Artificial Intelligence and Labor Income Share: Empirical Evidence from Chinese Listed Companies

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Abstract. While the global labor income share has faced a systemic decline, the impact of Artificial Intelligence (AI) remains a subject of intense debate. This paper utilizes a sample of Chinese A-share listed companies from 2009 to 2022 to empirically examine the relationship between AI application and corporate labor income share. By employing AI-related patent data to measure technological adoption at the micro-enterprise level, the study finds that AI application significantly increases the corporate labor income share.Mechanism analysis reveals that this positive effect is primarily driven by two channels: the mitigation of financing constraints through reduced information asymmetry, and the optimization of human capital structure as firms shift toward high-skilled labor. Further investigation indicates that the promoting effect of AI is more pronounced in non-state-owned enterprises and firms led by executives with digital backgrounds. These findings suggest that AI acts as a productivity-enhancing force that fosters a "human-machine collaborative" model rather than a simple substitution for labor. The study provides a theoretical basis for policies aimed at accelerating digital transformation while ensuring technological dividends are effectively shared with workers.

Keywords: Artificial Intelligence, Labor Income Share, Financing Constraints, Human Capital Structure, Chinese Listed Companies

1 Introduction

While the global labor income share has exhibited a systemic downward trend since the 1980s, the impact of Artificial Intelligence (AI) on this distribution pattern remains controversial, balancing between technological substitution and productivity-enhancing complementarity[6]. Although existing literature has explored technological change from macro-accounting or industry levels, research specifically focusing on generalized AI technology using a systematic sample of Chinese listed companies remains scarce. Specifically, current studies insufficiently explore mechanisms beyond single transmission paths and lack examination of contextual factors like executive characteristics and ownership nature. Based on this, this paper utilizes a sample of Chinese A-share listed companies from 2009 to 2022 to empirically examine how AI application affects corporate labor income share. We posit that AI drives

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labor remuneration proportion by enhancing total factor productivity and optimizing factor allocation, leading to the core hypothesis that AI application significantly increases the corporate labor income share . The marginal contributions of this paper are reflected in three aspects: it breaks through traditional industrial robot analysis by employing AI patent data to identify the net effect at the micro-enterprise level, providing new evidence for factor distribution in the digital economy; it integrates information asymmetry and human capital theories to reveal transmission paths through mitigating financing constraints and optimizing human capital structure, deepening the understanding of the internal logic between technology and distribution; and it examines the moderating effects of executive digital backgrounds and corporate ownership to provide a theoretical basis for the design of differentiated policies.

2 Theoretical Analysis and Research Hypotheses

2.1 Main Effect: The Net Impact of Artificial Intelligence on Labor Income Share

As a General Purpose Technology (GPT), the impact of Artificial Intelligence (AI) on the labor income share is not a simple linear relationship, but rather the result of a dynamic game between the "substitution effect" and the "complementary effect" [11].

While AI automates routine tasks[3], thereby fostering a "human-machine collaborative" production model[8,10]. AI technology can scale up corporate output and give rise to new tasks and occupations, forming a "productivity effect" and a "task creation effect"[5]. When AI significantly amplifies labor's productive capacity, firms—aiming to attract and retain core talent—tend to share a portion of the efficiency dividends with workers in the form of higher wages[6], thus driving up the share of labor in total output. Concurrently, AI technology effectively improves total factor productivity (TFP) by optimizing production processes and enhancing resource allocation efficiency[4]. High-skilled labor gains a wage premium due to its scarcity, and the growth rate of such compensation may even exceed the rate of return on capital, further pushing up the labor income share[1]. Thus, we propose:

H1: The application of artificial intelligence significantly increases the corporate labor income share.

2.2 Mechanism Path: Mitigation of Financing Constraints and Optimization of Human Capital Structure

AI also influences labor income share by reshaping resource acquisition and factor allocation through two channels. First, AI serves as a "hard signal" of innovation[9], mitigating information asymmetry and alleviating financing constraints. The easing of financing constraints implies that firms gain access to more abundant, low-cost capital, which can significantly increase the labor income share. Second, AI adoption forces enterprises to adjust human resource allocation[7], replacing low-skilled routine positions with high-skilled tasks. The human capital externalities of the city where the enterprise is located have a "productivity enhancement effect," which is conducive to promoting the innovative output of firms that minimize production costs[2]. This structural optimization increases the proportion of high-skilled employees who command higher wage premiums, raising overall compensation. Accordingly, we propose:

H2a: Artificial intelligence indirectly increases the labor income share by alleviating corporate financing constraints.

