International Review of Economics and Finance 102 (2025) 104292

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Artificial intelligence development and rural labor employment quality

Zhe Li [a], Minggang Liu [b], Lu Wang [c,d,*]

[a] School of Economic Management, Beijing City University, Beijing, China
[b] Smart Campus Construction Center, Central University of Finance and Economics, Beijing, China
[c] School of Marxism, Central University of Finance and Economics, Beijing, China
[d] Department of Assets and Logistics Management, Central University of Finance and Economics, Beijing, China

ARTICLE INFO

JEL classification:
J24
O33
Q10

Keywords:
Artificial intelligence
Rural areas
Employment Quality of labor

ABSTRACT

This paper aims to explore the impact of artificial intelligence (AI) development on the employment quality of rural labor and its underlying mechanisms. Based on panel data from 30 Chinese provinces from 2008 to 2022, the empirical analysis finds that AI development significantly enhances the employment quality of rural labor. Mechanism analysis reveals that AI improves employment quality by providing rural labor with more convenient learning and training opportunities, thereby enhancing skill levels and increasing job competitiveness. Heterogeneity analysis indicates that the positive effect of AI on rural labor employment quality is more pronounced in provinces with lower social security levels, higher innovation efficiency, located in the eastern region, and with higher education levels. This study offers a new perspective on AI's role in the rural labor market and provides a theoretical foundation for relevant policy-making.

1. Introduction

Employment is not only the most critical livelihood initiative, public sentiment project, and foundational undertaking but also the cornerstone of economic and social stability, directly affecting people's well-being and the long-term security of the nation (Wu, Chen, & Shi, 2025; Lan & Cui, 2024). However, the current employment landscape is becoming increasingly complex, posing severe challenges to employment stability. In particular, the employment issues faced by three key groups—college graduates, migrant workers, and urban disadvantaged populations—have become a focal point of concern across society. During the 14th collective study session of the Central Political Bureau, President Xi Jinping explicitly stated that "promoting high-quality and sufficient employment is the new positioning and mission of employment policies in the new era and on the new journey." He emphasized that while ensuring a reasonable expansion of employment, greater attention must be paid to improving employment quality. The 2024 No. 1 Central Document also repeatedly addresses rural employment issues, proposing measures such as "promoting multi-channel employment for rural labor," "strengthening dynamic monitoring of migrant worker employment," and "providing employment support for older migrant workers." These policies underscore the urgency and practical significance of enhancing the employment quality of rural labor. Compared to urban workers, rural laborers generally face disadvantages in knowledge accumulation and skill levels, making them less competitive in the job market. In terms of employment distribution, the proportion of rural employment in total national employment has declined from 41.6 % in 2018 to 37.4 % in 2022, indicating a continuous decrease in rural labor's share of overall

* Corresponding author. School of Marxism, Central University of Finance and Economics, Beijing, China.
E-mail addresses: 345403317@qq.com (Z. Li), loveswim@163.com (M. Liu), aizuguowanglu@163.com (L. Wang).

https://doi.org/10.1016/j.iref.2025.104292
Received 19 March 2025; Received in revised form 29 April 2025; Accepted 18 June 2025
Available online 18 June 2025

employment. In terms of wage income, urban residents had an average wage income of 31,321 yuan in 2023, whereas rural residents earned only 9163 yuan, reflecting a significant gap. Moreover, in terms of employment structure, migrant workers are predominantly concentrated in the manufacturing and construction industries, with these two secondary-sector industries accounting for 42.9 % of total employment. This concentration indicates that rural labor remains primarily engaged in physically intensive jobs, with relatively low representation in high-value-added and high-skilled positions (Chen et al., 2021). Therefore, compared to urban labor, rural labor still has substantial room for improvement in overall employment quality. Enhancing their vocational skills, expanding employment channels, and promoting industrial upgrading have become key strategies for improving rural employment conditions (Huang et al., 2022; Qin, 2010).

In recent years, with continuous innovation and breakthroughs in foundational technologies such as big data, cloud computing, and deep learning, artificial intelligence (AI) has increasingly become a prominent and widely discussed topic in both domestic and international academic circles (Qu & Jing, 2025; Gao et al., 2025). As a strategic general-purpose technology, AI plays a crucial role in driving a new wave of technological revolution and industrial transformation. The development of AI can be traced back to the introduction of industrial robots (Lyu & Liu, 2021). Initially, industrial robots—an early application of AI technology—were introduced into manufacturing processes, significantly improving production efficiency and quality (Mannuru et al., 2023; Wu, Chen, & Shi, 2025). Since then, China's industrial robotics industry has grown rapidly, driven by both technological innovation and rising market demand. Starting in 2013, China's industrial robotics market expanded at an accelerated pace, surpassing Japan to become the world's largest industrial robotics market. By 2021, China's share of the global robotics market had reached 33 %, underscoring not only the country's strong growth momentum in this field but also the powerful role of AI technology in driving industrial upgrading and economic development (Tan et al., 2025).

The rapid development of artificial intelligence (AI) has had a profound impact on society, and this impact is inherently dual in nature (Yin et al., 2025; Zhou et al., 2025). On one hand, the deep integration of AI with human intelligence has significantly enhanced productivity, reducing the pressure and risks faced by workers in hazardous, extreme environments and low-skilled, repetitive tasks. This technological advancement not only provides workers with a safer and more efficient work environment but also creates greater opportunities for them to realize their self-worth in the labor process. Additionally, the widespread adoption of AI has driven industrial transformation and upgrading, fostering the emergence of numerous new industries and job opportunities (Tschang & Almirall, 2021; Yang et al., 2022). For example, amid the rapid expansion of the digital economy, industries such as express delivery, food delivery, and ride-hailing have emerged. These sectors have relatively low skill requirements, offering new employment opportunities for rural laborers, effectively broadening their employment channels, and injecting new vitality into the diversified development of the economy. On the other hand, the rapid advancement of AI also presents several challenges. Some workers face difficulties in securing employment due to a mismatch between their skill levels and the demands of emerging job roles (Rampersad, 2020). This issue of structural unemployment not only affects individual career development but may also trigger a series of social tensions, such as widening income disparities and increasing social instability.

This study focuses on examining the impact of artificial intelligence (AI) on the employment quality of rural laborers. Empirical analysis reveals that the development of AI significantly enhances the employment quality of rural labor. Mechanism analysis indicates that AI improves employment quality by providing rural laborers with more accessible learning and training opportunities, thereby enhancing their skill levels and increasing their competitiveness in the job market. Further heterogeneity analysis shows that the positive effect of AI on rural employment quality varies significantly across different regions and conditions. Specifically, in provinces with lower levels of social security, AI plays a more pronounced role in improving employment quality by creating more job opportunities and increasing labor productivity. In provinces with higher innovation efficiency, the deep integration of AI with local industries further optimizes employment structures, generating more high-quality job opportunities for rural laborers. Moreover, in eastern regions, where economic foundations are stronger and industrial structures are more diversified, the application of AI has a more substantial impact on improving rural employment quality. Additionally, in provinces with higher levels of education, rural laborers experience faster skill enhancement, making them better equipped to meet the demand for highly skilled workers in the AI era.

