social equity. This article empirically tests the impact of artificial intelligence applications on the income share gap between labor and capital based on data from Chinese A-share listed companies from 2010 to 2022. Research has found that the application of artificial intelligence significantly widens the income gap between labor and capital, with the core mechanisms being the capital labor substitution theory and the theory of technological progress bias; Heterogeneity analysis shows that this effect is particularly prominent in non-state-owned enterprises (expanding by 0.35%) and labor-intensive industries (expanding by 0.28%), while state-owned enterprises do not show significant expansion due to policy constraints (salary control, job stability responsibilities) and technology intensive industries due to skill technology complementarity. This article suggests alleviating distribution polarization by strengthening worker skills training and designing profit sharing mechanisms, providing policy insights for coordinating technical efficiency and income equity.*

***Keywords***
*Artificial intelligence, The income gap between labor and capital, Substitution effect, Skill bias*

## 1. Introduction

In the context of the widespread application of artificial intelligence, there has been extensive discussion in the academic community about its impact on employment and income distribution. Some studies have shown that the introduction of artificial intelligence will reduce the demand for low skilled labor in enterprises, thereby generating substitution effects, leading to the disappearance of some positions and changes in employment structure (Wang Yongqin & Dong Wen, 2020; Li Lei et al., 2021). However, artificial intelligence may also have complex impacts on labor income share by increasing productivity and promoting innovation, creating new job opportunities and high skilled positions (Acemoglu &

Restrepo, 2018, 2019). However, these studies mostly explore the impact of artificial intelligence on the overall labor income share from a macro perspective, but there are few in-depth studies on its specific role in the labor capital income share gap. The gap between the share of capital income and the share of labor income in a company is an important indicator for measuring the fairness of income distribution within the company. In the context of the widespread application of artificial intelligence, the change in this gap not only concerns the vital interests of employees, but also affects the stability within the enterprise and the harmonious development of society.

In existing literature, although there is limited research directly on the impact of artificial intelligence on the income share gap between labor and capital, some indirectly related studies provide useful references for this article. For example, Yu Changlin et al. (2024) found that the introduction of artificial intelligence promotes the upgrading of enterprise skill structure, which may have different impacts on the income of management and employees. These studies suggest that artificial intelligence may have complex effects on the income share gap between labor and capital, but further in-depth exploration is needed.

This article aims to systematically review and analyze the impact of artificial intelligence applications on the income share gap between labor and capital based on existing literature, explore its mechanism of action, and examine the heterogeneous effects in different contexts. By constructing theoretical models and conducting empirical analysis, this article aims to provide new perspectives and evidence for understanding how artificial intelligence applications can change the internal income distribution pattern of enterprises, and provide useful references for policy makers to promote fairness in income distribution and stability in the labor market.

## 2. Literature Review and Research Hypothesis

### *2.1 Literature Review*

#### 2.1.1 The Impact of Artificial Intelligence Applications on Labor Income Share

He Xiaogang et al. (2023) pointed out through empirical research on Chinese industrial enterprises that the introduction of artificial intelligence significantly reduces the labor income share of enterprise employees. This finding is consistent with Gregory's (2016) view that the application of artificial intelligence and automation technology will gradually replace labor, reduce labor demand, and lead to a decrease in labor income share. In addition, Chao Xiaojing and Zhou Wenhui (2021) found that artificial intelligence has a significant impact on the skill structure and skill income gap of workers, which indirectly supports the view that the application of artificial intelligence will reduce employees' labor share. These studies indicate that the application of artificial intelligence reduces employees' share of labor income through substitution effects and changes in skill structure. (2) The existing literature mainly explains the impact of artificial intelligence on employee labor share based on the capital labor substitution theory (Acemoglu & Restrepo, 2018). This theory suggests that as artificial intelligence replaces some labor, especially low skilled labor, the demand for labor in enterprises decreases, leading to a decrease in the share of labor income.

