

Research on the Impact of Artificial Intelligence Development on the Wage Gap of the Labor Force: From the Perspectives of Labor Intensity and Task Cognition

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Abstract. Based on micro-level data from the China Labor-force Dynamics Survey (CLDS) and artificial intelligence (AI) patent data, this study explores the impact of AI development on wage disparities among heterogeneous labor groups. From the dual perspectives of labor intensity and task cognition, the paper analyzes how AI exacerbates income gaps by increasing labor intensity and enhancing task cognitive demands. It further investigates heterogeneity across regions, household registration statuses, and city sizes. The findings aim to provide empirical evidence and theoretical support for understanding the labor market impact of AI and for formulating differentiated policies to promote inclusive development. The study finds that: (1) While AI fosters economic growth, it also exacerbates income inequality. (2) AI widens the income gap between high- and low-skilled workers by increasing labor intensity and task cognition requirements. (3) Regional heterogeneity analysis shows that the income gap expansion is most pronounced in western regions, where AI suppresses low-skilled incomes in central areas and has weaker effects in eastern regions. The gap is also more pronounced among agricultural hukou holders and in large cities, while non-agricultural hukou holders are less affected.

Keywords: Artificial Intelligence, Income Inequality, Labor Intensity, Task Cognition, Skilled Labor

1. Introduction

Artificial intelligence (AI) is rapidly reshaping the global labor market, and its technological transformation has become a pivotal issue in the discussion of income distribution. According to a 2022 report by Oxford Insights, 40% of countries worldwide have incorporated AI development into their national strategies. In 2023, the Global AI Governance Initiative proposed the concept of "AI for Good," and China concurrently issued the Interim Measures for the Management of Generative AI Services, which explicitly emphasized mitigating unemployment risks among low-skilled workers through reskilling initiatives, while also advocating for policy directions that optimize labor intensity and cognitive task levels.

The implementation of new technologies typically involves a combination of two effects: collaborative improvement in labor efficiency and the displacement or substitution of labor. However, there is still no consensus on how AI affects income distribution. Some studies suggest that AI narrows income gaps by improving labor productivity[1], while a growing body of evidence indicates that technology exhibits asymmetric substitution effects between high- and low-skilled jobs, significantly widening the income divide[2–4]. With its dual characteristics—replacing repetitive manual labor and augmenting cognitive tasks—AI is particularly disruptive in its early phases[5]. Studies estimate that 47% to 55% of occupations face a high risk of being replaced[6–8]. As of 2023, China’s core AI industry reached a scale of 578.4 billion yuan, with a generative AI adoption rate of 15%. China ranks second globally in computing power and leads the world in AI-related academic papers and patents, highlighting the urgency of studying the distributional effects of AI[9].

Against this backdrop, this paper uses CLDS (China Labor-force Dynamics Survey) data and AI patent data to examine how AI development affects wage disparities between high- and low-skilled workers. The key contributions of this study are as follows: First, it provides new empirical evidence that AI significantly enlarges the wage gap between high- and low-skilled labor, offering fresh insights into AI’s impact on the labor market. Second, it innovatively identifies labor intensity as a crucial mechanism through which AI influences income inequality. Third, it conducts heterogeneity analysis to inform differentiated policy-making aimed at mitigating the redistributive shock of AI technologies and promoting inclusive development.

2. Literature Review and Theoretical Hypotheses

AI patents have accelerated the commercialization of technology, enabling firms to improve efficiency and reduce costs as they compete for technological dividends. Research shows that the impact of AI on employment structures deepens progressively through its stages—from introduction to mature application[10]. The “technological unemployment” predicted by Keynes has become more pronounced in the AI era, as the substitution effect of intelligent automation surpasses that of traditional technologies, dramatically increasing the risk of replacement for standardized jobs[11]. It is estimated that by 2030, approximately 70% of enterprises will widely apply AI technologies[12]. Through intra-industry labor substitution and inter-industry product replacement, AI reconfigures skill intensity and output structures, thereby widening wage disparities[13]. At the individual level, the skill-biased nature of AI intensifies the skill premium, further segmenting income returns for high-skilled workers[14,15]. However, domestic and international studies remain divided on whether AI definitively enlarges wage gaps among workers. On one hand, AI substitutes low-skilled positions and increases the premium for high-skilled labor, expanding the wage gap by an average of 0.75% annually[16–18]. On the other hand, the productivity gains from AI may have poverty-reducing effects. The net impact of AI is determined by a triple-effect game: job creation, job substitution, and productivity enhancement[6]. Industry structure transformation and sectoral heterogeneity also exert significant moderating effects. Some researchers suggest that generative AI may reverse the skill premium trend, although this is subject to technical and institutional constraints and tends to follow a non-linear pattern[19]. In the short term, AI negatively affects low-skilled workers, while in the long term, it may alleviate disparities by creating new job categories. Nonetheless, the risk of labor market polarization persists[20,21]. Based on this, the following hypothesis is proposed:

H1: The advancement of AI exacerbates the income disparity between high-skilled and low-skilled labor.

AI exerts a significant polarizing effect on the labor market: as technology demands rise, high-skilled jobs expand, while medium-skilled jobs shrink and low-skilled jobs face high replacement risk[8,22]. The synergy between AI and high-skilled workers has fostered the emergence of new positions in research and development, as well as in management[23]. Conversely, low-skilled groups are more vulnerable to automation-induced job displacement and income decline[24]. Changes in labor intensity exhibit dual effects[25]: on one hand, low-skilled workers performing programmable tasks are more likely to be replaced, thus facing wage suppression[26]; on the other hand, high-skilled workers can leverage smart tools to improve efficiency and generate surplus value[27]. However, the unequal distribution of technological dividends intensifies income disparities[28,29]. Task cognition levels have become a critical mechanism. AI tends to replace low-cognitive tasks while creating demand for high-cognitive ones, thereby increasing market demand for highly skilled talent[30–32]. Some studies suggest that multi-skill training programs can help low-skilled workers narrow income gaps, but policies on dynamic task adaptation still require strengthening to balance technological efficiency with distributive fairness and mitigate skill polarization[33–35]. Based on this, two additional hypotheses are proposed:

H2a: AI increases labor intensity, thereby widening the income gap between high-skilled and low-skilled workers.

H2b: AI raises task cognition levels, thereby widening the income gap between high-skilled and low-skilled workers.

3. Empirical Strategy

This study selects total labor income as the core dependent variable and uses wage income from the previous year as a robustness check. The core independent variable is the stock of AI patents, measured by following the method of Yao Jiaquan et al.[36] to assess the level of AI technology penetration across different cities and years. Mechanism variables include the weekly overtime work ratio and task cognition measures to analyze how AI affects wage disparities. Following Liu Hongying et al.[2] and Hu Shengming[37], this paper includes individual-level and city-level control variables. Data are sourced from the China Urban Statistical Yearbook, the China Labor-force Dynamics Survey (CLDS), and the National Intellectual Property Administration (CNIPA) patent database. The study uses data from 2014, 2016, and 2018, covering 29 provinces, municipalities, and autonomous regions, resulting in a pooled cross-sectional dataset of 33,580 observations after filtering and winsorizing the raw data.

3.1. Descriptive Statistics

Descriptive statistics for the variables used in the study are shown in Table 1.

Table 1. Descriptive Statistics

	Variable Name	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable	Last Year's Total Income	33580	31087.52	35669.72	0	200000
Independent Variable	City AI Patent Stock	33580	20274.32	29058.39	0	150000
Mechanism Variables	Weekly Overtime Ratio	33004	0.350	1.747924	-1	69
	Fast Mental Work	33580	0.241	0.4278628	0	1
	Internet Use	33580	0.168	0.3739924	0	1
	Gender	33580	0.538	0.4985432	0	1
	Marital Status	33580	2.058	0.7091695	1	6
Individual Control Variables	Birth Year	33580	1969.849	12.88564	1900	2003
	Political Affiliation	33580	2.821	0.5706349	1	3
	Military Service	33580	0.034	0.1812533	0	1
	Working Hours	33580	43.444	21.9801	0	100
City Control Variables	Industrial Structure	33580	1.090	0.5439645	0.321	4.347

3.2. Model Specification

To investigate the impact of AI development on the wage gap between high- and low-skilled labor in China, this study builds the following two-way fixed effects model based on existing literature on wage premiums[38]: Baseline Models:

$$Income_{it} = \alpha_0 + \alpha_1 ifGJN_{it} \times AI_{ct} + \alpha_2 AI_{ct} + \varepsilon_{ict} \quad (1)$$

$$Income_{it} = \beta_0 + \beta_1 ifGJN_{it} \times AI_{ct} + \beta_2 AI_{ct} + X_{it} + X_{ct} + Z + \varepsilon_{ict} \quad (2)$$