The contributions of this study are as follows: First, while existing research primarily focuses on the impact of AI on overall employment or specific labor groups, relatively little attention has been given to the employment quality of rural laborers. This study addresses this gap by specifically examining the rural labor force, filling an important void in the literature. Second, through mechanism analysis, this study identifies the role of AI in enhancing rural employment quality via skill improvement channels, offering a new perspective on the relationship between technological advancement and employment quality. Additionally, this study conducts heterogeneity analysis from multiple dimensions, including social security levels, innovation efficiency, regional differences, and educational attainment. This approach reveals the varying effects of AI on rural employment quality and provides valuable insights for designing region-specific policies. Finally, the findings of this study offer a theoretical foundation for government policymaking, contributing to the improvement of rural employment quality and supporting rural revitalization and urban-rural integration.

This paper is structured as follows. Section 2 presents the literature review and research hypotheses, systematically summarizing relevant domestic and international studies on AI and rural labor employment quality while identifying research gaps. Based on this, the study formulates research hypotheses to establish a theoretical foundation for the empirical analysis. Section 3 focuses on data and model specifications, detailing data sources, sample selection, variable definitions, and processing methods. An econometric model is constructed to accurately assess the impact of AI on rural labor employment quality, ensuring methodological rigor. Section 4 conducts regression analysis, including baseline regression and robustness tests. The baseline regression estimates key variables to reveal the relationship between AI development and rural labor employment quality, while robustness tests, such as variable substitution, verify the reliability of the findings. Section 5 delves into mechanism analysis, exploring how AI enhances employment quality through channels such as improved learning and training opportunities, industrial restructuring, and employment environment optimization.

Section 6 conducts heterogeneity analysis, examining the varying effects of AI across different dimensions. Finally, Section 7 summarizes the key findings and proposes targeted policy recommendations.

2. Literature review and research hypotheses

2.1. Literature review

Achieving fuller and higher-quality employment has always been a core objective of economic policies worldwide, serving not only as a key driver of economic growth but also as a crucial means to enhance social well-being and promote equity (Su et al., 2022). Existing research has explored various factors influencing employment quality from multiple perspectives. For instance, the emergence of innovative e-commerce poverty alleviation platforms has created new development opportunities for rural areas. Studies indicate that such platforms not only expand employment channels for rural labor but also have significant positive effects on workers' skill development, income levels, and resource allocation (Huang et al., 2020). This suggests that technological and business model innovations can effectively enhance employment quality for rural labor, thereby promoting sustainable rural economic development. Against the backdrop of the rapidly growing digital economy, the skill structure of the labor market has undergone significant transformations. Yunxia et al. (2023) found that digital economic development has increased the proportion of highly skilled and medium-high skilled labor while reducing the share of medium-low and low-skilled workers. This shift highlights the transformative impact of technological progress on labor markets and underscores the need for policymakers to prioritize skill enhancement and educational reforms to meet evolving employment demands. Furthermore, research on employment quality has examined different demographic groups. For example, studies on university graduates suggest that educational background, internship experience, and career planning significantly affect their employment quality (Mao et al., 2023; Zheng et al., 2022). For migrant workers, key determinants include policy support during urbanization, skills training, and social security measures (Chen & Tan, 2023; Wright & Clibborn, 2019). Female workers, on the other hand, face gender discrimination, career development barriers, and challenges in balancing work and family responsibilities, all of which significantly constrain their employment quality (Xie et al., 2015). Huang and Cheng (2023) further emphasized that employment quality across different groups is shaped by a combination of factors, requiring a multifaceted approach that integrates policy interventions, socio-cultural considerations, and individual capabilities to achieve overall improvements in employment quality. These studies collectively highlight the complexity of factors influencing employment quality.

As a transformative technological force, artificial intelligence (AI) has far-reaching impacts on both the macro and micro levels of the economy and society (Jin & Yu, 2025; Zhao & Chen, 2025). At the macro level, AI applications have significantly enhanced public health and urban safety performance (Liu et al., 2021) while fundamentally reshaping urban design and management, driving cities toward greater intelligence and efficiency (Al-Raeei, 2025). The widespread adoption of AI provides new approaches to sustainable urban development, enabling cities to better respond to complex and evolving environmental challenges. At the micro level, AI has profoundly influenced business operations and management models. In the pharmaceutical industry, for example, small pharmaceutical firms have leveraged AI to optimize research and development (R&D) processes, improving both efficiency and success rates (Kulkov, 2021). Large pharmaceutical companies, in turn, have integrated AI into key processes such as production and sales, facilitating a transition from traditional models to intelligent manufacturing, thereby enhancing their competitiveness and market responsiveness. Moreover, AI is widely applied in customer service, where AI-powered chatbots improve customer experience by accurately identifying needs and responding to inquiries in real time (Wang et al., 2022). Additionally, AI-driven business model innovation (Jorzik et al., 2023) and productivity enhancements (Czarnitzki et al., 2023) have provided strong momentum for corporate transformation, significantly improving firm performance (Wamba-Taguimdje et al., 2020; Mishra et al., 2022).

The impact of artificial intelligence (AI) on employment is equally significant. Extensive research indicates that the widespread adoption of AI technology has substantially reduced the demand for low-skilled workers nationwide (Xie et al., 2021) and has had a suppressing effect on workplace learning (Li et al., 2023). This technological transformation has led to structural shifts in labor market demand, with a sharp increase in recruitment for AI-related positions, while traditional non-AI jobs have faced a degree of displacement (Acemoglu et al., 2022). In the service sector, in particular, the extensive application of AI has fundamentally altered the nature of work tasks and the types of knowledge required (Li et al., 2024), placing higher demands on workers' skill levels and adaptability. While many studies have examined the impact of AI on the labor market, there remains a lack of systematic research on how AI development affects the employment quality of rural laborers. As an essential component of China's labor market, improving the employment quality of rural workers is crucial for rural revitalization and urban-rural integration. This study aims to address this research gap by conducting a systematic empirical analysis to uncover the mechanisms through which AI development influences rural labor employment quality. The findings will provide a theoretical foundation and practical guidance for policymaking, ultimately promoting high-quality employment for rural laborers in the AI era.

