

Has The Application of Artificial Intelligence Expanded the Internal Income Gap Within Enterprises?

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Abstract. This study explores the impact of artificial intelligence (AI) technology application on the internal wage gap within enterprises and the moderating role of employee scale. Using panel data from Chinese A-share listed companies from 2011 to 2022 and an AI application level index constructed through text mining methods, this paper analyzes through a fixed effects model and finds that the application of AI technology significantly increases the wage gap between management and ordinary employees, especially in non-state-owned enterprises, non-manufacturing, and high-tech industries. However, the effect of this wage gap increase is relatively weaker in large enterprises, indicating that company size can mitigate the impact of AI technology to a certain extent. This finding contributes to a deeper understanding of how technological progress shapes the internal wage structure of enterprises and is significant for enterprises and governments to formulate fair wage policies, providing new strategies to promote internal wage equality within enterprises.

Keywords: Artificial Intelligence; Income Gap; Listed Companies; Chinese Economy.

1. Introduction

In the current digital wave, the rapid development of artificial intelligence (AI) technology has become a key force driving global economic and social transformation [1]. As AI applications deepen across various fields, they not only affect enterprises' operational behaviors and performance outcomes, such as market value, financing behaviors, production efficiency, and innovation capabilities, but also have profound impacts on wage levels, employment structures, and income distribution patterns at the industry level [2-5].

On one hand, the long-term potential of AI technology to drive job and wage growth is significant. AI technology is shaping our daily lives, work, and public spaces, signaling profound impacts on employment and wage growth [6]. Meanwhile, analyses at the individual level reveal the heterogeneous impacts of new digital technologies on job stability and wage growth, highlighting the relationship between high digitalization risks, increased probability of occupational transitions, and slowed wage growth, while advancements in AI may improve individual work stability and wage growth [7]. Moreover, discussions on technological paradigm shifts indicate that while certain industries may decline, overall employment does not necessarily decrease, with the middle-income group likely affected the most, but new job opportunities also emerging [8]. In discussions on the impact of self-reliant agriculture and sustainable agriculture on 21st-century sustainable growth, Mahesh and others have emphasized the role of AI and digital technologies in enhancing agricultural production efficiency, increasing farmers' incomes, and promoting employment [9]. These studies demonstrate that AI technology not only promotes development in specific industries and fields but also fosters employment and wage growth on a broader economic level, showcasing AI technology's immense potential in driving economic development and job creation.

On the other hand, the impact of AI on income and employment presents significant structural differences, as evidenced in numerous studies. Technological transformations lead to competition among low-skilled populations in simple tasks, reducing their opportunities in complex tasks, thereby narrowing the income gap among low-skilled workers and widening it among high-skilled workers [10]. Research reveals the substitution effect of AI and automation technologies on low-skilled, repetitive jobs, with a smaller impact on high-skilled jobs requiring creative thinking and complex decision-making [11]. Further analysis using the AI Occupational Impact (AIOI) index examines AI's

specific effects on different occupations, finding slight but positive wage changes in AI-affected occupations without significant employment changes, especially in jobs requiring advanced software skills [12]. Additionally, studies extending AIOI measurements to 23 OECD countries show that AI application correlates positively with employment growth in computer-intensive occupations but negatively with average working hours in less computer-intensive jobs [13]. These findings indicate that AI application may lead to changes in skill requirements, thereby affecting the distribution of employment opportunities and income levels, particularly for workers lacking skills and capabilities compatible with AI technology.

Despite preliminary explorations into the impacts of automation technology and AI use on income gaps, existing research often relies on qualitative analysis or uses dummy variables, failing to accurately quantify the degree of AI application and lacking consensus on many specific issues. More critically, these studies mainly focus on income disparities among workers with different skills, overlooking income differences within companies, especially the wage gap between management and ordinary employees. In the era of artificial intelligence, some senior management positions may receive higher salaries due to their key roles in technological decision-making and implementation, while ordinary employees may face stagnant or declining wages, highlighting prominent income distribution contradictions within companies. Additionally, the development of AI technology may lead to human labor substitution, further affecting companies' employee scales. In some cases, companies may choose to lay off workers or lower ordinary employees' wages to adapt to technological changes and optimize cost structures. These changes not only affect employees' job security and income levels but may also exacerbate internal income inequality within companies.

