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Artificial Intelligence and Labour Productivity by Skill Stratification: Empirical Evidence from Chinese Municipal Provinces, 2000–2020

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Abstract

Artificial intelligence (AI) is reshaping labor productivity by enhancing production efficiency, transforming work patterns, and redefining labor market dynamics. However, the full potential of AI remains constrained by varying adoption rates and a persistent mismatch between technological advancements and workforce skill levels. Consequently, many regions have yet to realize substantial productivity gains. This study investigates the impact of AI on the productivity of high, medium, and low-skilled workers in four municipal provinces in China from 2000 to 2020. Employing Ordinary Least Squares (OLS) regression on a 21-year panel dataset, the research examines how three proxies of AI adoption, patents, research investments, and infrastructure development affect labor productivity across different skill tiers. The findings reveal significant heterogeneity: AI patents and research investments disproportionately benefit high-skilled workers. At the same time, infrastructure-based AI development is crucial to enhancing productivity for medium- and low-skilled workers. These results underscore the importance of skill-aligned AI strategies to ensure inclusive productivity growth. This study makes an urgent contribution to the discourse on digital transformation and labor market adaptation by offering evidence-based insights for policymakers. It emphasizes the need for coordinated efforts among research institutions, industries, and local governments to promote continuous learning and upskilling. Such collaboration is vital to equip the workforce with capabilities that align with emerging AI technologies, enhancing resilience, competitiveness, and adaptability in rapid technological change.

Keywords:

artificial intelligence; China; labour productivity; panel data; skill stratification.

Introduction

Artificial intelligence (AI) has become a key driver of China's economic development. AI has enhanced production efficiency, optimised resource allocation, facilitated industrial upgrading and innovation, and injected fresh impetus into China's economic growth. According to data released by the Ministry of Industry and Information Technology, the number of registered users of China's large-scale generative AI service model has surpassed 600 million, highlighting the country's rapid progress in the AI field. To capitalise on this wave of technological change, many nations have introduced AI-related development strategies. From a macro perspective on industrial revolutions, Germany has embraced a strategy aligned with Industry 4.0, aimed at improving the intelligence and global competitiveness of its manufacturing sector (Dauth et al., 2017). Similarly, Canada was the first country to develop an explicit AI strategy, implementing the Pan-Canadian AI Strategy in 2017, which invested CAD 125 million to nurture Canada's top AI talent (Oschinski & Wyonch,2017). For China, AI development presents a major opportunity, essential for addressing the challenges of an ageing population and achieving sustainable future growth. AI development has now been elevated to a national strategic priority in China (Acharya & Arnold, 2019). However, despite the increased investment, AI advancements have not yet resulted in significant productivity gains across businesses and regions.

Despite China's aggressive investment in AI infrastructure and research, empirical evidence on how these investments translate into productivity gains across workers of different skill levels remains scarce, particularly at the municipal level. Similarly, research on the skill stratification of AI's impact on labour productivity remains limited. Only a handful of studies have examined the effect of AI on China, but these have focused on industry-level and economic sector data. To date, there is no specific research examining the effects of AI on labour productivity using panel data from Chinese provinces, with a focus on occupational skills (Yang & Yao, 2008). Therefore, this study addresses this gap by asking: How do different proxies of AI investment affect labour productivity across skill stratification in China's municipal provinces? We also attempt to further contribute to the literature by investigating the impact of AI on labour productivity in Chinese municipalities by using three key proxy indicators: information transmission, social fixed asset investment in computer services and software industries, the number of AI patent applications, and research investment intensity.

