An Analysis of the Effect of Artificial Intelligence on Occupational Income Inequality in China*

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Abstract: Using data from the China Family Panel Studies, this paper empirically examines the impact of artificial intelligence (AI) on occupational income inequality by employing the Pareto coefficient to measure the degree of within-occupation income inequality in China. The results show that income inequality across occupations has markedly increased in recent years. Provinces with a relatively high level of occupational income inequality are concentrated primarily in the eastern and central regions in China, whereas the level is notably lower in the western region. Also, AI significantly widens occupational income gaps. Further, mediation analysis reveals that AI significantly aggravates occupational income inequality through two channels: industrial sophistication and technological innovation. Regional heterogeneity analysis indicates significant regional disparities in this effect. The impact is significant and strongest in Western China, significant but moderate in Eastern China, and statistically insignificant in Central China. Going forward, China should improve the regulatory and adjustment mechanisms for occupational earnings, establish a systematic occupational income monitoring system, and deepen the reform of the income distribution system. These measures will help narrow occupational income gaps driven by the skill premium and advance the achievement of common prosperity.

Keywords: Artificial intelligence; Industrial structure; Occupational income inequality; Technological innovation.

JEL classification: D31, D33, E25, O30

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1 Introduction

Artificial intelligence (AI) is driving a new wave of technological revolution and industrial transformation, and has emerged as a pivotal force reshaping the global economic landscape and national competitive strengths. The "Recommendations of the CPC Central Committee for Formulating in the 15th Five-Year Plan for National Economic and Social Development" identifies AI as a core tool for the forward-looking layout of future industries, advancing high-level technological self-reliance and self-improvement, and promoting the digital China initiative. This document also calls for the full implementation of the "AI Plus" initiative, which aims to further integrate AI with industrial development, cultural advancement, public well-being, and social governance, and thus to empower a wide range of economic sectors.

At the same time, the history of general-purpose technologies shows that every major technological revolution has profoundly reshaped factor allocation, income distribution patterns, and labor market structures. Compared with previous technological changes, AI affects a far broader range of production activities, with its influence extending from low-skill routine labor to high-skill cognitive work. Consequently, its impact on the income distribution system is more systemic, comprehensive, and structural. As the "AI Plus" initiative continues to expand across sectors in China, the distributional bias created by technological diffusion and the risk of widening income inequality have become major practical and theoretical concerns in both academia and policymaking circles.

The impact of technological progress on income distribution has long been a core study issue in economics. A well-established theoretical framework and extensive empirical evidence provide a solid foundation for studying the distributional effects of AI. Early classic studies document that technological progress is generally skill-biased by altering the demand structure of the labor market and it raises the relative returns to high-skilled workers and generates a skill premium, which has been identified as a key driver of widening wage gaps and income inequality (Autor et al., 1998; Katz and Murphy, 1992; Krueger, 1993). Building on this line of research, recent studies on AI suggest that its impact on income distribution not only follows the core logic of skill-biased technological change, but also exhibits a broader and deeper distributional bias, which may further amplify the risk of rising inequality.

At the macro level of factor income distribution, the diffusion of AI can fundamentally alter the structure of factor returns and income allocation, shifting income distribution more significantly toward capital and thereby increasing income inequality (Acemoglu, 2025). Empirical evidence from the European regional data also confirms that growth in AI-related innovation significantly reduces the regional labor share of income, lowers labor's share in national income, weakens the distributive position of labor at the macro level, and aggravates inequality between factors of production (Minniti et al., 2025). Within the labor market, AI exhibits an amplified skill-biased effect. For example, technological upgrading and industrial application further raise the relative returns to high-skilled, high-cognitive workers, continuously widening the skill premium and wage gap between high- and low-skilled workers, and intensifying labor market polarization (Acemoglu and Restrepo, 2019; Trajtenberg, 2018). More importantly, high-income groups, with more abundant capital endowments, are better positioned to capture corporate profits and asset appreciation gains generated by AI. In addition, firms' endogenous AI adoption decisions may further strengthen the concentration of returns toward capital, ultimately pushing up wealth and income inequality across society as a whole (Rockall et al., 2025).

According to the 2021 Report on the Distribution of Household Wealth and High Net Worth Household Wealth in China, wage income and business income account for similar shares of total income (34.3% and 33.5%, respectively) for the top 5% of income-earning households. In contrast, for ordinary households in the 40th-60th percentile of the asset distribution, wage income and transfer income account for 58.1% and 25.8% of total income, respectively, both slightly above the national average, while business income accounts for only 5.4%. In the early stage of reform and opening up, China's Gini coefficient stood at 0.28, indicating a relatively stable overall income gap. By 2018, however, the Gini coefficient had risen sharply to 0.474, and the income share of the top 10% of the population had surged from 26% in 1980 to 41.7% in 2008. These trends point to a worsening income inequality problem in China, particularly the growing occupational income inequality with significant regional heterogeneity in recent years; see, for example, the paper by Yuan et al. (2025) for details.

In sum, the existing literature provides a useful theoretical and empirical foundation, but several research gaps remain. Technological progress and income inequality have long been key research topics in economics, and in the new wave of technological revolution driven by AI, it is equally important to clarify the theoretical mechanisms through which AI affects income inequality and provide direct empirical evidence from China. In recent years, technological advancement and AI penetration have spread rapidly across industries and into household life in China. If AI significantly widens income inequality, the question of how to ensure that technological progress benefits the general public becomes even more critical.

This paper makes two main contributions. First, it empirically tests the effects of AI on income inequality through the channels of technological innovation and industrial sophistication, and examines the regional heterogeneity and heterogeneity across income groups. Second, this paper systematically reviews existing studies on the relationship between AI and income inequality, analyzes the current status of AI development and household income inequality in China, and develops a systematic analysis of the mechanisms through which AI affects income distribution in China. Based on this analysis, it proposes research hypotheses, conducts direct empirical tests of the impact of AI on income inequality, and draws conclusions that provide a theoretical basis for future policies aimed at ensuring technology benefits the public.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides the detailed research designs and econometric modeling tools for analyzing the impact. Section 4 presents the empirical results for assessing effects of AI on occupational income inequality with the detailed discussions. Finally, Section 5 concludes the paper.

2 Literature Review

With the large-scale deployment and industrial diffusion of AI, its real impact on income distribution and wealth gaps has become a core research topic in labor economics and development economics. A large body of research in the world including China has examined the direct impact of AI on income and wealth inequality, reaching two contrasting conclusions.