Therefore, how does the application of artificial intelligence to varying degrees affect the income gap between company management and ordinary employees? What role does employee scale play in this impact? Does this impact vary among different types of companies? Investigating these questions not only allows for a theoretical understanding of the differential impacts of artificial intelligence on income among different types of workers but also provides valuable policy recommendations for government departments adjusting and optimizing income distribution patterns. This relates not only to social equity issues but may also affect companies' long-term stability and employee morale.

This paper, based on the panel data of Chinese A-share listed companies from 2011 to 2022 and utilizing a newly constructed measure that more accurately depicts companies' artificial intelligence application levels, empirically analyzes the impact of artificial intelligence application on the internal income gap within enterprises. The research findings indicate that with the application of artificial intelligence technology, the income gap between management and ordinary employees within enterprises has increased, especially in non-state-owned enterprises, non-manufacturing sectors, and high-tech industries. This phenomenon is relatively mitigated in large enterprises, suggesting that company size plays an important role in moderating the impact of artificial intelligence technology on the income gap.

The main contributions of this paper are as follows: First, by systematically constructing an enterprise artificial intelligence application-level indicator based on text mining and word frequency statistics, it delves into the impact of artificial intelligence application on the income gap between internal management and ordinary employees. This extends related research on the factors affecting the internal income gap within companies from the perspective of technological shocks, providing a new theoretical perspective for exploring the governance mechanisms of internal wage disparities. Second, from the perspective of the moderating variable of employee scale, this paper explores the association among internal income disparities, artificial intelligence application, and employee scale within enterprises. Third, through heterogeneity analysis, it reveals the differential responses of different types of enterprises to artificial intelligence application, providing a basis for enterprises to formulate more personalized and effective wage management strategies. This also offers important reference information for the government when formulating relevant technological development and wage fairness policies.

2. Research Design

2.1. Data Sample

This paper uses the data of Chinese A-share listed companies from 2011 to 2022 as the research sample. The sample original data was screened and processed according to the following methods to ensure data validity and completeness: (1) companies with ST or *ST markings during the sample period were excluded; (2) samples of listed companies in the banking, insurance, and other financial sectors were excluded due to potential biases in the results; (3) samples lacking employee compensation, company characteristics, and employee structure data were excluded to ensure research based on sufficient and comprehensive information. Continuous variables were winsorized at the 1% and 99% levels to prevent extreme values from influencing the analysis results. Following these screening and processing methods, a total of 17,688 valid observations were obtained.

2.2. Variable Selection

2.2.1 Dependent Variable

The dependent variable of this study is the internal income gap (GAP), measured by the logarithm of the ratio of average management payment (AMP) to average employee payment (AEP), denoted as LnGAP. AMP is calculated by dividing the total management compensation disclosed in the company's annual report by the total number of senior management personnel; AEP is obtained by calculating the actual total compensation (including salary increases within the year, cash payments, excluding the annual salaries of directors, supervisors, and senior management) paid to non-management employees, then dividing by the total number of non-management employees.

2.2.2 Independent Variable

The core independent variable of this study is artificial intelligence (AI). This indicator aims to quantify the degree of investment and application of AI technology by listed companies. Given the diverse applications of AI technology and its critical role in corporate strategy, direct financial data or the number of industrial robots installed cannot fully capture its extensive impact. Therefore, this research adopts a measurement approach based on text mining technology, extracting information related to AI from the annual reports of listed companies. Utilizing Python web scraping technology, textual data from annual reports of A-share listed companies on the Shanghai and Shenzhen stock markets were collected. Following the methodology of Wu Fei and others, 15 AI-related feature words including "artificial intelligence," "business intelligence," "machine learning," etc., were selected [14]. The Jieba word segmentation tool was employed to process the text of annual reports, matching and counting the occurrences of these keywords. Finally, the frequencies of various keywords were aggregated, and the results were logarithmically transformed to construct a proxy indicator reflecting the enterprise's level of AI technology application. This method not only overcomes the limitations of previous studies that relied on specific physical inputs but also more comprehensively captures the dynamic progress and technical application levels of enterprises in the field of artificial intelligence.