2.1.2 The Impact of Artificial Intelligence Applications on Capital Income Share

Contrary to the impact on labor income share, there is relatively little research on the effect of artificial intelligence applications on capital income share, but they often have a positive impact on capital income share. The study by Yu Changlin et al. (2024) shows that the introduction of artificial intelligence has increased the demand for high skilled labor in enterprises, thereby increasing the labor income share of management. In addition, the application of artificial intelligence reduces the dependence of enterprises on low skilled labor, giving management greater say and control in decision-making and resource allocation, which may indirectly increase management's revenue share. (2) The existing literature on the impact of artificial intelligence on capital income share is mainly based on the theory of technological progress bias (Bentolita & Saint Paul, 2003). This theory suggests that technological progress may lean towards capital or managerial labor rather than ordinary employee labor, leading to an increase in their income share. This theoretical framework provides a new perspective for understanding the impact of artificial intelligence on the share of capital income.

2.1.3 Literature Review

(1) Based on the analysis of the above two parts, it can be seen that the application of artificial intelligence has different impacts on the share of labor income and capital income. On the one hand, the introduction of artificial intelligence has reduced employees' share of labor income; On the other hand, it may increase the revenue share of management through capital deepening and technological progress. The combined effects of these two factors have led to the widening of the income gap between labor and capital. Zheng Jingli et al. (2024) found that with the widespread application of artificial intelligence, the internal income distribution pattern of enterprises has undergone significant changes, with capital and management gaining a larger share in income distribution, while employees' labor income share has relatively decreased. (2) When explaining the impact of artificial intelligence on the income share gap between labor and capital, this article attempts to construct a comprehensive theoretical framework. This framework combines the theory of capital labor substitution and the theory of technological progress bias, and introduces the theory of industrial structure upgrading and enterprise transformation and upgrading (Alvarez Cuadrado et al., 2018). This framework believes that artificial intelligence, as an important manifestation of technological progress, not only reduces the share of labor income through substitution effects, but also increases the share of capital and management income through bias effects. At the same time, with the upgrading of industrial structure and the transformation and upgrading of enterprises, the position of management in income distribution has been further consolidated and enhanced, thereby exacerbating the income share gap between labor and capital. (3) The existing literature still has shortcomings in exploring the direct impact of artificial intelligence applications on the income share gap between labor and capital. Most studies mainly focus on its impact on labor income share or overall income distribution, with less direct exploration of changes in the income share gap between labor and capital.

### *2.2 Research Hypothesis*

Based on the theory of capital labor substitution (Acemoglu & Restrepo, 2018) and the theory of technological progress bias (Bentolita & Saint Paul, 2003), combined with existing literature and the research objectives of this paper, the following research hypotheses are proposed:

Assumption 1: The application of artificial intelligence significantly widens the income gap between labor and capital

Artificial intelligence exacerbates the allocation conflict between labor and capital through the capital enhancement effect and skill biased substitution. On the one hand, technological applications directly replace low skilled labor and reduce the marginal output of labor factors (Zheng Jingli et al., 2024); On the other hand, capital owners strengthen their control over surplus value through technological monopolies, thereby increasing the rate of return on capital (Acemoglu & Restrepo, 2018). Therefore, this article expects a significant positive correlation between the level of artificial intelligence application (Aif) and the gap in labor capital income share (Gap).

Assumption 2: The allocation effect of artificial intelligence exhibits ownership heterogeneity

There are significant differences between state-owned enterprises and non-state-owned enterprises in terms of technology application goals, policy constraints, and labor adjustment costs. State owned enterprises, due to their responsibility of stabilizing employment and regulating salaries (Liu Yalin et al., 2022), have weaker distribution effects of technological substitution; Non state-owned enterprises follow the logic of marketization and are more inclined to replace low skilled labor with technology to enhance capital returns (Xie Jie et al., 2022). Therefore, this article expects that the effect of artificial intelligence on widening the labor capital gap will be more significant in non-state-owned enterprises, but not significant in state-owned enterprises.

Assumption 3: The allocation effect of artificial intelligence exhibits industry heterogeneity

Labor intensive industries rely on low skilled labor, and the marginal effect of technological substitution is stronger; Technology intensive industries are partially offset by the distribution effect of technology shocks due to skill technology complementarity (Fan Haichao et al., 2024), while capital intensive industries are partially offset by capital deepening and economies of scale (Yin Heng et al., 2024). Therefore, this article expects that the effect of artificial intelligence on widening the labor capital gap is most significant in labor-intensive industries, and not significant in technology intensive and capital intensive industries.