One strand of the literature argues that the application and diffusion of AI significantly worsen income and wealth inequality, with supporting evidence from both theoretical frameworks and empirical tests. When the rate of return on capital persistently exceeds the rate of economic growth, capital concentration generated by technological progress further increases wealth inequality (Piketty, 2014), which provides a basic theoretical framework for understanding the distributional effects of AI-driven capital accumulation. Intelligent industrial transformation, a core real-economy application of AI, has significantly widened the income gap among urban residents in China. Its underlying mechanism is "creative destruction": while driving economic growth, it disrupts the employment prospects of vulnerable workers, thus exacerbating household income inequality to a certain extent (Gao et al., 2024). Empirical evidence based on panel data from the United States, the European Union, and Japan from 1995 to 2020 further documents a significant positive correlation between AI adoption, AI capital accumulation, and wealth inequality. An increase in AI capital stock significantly worsens wealth inequality, with a stronger effect in settings with higher initial wealth concentration. In such contexts, the gains from AI are more likely to accrue to top capital-owning groups, creating a positive "capital-technology-wealth" cycle and further widening the wealth gap (Skare et al., 2024). Evidence from county-level data in China reaches a similar conclusion: AI development aggravates the urban-rural income gap, mainly due to the uneven distribution of AI application and its returns between urban and rural areas. Cities can absorb AI technology more quickly and create high-skill, high-income jobs, while rural areas face constraints in infrastructure, resources, and skills, making it difficult to share the dividends of AI technology (Zhang et al., 2025).

Another strand of the literature reaches a different conclusion, arguing that AI does not necessarily exacerbate income distribution imbalances, and may instead raise the labor share of income and reduce wage inequality. AI tools can automate some tasks previously performed by high-skilled workers, thereby depressing the wages of high-skilled groups, raising the wages of low-skilled workers, and exerting downward pressure on the skill premium, which may alleviate wage inequality under specific conditions (Bloom et al., 2025). A study using China's "New Generation Artificial Intelligence Innovation and Development Pilot Zone" policy as an exogenous shock finds that AI shocks significantly increase firms' labor share of income. The main reason is that AI's job creation effect exceeds its substitution effect, and its contribution to labor productivity is greater than its contribution to capital returns, ultimately driving up the labor share of income (Fan et al., 2025). This process narrows the income gap between capital owners and ordinary workers, and significantly alleviates household income inequality. At the current stage, firm-level AI in China functions more as a "technological enabler" than a "technological substitute". By improving operational efficiency and facilitating human capital accumulation, it significantly raises the labor share of income of Chinese A-share listed firms, and partially mitigates the risk of distributional imbalances caused by capital concentration (Wang and Hu, 2025), thus, curbing the worsening of household income inequality.

3 Research Methodologies

3.1 Research Design

Existing studies have reached two contrasting conclusions on the direct impact of AI on income and wealth inequality, and no consensus has yet been reached. However, both the underlying logic and real-world transmission mechanisms suggest that AI has an inherent tendency to increase income inequality. On the one hand, the R&D and large-scale deployment of AI rely heavily on upfront capital investment, and the excess returns generated by technological upgrading tend to accrue first to capital owners, creating a positive cycle of "capital accumulation-technological upgrading-return concentration" and directly widening the factor income gap between capital owners and ordinary workers. On the other hand, AI has a highly uneven impact on the labor market: its substitution effect is more pronounced for low-skill, routine jobs, and its negative impact on vulnerable workers is far greater than its empowering effect on high-skilled workers, which will further widen wage differentials across skill groups. Based on this reasoning, this paper proposes the core hypothesis:

H1: Artificial intelligence significantly aggravates income inequality.

Also, existing studies show that AI can aggravate China's urban-rural income inequality by driving industrial restructuring and upgrading. In terms of the relationship between AI and industrial structure, AI development significantly promotes regional industrial transformation and upgrading by improving production efficiency, fostering new business formats and models, and deeply integrating with traditional industries. It not only effectively promotes industrial sophistication, but also significantly reduces the deviation of the industrial structure from equilibrium and facilitates the rationalization of industrial development (Zhang, 2025; Zou and Xiong, 2023). Specifically, this driving effect is reflected in two core dimensions. First, AI promotes industrial sophistication by pushing industries toward technology-intensive, high-value-added transformation, while increasing demand for medium- and high-skilled labor. Second, AI improves the rationalization of industrial structure by optimizing resource allocation and coordination efficiency across industries, indirectly facilitating the efficient operation of the industrial system, with a more prominent effect on industrial sophistication (Wang et al., 2024).

Industrial restructuring itself is a process of reallocating production factors to improve production efficiency, and its core lies in the transformation of the labor force structure, which further affects the employment structure. In addition, productivity differences across sectors can drive labor mobility between sectors, leading to changes in workers' income gaps (Han and Jiang, 2024). From the perspective of the relationship between industrial structure and income inequality, both industrial upgrading and structural imbalances significantly worsen urban-rural income inequality (Chen and Ma, 2022). Specifically, the positive impact of structural imbalances on income inequality mainly stems from widening wage gaps, while the impact of industrial upgrading mainly operates through exacerbating inequality in business income and property income. Based on this, this paper considers the second core hypothesis:

H2: Artificial intelligence exacerbates income inequality through its impact on industrial sophistication.

Against the backdrop of the rapid development of the digital economy, AI, as the core technological driving force, has penetrated into key areas of the socio-economic landscape, including innovation development and income distribution. One important manifestation is that AI exacerbates income inequality by driving technological innovation. From the perspective of the relationship between AI and technological innovation, firm-level identifiable evidence shows that AI investment significantly boosts corporate growth, which is primarily achieved through product innovation, as reflected in trademarks, product patents, and product updates (Babina et al., 2024). Meanwhile, empirical research on Chinese AI firms indicates that firms with "data-rich" government contracts significantly enhance their commercial AI software development (Beraja et al., 2023), suggesting that a data-intensive AI ecosystem stimulates innovation output. Further, based on procurement data from Chinese A-share listed firms, studies find that AI adoption significantly increases patent output and innovation efficiency, and drives innovation performance through mechanisms such as knowledge orchestration and data assetization (Feng et al., 2025). In addition, evidence from robotics applications also shows that AI implementation can significantly improve innovation efficiency in manufacturing firms (Wang et al., 2024).

The above studies have robustly confirmed that AI can effectively drive technological innovation output and improve innovation efficiency. As a key transmission channel linking AI and income inequality, the impact of technological innovation on income distribution also has solid empirical support. Regarding the relationship between technological innovation and income inequality, innovation-driven automation mainly induces wage structure differentiation through the "task substitution" mechanism. Specifically, AI-driven technological innovation replaces repetitive tasks performed by low-skilled workers while increasing the marginal output of high-skilled workers, thereby widening the wage gap between high- and low-skilled labor, which is one of the core explanations for rising wage inequality (Acemoglu and Restrepo, 2022). Cross-country industry panel studies further support this argument: while technological progress, measured by patents, raises overall industry wage levels, it has a significant negative impact on the labor share of income. This means that the rents generated by technological innovation are more likely to concentrate among business owners and high-skilled groups, rather than being fully passed on to ordinary workers, thus further widening the income distribution gap (Ghodsi et al., 2024). In samples from developing countries, similar studies have also confirmed that innovation shocks significantly increase income inequality (Qian et al., 2026). Based on the above discussion of AI's role in driving technological innovation, the exacerbating effect of technological innovation on income inequality, and empirical support from existing studies, this paper investigates the third core hypothesis:

H3: Artificial intelligence exacerbates income inequality through its impact on technological innovation.