H2b: Artificial intelligence indirectly increases the labor income share by optimizing the human capital structure.

3 Empirical Design

3.1 Data Sources and Sample Selection

The sample comprises Chinese A-share listed companies from 2009 to 2022. After excluding financial firms, ST companies, and those with missing data, a final sample of 11,420 observations was obtained. Micro-level financial data are from CSMAR, macro data from the China Statistical Yearbook, and patent data from CNIPA. All continuous variables are winsorized at the 1st and 99th percentiles.

3.2 Model Specification

To verify the effect of artificial intelligence application on corporate labor income share, this paper establishes the following regression model:

$$\mathrm{LS}_{i,t} = \alpha_0 + \alpha_1 \mathrm{AI}_{i,t} + \alpha_2 \mathrm{Control}_{i,t} + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{1}$$

Where $LS_{i,t}$ represents the labor income share of firm i in year t, and $AI_{i,t}$ measures the level of artificial intelligence. $Control_{i,t}$ denotes a series of control variables. γ_i and γ_t represent firm and year fixed effects, respectively. Standard errors are clustered at the firm level.

To quantify the degree of corporate financing constraints, this paper adopts the SA index method used by Hadlock and Pierce[12]. The specific formula for calculating this index is: $-0.737 \times \mathrm{Size} + 0.043 \times \mathrm{Size}^2 - 0.04 \times \mathrm{Age}$, Where Size represents firm size and Age represents firm age. This paper constructs Model (3) to test the impact of artificial intelligence on financing constraints:

$$\mathrm{ASA}_{i,t} = \alpha_3 + \beta_3 \mathrm{AI}_{i,t} + \gamma_3 \mathrm{Control3}_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{2}$$

In equation (2): |SA| is the absolute value of the SA index, $Control3_{i,t}$ represents a set of control variables that may interfere with financing constraints.

In this paper, the proportion of highly skilled employees in an enterprise $\mathrm{Hskill}_{i,t}$ is selected as the proxy variable for human capital structure, and model (2) is constructed for testing:

$$\mathrm{Hskill}_{i,t} = \alpha_2 + \beta_2 \mathrm{AI}_{i,t} + \gamma_2 \mathrm{Control2}_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{3}$$

In equation (3), $\text{Hskill}_{i,t}$ represents the proportion of highly skilled employees of firm i in year t, and $\text{Control2}_{i,t}$ covers a series of control variables related to human capital structure.

3.3 Variables and Descriptive Statistics

The dependent variable, Labor Income Share (*LS*), is measured as employee compensation divided by operating revenue. The core explanatory variable, Corporate AI Level (*AI*), is measured by the natural logarithm of AI-related patents. Control variables include Return on Assets (*ROA*), Firm Size (*Size*), Leverage (*Lev*), Firm Age (*FirmAge*), Nature of Ownership (*SOE*), and Operating Revenue Growth (*Growth*). Table 1 reports variable definitions and descriptive statistics. The mean of *LS* is 0.22, and the mean of *AI* is 1.93, indicating significant divergence in AI application among firms.

The specific definitions of each variable are detailed in Table 1.

Table 1. Definition of Main Variables

Variable	Variable Definition	Mean	Standard Deviation	Minimum	Maximum
LS	Employee compensation / Operating revenue	0.22	0.24	0	5.90
AI	Log of AI-related patents	1.93	1.26	0.69	8.36
ROA	Net profit / Total assets	0.42	0.23	0.01	8.00
Lev	Total liabilities / Total assets	0.03	0.12	-7.70	0.76
FirmAge	Current year - Listing year	2.96	0.34	1.10	4.25
Size	Log of total assets	22.57	1.54	19.51	30.87
SOE	1 for SOEs, 0 otherwise	0.32	0.47	0	1
Growth	Revenue growth rate	0.99	42.84	-28.59	4500.02