## 3. Data Processing and Basic Model Setting

### *3.1 Variable Description*

#### 3.1.1 Core Explanatory Variables

Artificial Intelligence Application Level (Aif): AI word frequency and (Lnwords) indicators are used to measure the application of artificial intelligence. Referring to Yao Weighted's (2024) approach, the construction method of this indicator is to calculate the frequency of 73 AI words based on the text content of the annual report of the listed company. The specific method is as follows: (1) Download the annual reports of listed companies from Juchao Information Network from 2000 to 2022 (2) Organize the raw data into panel data. (3) Calculate the text length of the entire annual report and the text length of the Chinese and English parts. (4) Build an artificial intelligence terminology dictionary and expand vocabulary to Python's jieba library. (5) Remove pause words, count the exact number of words as the AI word frequency sum, and finally perform natural logarithm processing.

3.1.2 Explained Variable

Labor income share (Ls): refers to the proportion of labor factor compensation in income distribution. Referring to the practices of Wang Xiongyuan and Huang Yujing (2017), Shi Xinzheng et al. (2019), the labor income share is represented by the proportion of total employee compensation in the total enterprise income: where the total employee compensation is: cash paid to and for employees+year-end payable employee compensation - beginning payable employee compensation - total executive compensation. The specific calculation formula is shown in equation (2).

Ls=total employee compensation/total operating revenue

Capital income share (Cs) refers to the proportion of capital element returns in income distribution. Refer to the approach of Liu Guangqiang and Kong Gaowen (2018). This article uses the proportion of total management compensation in the revenue share of a company to represent the share of capital income; The size of the management team is defined as "the total number of directors, supervisors, and senior executives - the number of independent directors - the number of unpaid directors, supervisors, and senior executives". The specific calculation formula is shown in equation (3).

Cs=total management compensation/total operating revenue

Gap between labor and capital income shares: Referring to the practices of Faley et al. (2013), Banker et al. (2016), Kong Dongmin et al. (2017), and Liu Guangqiang and Kong Gaowen (2018), this article measures the difference between labor income shares and capital income shares of employees. At the same time, in order to make the value of labor capital income share more in line with normal distribution, GAP was logarithmized.

3.1.3 Control Variables

Drawing on the approach of Liu Guangqiang and Kong Gaowen (2018), this article controls for the following enterprise characteristic variables: company size, natural logarithm of annual total assets; Asset liability ratio (lev), expressed as the ratio of year-end total liabilities to year-end total assets; Total asset net profit margin (ROA), expressed as the ratio of net profit to total assets; Growth rate of operating income, expressed as the ratio of current year's operating income to the previous year's operating income minus 1; The age of the company (Firmage) is measured by subtracting the year of establishment of the enterprise from the year in which the sample observation value is located and adding 1 to take the natural logarithm; The shareholding ratio of the largest shareholder (Top1) is represented by the ratio of the number of shares held by the largest shareholder to the total number of shares.

Section 2 Data Sources and Processing

Taking Chinese A-share listed companies as samples, the sample time interval is from 2007 to 2022. Among them, enterprise level data mainly comes from CSMAR database and Wind database. Before empirical testing, the following operations were performed on the variables involved: at the enterprise level, samples of enterprises with excessive missing values were excluded, and in order to eliminate the influence of outliers, the key variables were truncated by 1%.

Section 3 Model Construction

To examine the impact of artificial intelligence applications on the income share gap between labor and capital, the following econometric model is constructed:

$Gap_{i,t} = \alpha_0 + \alpha_1 Aif_{i,t} + \alpha_2 Controls_{i,t} + \gamma_i + \lambda_i + \mu_{i,t}$(1)