Based on the theoretical analysis, AI primarily exacerbates income inequality through its impact on industrial sophistication and technological innovation. The specific transmission mechanism is illustrated in Figure 1 below.

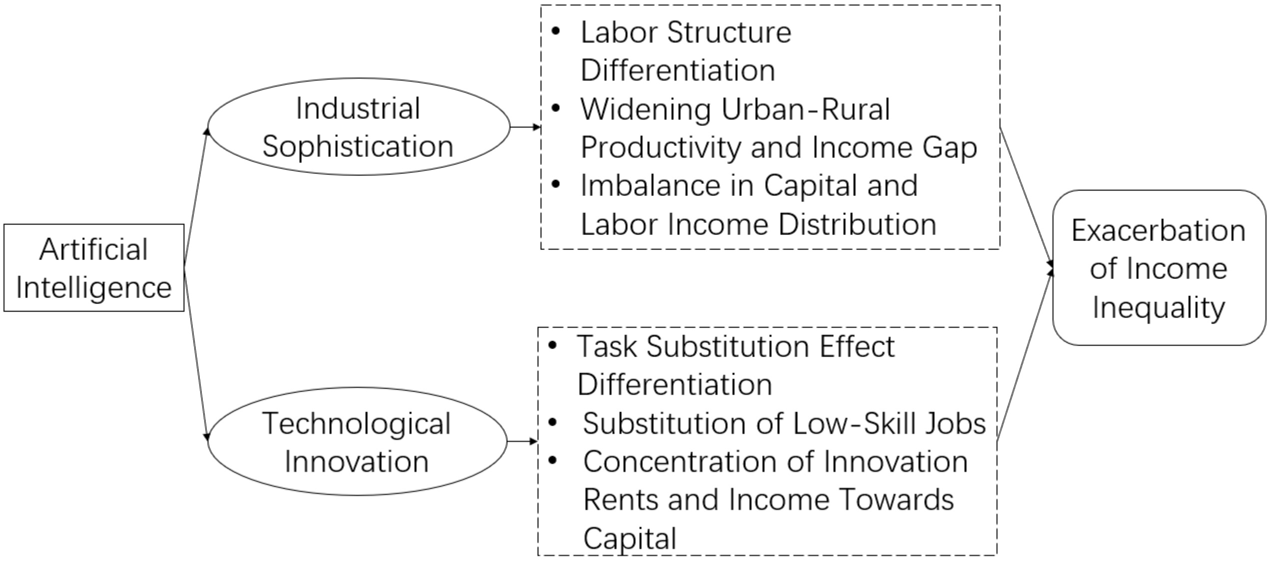

Figure 1. Mechanism pathway of artificial intelligence's impact on income inequality

3.2 Model Specification

This paper constructs the following two-way fixed-effects model to examine the impact of AI on occupational income inequality. The baseline regression model is given by

$$\mathrm{INEQ}_{p,t} = \alpha_0 + \alpha_1 \mathrm{AI}_{p,t} + \sum_k \alpha_k \mathrm{Controls}_{p,t} + \mu_p + \lambda_t + \varepsilon_{p,t}, \tag{1}$$

where $\mathrm{INEQ}_{p,t}$ denotes the level of occupational income inequality in province p in year t as the dependent variable, AI_{pt} represents the level of AI development as the core explanatory variable, $\mathrm{Controls}_{p,t}$ is a vector of provincial-level control variables, μ_p and λ_t capture province and year fixed effects to account for unobserved heterogeneity and common macro shocks, and $\varepsilon_{p,t}$ is the error term with standard errors clustered at the provincial level to address potential serial correlation and heteroskedasticity.

To verify the mediating roles of industrial sophistication and technological innovation, a standard three-step mediation model is then constructed. First, (2) is used test the effect of AI on the mediating variables $M_{p,t}$, which can be industrial sophistication $\text{UIS}_{p,t}$ or technological innovation $\text{INNO}_{p,t}$, while (3) examines the simultaneous effects of AI and the mediating variables on occupational income inequality, with all other variables defined consistently with the baseline model and $\mu_{p,t}$ and $\nu_{p,t}$ as the respective error terms.

$$M_{p,t} = \beta_0 + \beta_1 \text{AI}_{p,t} + \sum_k \beta_k \text{Controls}_{p,t} + \mu_p + \lambda_t + \mu_{p,t}, \tag{2}$$

and

$$\text{INEQ}_{p,t} = \gamma_0 + \gamma_1 \text{AI}_{p,t} + \gamma_2 M_{p,t} + \sum_k \gamma_k \text{Controls}_{p,t} + \mu_p + \lambda_t + \nu_{p,t}. \tag{3}$$

Specifically, when $M_{p,t}$ is replaced by $\text{UIS}_{p,t}$, the model tests the mediating effect of industrial sophistication; when replaced by $\text{INNO}_{p,t}$, it tests the mediating effect of technological innovation.

3.3 Variable Selection

Dependent Variable: Occupational income inequality in province p in year t (INEQ), which adopts the data on China's occupational income inequality calculated by Yuan et al. (2025), and measures the level of occupational income inequality across 31 provinces (including municipalities and autonomous regions) in China for 2014, 2016, 2018, 2020, and 2022, using the Pareto coefficient as the core metric.

Core Explanatory Variable: Level of artificial intelligence development (AI). This is measured by the number of AI-related patent applications (in thousands) in the region.

Mediating Variable: Industrial sophistication (UIS): A core dimension of industrial transformation and upgrading, reflecting the dynamic process by which the industrial structure evolves from a low-level to a high-level state in line with the historical and logical trajectory of economic development. Conventional measures such as the industrial structure hierarchy coefficient, Moore's structural change index, and the share of high-tech industries only capture the quantitative evolution of the three industrial sectors, neglecting the essence of industrial transformation and easily leading to "quantitative pseudo-sophistication". In fact, industrial sophistication includes both quantitative growth and qualitative improvement, with the latter covering the evolution of proportional relationships and the increase in labor productivity. A region is considered to have a high level of industrial sophistication only when industries with higher labor productivity account for a larger share of the economy.

Technological innovation (INNO): Technological innovation is measured by the natural logarithm of the number of granted patents.