2.2. Research hypotheses

The development of Artificial Intelligence (AI) has the potential to enhance the employment quality of rural labor by providing more accessible learning and training opportunities. According to human capital theory, education improves individuals' levels of human capital, and the accumulation of human capital enhances workers' competitiveness in the labor market, thereby promoting employment transitions and improving employment quality (Hatch & Dyer, 2004; Little, 2003). However, traditional education models are constrained by issues such as geographic limitations, uneven distribution of teaching resources, and disparities in resource allocation (Gunter, 2025), making it difficult to meet the large-scale and diverse skill development needs of rural labor (Wu et al., 2008). The emergence of AI technologies has effectively broken through these limitations. Through online education platforms, intelligent learning systems, and mobile learning terminals, rural workers can access a wealth of educational resources anytime and anywhere — ranging from basic digital skills training to specialized courses in agricultural technology, e-commerce operations, logistics management, and more — greatly expanding their knowledge base and skill reserves. This convenient mode of learning not only reduces the cost of education but also improves learning efficiency and quality through personalized learning paths and intelligent tutoring. Furthermore, from the perspective of AI's inherent mechanisms of influence, the development of AI has profound impacts on employment structures. On one hand, AI automates and replaces certain repetitive and standardized tasks, leading to a task displacement effect; on the other hand, AI technologies also create numerous new tasks and jobs, resulting in a task creation effect (Acemoglu & Restrepo, 2018). In this process, workers with higher skill levels and stronger learning adaptability are better positioned to seize emerging job opportunities, while those lacking skill upgrades face higher employment risks. Thus, the development of AI intensifies skill-biased technological change, whereby technological progress preferentially increases demand for high-skilled labor and widens employment and income gaps between groups with different skill levels (Acemoglu, 2002; Acemoglu & Restrepo, 2018). Based on this, AI not only directly promotes the skill enhancement of rural labor by providing accessible learning opportunities but also indirectly raises skill requirements by reshaping the structure of the job market.

Against this backdrop, rural workers who proactively leverage AI-empowered education and training resources to systematically improve their skillsets can better meet the demands of emerging industries, such as smart agriculture, rural e-commerce, and digital logistics (Akkem et al., 2023; Ben Ayed and Hanana, 2021), thereby obtaining more stable and higher-quality employment opportunities. Moreover, AI also assists rural laborers through intelligent recommendation and precise job-matching mechanisms, helping them find positions better aligned with their skills and preferences, thus further improving employment compatibility and stability. The continuous improvement of skill levels will enable rural workers to access higher-paying and more stable employment opportunities, thereby enhancing overall employment quality in rural areas and promoting the sustainable development of rural economies. Based on this, we propose Hypothesis 1.

Hypothesis 1. The development of artificial intelligence can enhance the employment quality of rural labor.

3. Data and model

3.1. Data

This study conducts an empirical analysis based on a continuous panel dataset covering 30 provinces in China from 2008 to 2022, excluding the Tibet Autonomous Region to ensure data comparability.[1] The data used in this research primarily come from the China Rural Statistical Yearbook, China Statistical Yearbook, China Tourism Statistical Yearbook, and China Population and Employment Statistical Yearbook, as well as statistical yearbooks published by the National Bureau of Statistics and individual provinces. Additionally, for missing data, interpolation methods were applied to minimize potential biases caused by data gaps.

This study takes the provincial-level development of artificial intelligence (AI) as the core explanatory variable, measuring AI development across provinces based on the number of AI enterprises. To enhance the interpretability of the regression results, this indicator is standardized per 10,000 enterprises and denoted as AI1. Additionally, to further capture the penetration of AI technology in the industrial sector, we introduce industrial robot installation density as a supplementary variable, reflecting the level of industrial robot adoption and application across provinces. This variable is calculated using data from the International Federation of Robotics (IFR) on industrial robot installations across different industries in China, combined with employment distribution data from the China Labor Statistical Yearbook. Specifically, the industrial robot installation density for each province is estimated based on the proportion of industry employment within that province relative to the national total, weighted by the number of robots installed in each industry nationwide. To improve readability, this indicator is also standardized per 10,000 units and denoted as AI2. This dual-measurement approach provides a more comprehensive assessment of regional AI development and its impact on the labor market.

This study defines rural labor employment quality (Quality) as the dependent variable, measuring the extent to which rural labor shifts from agriculture to non-agricultural industries. Specifically, we use the proportion of rural workers employed in the primary sector relative to the total rural labor force to represent the employment structure. By examining changes in this ratio, we assess trends in employment quality over time. To quantify this, rural labor employment quality is calculated as the proportion of rural workers employed outside the primary sector. This indicator reflects the transition of rural labor from traditional agriculture to industries such as manufacturing and services, offering insights into rural industrial upgrading, labor force restructuring, and broader economic development. A higher level of rural labor employment quality indicates a greater share of workers moving into higher-productivity sectors, thereby accelerating rural economic transformation and urban-rural integration. As such, this metric is crucial for understanding changes in the rural labor market and regional economic development.

To comprehensively examine the factors influencing rural labor employment quality, this study carefully selects a series of control variables to minimize potential omitted variable bias and enhance the explanatory power and reliability of the model. First, disposable income (Income) is a key indicator of rural residents' economic conditions. Its growth not only reflects household financial strength but may also significantly influence employment choices and career development paths. Second, urbanization rate (Urbanization), a crucial measure of urbanization progress, is calculated as the proportion of the urban population to the total population at year-end. A

[1] This is mainly due to the severe data missing problem in Tibet.

higher urbanization rate is typically associated with the rapid development of non-agricultural industries, offering rural laborers more employment opportunities and facilitating their transition from agriculture to sectors such as manufacturing and services. Additionally, the Theil index (Theil), based on entropy theory, effectively measures income inequality and is particularly sensitive to changes in the urban-rural income gap. This metric provides insights into the dynamic shifts in income distribution during economic development and its potential impact on rural employment structures. To further analyze income distribution within rural areas, we incorporate the provincial-level rural Gini coefficient (Gini), which captures disparities in economic conditions and employment opportunities among different rural groups, offering a more detailed perspective on employment quality.

Beyond these key variables, this study includes additional controls to ensure the comprehensiveness and accuracy of the analysis. Population density (Population_density) reflects the spatial distribution of people within a region, shedding light on the effects of population concentration on employment opportunities and quality. Car ownership rate (Car), measured as the ratio of private car ownership to the total population, serves as a proxy for infrastructure development and economic activity, highlighting the potential influence of transportation accessibility and economic vitality on employment. Electricity generation (Electricity), a critical indicator of energy supply, reflects the foundational support for industrial and agricultural production, directly affecting firms' production efficiency and capacity to absorb labor. Lastly, fertilizer application intensity (Fertilizer), defined as the ratio of fertilizer usage to cultivated land area, represents agricultural intensification and its implications for labor absorption in rural employment. By incorporating these factors, this study aims to more accurately assess the mechanisms influencing rural labor employment quality and ensure the robustness of the regression analysis.