2.2.3 Moderating Variable

This paper selects employee scale as the moderating variable, namely the total number of employees of listed companies, referring to the number of employees disclosed in the listed company's annual report.

2.2.4 Control Variables

The control variables section of the article includes two types of control variables: basic company characteristics and governance structure. The basic company characteristic attributes cover indicators such as company size (Size), leverage ratio (Lev), capital expenditure (Outcap), and return on equity (ROE). Regarding governance structure, factors considered include the shareholding ratio of the top ten shareholders (Top10), the equity ratio of management (Mshare), and whether the positions of

chairman and general manager are combined (Dual). These variables are included to account for various aspects that could influence the study's outcomes beyond the main variables of interest, ensuring a more comprehensive and accurate analysis. The main variable names, symbols, and definitions can be found in Table 1.

Table 1. Variable definition

Variable Type	Variable Name	Variable Symbol	Definition
Dependent Variable	Income Gap	LnGAP	Natural logarithm of the ratio of average management compensation to average employee compensation
	Average Management Payment	LnAMP	Natural logarithm of average management compensation
	Average Employee Payment	LnAEP	Natural logarithm of average employee compensation
Core Independent Variable	Artificial Intelligence	AI	Natural logarithm of the total frequency of AI-related keywords in listed companies' annual reports
Moderating Variable	Employee Size	Employee	Natural logarithm of the number of employees in the enterprise
Control Variables	Company Size	Size	Natural logarithm of the number of employees in the enterprise
	Leverage Ratio	Lev	Natural logarithm of annual total assets of the enterprise
	Capital Expenditure	Outcap	Total liabilities at the end of the year / Total assets at the end of the year
	Return on Equity	ROE	Natural logarithm of cash paid for purchasing fixed assets, intangible assets, and other long-term assets
	Top 10 Shareholders' Shareholding Percentage	Top10	Average balance of shareholders' equity
	Management Shareholding Percentage	Mshare	Shares held by the top ten shareholders / Total number of shares
	Dual Role of Chairman and CEO	Dual	1 if the chairman and general manager are the same person, otherwise 0

2.3. Econometric Model

To further investigate the impact of artificial intelligence on the internal income gap within enterprises, this paper constructs Model 1:

$$Y_{i,t} = \alpha + \beta AI_{i,t} + \gamma Controls_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

In Model (1), i and t represent different enterprises and years, respectively. The dependent variable $Y_{i,t}$ represents the internal income gap, average management payment versus average employee payment within the enterprise. The core independent variable $AI_{i,t}$ measures the level of application of artificial intelligence technology by the enterprise. Control variables $Controls_{i,t}$ include the basic characteristics and governance structure of the enterprise. Moreover, by introducing firm-specific fixed effects λ_i and time fixed effects λ_t , the model can exclude biases caused by enterprise-specific factors that do not change over time and general time trends. $\varepsilon_{i,t}$ represents the random error term.

To further explore the direct impact of employee scale on the internal income gap and its moderating effect, this paper introduces employee scale ($Employee_{i,t}$) as an independent variable and adds the interaction term of AI and employee scale ($AI \times Employee$) to capture the potential moderating effect, constructing Model (2):

$$Y_{i,t} = \alpha + \beta_1 AI_{i,t} + \beta_2 Employee_{i,t} + \beta_3 AI_{i,t} \times Employee_{i,t} + \gamma Controls_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

Here, $Employee_{i,t}$ is reflected by the total number of employees hired by the enterprise. The control variables remain the same as in Model (1). If β_3 is significant, it indicates that employee scale has a moderating effect on the impact of artificial intelligence application on the internal income disparity, and vice versa.