Control Variables: The control variables include the share of value-added of the secondary industry (IND), industrial structure advancement (STR), human capital level (CAP), financial development (FIN), foreign direct investment (FDI), per capita fiscal expenditure (PCFE), and average years of education (EDU). Among them, industrial structure advancement (STR) is measured by the ratio of the value-added of the tertiary industry to that of the secondary industry, which focuses on depicting the progressive evolution of leading industries from the primary industry dominated by labor input, to the secondary industry dominated by capital input, and finally to the tertiary industry dominated by knowledge, technology, and service input. Human capital level (CAP) is measured by the proportion of college and university students in the total population. Financial development (FIN) is measured by the ratio of the year-end balance of RMB loans from financial institutions to GDP. Foreign direct investment (FDI) is measured by the ratio of actually utilized foreign capital (converted at the current exchange rate) to GDP.

4 Empirical Studies on AI Effects

4.1 Data Description

The income data used in this study comes from the China Family Panel Studies (CFPS) released by the Institute of Social Science Survey at Peking University, which can be downloaded from the web site at https://www.isss.pku.edu.cn/cfps/en/. Launched in 2010, the survey collects tracking data at the individual, household, and community levels to reflect changes in the demographic characteristics, income and expenditure, agricultural production, economic activities, and non-economic well-being of Chinese families. It adopts a stratified multi-stage sampling method, with results representative of approximately 95% of China's population. This study uses data from the adult database for 2014, 2016, 2018, 2020, and 2022. The income data selected for this study includes annual net work income from the "current main job", including wages, bonuses, cash benefits, and in-kind subsidies, after deducting taxes and social insurance contributions. Occupational classification is based on the Erikson-Goldthorpe-Portocarero (EGP) classification system used in the CFPS adult database. The sample is restricted to currently employed individuals with a minimum employment age of 25 years.

Table 1 reports the descriptive statistics of the core and control variables at the provincial level in China from 2014 to 2022. The mean value of income inequality first rises and then falls, peaking at 0.379 in 2018 and remaining at a relatively high level overall. Its standard deviation fluctuates between 0.095 and 0.132, reflecting regional heterogeneity in income disparities, which is consistent with the worsening income inequality in China mentioned earlier. AI development shows a rapid upward trend, rising from 0.710 in 2014 to 4.444 in 2020 with a slight decline in 2022, and its standard deviation expands significantly from 1.064 to 6.855, indicating that while AI is spreading rapidly, regional development disparities remain prominent. Industrial sophistication continues to rise, reaching 2.227 in 2022, reflecting the trend of industrial transformation toward high-value-added sectors. Among the control variables, IND shows slight fluctuations, CAP, FIN, PCFE, and EDU show an overall upward trend, and FDI declines slightly. The characteristics of the variables are consistent with the research background and hypotheses, providing reliable data support for the subsequent empirical analysis.

Table 1. Descriptive Statistics of Variables

	2014		2016		2018		2020		2022	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
INEQ	0.304	0.132	0.351	0.107	0.379	0.122	0.361	0.095	0.356	0.098
AI	0.710	1.064	1.574	2.433	2.542	4.077	4.444	6.855	4.203	6.309
UIS	1.224	0.428	1.365	0.485	1.629	0.547	1.779	0.562	2.227	0.679
IND	0.429	0.077	0.392	0.072	0.380	0.070	0.364	0.068	0.381	0.080
STR	1.191	0.640	1.415	0.727	1.515	0.752	1.614	0.806	1.484	0.860
CAP	0.019	0.005	0.020	0.005	0.020	0.005	0.023	0.006	0.026	0.006
FIN	1.394	0.424	1.606	0.490	1.625	0.490	1.763	0.419	1.771	0.390
FDI	0.023	0.023	0.019	0.014	0.016	0.011	0.015	0.012	0.014	0.019
PCFE	1.201	0.640	1.477	0.839	1.694	0.958	1.856	0.980	1.995	1.161
EDU	9.024	1.126	9.164	1.127	9.332	1.074	9.501	1.062	9.669	1.093

Note: S.D. stands for the standard deviation.

4.2 Development Status of AI in China

First, China's provincial-level AI development exhibits significant geographical disparities and evolutionary trends as follows. Areas with high-intensity AI activities are gradually expanding and the overall level has risen significantly. The eastern coastal provinces such as Guangdong, Jiangsu, Zhejiang, and Shanghai have long held a leading position, with Guangdong showing particularly strong growth momentum. Meanwhile, Shanghai and Beijing have maintained a high concentration of AI activities, supported by policy incentives and strong R&D capabilities. The central provinces such as Hubei, Henan, and Shandong have shown steady improvement, while the western provinces such as Qinghai, Tibet, and Gansu remain at a low overall level. Despite some progress, the gap with the eastern region remains significant, and the problem of unbalanced regional development persists.

From 2014 to 2022, China's AI development shows a significant upward trend and regional expansion. In 2014, the overall level of AI development was low nationwide, with only the eastern coastal provinces showing relatively prominent performance, reflecting the early-mover advantages of these regions in the AI field. Meanwhile, the central and western regions as a whole had a late start and generally low level of development. By 2016, the eastern coastal region further consolidated its leading position, with better performance in Jiangsu and Zhejiang, and the central region including Hubei and Hunan also began to show initial results of AI development. In 2018, the national level of AI improved significantly, with the Yangtze River Delta and Bohai Rim becoming the core growth drivers; Beijing, Tianjin, and Hebei showed strong growth momentum, while the western region, despite a low starting point, exhibited a clear upward trend. By 2020, the central provinces such as Henan and Anhui became more prominent in the AI field, showcasing the rising trend of Central China, and the eastern coastal region had formed three major AI highlands centered on the Bohai Rim, Yangtze River Delta, and Pearl River Delta. By 2022, the national level of AI had achieved a significant leap compared with 2014, with further improvement and expanded coverage in the central region, and notable progress in some western provinces despite a slower pace of development. Finally, Figure 2 depicts the spatial-temporal pattern and evolutionary characteristics of AI development levels more clearly, categorizing the levels across provinces into four tiers.

4.3 Baseline Regression

Table 2 based on Model I in (1) reports the baseline regression results of the impact of AI on occupational income inequality for each sub-model including partial regressors in each column. The coefficient of the core explanatory variable AI is significantly positive at the 1% statistical level in all specifications. As control variables are gradually introduced, the coefficient decreases slightly from 0.008 to 0.005, but the significance level remains highly stable. This indicates that the exacerbating effect of AI development on occupational income inequality is highly robust, directly validating the core research hypothesis H1 of this paper.