Among them, i and t represent the company and year respectively, and the dependent variable $Gap_{i,t}$ represents the share of labor and capital income. In the benchmark regression, the natural logarithm of the difference between the labor share and capital share of listed company employees is used to measure it; $Aif_{i,t}$ As the core explanatory variable, the benchmark regression is measured using the frequency of artificial intelligence keywords in the annual reports of listed companies (Lnwords). In the alternative indicator test, the frequency of artificial intelligence keywords in the MD&A section of the annual reports of listed companies (Lnwords_MD&A) and the number of artificial intelligence patents applied for by listed companies in the current year (Lnpatents) are used as alternative indicators. $\gamma_i$ For the fixed effect of the enterprise, $\lambda_i$+ is the fixed effect of the year, and $\mu_{i,t}$ is the error term.$Controls_{i,t}$ Representing control variables, this article includes the following control variables: company size (size), debt to asset ratio (lev), net profit margin of total assets (ROA), revenue growth rate (Growth), company age (Firmage), and shareholding ratio of the largest shareholder (Top1).

## 4. Empirical Results and Analysis

### *4.1 Analysis of Benchmark Regression Results*

4.1.1 Descriptive Statistics

In this study, we used multiple key variables to explore in depth the impact of artificial intelligence application level on the income share gap between labor and capital in enterprises. According to the provided descriptive analysis tables, the basic statistical characteristics of each variable can be summarized as follows: (1) Table 1 reports the descriptive statistical results of 13685 observations of A-share listed companies from 2010 to 2022. The mean value of the core variable labor capital income share gap (Gap) is 0.154 (standard deviation 0.092), with minimum and maximum values of 0.032 and 0.378, respectively, indicating significant differences in labor and capital income distribution among enterprises (Xie et al., 2022).

The average level of artificial intelligence application (Aif) is 1.952 (standard deviation 1.144), with an interval of [0.693, 5.866], showing a significant right skewed distribution, consistent with the conclusion of Wang Xiyuan et al. (2023) on the uneven application of enterprise technology, indicating that a few enterprises have entered the stage of deep intelligence, while the majority are still in the initial exploration stage. In the controlled variables, the average company size (Size) is 22.203 (natural logarithm), and the average asset liability ratio (Lev) is 40.3%, which conforms to the characteristics of medium leverage ratio of Chinese listed companies (Liu Yalin et al., 2022); The average net profit margin (Roa) of total assets is 4.2%, but the minimum value is -8.1%, reflecting the operational volatility risk of some enterprises (Yin Heng et al., 2024); The average growth rate of operating revenue is 14.8%, with a standard deviation of 25.8%, highlighting the differentiation of market performance (Zheng Haotian and Jin Weidong, 2024). The logarithmic mean age of the company (Firmage) is 2.927, corresponding to approximately 19 years of establishment. The sample covers companies from start-up to mature stages, which helps to control the impact of the lifecycle on distribution structure.

It is worth noting that the distributions of Gap and Aif are both skewed to the right (Gap skewness is 1.24, Aif skewness is 1.57), suggesting that high AI application enterprises may be accompanied by greater labor capital distribution differences. This asymmetric effect will be tested through regression analysis in the future (Sun Feng'e, 2023). In addition, the standard deviation between variables is generally high, which is consistent with the heterogeneity characteristics of A-share enterprises. The model introduces individual and time fixed effects to control for potential omitted variables (Song Huasheng & Lu Liqi, 2024).

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Gap | 13685 | .154 | .092 | .032 | .378 |
| Aif | 13685 | 1.952 | 1.144 | .693 | 5.866 |
| Size | 13685 | 22.203 | 1.146 | 20.485 | 24.630 |
| Lev | 13685 | .403 | .184 | .109 | .738 |
| Roa | 13685 | .042 | .052 | -.081 | .139 |
| Growth | 13685 | .148 | .258 | -.273 | .767 |
| Firmage | 13685 | 2.927 | .325 | 1.099 | 3.611 |

4.1.2 Basic Model Verification

To test the predictions of the theoretical model, we examined the impact of artificial intelligence applications on the income share gap between labor and capital based on the model.

| variable | (1) | (2) |
| --- | --- | --- |
| | Gap | Gap |
| *Aif* | 0.0083*** | 0.0025** |
| | (0.0006) | (0.0012) |
| *Size* | | -0.0125** |
| | | (0.0027) |
| *Lev* | | -0.0275** |
| | | (0.0108) |
| *Roa* | | -0.3265*** |
| | | (0.0186) |
| *Growth* | | -0.0265*** |
| | | (0.0023) |
| *Firmage* | | -0.0311* |
| | | (0.0180) |
| *Cons* | 0.1378*** | 0.4670*** |
| | (0.0012) | (0.0614) |
| $R^2$ | 0.0177 | 0.2281 |
| Individual fixed | Controlled | Controlled |
| Fixed time | Controlled | Controlled |
| *N* | 13685 | 13685 |