4 Empirical Results and Analysis

As shown in Table 2, column (1) reports the baseline regression results without fixed effects. Column (2) introduces year fixed effects, and column (3) further includes all control variables while controlling for both year and individual fixed effects. Across all three sets of results, the estimated coefficients for Artificial Intelligence (AI) are consistently positive and significant at the 1% level. Taking column (3)—which controls for all covariates and dual fixed effects—as the benchmark, the estimated regression coefficient for AI is 0.003, passing the 1% significance level test. This implies that, ceteris paribus, a one-unit increase in the level of AI application significantly raises the corporate labor income share by 0.003 units. Regarding the control variables, the regression coefficients for firm size (Size) and return on assets (ROA) are both significantly negative, suggesting that expansion in firm scale or improvement in profitability is often accompanied by an increase in the proportion of capital factor input, thereby exerting a crowding-out effect on the labor income share. The coefficient for the ownership dummy variable (SOE) is 0.007 but does not reach statistical significance. The regression results for the remaining control variables are fundamentally consistent with existing literature and thus are not analyzed individually. Based on the aforementioned empirical evidence, the core hypothesis of this paper is verified: the deepening application of AI has a significant positive promoting effect on corporate labor income share, and H1 is supported.

Table 2. .Baseline Regression Results

	LS (1)	*LS* (2)	*LS* (3)
AI	0.006***	0.005***	0.003***
	(6.095)	(4.416)	(2.945)
Controls	Yes	Yes	Yes
Year Fixed Effects	Not Controlled	Controlled	Controlled
Individual Fixed Effects	Not Controlled	Not Controlled	Controlled
Observations	11,420	11,420	11,420
R-squared	0.157	0.186	0.188

To ensure the reliability of the conclusions, this paper conducted multiple robustness tests. The conclusions remain robust after replacing variable measures and excluding the impact of extreme years (2015 and 2020). Additionally, to address potential endogeneity issues, a 2SLS regression was performed using the 1984 fixed telephone density as an instrumental variable, and the conclusions remain unchanged. In summary, the empirical results support that artificial intelligence has a significant positive promoting effect on the corporate labor income share.

5 Further Research

Table 3 reports the mechanism analysis results based on the path testing method. Column (1) presents the impact of artificial intelligence on corporate financing constraints (ASA). The results show that the regression coefficient for AI is significantly negative at the 1% level, with a value of -0.015, indicating that the application of artificial intelligence can significantly alleviate corporate information asymmetry and reduce external financing costs, thereby generating a "financing constraint mitigation effect." Since the easing of financing constraints provides enterprises with more abundant funds for labor costs and welfare incentives, it subsequently promotes an increase in the labor income share.

Column (2) examines the impact of artificial intelligence on human capital structure (Hskill). The results show that the regression coefficient for AI is significantly positive and passes the 1% significance level test. This indicates that while artificial intelligence substitutes for routine positions, it also creates greater demand for high-skilled labor. By promoting the transformation of the human capital structure toward higher skill levels, it enhances the overall bargaining power and compensation levels of workers. In summary, artificial intelligence indirectly drives the growth of corporate labor income share through two channels: "alleviating financing constraints" and "optimizing human capital structure." The mechanism hypotheses of this paper are thus verified, and H2 is supported.

Table 3. Mechanism Testing

	ASA	*Hskill*
	(1)	(2)
AI	-0.011***	0.161***
	(-6.150)	(2.717)
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Observations	11,452	11,152
R-squared	0.831	0.021

6 Conclusions and Policy Implications

This study confirms that artificial intelligence (AI) application significantly increases the corporate labor income share among Chinese listed companies from 2009 to 2022. Mechanism tests indicate this positive effect is primarily driven by alleviating financing constraints and optimizing human capital structure, with stronger impacts observed in non-state-owned enterprises and firms with digitally-backgrounded executives.

Based on these findings, two key implications are proposed. First, enterprises should accelerate AI transformation while concurrently investing in employee digital literacy training to foster "human-machine collaboration," ensuring technological dividends are effectively shared with workers. Second, firms are advised to optimize governance structures by introducing executives with digital backgrounds, facilitating the conversion of technology into productivity and labor welfare.

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Disclosure of Interests

The author declares that there are no competing interests to declare that are relevant to the content of this article.

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