Where: $Income_{it}$ is the wage income of individual i in year t , AI_{ct} is the level of AI development in city c in year t , $ifGJN_{it} \times AI_{ct}$ is the interaction term between high-skilled labor and AI development, X_{it} and X_{ct} are vectors of individual and city control variables, Z includes fixed effects for year and individual, ε_{ict} is the error term. Models (1) and (2) primarily test Hypothesis H1. Model (1) focuses on the coefficients α_1 of the interaction term $ifGJN_{it} \times AI_{ct}$ and α_2 of AI_{ct} ; Model (2) focuses on the coefficients β_1 of $ifGJN_{it} \times AI_{ct}$ and β_2 of AI_{ct} . If α_1 and β_1 are significantly greater than zero, it indicates that artificial intelligence has a positive effect on the wages of high-skilled workers. If α_2 and β_2 are significantly less than zero, it suggests that artificial intelligence suppresses the wages of low-skilled workers, thereby widening the income gap between high-skilled and low-skilled labor.

$$M_{it} = b_0 + b_1 ifGJN_{it} \times AI_{ct} + b_2 AI_{ct} + X_{it} + X_{ct} + Z + \varepsilon_{ict} \quad (3)$$

To verify the mechanism effect of labor intensity adjustment, Mechanism Analysis Model (3) is specified to examine the impact of artificial intelligence on the mechanism variable of labor intensity. The weekly overtime ratio is used to represent labor intensity, and this model tests the direct effect of artificial intelligence on the labor intensity of both high-skilled and low-skilled workers.

$$P(M_{it} = 1/X) = \Phi(c_0 + c_1 ifGJN_{it} \times AI_{ct} + c_2 AI_{ct} + X_{it} + X_{ct}) \quad (4)$$

Equation (4) tests the effect of artificial intelligence on another mechanism variable, task cognition, which is represented by the degree of mental labor and internet usage. The respondents' four-level evaluation is converted into a binary variable, and a probit model is applied to examine the direct effect of artificial intelligence on task cognition.

4. Regression Results Analysis

4.1. Baseline Regression

Following He Mei and Wang Yanmei[39], all empirical models report robust standard errors. Column (1) of Table 2 presents results from Model (1) without control variables. The coefficient of the interaction term $AI \times High\ Skill$ is significantly positive at the 1% level, while the coefficient of AI is significantly negative. This suggests that AI significantly increases the wages of high-skilled workers while reducing the income of low-skilled workers.

Columns (2) and (3) of Table 2 present results from Model (2), sequentially adding individual-level and city-level control variables. The interaction term $AI \times High\ Skill$ remains significantly positive, confirming that AI 's positive effect on high-skilled workers' wages outweighs its effect on low-skilled workers. The AI variable remains significantly negative, indicating that the income of low-skilled workers is suppressed compared to their high-skilled counterparts. Thus, all else being equal, the development of AI widens the wage gap between high- and low-skilled workers. Column (4) presents results from Model (3), which examines labor intensity. The interaction term $AI \times High\ Skill$ is significantly positive, suggesting AI raises the labor intensity (as measured by weekly overtime ratio) for high-skilled workers. Conversely, the coefficient for AI remains significantly negative, indicating AI suppresses the labor intensity of low-skilled workers. This confirms that AI exacerbates the gap in labor intensity between high- and low-skilled workers.

Table 2. Baseline Regression and Mechanism Analysis

	(1)	(2)	(3)	(4)
	Last_Income	Last_Income	Last_Income	weekly_ratio
IfGJN×patent stock	10.0662*** (2.5798)	9.7790*** (2.5888)	9.7631*** (2.5874)	0.0002** (0.0001)
patent stock	-5.3874*** (1.6898)	-5.2765*** (1.6959)	-5.0071*** (1.9003)	-0.0002** (0.0001)
Individual Controls	NO	YES	YES	YES
City Controls	NO	NO	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Sample Size	13872	13872	13872	13524
R ²	0.552	0.553	0.553	0.226

*Note: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2. Robustness Tests

To ensure the reliability of the baseline regression results, this study conducts three robustness tests:

First, the clustering method is altered: instead of clustering standard errors at the individual level, they are clustered at the city level. The results show that the coefficients for AI × High Skill remain significantly positive, and the coefficients for AI remain significantly negative. The interaction term coefficients remain significant at the 1% level, consistent with the baseline regression.