Table 2 reports the basic model regression results of the impact of artificial intelligence applications on the gap in labor capital income share. Column (1) only includes the core explanatory variables of artificial intelligence application level (Aif) and individual and time fixed effects. Column (2) further introduces control variables such as enterprise size (Size), asset liability ratio (Lev), total asset net profit margin (Roa), revenue growth rate (Growth), and company age (Firmage).

The results show that the coefficient of Aif in column (1) is 0.0083, which is significant at the 1% level, indicating that the application of artificial intelligence has significantly widened the income share gap between labor and capital, preliminarily verifying the research hypothesis. This result is consistent with the conclusion of Zheng Jingli et al. (2024) that artificial intelligence exacerbates the conflict between labor and capital distribution, indicating that technological applications may widen the distribution gap by replacing low skilled labor and increasing capital returns (Acemoglu&Restrepo, 2018). After introducing the control variable in column (2), the coefficient of Aif decreased to 0.0025, but still maintained a significance level of 5%, indicating that the widening effect of artificial intelligence on labor capital gap still exists after controlling for enterprise characteristics, but the degree of influence has weakened.

In addition, the $R^2$ value of the model is 0.2163, indicating that the model can to some extent explain the changes in the income share gap between labor and capital, but there is still significant room for improvement. This may be because the income share gap between labor and capital is influenced by multiple complex factors, and the variables included in this model cannot fully cover these factors.

In summary, this study found that the improvement of artificial intelligence applications will widen the income gap between labor and capital. Meanwhile, factors such as company size, debt to asset ratio, net profit margin of total assets, and revenue growth rate also have a significant impact on the gap in labor capital income share. These findings provide useful insights into the causes of the income share gap between labor and capital, and offer decision-making references for policy makers.

*4.2 Robustness Test*

| variable | Replace core explanatory variables | Lagged dependent variable | random sampling | Increase control variables |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Gap | L.Gap | Gap | Gap |
| Digital intangible assets | 0.0003***<br>(0.0000) | | | |
| *Aif* | | 0.0056***<br>(0.0016) | 0.0021*<br>(0.0012) | 0.0024*<br>(0.0012) |
| *Size* | -0.0118***<br>(0.0027) | -0.0242***<br>(0.0039) | -0.0127***<br>(0.0027) | -0.0123***<br>(0.0027) |
| *Lev* | -0.0276**<br>(0.0109) | -0.0181<br>(0.0147) | -0.0264**<br>(0.0106) | -0.0261**<br>(0.0108) |
| *Roa* | -0.3280***<br>(0.0185) | -0.2518***<br>(0.0231) | -0.3240***<br>(0.0185) | -0.3255***<br>(0.0185) |
| *Growth* | -0.0265***<br>(0.0023) | 0.0536***<br>(0.0036) | -0.0270***<br>(0.0023) | -0.0267***<br>(0.0023) |
| *Firmage* | -0.0310*<br>(0.0180) | -0.0285<br>(0.0280) | -0.0289<br>(0.0176) | -0.0306*<br>(0.0179) |
| High tech industry is 1, otherwise it is 0. Digital intangible assets | | | | 0.0190***<br>(0.0071) |

| | | | | |
|---|---|---|---|---|
| *Cons* | 0.4552***<br>(0.0617) | 0.6753***<br>(0.0962) | 0.4711***<br>(0.0616) | 0.4485***<br>(0.0609) |
| $R^2$ | 0.2279 | 0.1628 | 0.2218 | 0.2303 |
| Individual fixed | Controlled | Controlled | Controlled | Controlled |
| Fixed time | Controlled | Controlled | Controlled | Controlled |
| *N* | 13685 | 9388 | 13441 | 13685 |

To verify the robustness of the core hypothesis that the application of artificial intelligence widens the gap in labor capital income share, this study tested it through four methods: replacing the core explanatory variable, lagged dependent variable, random sampling, and adding industry control variables (Table 3). The results indicate that the expansion effect of artificial intelligence on the labor capital distribution gap has significant robustness, supporting the reliability of the research hypothesis.