3.2. Model

To empirically examine the impact of artificial intelligence on rural labor employment quality, the following model is constructed.

$$Quality_{it} = \alpha + \beta^{*} AI_{it} + \lambda Controls_{it} + province_{i} + year_{t} + \varepsilon_{it} \tag{1}$$

In this model, Quality represents rural labor employment quality, AI denotes artificial intelligence, and Controls includes a set of control variables. Province and year represent province fixed effects and time fixed effects, respectively, while standard errors are clustered at the provincial level. The coefficient β is the parameter to be estimated, reflecting the impact of artificial intelligence on rural labor employment quality. A significantly positive β indicates that artificial intelligence has a positive effect on improving rural labor employment quality.

4. Regression results

4.1. Baseline regression

The baseline regression results are presented in Table 1. In Column (1), the coefficient of AI development level measured by the number of AI enterprises (AI1) is significantly positive at the 5 % significance level. Similarly, in Column (2), the coefficient of AI development level measured by industrial robot installation density (AI2) is also significantly positive at the same significance level. These findings indicate that the development of artificial intelligence, whether reflected in the growth of AI enterprises or the expansion of industrial robot applications, significantly enhances the quality of rural labor employment. Therefore, Hypothesis 1 is validated, confirming that AI development effectively promotes rural labor employment quality. This result not only supports the theoretical expectation that technological progress optimizes rural employment structures but also provides new empirical evidence

Table 1
Baseline regression.

	(1)	(2)
	Quality	Quality
AI1	0.018** (2.161)	
AI2		0.011** (2.346)
Income	−0.017* (−1.810)	−0.015* (−1.709)
Urbanization	−0.966 (−1.485)	−1.040 (−1.572)
Theil	0.643 (0.677)	0.452 (0.488)
Gini	0.190 (1.439)	0.202 (1.532)
Population_density	−0.002* (−1.886)	−0.002* (−1.971)
Car	3.693*** (3.467)	3.623*** (3.392)
Electricity	−0.011 (−0.663)	−0.011 (−0.695)
Fertilizer	1.062 (0.264)	0.935 (0.233)
_cons	1.471** (2.320)	1.541** (2.456)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	450	450
R2	0.841	0.841

Note: *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively, with t-values reported in parentheses.

for leveraging AI to drive rural economic development.

This finding positively confirms the role of artificial intelligence in broadening the channels for rural labor force skill training and enhancing their professional competitiveness. However, it is important to note that while AI development creates new opportunities for skill acquisition, it may also intensify skill polarization within the rural labor market. On the one hand, high-skilled workers or those who can quickly adapt to new technological requirements are more likely to leverage AI-driven training and transformation opportunities to improve their employment quality.

On the other hand, rural workers with lower skill levels and limited learning capacity may face greater employment risks due to their inability to effectively engage in skill upgrading, and may even be displaced by emerging technologies. Existing literature highlights that AI and automation technologies often exhibit strong skill biases and employment polarization effects — that is, middle- and low-skill jobs are more likely to be replaced by machines, while the demand for high-skill jobs increases (e.g., Acemoglu & Restrepo, 2020; Autor, 2015), thereby exacerbating labor market stratification and inequality.

4.2. Robustness tests

4.2.1. Double clustering

In the baseline regression analysis, we use province-level clustered standard errors to control for potential standard error bias caused by provincial-level heterogeneity, ensuring the robustness of the estimation results. Furthermore, in the robustness check, we further cluster the standard errors at both the province and year levels to account for potential time-related correlations, thereby enhancing the robustness and reliability of the results. The regression results, shown in Table 2, indicate that the coefficients of the core explanatory variables, AI1 (normalized index of AI enterprises) and AI2 (normalized index of industrial robot installation density), remain significantly positive, further confirming the positive impact of AI development on the improvement of rural labor employment quality. This result suggests that, whether using a single-clustered standard error or a more stringent double-clustered standard error setting, the conclusion that AI drives the shift of rural labor to higher-quality employment remains robust.

4.2.2. Lagged by one period

Considering that the impact of AI development on rural labor employment quality may not be immediate and could involve a certain lag effect, this study further employs the lagged one-period AI development level as the core explanatory variable and re-conducts the regression analysis to examine whether this lag effect affects the robustness of the conclusion. The regression results, shown in Table 3, indicate that the coefficients of the lagged one-period AI development levels (AI1 and AI2) remain significantly positive, suggesting that the positive impact of AI development on rural labor employment quality holds over time. This result implies that, even though the effect of AI development on rural labor employment quality may not be immediate and instead gradually manifests over time, its positive promotion effect remains robust, further strengthening the reliability of the research conclusions.

4.2.3. Changing the dependent variable

To further verify the robustness of the research conclusions, this study replaces the dependent variable and constructs a rural-urban labor employment quality comparison indicator (Quality2), which measures the relative employment quality gap between rural and urban labor by calculating the difference in per capita disposable income between rural and urban areas relative to urban per capita disposable income. This indicator offers a more intuitive reflection of the relative employment quality of rural labor compared to urban areas, thereby providing a deeper understanding of the impact mechanism of artificial intelligence. The regression results, shown in Table 4, indicate that even with the replacement of the dependent variable, the coefficients of AI development levels (AI1 and AI2) remain significantly positive, suggesting that the positive impact of AI on rural labor employment quality remains robust. This result further strengthens the reliability and generalizability of the research, indicating that AI development not only helps improve the

Table 2
Double clustering.

	(1)	(2)
	Quality	Quality
AI1	0.018* (1.967)	
AI2		0.011*** (3.274)
Income	−0.017* (−1.844)	−0.015 (−1.758)
Urbanization	−0.966 (−0.895)	−1.040 (−0.954)
Theil	0.643 (0.839)	0.452 (0.594)
Gini	0.190 (0.994)	0.202 (1.041)
Population_density	−0.002** (−2.188)	−0.002** (−2.315)
Car	3.693*** (3.904)	3.623*** (3.807)
Electricity	−0.011 (−1.188)	−0.011 (−1.224)
Fertilizer	1.062 (0.241)	0.935 (0.218)
_cons	1.471* (1.796)	1.541* (1.912)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	450	450
R2	0.841	0.841

Table 3
Lagged by one period.

	(1)	(2)
	Quality	Quality
L.AI1	0.022** (2.416)	
L.AI2		0.012*** (2.998)
Income	−0.015* (−1.851)	−0.014* (−1.817)
Urbanization	0.242 (0.439)	0.186 (0.339)
Theil	1.123* (1.709)	0.952 (1.512)
Gini	0.130 (0.954)	0.134 (0.988)
Population_density	−0.001 (−1.588)	−0.001* (−1.732)
Car	3.444*** (3.588)	3.386*** (3.531)
Electricity	−0.012 (−0.726)	−0.014 (−0.810)
Fertilizer	−2.852 (−1.138)	−2.722 (−1.052)
_cons	0.592 (1.145)	0.659 (1.296)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	420	420
R2	0.875	0.875

Table 4
Changing the dependent variable.