From an intrinsic perspective, the R&D and large-scale application of AI involve high capital and skill thresholds. High-income groups, with more abundant capital endowments and stronger technological absorption capacity, can prioritize investment in AI-related fields and capture the excess returns from technological progress, forming a positive cycle of "capital accumulation-technological upgrading-return concentration". Meanwhile, the structural shock of AI to the labor market leads to a continuous rise in the relative returns to high-skill, high-cognitive jobs, which manifests as widening income disparities between workers in technology-intensive industries and those in traditional industries within high-income groups. In addition, firms adopting

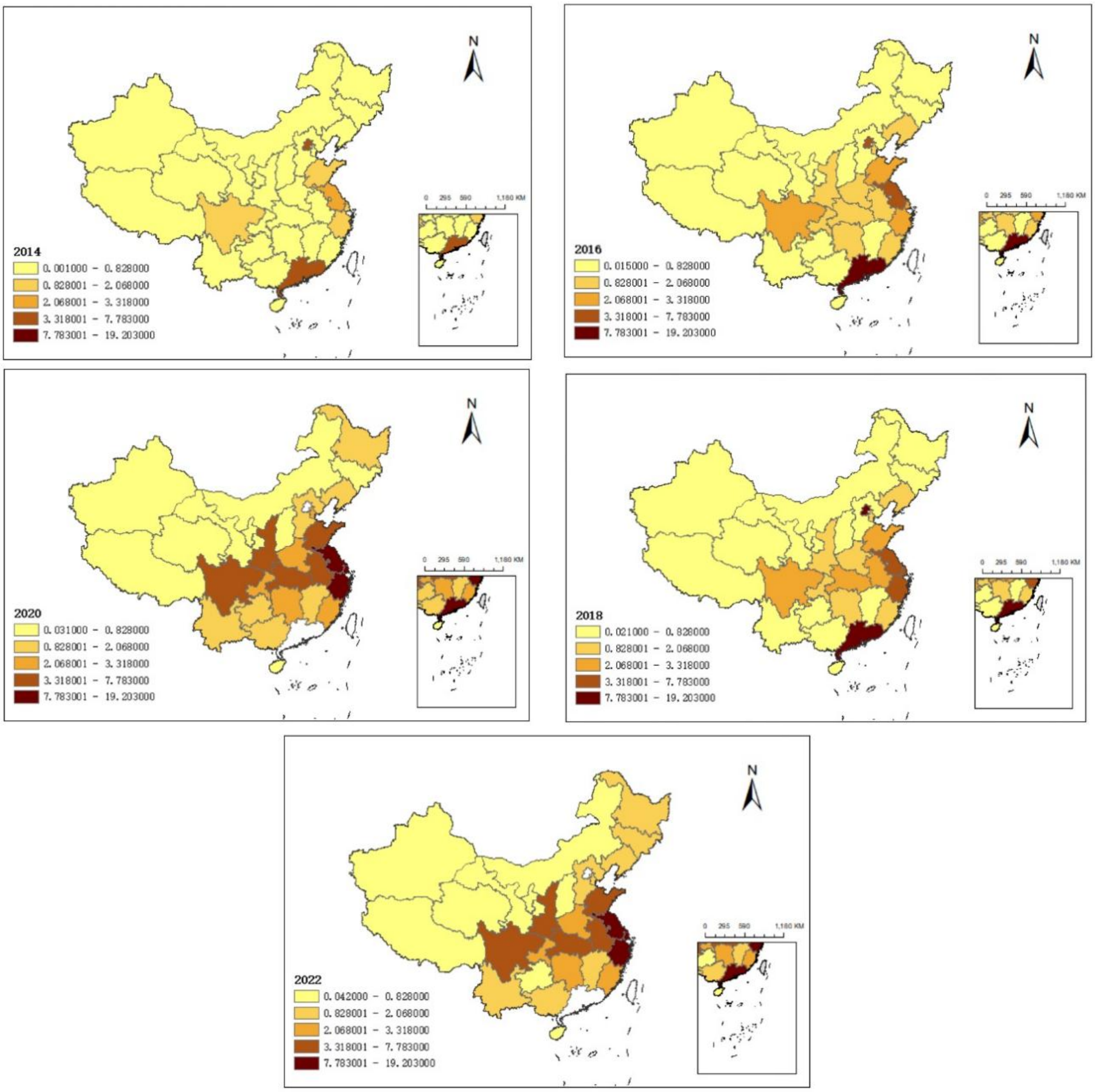

Figure 2. Spatial and temporal evolution of the level of AI development in China's 31 provinces for the year 2014 (the top left panel), 2016 (the right top panel), 2018 (the left central panel), 2020 (the right central panel) and 2022 (the bottom panel), respectively.

Table 2. Results for baseline regression with sub-models in columns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI	0.008***	0.008***	0.006***	0.006***	0.006***	0.006***	0.005***
	(4.66)	(4.26)	(3.84)	(4.12)	(3.91)	(3.92)	(3.55)
IND		-0.009	0.327	0.288	0.229	0.217	0.120
		(-0.07)	(1.42)	(1.36)	(0.99)	(0.88)	(0.44)
STR			0.041**	0.034**	0.036**	0.034**	0.009
			(2.56)	(2.14)	(2.55)	(2.32)	(0.37)
CAP				2.816	2.883	2.754	-0.904
				(1.14)	(1.25)	(1.23)	(-0.41)
FIN					-0.029	-0.028	0.011
					(-0.86)	(-0.83)	(0.30)
FDI						0.205	-0.172
						(0.45)	(-0.40)
PCFE							-0.023
							(-1.67)
EDU							0.034*
							(2.03)
Constant	0.329***	0.333***	0.147	0.112	0.177	0.182	0.003
	(23.55)	(5.36)	(1.28)	(0.90)	(1.36)	(1.34)	(0.02)
Observations	155	155	155	155	155	155	155
R-squared	0.110	0.110	0.125	0.146	0.157	0.157	0.221

Note: t-values calculated based on robust standard errors clustered at the provincial level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. This note applies to Tables 3 - 5.

AI technologies can gain higher profits in market competition through efficiency advantages, further concentrating returns among capital owners and core technical personnel, thereby exacerbating inequality within high-income groups.

Among the control variables, industrial structure advancement has a significant impact on income inequality. By adopting AI-based production technologies, firms can accelerate the intelligent transformation of production chains, thereby more accurately matching market supply and demand, avoiding blindness and randomness in the production process, and ultimately improving labor productivity. This promotes the coordinated development of industries and the rationalization of the industrial structure. Meanwhile, AI-driven technological innovation inevitably facilitates industrial integration and promotes the overall advancement of the industrial structure. At the same time, industrial structure advancement has a threshold effect on income inequality: when the level of economic development is low, improvement in industrial structure advancement does not worsen income inequality, but once economic development crosses a certain threshold, further advancement has a significant negative impact on income inequality. This paper further examines the mediating effect of industrial structure optimization in subsequent sections.