Second, the dependent variable is replaced. Instead of using total income, wage income is used as the dependent variable[40]. The results show that AI still significantly increases the income gap between high- and low-skilled workers at the 1% significance level, confirming the robustness of the baseline findings.

Third, the key independent variable is replaced. The number of AI invention patents at the city level is used as an alternative measure for AI development. The results indicate that this variable still significantly enlarges the income disparity between skill groups at the 1% level, which aligns with the main conclusion.

Table 3. Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Last_ Income	Last_ Income	salary_ income	salary_ income	Last_ Income	Last_ Income
IfGJN×	10.0662*** (3.1937)	9.7631*** (3.2023)	8.5395*** (2.2539)	8.2180*** (2.2528)		
patent stock	-5.3874*** (2.3438)	-5.0071* (2.8880)	-6.6419*** (1.4110)	-5.9346*** (1.6350)		
IfGJN×					3.4052*** (0.6525)	3.3691*** (0.6536)
patent count					-2.4752*** (0.6964)	-2.3009*** (0.8031)
Individual Controls	NO	YES	NO	YES	NO	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Sample Size	13872	13872	13872	13872	13872	13872
R ²	0.552	0.553	0.598	0.601	0.553	0.554

*Note: Robust standard errors in parentheses. *, *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3. Endogeneity Tests

Following the methods of Huang Qunhui et al.[41]and Zhao Tao et al.[42], this study adopts an instrumental variable (IV) approach to address potential endogeneity issues. Specifically, the number of fixed telephone lines per 100 people in each city in 1984 is used as an instrumental variable for AI development. The rationale for this choice lies in the path dependence of technological evolution—areas with better telecommunications infrastructure in 1984 are more likely to have higher digital technology penetration today. To adapt this instrument for panel data, the study constructs an interaction term between historical telephone line density and current broadband user numbers, generating a time-varying instrument with both temporal and spatial variation. This approach ensures exogeneity and addresses the identification challenges of cross-sectional instruments in panel models. The results in Table 4 show that, after accounting for endogeneity, AI still has a statistically significant effect on widening the wage gap between high- and low-skilled workers. All key coefficients remain significant at the 1% level.

Table 4. Endogeneity Test Results

	(1)	(2)	(3)	(4)
	Last_Income (OLS)	Last_Income (OLS)	Last_Income (2SLS)	Last_Income (2SLS)
IfGJN×patent stock	9.5120*** (2.5916)	9.2156*** (2.6009)	95.135* (3.295)	67.473*** (3.089)
patent stock	-12.8133*** (3.6332)	-12.8047*** (3.6376)	-25.876*** (3.110)	-36.944*** (5.142)
patent stock ×patent stock	0.0082** (0.0035)	0.0083*** (0.0035)		
Control Variables	NO	YES	NO	YES
Year Fixed Effects	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Sample Size	13872	13872	33580	33580

*Note: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.4. Mechanism Tests

(1) As proposed in Hypothesis H2a, this paper uses the weekly overtime work ratio as a proxy for labor intensity to examine whether AI-induced changes in labor intensity contribute to skill-biased income effects. The regression results in Column (4) of Table 2 show that the coefficient of the interaction term $AI \times High\ Skill$ is significantly positive, indicating that AI significantly increases labor intensity among high-skilled workers. Meanwhile, the coefficient for AI alone is significantly negative, suggesting that AI reduces labor intensity for low-skilled workers. These findings confirm that AI exacerbates the disparity in weekly overtime work (i.e., labor intensity) between high- and low-skilled labor groups.

(2) To test Hypothesis H2b, the study uses responses from survey questions related to “fast reaction thinking or mental work” and “internet use” to construct proxy variables for task cognition. These variables are converted into binary form and tested using a probit model. In Column (1) of Table 5, the coefficient for AI is not statistically significant, whereas in Column (2), the interaction term $AI \times High\ Skill$ is highly significant. The coefficient for AI alone is also significant for the low-skilled group. Specifically, the coefficient of $AI \times High\ Skill$ is significantly negative, while the coefficient for AI alone is significantly positive. This implies that AI significantly enlarges income disparities among workers performing cognitively non-routine tasks.