The findings of this study can provide valuable insights for policymakers, industry leaders, and educational institutions in China by identifying which proxies have a significant effect in influencing China's labour productivity in municipal provinces. Our results potentially inform stakeholders who can better allocate resources and design targeted policies to enhance productivity. For instance, if information transmission and software-related investments are found to have a strong positive correlation with labour productivity, local governments can prioritise digital infrastructure and support for tech startups in these areas. Conversely, if AI patent applications or research investments show limited or no impact, it may indicate a need to bridge the gap between innovation and practical application through better technology transfer mechanisms, workforce upskilling, and industry-academia collaboration. Ultimately, the study's evidence-based approach can guide strategic investments, promote balanced regional development, and help shape a future-ready workforce in alignment with China's broader digital and economic transformation goals.

Literature Review

Theoretically, the relationship between technological progress and productivity is not new and was already observed during the first wave of digitalization. In the 1980s, Nobel Prize winner Robert Solow famously claimed that "computers are everywhere except in statistics" (David, 1990). According to Romer's (1990) model of technological change, the adoption of AI leads to productivity changes across industries. Technological developments also affect factors of production, such as labour, to which firms will allocate optimally and directly or indirectly affect the share of employment and output value of each industry, i.e., changes in industrial structure. According to Romer (1990), AI can cause changes in the allocation of factors of production between industries, thus affecting labour productivity. This theory of technological progress also explains that the combined input productivity of all factors is called TFP, and an increase in TFP indicates that it is possible to produce the same amount of goods with the same resources or with fewer resources.

After 1985, Romer (1990) and Lucas (1988) began to criticise the shortcomings of neoclassical economic growth theory based on Schultz's theory of human capital. They no longer confined their inquiry to labour and capital but tried to analyse long-term economic development from a new perspective. In the process, the theory of endogenous economic growth was gradually developed. Scholars began to redefine labour as an investment in human capital, i.e., labour inputs include both the demographic size of the workforce and the quality of the workforce, with the quality of the workforce (knowledge, skills) often being more important. The endogenous growth theory also argues that productivity improvements can be tied directly to faster innovation and more investments in human capital from governments and private sector institutions.

Nonetheless, there is a new body of research on the impact of AI on labour productivity. The literature review process shows that there are many relevant research perspectives, and no unified conclusions have been made (Chen et al., 2020; Damioli et al., 2021). AI technology is still in its formative years at the 'weak AI' stage, and there is a range of academic opinions on its net impact on the labour market, but no consensus has been reached. Although AI technology is seen as the main force in the new wave of technological progress, however, AI is far different from previous technological revolutions because its penetration into social life and its impact on the economy cannot be compared to previous technological revolutions. As a result, the employment structure in the market has not reached a balance in terms of demand and supply of labour, which has created a mismatch between the needs of human resources to adapt to more complex technology.

AI has significantly influenced labour productivity across various industries. Recent studies have shown that AI technologies, including generative AI and robotics, have started to exert a noticeable effect on the economy. For instance, a study by Damioli et. al (2021) found that AI patent applications generate a positive effect on companies' labour productivity, particularly in small and medium-sized enterprises (SMEs) and service industries. This suggests that the ability to quickly readjust and introduce AI-based applications in the production process is a crucial determinant of the observed impact of AI. Moreover, generative AI has emerged as an important workplace technology, with surveys indicating that a significant portion of workers use AI tools regularly. According to Bick, Blandin, and Deming (2025), generative AI is not just an occasional tool but an integral part of work routines for many users. Their research shows that AI-assisted work hours account for a substantial share of total work hours, leading to meaningful time savings and productivity gains. The transformative nature of AI is also evident in the rising trends of AI technological developments, particularly in telecommunications, software services, and electronics manufacturing sectors. These advancements have the potential to disrupt almost all industries and businesses on a global scale, echoing the profound social and economic changes brought about by past general-purpose technologies (Ernst, 2022).