(1) Replace core explanatory variables

Column (1) replaces the AI application level (Aif) with digital intangible assets (such as algorithm patents, data assets), with a coefficient of 0.0003 and significant at the 1% level, indicating that the adjustment of technology substitution indicators has not changed the core conclusion. This result is consistent with the findings of Zheng Jingli et al. (2024) that the capital deepening effect of digital intangible assets also widens the distribution gap by squeezing the share of labor income. The sign and significance of the control variables are consistent with the baseline model, with $R^2$ stable at 0.2279, indicating that the model has low sensitivity to technical variables, further verifying the universality of the impact of artificial intelligence technology (Acemoglu & Restrepo, 2018).

(2) Lagged dependent variable

Column (2) uses a lagged gap as the dependent variable, and the coefficient of Aif increases to 0.0056 (1% significant), indicating that the impact of artificial intelligence on distribution inequality is persistent. This result supports the "cumulative effect of technological shocks" proposed by Acemoglu & Restrepo (2018), which suggests that the capital biased technological progress of artificial intelligence will strengthen the distribution imbalance over time. The moderating effect of enterprise size and total asset net profit margin (Roa) is more significant in the long-term perspective (Yin Heng et al., 2024), highlighting the long-term structural impact of technology application on labor management relations.

(3) Random Sampling and Sample Selection

Column (3) excludes data from 2009 and 2011 to exclude disturbances from the global financial crisis and policy interventions, and the Aif coefficient remains 0.0021 (10% significant), consistent with the direction of the benchmark model. Although the significance has slightly decreased (possibly due to sample reduction leading to reduced statistical power), the results still support the core hypothesis that artificial intelligence widens the distribution gap (Song Huasheng & Lu Liqi, 2024). The fluctuation of the control variable coefficient is small, with an $R^2$ of 0.2218, indicating that the model has strong resistance to abnormal periods, and the conclusion is not affected by short-term exogenous shocks.

(4) Increase industry heterogeneity control

Column (4) introduces a dummy variable for the high-tech industry (coefficient 0.0190, 1% significant), indicating that high-tech enterprises further exacerbate the polarization of labor capital distribution due to their technology intensive nature (Fan Haichao et al., 2024). The Aif coefficient remains at 0.0024 (10% significant), indicating that industry heterogeneity has not changed the marginal effects of artificial intelligence, and the distribution impact of technological shocks has cross industry universality. There was no substantial change in the sign and significance of the control variables, and $R^2$ increased to 0.2303. The explanatory power of the model was enhanced, supporting the robustness of the conclusion.

All four types of tests show that the application of artificial intelligence has a significant robustness in widening the gap between labor and capital income shares. Although there have been fluctuations in the significance of coefficients in some tests (such as a decrease in the significance of column 3 due to sample reduction), the core conclusion has not been affected by disruptive factors.

Section 3 Heterogeneity Analysis

4.2.1 Different ownerships

When exploring the impact of artificial intelligence applications on the income share gap between labor and capital, we conducted heterogeneity analysis for enterprises of different ownership types.

For state-owned enterprises, the impact of artificial intelligence applications on the income share gap between labor and capital is not significant. Specifically, the Aif coefficient is not significant (-0.0007), possibly due to stronger policy constraints on state-owned enterprises (such as salary control and union power), which suppress the polarization effect of technology on distribution (Liu Yalin et al., 2022).

This is because artificial intelligence applications will face different labor adjustment costs after upgrading their skill structure. Considering the stable employment responsibility undertaken by state-owned enterprises, even if the use of artificial intelligence can improve production efficiency, it is not possible to lay off employees on a large scale, and the labor adjustment cost is high. Therefore, the labor income share of employees in the labor capital income share is not significantly affected.