	(1)	(2)
	Quality2	Quality2
AI1	0.002** (2.376)	
AI2		0.002*** (4.091)
Income	0.001 (1.357)	0.001 (1.659)
Urbanization	−1.683*** (−13.834)	−1.693*** (−14.182)
Theil	−1.282*** (−8.336)	−1.311*** (−8.657)
Gini	0.010 (0.751)	0.011 (0.817)
Population_density	−0.000** (−2.596)	−0.000*** (−3.017)
Car	0.488*** (6.071)	0.477*** (5.976)
Electricity	−0.003 (−0.967)	−0.003 (−1.074)
Fertilizer	−0.018 (−0.052)	−0.009 (−0.028)
_cons	0.344*** (4.639)	0.354*** (4.872)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	450	450
R2	0.993	0.993

employment quality of rural labor but also narrows the employment quality gap between rural and urban areas, offering a new perspective for promoting urban-rural integration development.Table 5 shows the result.

4.2.4. Instrumental variable

The average number of robot installations in the United States, Germany, South Korea, and Japan. With the advancement of

Table 5
Instrumental variable.

	(1)	(2)
	Quality2	Quality2
AI1		0.122** (2.635)
IV	−185.350** (−2.120)	
Income	0.055 (1.100)	−0.028** (−2.679)
Urbanization	−11.067 (−1.150)	−0.057 (−0.046)
Theil	−1.046 (−0.070)	0.821 (0.380)
Gini	1.530* (1.960)	0.001 (0.003)
Population_density	−0.001 (−0.300)	−0.002** (−2.093)
Car	3.970 (0.710)	3.899*** (2.904)
Electricity	1.349** (2.430)	−0.146*** (−3.681)
Fertilizer	−14.494 (−1.010)	4.516 (0.823)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	390	390

economic globalization and the evolving landscape of international competition, major manufacturing countries have exhibited a high degree of convergence in the scale of their adoption of artificial intelligence technologies and equipment. The spillover effects generated by the application of industrial robots in the United States, Germany, South Korea, and Japan are correlated with China's industrial robot installation density, while satisfying the exogeneity requirement for an instrumental variable. The regression results for the first and second stages are presented in columns (1) and (2), respectively. The LM statistic is significant, indicating that there is no weak instrument problem. The coefficient in column (2) remains significantly positive, suggesting that the conclusion remains robust.

5. Mechanism analysis

The rapid development of artificial intelligence and digital technologies has provided rural labor with more convenient and efficient learning and training opportunities, enabling workers to enhance their skills through online courses, intelligent education platforms, and remote vocational training. To quantify this impact, we use the number of workers who have completed training (Trained) as an indicator of skill improvement among rural labor. The regression results, shown in Table 6, reveal that the coefficients of AI1 and AI2 are both significantly positive, indicating that the development of AI has significantly increased the output of labor after training. This finding suggests that AI has not only expanded the channels through which rural labor can access skill training but also effectively enhanced their professional competitiveness, thereby promoting the improvement of rural labor employment quality.

6. Heterogeneity analysis

6.1. Heterogeneity analysis of social security level

To explore the heterogeneity of social security levels (SS) in the impact of artificial intelligence development on rural labor employment quality, this study uses the ratio of social security and employment expenditures to general budget expenditures as an indicator to reflect its stabilizing effect on the labor market. Further, based on the median social security level in each province, the sample is divided into high social security level group (High SS) and low social security level group (Low SS). The results of the grouped regression shown in Table 7 indicate that in provinces with low social security levels, the impact of AI development on improving rural labor employment quality is more significant, while in provinces with high social security levels, this effect is relatively weaker. This result suggests that in regions with weaker social security systems, AI technology may more directly promote employment structure optimization and improve the employment quality of rural labor, whereas in regions with well-established social security systems, its impact on employment quality is relatively limited.

In provinces with lower social security levels, rural labor typically faces greater employment instability, and the social security system's safety net is weaker, making labor more reliant on market opportunities to improve their employment conditions. In this context, the development of AI can more directly drive the transfer of rural labor to higher-quality jobs, such as creating more high-skill employment opportunities through emerging industries like intelligent manufacturing and digital agriculture, thus significantly enhancing the employment quality of rural labor. In contrast, in provinces with higher social security levels, government-provided safety nets are more comprehensive, labor mobility is relatively lower, and reliance on new employment opportunities brought by technology is smaller. Therefore, the marginal effect of AI development on rural labor employment quality is weaker. This mechanism explains the more significant role of AI in improving rural labor employment quality in areas with low social security.

Table 6
Mechanism analysis.

	(1)	(2)
	Trained	Trained
AI1	11.540*** (3.437)	
AI2		9.594*** (4.232)
Income	−2.373 (−1.199)	−1.792 (−1.133)
Urbanization	601.867** (2.387)	556.519** (2.415)
Theil	118.797 (0.392)	−31.837 (−0.116)
Gini	−3.248 (−0.109)	−1.153 (−0.038)
Population_density	0.087 (0.748)	0.031 (0.370)
Car	−664.921** (−2.294)	−718.746** (−2.703)
Electricity	10.811 (0.806)	8.066 (0.690)
Fertilizer	424.233 (0.559)	575.734 (0.850)
_cons	−129.619 (−0.783)	−74.252 (−0.482)
Year_Fixed	YES	YES
Firm-Fixed	YES	YES
N	450	450
R2	0.961	0.964

Table 7
Heterogeneity analysis of social security level.

	(1)	(2)	(3)	(4)
	Quality	Quality	Quality	Quality
	High SS	Low SS	High SS	Low SS
AI1	−0.015 (−0.876)	0.037*** (4.103)		
AI2			−0.043* (−1.733)	0.014*** (3.263)
Income	−0.013 (−1.039)	−0.023** (−2.451)	−0.011 (−0.987)	−0.022** (−2.240)
Urbanization	−1.697 (−1.530)	−2.217* (−1.793)	−1.286 (−1.421)	−2.489* (−1.860)
Theil	−0.236 (−0.137)	2.202 (1.140)	0.450 (0.249)	1.888 (0.940)
Gini	−0.085 (−0.543)	0.167 (1.264)	−0.066 (−0.446)	0.223 (1.558)
Population_density	0.001 (0.487)	−0.003*** (−2.934)	0.001 (0.635)	−0.003*** (−3.078)
Car	2.489** (2.252)	4.808** (2.348)	2.553** (2.568)	4.872** (2.415)
Electricity	0.021 (0.700)	−0.080*** (−2.903)	0.017 (0.578)	−0.068** (−2.597)
Fertilizer	1.837 (0.457)	1.278 (0.260)	1.513 (0.414)	1.651 (0.313)
_cons	0.764 (1.041)	3.091*** (3.519)	0.437 (0.591)	3.212*** (3.563)
Year_Fixed	YES	YES	YES	YES
Firm-Fixed	YES	YES	YES	YES
N	224	223	224	223
R2	0.917	0.831	0.919	0.829
Empirical p-value	0.010**		0.000***	

6.2. Heterogeneity analysis of innovation efficiency

In the heterogeneity analysis of this paper, we focus on the impact of innovation efficiency on the relationship between artificial intelligence development and rural labor employment quality. Innovation efficiency (Efficiency) is defined as the input-output ratio of innovation activities, that is, the relative ability to maximize innovation output with a given level of innovation input. Specifically, if a region can achieve more output with less innovation input, it is considered to have high innovation efficiency.