4.4 Endogeneity Test

Table 3 reports the regression results of the endogeneity test using the instrumental variable (IV) method. To address the potential reverse causality issue in the baseline regression (i.e., high income inequality may negatively affect AI investment), this paper selects the one-period lagged AI (L.AI) as the instrumental variable. This choice strictly adheres to the two core conditions for valid instrumental variables. First, the one-period lagged AI is highly correlated with the current level of AI, satisfying the relevance requirement. Second, the lagged AI cannot have a reverse causal effect on current occupational income inequality, effectively avoiding reverse causality bias and meeting the exogeneity requirement.

Table 3. Instrumental variables approach

	AI	$INEQ$
L.AI	1.0560***	
	(19.66)	
AI		0.0028**
		(2.27)
IND	14.8479***	0.3342
	(3.80)	(1.27)
STR	1.9677***	0.0350
	(6.54)	(1.36)
CAP	-83.5880	-2.2390
	(-1.51)	(-0.80)
FIN	0.4064	0.0285
	(0.73)	(0.74)
FDI	-23.5680	0.6639
	(-0.76)	(1.27)
PCFE	-0.4547	-0.0343**
	(-1.54)	(-2.40)
EDU	0.3567	0.0219
	(0.94)	(1.29)
Constant	-8.8571***	0.0188
	(-2.84)	(0.13)
Kleibergen-Paap rk LM statistic:		4.275**
Kleibergen-Paap rk Wald F statistic:		386.625 (>16.38)
Observations	124	124
R-squared	0.830	0.229

Three tests are conducted to verify the validity of the instrumental variable. The first-stage regression results show that the coefficient of the instrumental variable L.AI on the endogenous variable AI is 1.0560, statistically significant at the 1% level, indicating a strong correlation between the instrumental variable and the endogenous variable. The Kleibergen-Paap rk LM (Kleibergen and Paap, 2006) statistic is 4.275, rejecting the null hypothesis of "unidentifiable instrumental variables" at the 1% significance level, confirming that the instrumental variable is identifiable. Also, the Kleibergen-Paap rk Wald F statistic is 386.625, which is far greater than the critical value of 16.38 at the 10% significance level, rejecting the null hypothesis of "weak instruments" and indicating no weak instrument problem. These three tests confirm that the selected instrumental variable is valid and can be used to address endogeneity issues.

The second-stage regression results show that the coefficient of the core explanatory variable AI is 0.0028, significantly positive at the 5% statistical level. This is consistent with the sign of the AI coefficient (0.005-0.008) from the baseline regression, with only a slight difference in magnitude. This indicates that after addressing endogeneity issues such as reverse causality, the exacerbating effect of AI development on occupational income inequality remains valid, further strengthening the robustness of the baseline regression results and reaffirming the reliability of hypothesis H1. The signs and significance of the control variables are generally consistent with the baseline regression, among which per capita fiscal expenditure (PCFE) remains significantly negative, and the coefficient of average years of education (EDU) is positive, further supporting the conclusions from the baseline analysis. Overall, the IV test effectively addresses the endogeneity problem, making the causal relationship between AI and occupational income inequality more compelling, and providing a more robust foundation for the subsequent mediation effect tests.

4.5 Heterogeneity Analysis

Table 4 reports the results of the heterogeneity analysis of the impact of AI on occupational income inequality, conducted from two dimensions: income group heterogeneity and regional heterogeneity.

In terms of income group heterogeneity, columns (1)-(3) use the Pareto coefficients for the highest, middle, and lowest occupational groups as the dependent variables to examine the differential impacts of AI on income inequality within different occupational groups. The results show that the coefficient of AI on inequality within the highest occupational group is 0.007, but statistically insignificant; the coefficients on inequality within the middle and lowest occupational groups are 0.010 and 0.006, respectively, both significantly positive at the 1% level. This indicates that AI significantly exacerbates income inequality within the middle and lowest occupational groups, but has no significant impact on inequality within the highest occupational group. From an intrinsic perspective, this is closely related to the "income effect" of AI. On the one hand, AI generates a "spillover effect" for low-income individuals. It substitutes low-skill repetitive jobs and creates high-skill positions, thus, exacerbating income differentiation within the lowest occupational group. On the other hand, for middle-income groups, the skill-

Table 4. Results for heterogeneity analysis

	High inequality	Moderate inequality	Low inequality	Eastern region	Central region	Western region
AI	0.007	0.010***	0.006***	0.004**	0.014	0.033*
	(1.59)	(3.01)	(3.91)	(2.61)	(1.65)	(2.24)
IND	-0.629	-0.707	-0.460**	0.304	-0.011	-0.519
	(-1.15)	(-1.37)	(-2.14)	(1.13)	(-0.02)	(-0.31)
STR	-0.091	-0.091	-0.075**	0.013	-0.047	-0.167
	(-1.18)	(-1.39)	(-2.54)	(0.54)	(-0.35)	(-0.61)
CAP	-13.066*	-10.744*	-3.165	-1.628	-1.528	-3.685
	(-2.04)	(-1.86)	(-1.46)	(-0.59)	(-0.41)	(-0.82)
FIN	0.042	0.040	0.026	-0.002	0.001	0.111
	(0.60)	(0.59)	(0.63)	(-0.09)	(0.02)	(1.11)
FDI	0.123	1.111	0.512	-0.622	0.681	0.668
	(0.10)	(1.05)	(1.02)	(-1.69)	(0.56)	(0.20)
PCFE	-0.031	-0.041	-0.009	0.039	0.086***	-0.052**
	(-0.41)	(-0.49)	(-0.24)	(1.42)	(5.05)	(-2.47)
EDU	0.084**	0.064	0.023	0.018	-0.046	0.023
	(2.16)	(1.40)	(1.02)	(0.46)	(-0.85)	(1.15)
Constant	0.293	0.172	0.132	0.036	0.737	0.483
	(0.92)	(0.59)	(0.92)	(0.11)	(0.92)	(0.53)
Observations	130	130	130	60	45	50
R-squared	0.124	0.248	0.236	0.333	0.166	0.232

biased nature of AI becomes more pronounced, significantly increasing the marginal output and relative returns of high-skill middle-income workers, thereby intensifying income inequality within the middle occupational group. For the highest occupational group, however, members already have a high level of capital endowment and technological absorption capacity, so the distribution of excess returns brought by AI within this group shows relatively limited variation, resulting in a statistically insignificant impact on within-group inequality.