Despite AI having significantly influenced labour productivity across various skill stratifications, the literature found that there are still limited studies that have emerged to discuss the impact of AI on labour productivity by skill composition. With regards the empirical evidence of AI in influencing high-skilled labour productivity, Somers, (2023) showed that AI can boost the productivity of highly skilled workers by nearly 40% when used within the boundary of its capabilities. This improvement is particularly evident in tasks that require cognitive effort and expert judgment. However, when AI is used outside its capabilities, worker performance can drop by an average of 19 percentage points. For medium-skilled workers, AI technologies have shown to enhance productivity by automating routine tasks and allowing workers to focus on more complex activities. According to Bick, Blandin, and Deming (2025), generative AI-assisted work hours account for a substantial share of total work hours, leading to meaningful time savings and productivity gains. Their research indicates that AI-assisted work can improve overall productivity by an average of 14%, with medium-skilled workers benefiting significantly from these advancements.

For low-skilled workers, the literature reveals that the impact of AI on low-skilled workers is uncertain and depends on the scope of the job and industry needs. AI can increase productivity by automating repetitive tasks and allowing workers to focus on more complex and rewarding activities (Reddy, 2024). The productivity of medium-skilled workers can be improved through AI-driven training programs, making them more adaptable to changing job requirements. Conversely, low-skilled workers are most vulnerable to job displacement due to automation. Meanwhile, a study by Selesi-Aina et. al (2024) indicated that up to 800 million jobs could be automated by 2030, with low-skilled workers most affected. The transformative nature of AI is also evident in the increasing trend of AI technology, particularly in the telecommunications, software services, and electronics manufacturing sectors.

In conclusion, most studies in the early stages of the field of AI still focus on qualitative studies, and there is a lack of numerical empirical research that examines the specific effects of AI on labour productivity. This may be due to the lack of labour market data in China to support micro-studies on labour productivity effects. Another reason is the difficulty of studying the range of AI applications in China now, especially the uneven scope and level of use of automated and computerised equipment in manufacturing firms, and the lack of a practical basis for representative studies. Therefore, as the national focus on AI expands and the scope of application expands, more data is needed at the industry or sector, national or regional level to strengthen the empirical research database in this field.

Method

Data and Scope of Study

Taking into consideration the availability of AI data, to examine the impact of AI on labour productivity by labour stratification, this study focuses on municipal provinces during the period of 2000 to 2020 (T=21). The municipal province in this study consists of Beijing, Tianjin, Shanghai, Chongqing. Our study focuses on municipal province because they serve as key engines of economic growth, technological innovation, and policy experimentation in China. Municipalities such as Beijing, Shanghai, Tianjin, and Chongqing are directly governed by the central government and often receive preferential policy support, infrastructure investment, and research funding. These regions are typically home to clusters of high-value industries, leading universities, and leading research institutions, making them prime sites for observing the diffusion and impact of advanced technologies such as artificial intelligence. In addition, municipal regions often act as early adopters of national policies, such as those under Made in China 2025 and digital economy initiatives, making them important case studies for assessing how such policies affect labour productivity and skill allocation (Yang, 2022).

This study employs Ordinary Least Squares (OLS) estimators with robust standard errors to compare the effects of AI on labour productivity across different skill levels in China's municipal provinces. OLS estimators with robust standard errors are employed in this study to compare the effects of AI on labour productivity by provinces and labour skills in China (Huber, 1992). This technique effectively deals with small problems of normality and heteroscedasticity, with some observations showing many residuals, leverage, or effects, as well as dealing with the effects of sequence correlation on standard errors that may be involved. With robust options, the coefficients of point estimation are preserved, but the standard error accounts for heterogeneity and lack of normality, as well as the fact that observations within regions are usually not independent (Huber, 1992; Yunus & Zouya,2024).