For the grouping analysis, we divide the provinces into two categories based on the median innovation efficiency: high innovation efficiency provinces (High Efficiency) and low innovation efficiency provinces (Low Efficiency). The results in Table 8 show that in provinces with high innovation efficiency, the development of artificial intelligence significantly improves the employment quality of the rural labor force. This finding suggests that an efficient innovation system is better able to absorb and apply AI technologies, thereby promoting industrial upgrading and optimizing employment structures to create more high-quality job opportunities for rural workers. However, in provinces with low innovation efficiency, AI development exerts a significant negative impact on the employment quality of the rural labor force. To further investigate this seemingly counterintuitive result, this paper conducts additional analysis. First, from a measurement perspective, the innovation efficiency indicator used in this study is based on the input-output ratio of innovation, which can effectively reflect resource allocation efficiency, but may to some extent overlook the quality of innovation outputs or differences in input intensity across regions, thus presenting certain measurement limitations. Second, from a substantive mechanism perspective, regions with low innovation efficiency often suffer from insufficient technological absorption capacity, a traditional industrial structure, and a shortage of education and training resources. In the context of widespread AI diffusion, these regions lack the ability to transform new technologies into drivers of employment growth. Instead, AI development

Table 8
Heterogeneity analysis of innovation efficiency.

	(1)	(2)	(3)	(4)
	Quality	Quality	Quality	Quality
	High Efficiency	Low Efficiency	High Efficiency	Low Efficiency
AI1	0.017** (2.133)	−0.245* (−1.716)		
AI2			0.009* (1.791)	−0.039* (−2.039)
Income	−0.015* (−1.894)	−0.024*** (−3.081)	−0.013 (−1.600)	−0.028*** (−3.121)
Urbanization	−2.220*** (−2.861)	0.771 (0.874)	−2.341*** (−3.018)	0.574 (0.798)
Theil	−0.383 (−0.370)	2.008 (1.383)	−0.630 (−0.623)	2.040 (1.486)
Gini	0.274* (1.844)	0.110 (1.030)	0.302* (1.920)	0.153 (1.300)
Population_density	−0.003*** (−3.387)	0.002** (2.250)	−0.003*** (−3.553)	0.002** (2.155)
Car	3.374*** (4.075)	0.404 (0.144)	3.255*** (3.783)	0.923 (0.338)
Electricity	−0.006 (−0.315)	0.038 (0.836)	−0.005 (−0.280)	0.017 (0.471)
Fertilizer	−0.257 (−0.057)	−5.538 (−1.395)	−0.581 (−0.133)	−5.693 (−1.460)
_cons	2.561*** (3.749)	−0.668 (−0.930)	2.674*** (3.982)	−0.477 (−0.800)
Year_Fixed	YES	YES	YES	YES
Firm-Fixed	YES	YES	YES	YES
N	270	178	270	178
R2	0.919	0.794	0.919	0.793
Empirical p-value	0.000***		0.000***	

may exacerbate skill mismatches and structural employment conflicts, exposing rural workers — especially low-skilled workers — to a greater risk of marginalization. This reflects the potential of AI development to "widen inequalities" across regions (Acemoglu & Restrepo, 2018).

6.3. Heterogeneity analysis of geographic regions

In the heterogeneity analysis of the impact of artificial intelligence development on rural labor employment quality, this paper divides provinces into three regions based on their geographic location: Eastern region (East = 1), Central region (Middle = 1), and Western region (West = 1). According to the grouped regression results in Table 9, the positive effect of artificial intelligence development on rural labor employment quality is significant only in the Eastern region, while it is not significant in the Central and Western regions.

This heterogeneity in results may stem from significant regional differences in institutional environments and infrastructure development. First, the eastern region, with its well-developed digital infrastructure, efficient transportation and communication networks, and higher levels of public service provision, has substantially narrowed the "digital divide," providing strong support for the application and diffusion of AI technologies. Robust infrastructure not only reduces the cost of technology adoption but also accelerates the coverage and expansion of AI application scenarios — such as smart agriculture, rural e-commerce, and digital logistics — in rural areas, thereby effectively improving the employment quality of the rural labor force. In contrast, the central and western regions lag significantly behind in terms of digital infrastructure penetration, internet coverage, and overall informatization, with a more pronounced "digital divide" that limits the breadth and depth of AI technology application in rural areas. Moreover, these regions' industrial structures are still dominated by traditional agriculture and primary manufacturing, with sluggish development in emerging industries and the digital economy, failing to generate sufficient AI-driven new job opportunities for rural workers. This weakens the positive impact of AI development on employment quality. Second, the labor markets in the eastern region exhibit greater adaptability to technological change. Rural workers in these areas generally possess higher levels of education, and the skill training systems are more complete, enabling them to more rapidly acquire and apply new skills related to AI technologies. This higher level of human capital allows rural workers to better seize AI-enabled employment opportunities and transition toward higher value-added jobs. In contrast, the central and western regions suffer from lower labor force quality and limited access to skill training resources, making it more difficult for workers to adapt to the skill-biased technological change brought about by AI, and placing them at a relative disadvantage during employment structure adjustments. Finally, differences in policy environments and innovation ecosystems also contribute to the regional divergence. Governments in the eastern region provide stronger support for AI industry development, with a higher concentration of innovation resources, which helps foster a virtuous cycle of technology promotion and application. In contrast, the central and western regions lag behind in terms of policy guidance, talent attraction, and innovation system development, further constraining the positive role of AI in improving employment outcomes for the rural labor force.

6.4. Heterogeneity analysis of educational level

In the heterogeneity analysis, this paper uses the average years of education per capita to measure the overall education level of each province (Edu) and divides the provinces into high education level provinces (High Edu) and low education level provinces (Low Edu) based on the median of this indicator. According to the grouped regression results in Table 10, the positive effect of artificial intelligence development on rural labor employment quality is more significant in provinces with a higher education level.