In contrast, the results of non-state-owned holding enterprises show significant heterogeneity. Specifically, the Aif coefficient is 0.0035 (1% significant), indicating that artificial intelligence has significantly widened the income gap between labor and capital in non-state-owned enterprises. Non state-owned enterprises have higher employment flexibility and a wider range of choices, lower labor adjustment costs, and can carry out a certain degree of layoffs, reducing employees' share of labor income. Moreover, based on the non-state-owned holding attribute, it will exacerbate the widening internal salary gap and increase the share of capital income.

In summary, our heterogeneity analysis results indicate that the impact of artificial intelligence applications on the income share gap between labor and capital varies significantly among enterprises of different ownership types.

4.2.2 Different Industry Categories

Secondly, we conducted heterogeneity analysis on enterprises in different industry categories. Specifically, we divided enterprises into three categories: labor-intensive industries, technology intensive industries, and capital intensive industries, and examined the significant impact of artificial intelligence applications on the income share gap between labor and capital in these three types of enterprises.

In labor-intensive industries, the application of artificial intelligence has had a significant impact on the income share gap between labor and capital. Specifically, the Aif coefficient is 0.0028 (10% significant), indicating that the widening effect of artificial intelligence on labor capital gap is most prominent in labor-intensive enterprises. This result is consistent with the theory of skill biased technological progress (Acemoglu & Restrepo, 2018), which states that labor-intensive industries rely on low skilled labor, and technological substitution directly compresses the share of labor income (Zheng Haotian & Jin Weidong, 2024). This process is often accompanied by the substitution of employee labor, which may lead to a decrease in the share of labor income and an expansion of the income gap between labor and capital.

Compared to technology intensive and capital intensive industries, this impact is not significant. Specifically, the Aif coefficient for non technology intensive industries is -0.0028 (not significant), which may be due to the strong complementarity between high skilled labor and technology, and the application of technology has enhanced employees' bargaining power (Fan Haichao et al., 2024). The Aif coefficient of capital intensive industries is 0.0011 (not significant), reflecting that capital deepening may balance distribution through economies of scale and offset some technological shocks (Yin Heng et al., 2024).

The $R^2$ of the grouping model ranges from 0.2108 to 0.2866, significantly higher than the baseline model, indicating that heterogeneity analysis can more accurately capture the allocation effects of technological shocks. The results indicate that the hypothesis of artificial intelligence widening the labor capital gap holds true in non-state-owned enterprises and labor-intensive industries, but is not significant in state-owned enterprises and technology intensive industries. This provides a basis for designing differentiated policies: labor protection and skills training should be strengthened for labor-intensive industries (Guo Kaiming, 2019), while profit sharing mechanisms should be promoted for non-state-owned enterprises (Acemoglu & Restrepo, 2018).

| variable | state-owned | Non-state | capital-intensive | technology-intensive | labor-intensive |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Gap | Gap | Gap | Gap | Gap |
| *Aif* | -0.0007 | 0.0035*** | 0.0011 | -0.0028 | 0.0028* |
| | (0.0027) | (0.0014) | (0.0016) | (0.0040) | (0.0017) |
| *Size* | -0.0137** | -0.0124*** | -0.0095*** | -0.0430*** | -0.0122*** |
| | (0.0065) | (0.0028) | (0.0035) | (0.0161) | (0.0038) |
| *Lev* | -0.0151 | -0.0301*** | -0.0313** | -0.0085 | -0.0236 |
| | (0.0270) | (0.0114) | (0.0128) | (0.0519) | (0.0158) |
| *Roa* | -0.3208*** | -0.3253*** | -0.3785*** | -0.3107** | -0.2714*** |
| | (0.0413) | (0.0207) | (0.0269) | (0.1238) | (0.0247) |
| *Growth* | -0.0284*** | -0.0258*** | -0.0270*** | -0.0396*** | -0.0258*** |
| | (0.0045) | (0.0026) | (0.0028) | (0.0140) | (0.0034) |
| *Firmage* | -0.0324 | -0.0300 | -0.0025 | -0.0460 | -0.0532** |
| | (0.0494) | (0.0194) | (0.0260) | (0.0515) | (0.0257) |
| *Cons* | 0.5206*** | 0.4347*** | 0.3664*** | 1.2063*** | 0.5123*** |
| | (0.1541) | (0.0666) | (0.0813) | (0.3944) | (0.897) |
| $R^2$ | 0.2108 | 0.2383 | 0.2564 | 0.2866 | 0.2156 |
| Individual fixed | Controlled | Controlled | Controlled | Controlled | Controlled |
| Fixed time | Controlled | Controlled | Controlled | Controlled | Controlled |
| *N* | 3861 | 9824 | 6745 | 377 | 6563 |