3. Empirical Analysis

3.1. Descriptive Statistics

Table 2 reports the descriptive statistics of the main variables. As shown in Table 2, the average value of the artificial intelligence variable is 0.29, indicating that the frequency of occurrence of AI-related keywords in the research sample is relatively low. However, the maximum value reaches 5.60, showing that some companies frequently mention AI-related content in their annual reports. The average value of management average payment (LnAMP) is 13.21, with a standard deviation of 0.88, reflecting the variation in management payment levels across different enterprises. The average value of ordinary employee average payment (LnAEP) is 11.63, with a standard deviation of 0.55, indicating a more concentrated distribution of ordinary employee compensation compared to management compensation. The average value of employee scale is 7.85, with a standard deviation of 1.23, showing a broad distribution of enterprise sizes in the sample. The income gap (LnGAP), the natural logarithm of the ratio of management to ordinary employee payment, has an average value of 1.81 and a median of 1.76, with a maximum value reaching 4.49, revealing significant wage disparities between management and ordinary employees within the sample enterprises.

Table 2. Descriptive statistical results

Variable	Sample Size	Mean	Standard Deviation	Median	Minimum	Maximum
LnGAP	17,688	1.812836	0.5453352	1.758969	0	4.48939
LnAMP	17,688	13.21228	0.8840901	13.22255	0	16.72487
LnAEP	17,688	11.63436	0.5491608	11.60811	9.462213	16.99909
Employee	17,688	7.852971	1.233045	7.798113	3.332205	12.95641
AI	17,688	0.2900065	0.6598769	0	0	5.602119
Size	17,688	22.44209	1.294353	22.27659	18.37014	28.34125
Lev	17,688	0.4349379	0.2006937	0.4336258	0.0070799	0.9943666
Outcap	17,688	18.78708	1.818128	18.83034	0	25.87382
ROE	17,688	0.069333	0.1299862	0.0704428	-2.187362	1.536327
Top10	17,688	55.74344	15.31409	55.8328	1.3103	97.4992
Mshare	17,688	10.13787	17.30654	0.2005	0	89.725
Dual	17,688	0.2394844	0.4267809	0	0	1

3.2. Baseline Model and Moderating Effect Analysis

Table 3 lists the regression results for four main effect models. Firstly, the coefficient of AI in Model (1) is 0.0154 and significant at the 1% level, indicating a positive relationship between the use of AI and the wage gap. Specifically, as enterprises increase their investment or application frequency in artificial intelligence, the wage gap between management and ordinary employees widens. This phenomenon may partially stem from the technology substitution effect, where AI technology replaces some low-skill labor, reducing demand for these workers and thereby suppressing their wage growth. Conversely, for high-skill labor, especially management, who can complement new technologies, the application of AI technology might enhance their work efficiency and value creation capacity, thereby elevating their compensation levels.

Further, in Model (4) which includes employee scale (Employee) and its interaction with AI (AI×Employee), the coefficient of AI significantly increases to 0.0866, while the coefficient of AI×Employee is -0.0100, also significant at the 1% level. This indicates a significant moderating effect of employee scale on the impact of AI on the wage gap. The positive coefficient of AI reaffirms its role in increasing the wage gap, while the negative interaction effect of AI with employee scale

suggests that in larger enterprises, the push effect of AI on the wage gap is somewhat restrained. This could be because large enterprises typically have stronger resource allocation capabilities and more comprehensive employee training systems, which can mitigate the substitution effect of AI technology on low-skill labor through skill enhancement and job adjustment measures. Additionally, large enterprises might pay more attention to maintaining organizational balance and promoting technology and human resource complementarity when introducing AI technology, thereby somewhat mitigating the expansion of the wage gap.

The adjusted R-squared values, increasing from 0.6729 in Model (1) to 0.7203 in Model (4), indicate that Model (4), which includes employee scale and AI interaction terms, has a greater explanatory power than Model (1), which only considers AI. This demonstrates how more complex factors jointly influence the formation of the wage gap. Additionally, the positive impact of AI on average management payment (LnAMP) is more significant, with a coefficient of 0.0339, indicating that management's key role in AI decision-making and implementation results in higher payment. Meanwhile, the impact of AI on the average payment of ordinary employees (LnAEP) is not significant, suggesting that the wage growth of ordinary employees has not correspondingly increased with the application of AI technology.