This phenomenon is likely closely related to the impact of education level on the labor force's skill structure and adaptability. Regions with a higher education level typically have better educational resources and more comprehensive education systems, providing the labor force with more systematic artificial intelligence-related knowledge and skills training. In these regions, the labor force can adapt more quickly to new job demands brought about by employment structure adjustments due to artificial intelligence, thereby significantly improving employment quality. In contrast, low education level regions may face greater challenges in effectively implementing artificial intelligence education due to a lack of educational resources, insufficient teaching staff, and outdated curricula. This results in greater difficulties for the labor force in improving skills and adapting to new employment opportunities. Therefore, education level plays a crucial moderating role in the relationship between artificial intelligence development and rural labor employment quality. This suggests that policymakers should prioritize the balanced distribution of educational resources to reduce regional education disparities and promote the overall improvement of rural labor employment quality through artificial intelligence technology.

7. Conclusion

This empirical analysis reveals that the development of artificial intelligence has a significant positive impact on the employment quality of rural labor, and this conclusion holds under various robustness checks. Mechanism analysis shows that artificial intelligence enhances the skill levels of rural labor, thereby improving their employment competitiveness and driving the improvement of employment quality. Additionally, heterogeneity analysis finds that the effect of artificial intelligence on rural labor employment quality varies significantly across different regions and conditions, particularly being more pronounced in provinces with lower social security levels, higher innovation efficiency, eastern regions, and higher education levels.

To fully leverage the potential of artificial intelligence in enhancing rural labor employment quality and promoting rural revitalization and urban-rural integration, the government should adopt targeted policies from multiple dimensions. First, greater

Table 9
Heterogeneity analysis of geographic regions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fee	Fee	Fee	Fee	Fee	Fee
	East = 1	West = 1	Middle = 1	East = 1	West = 1	Middle = 1
AI1	0.043** (2.570)	−0.021 (−0.546)	−0.027 (−0.480)			
AI2				0.023*** (3.899)	−0.011 (−0.195)	0.009 (0.261)
Income	−0.018* (−2.016)	0.015 (0.960)	0.010 (0.830)	−0.016 (−1.746)	0.012 (0.580)	0.007 (0.518)
Urbanization	−2.597 (−1.768)	−1.278 (−1.758)	−0.506 (−0.580)	−2.763 (−1.682)	−1.283* (−1.829)	−0.247 (−0.231)
Theil	−2.354 (−0.732)	0.130 (0.203)	2.946** (2.862)	−3.636 (−1.175)	0.199 (0.262)	3.038** (2.939)
Gini	0.155 (0.475)	0.168 (0.759)	0.086 (0.662)	0.185 (0.592)	0.157 (0.703)	0.076 (0.538)
Population_density	−0.003** (−2.718)	−0.010*** (−6.458)	0.001 (0.329)	−0.003** (−2.927)	−0.010*** (−5.629)	−0.000 (−0.032)
Car	5.752** (2.586)	1.012 (1.083)	6.842*** (3.550)	5.515** (2.595)	1.105 (0.856)	6.623** (2.873)
Electricity	−0.128** (−2.339)	−0.052** (−2.501)	−0.021 (−0.513)	−0.131*** (−3.188)	−0.052** (−2.429)	−0.025 (−0.605)
Fertilizer	1.668 (0.306)	3.330 (0.643)	−0.173 (−0.121)	1.918 (0.324)	3.585 (0.758)	1.612 (0.420)
_cons	4.467*** (3.632)	1.787*** (3.610)	−0.889 (−1.227)	4.648*** (3.663)	1.783*** (3.457)	−0.703 (−0.748)
Year_Fixed	YES	YES	YES	YES	YES	YES
Firm-Fixed	YES	YES	YES	YES	YES	YES
N	165	165	120	165	165	120
R2	0.845	0.887	0.947	0.845	0.887	0.947

Table 10
Heterogeneity analysis of educational level.

	(1)	(2)	(3)	(4)
	Fee	Fee	Fee	Fee
	High Edu	Low Edu	High Edu	Low Edu
AI1	0.025** (2.552)	−0.076 (−1.402)		
AI2			0.015*** (2.791)	−0.050** (−2.246)
Income	−0.016 (−1.679)	0.005 (0.424)	−0.014 (−1.540)	−0.001 (−0.156)
Urbanization	−1.448 (−1.679)	−1.282 (−0.742)	−1.606* (−1.773)	−0.906 (−0.523)
Theil	0.879 (0.623)	0.976 (1.614)	0.570 (0.422)	1.675*** (3.472)
Gini	0.355 (1.339)	0.061 (0.441)	0.394 (1.504)	0.071 (0.512)
Population_density	−0.002** (−2.218)	−0.001 (−0.444)	−0.002** (−2.360)	0.000 (0.077)
Car	4.478*** (3.290)	1.163 (1.304)	4.339*** (3.161)	1.446* (1.725)
Electricity	−0.025 (−0.938)	−0.017 (−0.936)	−0.023 (−0.945)	−0.019 (−1.001)
Fertilizer	1.766 (0.310)	−3.203 (−0.702)	1.384 (0.250)	−3.957 (−1.130)
_cons	2.029** (2.323)	0.860 (0.852)	2.177** (2.503)	0.532 (0.458)
Year_Fixed	YES	YES	YES	YES
Firm-Fixed	YES	YES	YES	YES
N	270	175	270	175
R2	0.837	0.961	0.837	0.962
Empirical p-value	0.000***		0.000***	

investment should be made in rural labor skills training, utilizing artificial intelligence technologies to build convenient and efficient learning platforms to help improve their skill levels and better meet the demands of emerging industries. Second, efforts should be made to promote the upgrading of industrial structures in rural areas, encouraging the development of emerging industries such as smart agriculture and rural e-commerce to create more high-quality job opportunities for rural labor. Furthermore, the government must improve the social security system, especially in regions with low social security levels, by increasing social security and employment expenditures to enhance employment stability for rural labor and mitigate the employment structural adjustment pressures brought about by the development of artificial intelligence. At the same time, regional coordinated development should be promoted, strengthening cooperation between the central and western regions and the eastern regions, facilitating the flow of technology, capital, and talent, and narrowing the development gap between regions. Finally, attention should be given to the balanced distribution of educational resources, increasing support for educationally disadvantaged areas, improving the overall education level of rural labor, and enhancing their adaptability to artificial intelligence technology, thus reducing regional educational disparities and promoting the overall improvement of rural labor employment quality.

Author statement

Zhe Li: Conceptualization; Data Interpretation; Manuscript Revision & Editing; Formal analysis; Writing - Original Draft. Minggang Liu: Policy Implications Analysis; Methodology; Software; Investigation; Formal analysis. Lu Wang*: Policy Implications Analysis; Manuscript Revision & Editing; Language & grammar proofreading.

Declaration of interest

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature, 40*(1), 7–72.

Acemoglu, D., Autor, D., Hazell, J., et al. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics, 40*(S1), S293–S340.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *The American Economic Review, 108*(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188–2244.

Akkem, Y., Biswas, S. K., & Varanasi, A. (2023). Smart farming using artificial intelligence: A review. *Engineering Applications of Artificial Intelligence, 120*, Article 105899.