Empirical Model

This study follows the basic methodology of Yunus and Zouya (2024) to construct a model assessing the impact of AI on labour productivity by skill levels. Our model differs from theirs by incorporating three distinct AI proxies to evaluate the effects of AI on labour productivity across high-skilled, medium-skilled, and low-skilled occupations in municipal provinces in China. The basic model for the three different occupational skill levels is presented below:

$$lnLP\_HS_{it=}\alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4 \boldsymbol{ln}\, TRAIN_{\ it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \quad (1)$$

$$lnLP\_MS_{it=}\alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4 \boldsymbol{ln}\, TRAIN_{\ it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \quad (2)$$

$$lnLP\_LS_{it=}\alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4 \boldsymbol{ln}\, TRAIN_{\ it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \quad (3)$$

Where, i represents the municipal provinces, and t is the time index. Labour productivity is measured as value-added per worker for high-skilled occupations (LP_HS), medium-skilled occupations (LP_MS), and low-skilled occupations (LP_LS). The K/L ratio, representing capital per worker (or capital intensity), is approximated by gross investments in fixed capital per worker.AI is measured using three proxies: social fixed asset investment in information transmission, computer services, and software industries (SFA_INV_ITCS) (Borland & Coelli, 2017); investment intensity in scientific research funds (INV_SRF) (Zouya & Yunus, 2024); and AI patent applications (AI_PATENT) (Damioli et al., 2021). QEDU refers to education expenditure as a share of total expenditure (Yunus et.al, 2015). TRAIN represents the cost of training per employee (Yunus, 2023; Mohamad & Yunus, 2024). Yit represents other factors typically considered when discussing labour productivity, such as: RD refers to research and development investment. GDP refers to the gross regional product. TRADE, which is the degree of trade openness, calculated as the proportion of total imports and exports to GDP (Zouya& Yunus, 2024). FDI refers to foreign direct investment as a percentage of GDP (Lai & Yunus, 2024; Yunus & Zouya,2024; Yunus &Abdullah, 2022a; 2022b). εit is the error term, which captures province-specific productivity shocks that vary over time.

Results and Discussion

Correlation Results

In this study, correlation analyses were performed as a preliminary step to assess the validity of the variables before analysing the OLS estimation results. Specifically, we conducted validity tests on the variables used as the main determinants of labour productivity. We employed correlation analysis due to the lack of studies that performed validity tests in the context of labour productivity (Yunus & Abdullah, 2022b). Consequently, the validity of the proxies was assessed based on their correlation values.

If the correlation coefficient between independent variables shows a positive value, it is interpreted as an indicator of a strong relationship with the dependent variable (Yunus, 2023). As shown in Table 1, the positive coefficients obtained from this correlation analysis provide strong evidence that almost all variables used in this study can be considered as influential factors affecting labour productivity in the overall labour productivity of China. Furthermore, the observed positive correlations between labour productivity and independent variables also indicate a clear trend in most labour productivity for all skill levels of labour in China who have benefited from exploiting the opportunities of new levels of automation brought by AI technology in their jobs. The results of the correlation analysis in this study provide a more accurate picture than individual data points.

In relation to the negative correlation found in this study between the variable number of AI patents and social fixed asset investment in the information transmission, computer services and software industries in China, this may suggest that increased patenting activity in artificial intelligence does not necessarily align with or drive higher levels of fixed asset investment in these sectors. This could indicate a possible disconnect between the innovation occurring in AI patents and capital investment due to factors such as uncertainty in the commercial viability of AI technologies. Thus, a possible focus on intangible assets (such as software or algorithms) rather than physical infrastructure, or a preference for investing in research and development over fixed assets.

Table 1. Correlation Results for Labour Productivity for All Occupational Skills in Municipal Provinces, 2000-2020