Table 3. Baseline Regression Results

	(1)	(2)	(3)	(4)
VARIABLES	LnGAP	LnAMP	LnAEP	LnGAP
AI	0.0154*** (0.1497)	0.0339*** (0.0096)	0.0030 (0.0047)	0.0866*** (0.0303)
Employee				0.3695*** (0.0071)
AI×Employee				-0.0100*** (0.0037)
Size	0.0844*** (0.0079)	0.1691*** (0.0136)	0.1053*** (0.0066)	-0.1287*** (0.0084)
Lev	-0.0557** (0.0280)	-0.1131** (0.0478)	-0.0313 (0.0234)	-0.1346*** (0.0259)
Outcap	0.0248*** (0.0030)	0.0201*** (0.0051)	-0.0135*** (0.0025)	0.0063** (0.0028)
ROE	0.2996*** (0.0229)	0.3538*** (0.0391)	0.0575*** (0.0191)	0.3148*** (0.0211)
Top10	0.0005 (0.0003)	-0.0027*** (0.0006)	-0.0008*** (0.0003)	0.0010*** (0.0003)
Mshare	-0.0014*** (0.0004)	-0.0022*** (0.0006)	-0.0013*** (0.0003)	-0.0010*** (0.0003)
Dual	0.0266*** (0.0085)	0.0130 (0.0145)	-0.0062 (0.0071)	0.0264*** (0.0079)
Constant	-0.5694*** (0.1531)	9.2232*** (0.2618)	9.5910*** (0.1280)	1.6669*** (0.1497)
ID	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	17,688	17,688	17,688	17,688
adj. R-sq	0.6729	0.6361	0.7746	0.7203

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.3. Heterogeneity Analysis

The heterogeneity test explores differences in the impact of artificial intelligence (AI) technology application on the wage gap between management and ordinary employees (LnGAP) across various dimensions. Specific testing dimensions include state-owned enterprises versus non-state-owned enterprises, manufacturing versus non-manufacturing industries, and high-tech industries versus non-high-tech industries, aiming to reveal differences in the impact of AI on the wage gap by industry and ownership type. Regression results are presented in Table 4.

In the comparison between state-owned and non-state-owned enterprises, the impact of AI on the wage gap is more significant in non-state-owned enterprises (coefficient = 0.0249, $p < 0.01$), while it is not significant in state-owned enterprises. This may reflect the greater flexibility of non-state-owned enterprises in adopting new technologies to enhance efficiency and competitiveness, which could lead to an increase in the wage gap between management and ordinary employees. State-owned enterprises, due to stricter wage control policies and considerations of fairness, may limit the impact of AI technology on wage structures.

The analysis of manufacturing versus non-manufacturing industries shows that in non-manufacturing industries, the positive impact of AI on the wage gap is more significant (coefficient = 0.0475, $p < 0.01$), while this impact is not significant in manufacturing industries. This result may be related to the broader and deeper application of technology in non-manufacturing industries, particularly in the service sector, where AI technology applications may focus more on improving decision-making efficiency and service quality, thereby increasing the demand for high-skilled labor, which often includes top management, further widening the wage gap.

The comparison between high-tech and non-high-tech industries further reveals the industry-specific effects of AI application. Although the impact of AI on the wage gap in both high-tech and non-high-tech industries is not statistically significant, the positive coefficients suggest a trend where AI technology application is associated with an increase in the wage gap in high-tech industries. This could be because high-tech industries rely more on high-skilled talent, including research, development, and management personnel, whose utilization of AI technology directly affects the core competitiveness of the enterprise, potentially earning higher payment and exacerbating the wage gap.