Al-Raeei, M. (2025). The smart future for sustainable development: Artificial intelligence solutions for sustainable urbanization. *Sustainable Development, 33*(1), 508–517.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives, 29*(3), 3–30.

Ben Ayed, R., & Hanana, M. (2021). Artificial intelligence to improve the food and agriculture sector. *Journal of Food Quality, 2021*(1), Article 5584754.

Chen, N., Chen, J., & Ko, P. C. (2021). Active aging in the countryside: Space, place and the performance of leisure–work lifestyles in contemporary rural China. *Population, Space and Place, 27*(6), Article e2429.

Chen, B., & Tan, D. (2023). Industrial robots and the employment quality of migrant workers in the manufacturing industry. *Sustainability, 15*(10), 7998.

Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188–205.

Gao, Y., Liu, S., & Yang, L. (2025). Artificial intelligence and innovation capability: A dynamic capabilities perspective. *International Review of Economics & Finance*, Article 103923.

Gunter, A. (2025). The geography of distance education: spatial disparities, accessibility, and impact across place. *South African Geographical Journal*, 1–19.

Hatch, N. W., & Dyer, J. H. (2004). Human capital and learning as a source of sustainable competitive advantage. *Strategic Management Journal, 25*(12), 1155–1178.

Huang, Z., & Cheng, X. (2023). Environmental regulation and rural migrant workers' job quality: Evidence from China migrants dynamic surveys. *Economic Analysis and Policy, 78*, 845–858.

Huang, C. C., Jin, H., Zhang, J., et al. (2020). The effects of an innovative e-commerce poverty alleviation platform on Chinese rural laborer skills development and family well-being. *Children and Youth Services Review, 116*, Article 105189.

Huang, Q., Zheng, X., & Wang, R. (2022). The impact of the accessibility of transportation infrastructure on the non-farm employment choices of rural laborers: Empirical analysis based on China's micro data. *Land, 11*(6), 896.

Jin, C. X., & Yu, J. Q. (2025). Does the popularization of artificial intelligence increase the risk of corporate digital responsibility? *Finance Research Letters*, Article 107375.

Jorzik, P., Yigit, A., Kanbach, D. K., et al. (2023). Artificial intelligence-enabled business model innovation: Competencies and roles of top management. *IEEE Transactions on Engineering Management, 71*, 7044–7056.

Kulkov, I. (2021). The role of artificial intelligence in business transformation: A case of pharmaceutical companies. *Technology in Society, 66*, Article 101629.

Lan, S., & Cui, M. (2024). Enterprise digital transformation and employment: Spillover effect within supply chains. *Finance Research Letters, 67*, Article 105928.

Li, W., Qin, X., Yam, K. C., et al. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management, 104*, Article 104935.

Li, C., Zhang, Y., Niu, X., et al. (2023). Does artificial intelligence promote or inhibit on-the-job learning? Human reactions to AI at work. *Systems, 11*(3), 114.

Little, A. W. (2003). Motivating learning and the development of human capital. *Compare: A Journal of Comparative and International Education, 33*(4), 437–452.

Liu, W., Xu, Y., Fan, D., et al. (2021). Alleviating corporate environmental pollution threats toward public health and safety: the role of smart city and artificial intelligence. *Safety Science, 143*, Article 105433.

Lyu, W., & Liu, J. (2021). Artificial intelligence and emerging digital technologies in the energy sector. *Applied energy, 303*, Article 117615.

Mannuru, N. R., Shahriar, S., Teel, Z. A., et al. (2023). Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. *Information Development*, Article 02666669231200628.

Mao, B., Feng, T., Su, H., et al. (2023). A novel approach to employment quality evaluation of college graduates with probabilistic linguistic MAGDM. *Journal of Intelligent and Fuzzy Systems, 45*(3), 3875–3886.

Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science, 50*(6), 1176–1197.

Qin, H. (2010). Rural-to-urban labor migration, household livelihoods, and the rural environment in chongqing municipality, southwest China. *Human Ecology, 38*, 675–690.

Qu, G., & Jing, H. (2025). Is new technology always good? Artificial intelligence and corporate tax avoidance: Evidence from China. *International Review of Economics & Finance, 98*, Article 103949.

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research, 116*, 68–74.

Su, C. W., Yuan, X., Umar, M., et al. (2022). Does technological innovation bring destruction or creation to the labor market? *Technology in Society, 68*, Article 101905.

Tan, J., Chang, S., Zheng, Y., et al. (2025). Effects of artificial intelligence in the modern business: Client artificial intelligence application and audit quality. *International Review of Financial Analysis*, Article 104271.

Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. *Academy of Management Perspectives, 35*(4), 642–659.

Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., et al. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924.

Wang, X., Lin, X., & Shao, B. (2022). How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management, 66*, Article 102535.

Wright, C. F., & Clibborn, S. (2019). Migrant labour and low-quality work: A persistent relationship. *Journal of Industrial Relations, 61*(2), 157–175.

Wu, B., Chen, H., & Shi, Y. (2025a). Influence of artificial intelligence development on supply chain diversification. *Finance Research Letters, 78*, Article 107210.

Wu, J., Guo, C., Liu, X., et al. (2025b). Policy-driven employment structure transformation: The role of innovation and education investment. *International Review of Economics & Finance*, Article 103930.

Wu, F., Zhang, D., & Zhang, J. (2008). Unequal education, poverty and low growth—A theoretical framework for rural education of China. *Economics of Education Review, 27*(3), 308–318.

Xie, M., Ding, L., Xia, Y., et al. (2021). Does artificial intelligence affect the pattern of skill demand? Evidence from Chinese manufacturing firms. *Economic Modelling, 96*, 295–309.

Xie, F., Xu, D., Liu, S., et al. (2015). The influence of gender and other characteristics on rural laborers' employment patterns in the mountainous and upland areas of sichuan, China. *Journal of Mountain Science, 12*, 769–782.

Yang, C. H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy, 51*(6), Article 104536.

Yin, H., Yin, X., & Wen, F. (2025). Artificial intelligence and climate risk: A double machine learning approach. *International Review of Financial Analysis*, Article 104169.

Yunxia, W., Neng, H., & Yechi, M. (2023). The effect of digital economy development on labor employment: Empirical evidence from listed companies in China. *Journal of Global Information Management, 31*(6), 1–27.

Zhao, N., & Chen, W. (2025). How can artificial intelligence adoption enhance manufacturing firms' green management capability? *Finance Research Letters*, Article 107475.

Zheng, S., Wu, G., Zhao, J., et al. (2022). Impact of the COVID-19 epidemic anxiety on college students' employment confidence and employment situation perception in China. *Frontiers in Psychology, 13*, Article 980634.

Zhou, X., Li, G., Wang, Q., et al. (2025). Artificial intelligence, corporate information governance and ESG performance: Quasi-experimental evidence from China. *International Review of Financial Analysis, 102*, Article 104087.