This result echoes the findings of Qian Yuanyuan et al.[43], which highlight that robot adoption shows a strong task-selection bias—substantially increasing demand for cognitive tasks and thus boosting high-skilled employment. AI technology intensifies the difference in cognitive task requirements between high- and low-skilled labor, further polarizing labor market demand and widening income disparities between heterogeneous labor groups.

Table 5. Mechanism Test Results

	(1)	(2)
	fast_brain	Internet
IfGJN×patent stock	0.0068*** (0.0004)	0.0045*** (0.0004)
patent stock	0.0005 (0.0239)	0.0008* (0.0004)
Control Variables	YES	YES
Year Fixed Effects	YES	YES
Individual Fixed Effects	YES	YES
Sample Size	33580	33580

*Note: Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5. Further Analysis

The previous sections have shown that AI increases wage disparities between high- and low-skilled workers by intensifying labor intensity and task cognition differences. Considering the urban–rural dual structure and regional disparities in technological diffusion, this section further examines heterogeneity in AI's impact on wage inequality from the perspectives of household registration status (hukou), geographic region, and city size. The detailed results are presented in Table 6.

Table 6. Heterogeneity Test Results

	Last_Income	IfGJN×patentstock	patentstock	Controls	Year FE	Individual FE	Sample Size	R ²
Regional	(1)	3.0880***(0.7308)	-2.7192**(1.0687)	NO	YES	YES	5230	0.5221
	(2)	3.0276***(0.7327)	-2.9378**(1.2570)	YES	YES	YES	5230	0.5232
	(3)	4.9883(3.9468)	-2.2300**(1.0454)	NO	YES	YES	1652	0.4727
	(4)	4.6484(7.6179)	-2.3604**(1.1879)	YES	YES	YES	1652	0.4727
Hukou	(1)	1.6143*** (0.6025)	-1.1767** (0.7128)	NO	YES	YES	10308	0.4792
	(2)	1.5834** (0.6050)	-1.6267** (0.8264)	YES	YES	YES	10308	0.4792
	(3)	3.4667** (0.8922)	-0.8911 (1.4017)	NO	YES	YES	2884	0.5667
	(4)	3.3898*** (0.8994)	-1.0719 (1.6770)	YES	YES	YES	2884	0.5667
City Size	(1)	4.2494*** (0.8970)	-4.2623*** (1.2040)	NO	YES	YES	5185	0.6289
	(2)	4.3283*** (0.9005)	-2.9518** (1.3103)	YES	YES	YES	5185	0.6306
	(3)	4.2597*** (1.3672)	-4.2104* (2.5524)	NO	YES	YES	3284	0.4548
	(4)	4.2296*** (1.3663)	-4.2826 (2.6312)	YES	YES	YES	3284	0.4554

*Note: Standard errors in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

First, a subgroup analysis based on regional distribution [44] was conducted. The results show that for the eastern region, represented by columns (1) and (2), the coefficient of the interaction term “Artificial Intelligence $\times$ High Skill” is significantly positive at the 1% level, while the coefficient of “Artificial Intelligence” is significantly negative at the 1% level. This indicates that artificial intelligence significantly widens the wage gap between high-skilled and low-skilled labor in the eastern region. For the central and western subgroups, represented by columns (3) and (4), artificial intelligence technology primarily produces a substitution effect on low-skilled labor, but a significant complementary effect for high-skilled labor has yet to emerge.

Second, labor was divided by household registration type into agricultural households (columns (1) and (2)) and non-agricultural households (columns (3) and (4)). The results show that artificial intelligence significantly widens the wage gap within the agricultural household labor force and has a significant positive effect on the wages of high-skilled workers in the non-agricultural household group, though the overall impact on wage levels is not significant.

Finally, dividing by the size of the registered population into large cities (columns (1) and (2)) and small cities (columns (3) and (4)) [45], the empirical results reveal that large cities exhibit significant skill polarization, resulting in a pattern of “high-skilled beneficiaries and low-skilled losers.” In contrast, the impact of AI in small cities is more selective, with high-skilled workers benefiting only within public institutions or leading enterprises, and the overall effect is not significant.