Table 4. Heterogeneity Test

	(1)	(2)	(3)	(4)	(5)	(6)
	State-owned	Non-state-owned	Manufacturing	Non-manufacturing	High-tech	Non-high tech
VARIABLES	LnGAP	LnGAP	LnGAP	LnGAP	LnGAP	LnGAP
AI	0.0129 (0.0138)	0.0249*** (0.0089)	0.00562 (0.0096)	0.0475*** (0.0118)	0.0133 (0.0085)	0.0232 (0.0146)
Constant	0.2533 (0.2785)	0.0471 (0.2048)	0.3673* (0.2083)	-0.3016 (0.2807)	0.3878* (0.2193)	-0.0855 (0.2558)
Controls	YES	YES	YES	YES	YES	YES
ID	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Observations	7274	10389	11336	6307	9844	7802
adj. R-sq	0.5388	0.5367	0.5191	0.5656	0.5018	0.5758

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.4. Robustness Test

To further verify the reliability of the regression results, this paper uses the instrumental variable method to eliminate interference from omitted variable bias on the results. Research and development expenditure (R&D) is used as the instrumental variable for AI. On one hand, R&D investment is the foundation of technological innovation and application, including AI technology; on the other hand, enterprises with higher R&D expenditure are likely more inclined to adopt or develop the latest AI technologies. The corresponding regression results, presented in Table 5, show that after mitigating endogeneity issues with the instrumental variable, the regression coefficient of AI remains significantly positive, indicating that the application of artificial intelligence technology significantly widens the internal income gap within enterprises, consistent with the baseline regression results.

Table 5. Robustness test results

	(1)	(2)
	First stage	Second stage
VARIABLES	AI	LnGAP
R&D	0.0176*** (0.0065)	
AI		0.4887** (0.2382)
Constant	-3.4964*** (0.2686)	1.1079 (0.8449)
Controls	YES	YES
ID	YES	YES
Year	YES	YES
Kleibergen-Paap rk Wald F statistic	627.473	627.473
Observations	14559	14559
adj. R-sq	0.5714	0.6764

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

This paper, using data from Chinese A-share listed enterprises from 2011 to 2022, investigates the relationship between the application of artificial intelligence technology and the wage gap between management and ordinary employees, and examines the moderating effect of employee scale on this relationship. The findings reveal that: first, with the introduction of AI technology, the wage gap has increased, indicating that management, compared to ordinary employees, is more likely to benefit from the productivity improvements brought about by AI technology; second, the analysis of the moderating effect of employee scale shows that in large enterprises, the increase in the wage gap due to AI technology is relatively weaker. Third, the results of the heterogeneity analysis indicate that in non-state-owned enterprises, non-manufacturing industries, and high-tech industries, the positive impact of AI technology on the wage gap is more significant.

Based on these conclusions, this paper offers the following policy recommendations: first, in response to the increased wage gap caused by the introduction of AI technology, the government and enterprises should work together to improve the skills and quality of ordinary employees, including establishing skill improvement funds, encouraging in-job training, and collaborating with educational institutions to develop training courses for future skill needs, especially providing transition training programs for low-skill employees to help them acquire AI-related knowledge and skills, thereby

reducing the wage gap caused by technology substitution. Second, considering that the increase in the wage gap due to AI technology is relatively weaker in large enterprises, policymakers should enact favorable policies and provide support to encourage small and medium-sized enterprises to adopt AI technology. This includes offering specialized technical support and financial assistance to help these enterprises effectively manage wage structure adjustments during the technology transition process, ensuring the benefits of technological upgrades are more equitably distributed among all employees. Third, in light of the heterogeneity analysis results showing a more significant impact of AI technology on the wage gap in non-state-owned enterprises, non-manufacturing industries, and high-tech industries, government agencies should develop industry-specific guidelines and policies. These should guide industries in considering wage fairness issues during the technology application process and offer tax incentives or subsidies to enterprises that can demonstrate their technological innovation activities contribute to reducing wage inequality. Fourth, enterprises are encouraged to establish more transparent and fair wage decision-making mechanisms. Enterprises should periodically review their wage structures to ensure transparency in wage decisions and take steps to eliminate unjustified wage disparities. Additionally, there should be enhanced oversight of management payment to prevent management from inappropriately increasing their own wages through technological advancements while neglecting the interests of ordinary employees.

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