In terms of regional heterogeneity, columns (4)-(6) examine the differential impacts of AI on occupational income inequality in Eastern, Central, and Western China, respectively. The results show that the coefficients of AI in Eastern, Central, and Western China are 0.004, 0.014, and 0.033, respectively, showing a gradient pattern of “low in the east and high in the west”. In terms of significance, the coefficient is significantly positive at the 5% level in Eastern and Western China, but statistically insignificant in Central China. This result is highly consistent with the real-world context of unbalanced regional development and uneven AI application in China. The economically developed the eastern region has an early start and wide penetration of AI technologies, with relatively mature technology diffusion and benefit distribution mechanisms, leading to a significant but moderate exacerbating effect on occupational income inequality. In contrast, the western region has a weaker economic foundation and a late start in AI adoption, so the technological change has a more intense impact on the local employment structure and production efficiency, resulting in a significant and much stronger exacerbating effect on occupational income inequality than in the eastern region. The central region is in a transitional phase of industrial transformation and AI application, where large-scale AI deployment and penetration have not yet occurred, so its income distribution effect has not shown significant statistical characteristics.

Overall, the heterogeneity analysis further confirms the significant regional structural differences in the exacerbating effect of AI on occupational income inequality, and provides important empirical evidence for the future development of differentiated policies to ensure widespread access to technological benefits and mitigate cross-regional income disparities.

4.6 Robustness Test

To test the robustness of the baseline model, this paper applies 1% winsorization at both tails to the explanatory variables and control variables used in the model, where the suffix "_w" denotes that the variable has undergone winsorization. The results in Table 5 show that the impact of artificial intelligence on occupational income inequality remains statistically significant, consistent with the findings of the baseline regression. Additionally, among the control variables, industrial structure advancement (STR) still passes the significance test. Therefore, the baseline model of this paper is robust.

The share of value-added of the secondary industry (IND) generally reflects the activity level of the industrial and manufacturing sectors in the economy. However, against the backdrop of rapid AI development, the transformation, upgrading, and rising automation of the secondary industry may lead to complex changes in the employment structure and income distribution patterns. On the one hand, automation continuously fosters new technologies, widening income disparities among high-income labor groups. On the other hand, as industries shift toward higher-value-added sectors, overall economic improvement may help alleviate income inequality to a certain extent. These dual effects may interact with each other. If the sample data fails to adequately capture these complex factors, it will not accurately reflect their impact on the dependent variable, ultimately leading to insignificant regression coefficients.

In addition, three control variables show significant results in the regression analysis: industrial structure advancement (STR), average years of education (EDU), and per capita fiscal expenditure (PCFE). First, the significance of STR reflects the important impact of economic structural optimization on income inequality. With continuous technological progress, especially the rapid development of AI, the industrial structure is gradually shifting toward high-

Table5: Results for robustness test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI	0.008***	0.008***	0.007***	0.006***	0.007***	0.007***	0.005***
	(5.06)	(4.53)	(3.91)	(4.22)	(4.20)	(4.14)	(3.96)
IND_w		-0.004	0.317	0.271	0.188	0.174	0.088
		(-0.03)	(1.39)	(1.29)	(0.85)	(0.74)	(0.34)
STR_w			0.039**	0.031*	0.034**	0.032**	0.009
			(2.43)	(1.94)	(2.38)	(2.19)	(0.38)
CAP_w				3.403	3.495*	3.342*	-0.090
				(1.49)	(1.83)	(1.78)	(-0.05)
FIN_w					-0.041	-0.040	-0.002
					(-1.61)	(-1.55)	(-0.07)
FDI_w						0.246	-0.105
						(0.54)	(-0.26)
$PCFE_w$							-0.022**
							(-1.81)
EDU_w							0.031*
							(1.99)
Constant	0.326***	0.327***	0.150	0.107	0.199	0.204	0.036
	(24.06)	(5.36)	(1.32)	(0.88)	(1.59)	(1.57)	(0.22)
Observations	155	155	155	155	155	155	155
R-squared	0.140	0.140	0.155	0.191	0.216	0.217	0.284

tech, high-value-added sectors. This process is often accompanied by a shift in labor demand, with increased demand for high-skilled labor and decreased demand for low-skilled labor. As a result, industrial structure advancement may exacerbate the skill-biased income distribution effect, allowing high-skilled, highly educated workers to earn higher incomes, thus partially explaining income inequality.

Second, the significance of EDU highlights the key role of education in shaping income distribution patterns. Education is a vital way to enhance individual skills, knowledge, and abilities, and significantly affects an individual's competitiveness in the labor market. With the widespread application of AI technologies, the educational requirements for the workforce are constantly rising. Individuals with higher levels of education are often better able to adapt to the challenges posed by technological progress, obtaining better job opportunities and higher income levels. Therefore, unequal access to educational resources exacerbates income inequality.

Finally, PCFE represents government spending aimed at regulating social income distribution and meeting public needs, serving as a necessary guarantee for economic and social development. For high-income earners, while they may already have access to high-quality education, healthcare, and other resources, government investment in these areas can improve the overall level of education and healthcare in society, promoting overall economic and social development. This also helps stabilize the income levels of high-income earners and alleviate income inequality to a certain extent.

4.7 Mediation Effect Test of Industrial Sophistication

Table 6 reports the test results of the impact of AI on occupational income inequality through industrial sophistication, to verify research hypothesis H2. According to the three-step mediation test method: Step 1 (Equation (1)): The total effect of AI on occupational income inequality is tested. The results show that the coefficient of AI is significantly positive, indicating that AI development significantly exacerbates occupational income inequality, consistent with the baseline regression conclusions. Step 2 (Equation (2)): The impact of AI on the mediating variable industrial sophistication is tested. The coefficient of AI is significantly positive at the 1% level, suggesting that higher levels of AI development are associated with greater industrial sophistication, which aligns with the theoretical logic of AI driving industrial transformation and upgrading. Step 3 (Equation (3)): After introducing the mediating variable, the coefficient of industrial sophistication is significantly positive, indicating that industrial sophistication is an important factor exacerbating occupational income inequality. Meanwhile, the coefficient of AI remains positive but becomes statistically insignificant, showing that industrial sophistication plays a full mediating role between AI and occupational income inequality.

Furthermore, the significance of the mediation effect is tested using the Sobel, Aroian, and Goodman methods[1], with all results significant at the 5% level. The mediation effect coefficient is 0.003, accounting for 52.9% of the total effect. This means that more than half of the exacerbating effect of AI on occupational income inequality is realized through driving industrial sophistication, with the transmission path being "AI $\longrightarrow$ Industrial Sophistication $\longrightarrow$ Occupational income inequality". These findings fully confirm hypothesis H2.

4.8 Mediation Effect Test of Technological Innovation

Table 7 reports the test results of the impact of AI on occupational income inequality through technological innovation, to verify research hypothesis H3. Following the same three-step mediation test framework: Step 1 (Equation (1)): The total effect of AI on occupational income inequality is significantly positive, consistent with the baseline regression conclusions. Step 2 (Equation (2)): The coefficient of AI on technological innovation is significantly positive at the 1% level, suggesting that higher levels of AI development lead to greater technological innovation, aligning with the theoretical logic of AI driving technological innovation. Step 3 (Equation

[1]For details about these three tests, the reader is referred to the papers by Aroian (1947), Goodman (1960) and Sobel (1982), respectively.