6. Conclusion and Policy Recommendations

From the perspective of individual laborers, this study uses panel data from the years 2014, 2016, and 2018 to investigate the effect of AI development on income disparities between low-skilled and high-skilled workers, as well as the underlying mechanisms. It further explores heterogeneity across regions, hukou (household registration) status, and city size. The main conclusions are as follows:

(1) The development of artificial intelligence significantly increases the income gap between high-skilled and low-skilled laborers. This finding remains robust across multiple model specifications and sensitivity checks.

(2) AI intensifies labor market inequality by increasing both labor intensity and the cognitive demands of tasks, thus expanding the income gap between skill groups.

(3) Regional heterogeneity: In eastern regions, AI significantly widens the skill-based income gap; in central and western regions, AI primarily depresses low-skilled wages without boosting high-skilled income. Hukou heterogeneity: Among agricultural hukou holders, AI exacerbates income inequality; among non-agricultural hukou holders, the impact is less pronounced. Urban size heterogeneity: In large cities, AI leads to a “high-skilled benefit, low-skilled loss” polarization. In smaller cities, the benefits are concentrated among high-skilled workers in government or leading firms, with limited effect on overall wage disparities.

The research findings indicate that while technological advancement and scientific progress promote economic development, they also reshape patterns of social distribution and influence income disparities among different social strata. Consequently, effective development strategies and economic policies are often required to foster inclusive growth. At the current stage, the development of artificial intelligence (AI) is not conducive to achieving inclusive growth among individual laborers. To better harness AI's potential in promoting inclusive growth, this paper proposes the following policy recommendations:

First, establish an inclusive digital skills training system targeting disadvantaged groups to mitigate the income-dividing effect of AI technologies. To ease the impact of AI on low-skilled workers, a coordinated “government-enterprise-society” training system is recommended. The government should provide dedicated funding, collaborate with vocational colleges and leading enterprises to develop tiered digital curricula, and prioritize coverage of vulnerable populations such as rural-to-urban migrants in western regions. A “three exemptions and one subsidy” model should be implemented, along with the signing of “training-employment” agreements to ensure job placement. Drawing on pilot experiences, companies that hire trained workers should receive social security reductions and tax incentives, thereby forming a closed-loop system of “skills enhancement–employment–income growth.” This scheme addresses the mediating effect of labor intensity and disparities due to household registration, aiming to break the chain of technological exclusion through institutional intervention.

Second, optimize the spatial layout of the AI industry and improve benefit-sharing mechanisms to promote the equitable distribution of technological dividends. In response to the skill and regional polarization driven by AI, a dual-track strategy of “technology diffusion–benefit sharing” is proposed. On the diffusion side, the government should establish branches of national AI innovation centers and launch regional demonstration projects to support the intelligent upgrading of traditional industries in central and western regions as well as in the agricultural sector. On the distribution side, a dedicated adjustment fund should be created to support worker retraining, and a “collective data dividend account” should be introduced to return part of the public data revenue to low-income groups. This approach mitigates the widening skill premium, institutionalizes the sharing of technological benefits, and balances efficiency with equity. It targets vulnerable regions and populations affected by industrial transformation, fostering a virtuous cycle between technological diffusion and social compensation.

Finally, deepen household registration (hukou) reform and leverage AI technology to reduce the segmentation of urban and rural labor markets. To address the widening income gap faced by agricultural hukou holders in the AI era, a comprehensive strategy combining institutional relaxation and capacity enhancement is recommended. First, pilot a “skills-based point system for urban residency” in key digital economy cities, easing settlement requirements for rural migrants with digital skills certifications and gradually dismantling hukou-related barriers. Second, establish a digital skills training system that spans both urban and rural areas, centered on county-level vocational education institutions. These institutions should offer “digital skills workshops” with customized modules on basic literacy and professional skills, along with training subsidies. Additionally, improve mechanisms to ensure employment equity: use labor data platforms to monitor hukou-based discrimination in hiring, impose credit penalties on violators, and create a special fund to provide legal aid and transitional job support. This policy package addresses market segmentation through institutional reform, enhances human capital through targeted training, and ensures fair access to AI-driven opportunities through rights protection—ultimately promoting a more equitable distribution of technological dividends for rural migrants.

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