## 5. Conclusion and Policy Suggestions

### *5.1 Conclusion*

This article is based on data from A-share listed companies from 2010 to 2022, and systematically examines the impact and mechanism of artificial intelligence applications on the gap in labor capital income share. The research results indicate that:

(1) Artificial intelligence significantly widens the income gap between labor and capital. Benchmark regression shows that for every 1 unit increase in the level of artificial intelligence application (Aif), the average gap widens by 0.25% (5% significant), verifying the core hypothesis that technology shocks widen the distribution gap through capital enhancement effects and skill biased substitution (Acemoglu & Restrepo, 2018). This result is consistent with the conclusion of Zheng Jingli et al. (2024), indicating that artificial intelligence leads to a relative decrease in labor income share and an increase in capital income share by replacing low skilled labor and improving capital return rate. As pointed out by Acemoglu & Restrepo (2018), technological progress often tends to favor capital over labor, especially

in the context of widespread automation technology, where the marginal output of capital significantly increases while the marginal output of labor relatively decreases, resulting in an increase in the share of capital income and a decrease in the share of labor income.

(2) The heterogeneity effect is significant. In non-state-owned enterprises and labor-intensive industries, the distribution polarization effect of artificial intelligence is particularly prominent (significant Aif coefficients of 0.35% and 0.28%, respectively), while the effect is not significant in state-owned enterprises and technology intensive industries. The former originates from the flexibility of technological substitution under market-oriented mechanisms (Xie Jie et al., 2022), while the latter is constrained by policies (Liu Yalin et al., 2022) or buffered by skill technology complementarity (Fan Haichao et al., 2024).

*5.2 Policy Recommendations*

Based on research findings, this article proposes the following policy recommendations:

Firstly, the government should increase its efforts in providing on-the-job education and vocational skills training for workers, in order to enhance their ability to adapt to new technologies and automated production. Encourage companies to conduct pre job training for new skills to help workers smoothly transition to new job positions and mitigate the impact of robot applications on the labor market. This measure aims to stabilize and increase the share of labor income by improving the skill level of workers and alleviating the substitution effect of artificial intelligence on low skilled labor.

Secondly, establish a sound social security system to provide necessary living security and reemployment support for labor force who have lost their jobs due to robot applications. The government should accelerate the reform of the unemployment insurance system to ensure that the basic living needs of unemployed people are met during the transition period, thereby reducing the negative impact of technological progress on the labor market. This not only helps maintain social stability, but also provides opportunities for workers to switch jobs and re-enter the workforce.

Furthermore, the government can consider imposing reasonable taxes on the excess profits generated by robot applications and using a portion of the tax revenue to subsidize low-income workers or invest in education and skills training programs. By adjusting tax policies, the widening trend of the income share gap between labor and capital can be alleviated to a certain extent, and the redistribution effect of income can be achieved.

Finally, encourage enterprises to establish and improve labor management negotiation mechanisms, strengthen communication and negotiation between trade unions and employers, and ensure that workers' voice in income distribution is protected. By building harmonious labor relations, enhancing the status of workers, and jointly addressing the challenges brought by robot applications. This helps to form a more fair and reasonable income distribution pattern within the enterprise, promoting sustainable development of the enterprise and common prosperity of society.

*5.3 Conclusion*

Artificial intelligence has reshaped the distribution pattern of labor capital income share in enterprises, but its social effects depend on the synergistic optimization of technology application and institutional environment. This article reveals the asymmetric characteristics of technological shocks through empirical analysis, providing micro evidence for policy design that prioritizes efficiency while considering fairness. Only through the dual drive of technological innovation and institutional innovation can we achieve a win-win situation between technological progress and income distribution justice, and provide useful reference and inspiration for policy makers. In the future, with the further popularization and application of artificial intelligence, how to balance technological progress and income distribution fairness will become a common concern of all sectors of society.

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