Table 6: Mediation effect test results for industrial sophistication

	(1) INEQ	(2) UIS	(3) INEQ
AI	0.005***	0.042***	0.002
	(3.56)	(4.82)	(1.19)
UIS			0.062**
			(2.47)
IND	0.120	0.031	0.118
	(0.88)	(0.29)	(0.86)
STR	0.009	-0.105	0.015
	(0.37)	(-1.21)	(0.59)
CAP	-0.904	24.379***	-2.404
	(-0.41)	(5.17)	(-1.03)
FIN	0.011	-0.308***	0.03
	(0.30)	(-3.95)	(0.74)
FDI	-0.172	-4.287***	0.092
	(-0.40)	(-4.33)	(0.22)
PCFE	-0.023	0.426***	-0.049***
	(-1.61)	(4.68)	(-3.12)
EDU	0.034**	0.345***	0.013
	(2.03)	(5.01)	(0.51)
_cons	0.003	-2.197***	0.138
	(0.02)	(-4.09)	(0.45)
R-squared	0.221	0.8024	0.2455
Observations	155	155	155
Sobel test		0.003**(2.117)	
Aroian test		0.003**(2.070)	
Goodman test		0.003**(2.167)	
Mediating effect coefficient		0.003**(2.117)	
Direct effect coefficient		0.002(1.193)	
Total effect coefficient		0.005***(3.560)	
Proportion of mediating effect		0.529	

3): After introducing the mediating variable, the coefficient of technological innovation is significantly positive, indicating that technological innovation is an important factor exacerbating occupational income inequality. The coefficient of AI remains positive but becomes statistically insignificant, showing that technological innovation plays a full mediating role between AI and occupational income inequality.

Table 7: Results for mediation effect of technological innovation

	(1) INEQ	(2) INNO	(3) INEQ
AI	0.005***	0.013***	0.002
	(3.56)	(4.93)	(1.02)
INNO			0.225*
			(1.75)
IND	0.12	-0.164	0.157
	(0.85)	(-1.31)	(1.10)
STR	0.009	-0.056***	0.021
	(0.38)	(-3.76)	(0.83)
CAP	-0.904	1.631	1.27
	(-0.41)	(1.48)	(0.57)
FIN	0.011	-0.034	0.019
	(0.31)	(-0.92)	(0.52)
FDI	-0.172	0.234	0.224
	(-0.40)	(0.61)	(0.54)
PCFE	-0.023	0.03***	0.029**
	(-1.68)	(3.89)	(2.45)
EDU	0.034**	0.023***	0.029*
	(2.04)	(3.91)	(1.81)
_cons	0.003	0.19**	-0.039
	(0.02)	(2.51)	(-0.15)
R-squared	0.221	0.6651	0.2304
Observations	155	155	155
Sobel test		0.003***(1.721)	
Aroian test		0.003***(1.705)	
Goodman test		0.003***(1.738)	
Mediating effect coefficient		0.003*(1.721)	
Direct effect coefficient		0.002(1.016)	
Total effect coefficient		0.005***(3.560)	
Proportion of mediating effect		0.605	

The Sobel, Aroian, and Goodman tests all confirm the significance of the mediation effect. The mediation effect accounts for 60.5% of the total effect, meaning that more than 60% of the exacerbating effect of AI on occupational income inequality is realized through driving technological innovation, with the transmission path being "AI ⟶ Technological Innovation ⟶ Occupational income inequality". These findings fully confirm hypothesis H3.

5 Conclusion and Recommendations

5.1 Research Conclusion

Using micro-level data from the CFPS database, this paper first measures the degree of occupational income inequality with the Pareto coefficient, then explores the factors influencing occupational income inequality from the perspective of AI, and further analyzes the mediating mechanisms through which AI affects occupational income inequality. The main conclusions are as follows:

First, an increase in AI development significantly exacerbates occupational income inequality. Second, heterogeneity analysis shows that AI significantly aggravates income inequality within the middle and lowest occupational groups, but has no significant impact on inequality within the highest occupational group. In terms of regional heterogeneity, the impact of AI on occupational income inequality exhibits distinct regional characteristics: the effect is significant and strongest in Western China, significant but moderate in Eastern China, and statistically insignificant in Central China. This indicates that the rapid development of AI has a relatively mild impact on income distribution in the eastern region, while the shock to the employment structure and production efficiency in the western region is more intense, significantly exacerbating occupational income inequality in the region. The central region, being in a transitional phase of industrial transformation and AI application, has not yet fully experienced the distributional effects of the technology. Third, mediation effect analysis shows that industrial sophistication and technological innovation both play a full mediating role between AI and occupational income inequality, identifying two core transmission mechanisms: "AI $\longrightarrow$ Industrial Sophistication $\longrightarrow$ Occupational income inequality" and "AI $\longrightarrow$ Technological Innovation $\longrightarrow$ Occupational income inequality".

5.2 Policy Implications

Based on the above conclusions, this paper proposes the following policy implications: First, improve the regulatory and adjustment mechanisms for occupational earnings, and establish a systematic occupational income monitoring system. Regularly publish occupational income reports to track changes in income disparities across different occupations. Implement a dynamic adjustment mechanism for the minimum wage standard to ensure that the wages of low-income occupations rise reasonably with economic growth. Increase tax incentives and subsidies for high-skilled workers, while encouraging firms to invest in employee training to reduce income disparities caused by the skill premium.

Second, promote balanced regional development and narrow the gap between developed and underdeveloped regions. Increase investment in the central and western regions, particularly in infrastructure construction, educational resources, and public services, to facilitate balanced regional economic development. Implement industrial transfer policies, encouraging labor-intensive or resource-consuming industries in the eastern region to relocate to the central and western regions, thereby stimulating local employment and economic growth. Develop characteristic industries by leveraging the unique natural resources and ethnic cultures in the Western region to build competitive industrial clusters.

Third, reduce within-region income inequality. Deepen the reform of the income distribution system, using taxation, social security, and transfer payments to regulate excessively high incomes and guarantee the basic living standards of low-income groups. Promote the modernization of rural agriculture to increase farmers' incomes and narrow the urban-rural income gap. Strengthen education and skills training, especially in rural and underdeveloped areas, to improve the quality of the labor force and employability, thereby increasing access to high-income jobs.

Finally, formulate a scientific AI development plan that focuses not only on its role in improving overall economic efficiency, but also on its impact on the employment structure to avoid exacerbating income inequality. Promote the deep integration of AI with traditional industries to enhance the technological level and production efficiency of traditional industries, thereby creating more high-quality employment opportunities.

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