Variables	LP	K/L	SFA_INV_ITCS	INV_SRF	AI_PATENT	GDP	TRAIN	QEDU	RD	FDI	TRADE
LP	1.000	0.523	0.618	0.472	0.619	0.762	0.652	0.681	0.409	0.702	0.511
K/L	0.453	1.000	0.471	0.417	0.761	0.423	0.576	0.720	0.517	0.613	0.421
SFA_INV_ITCS	0.621	-0.562	1.000	-0.512	-0.410	0.525	0.611	0.548	-0.612	0.619	0.591
INV_SRF	0.678	-0.601	0.423	1.000	-0.632	0.619	0.512	0.423	0.518	-0.590	0.743
AI_PATENT	0.572	0.162	0.224	-0.357	1.000	0.424	0.492	0.428	-0.643	0.423	0.493
GDP	0.612	0.432	0.564	0.717	0.648	1.000	0.527	0.700	0.588	0.721	0.590
TRAIN	0.544	0.789	0.713	0.642	0.711	0.562	1.000	0.608	0.612	0.612	-0.612
QEDU	0.654	0.678	0.583	-0.751	0.631	0.643	0.713	1.000	0.782	0.603	0.436
RD	0.621	0.652	0.572	0.643	0.704	0.542	0.654	0.703	1.000	0.571	0.547
FDI	0.511	0.521	0.235	0.665	0.731	-0.335	0.541	0.412	0.614	1.0000	0.618
TRADE	0.352	-0.342	-0.234	0.619	0.350	0.508	0.727	0.714	0.654	0.582	1.000

The results of this study may reflect a structural imbalance in which rapid innovation outweighs the willingness or willingness of firms to invest in supporting industries or infrastructure needed to effectively implement AI technologies. Alternatively, the negative relationship found in this study could indicate inefficiencies in policy implementation or market coordination, where the generation of new AI technologies is not matched by corresponding growth in the industries expected to adopt and benefit from them. Notably, all correlation coefficients of all variables are less than 0.8, indicating the absence of multicollinearity in the study model (Gujarati, 2021).

Regression Results

The results in Table 2 present the regression analysis of the impact of AI on labour productivity across different occupational skill levels in municipal provinces in China. The findings indicate that social fixed asset investment in information transmission, computer services, and software industries (SFA_INV_ITCS) has a significant positive effect on the productivity of medium- and low-skilled workers, increasing by 29.4% and 21.0%, respectively. Conversely, it does not statistically influence the productivity of high-skilled workers. This result suggests that there remains a gap between the rapid advancement of AI and its practical application in AI-related industries within municipalities under the Central Government (Hou & Zhu, 2018). One contributing factor is the mismatch between the government's substantial investment in AI and the demand for highly skilled personnel, as the education gap has led to a shortage of highly skilled workers in various provinces (Jiang & Zou, 2018).

Table 2. Labour Productivity by Occupational Skills in Municipal Provinces, 2000-2020

Labour Productivity	**High-Skilled Occupation (*LP_HS*) (1)**		**Middle-Skilled Occupation (*LP_MS*) (2)**		**Low-Skilled Occupation (*LP_LS*) (3)**	
	coeff.	**s.e**	**coeff.**	**s.e**	**coeff.**	**s.e**
K/L	0.234	(0.021) ***	0.125	(0.029) *	-0.154	(0.124) **
SFA_INV_ITCS	-0.122	(0.054)	0.294	(0.021) *	0.210	(0.048) **
INV_SRF	0.522	(0.067) **	0.190	(0.080)	0.392	(0.063) *
AI_PATENT	0.252	(0.076) ***	0.006	(0.036)	0.445	(0.075) ***
Other Control Variables						
GDP	0.480	(0.076)	0.589	(0.070) *	0.703	(0.006) *
TRAIN	0.162	(0.165)	-0.298	(0.079) ***	-0.349	(0.162) ***
QEDU	0.545	(0.210) *	0.160	(0.101)	0.576	(0.006) **
RD	-0.093	(0.072) ***	-0.479	(0.082)	-0.189	(0.068)
TRADE	0.252	(0.057) ***	-0.013	(0.027)	0.170	(0.056) ***
FDI	0.039	(0.040) ***	0.023	(0.019)	0.226	(0.039) ***
Number of obs	84		84		84	
R-squared	0.837		0.825		0.813	
Prob > F	0.000		0.000		0.000	

Entries in parentheses are robust standard errors, and all variables are transformed into natural log. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Our results indicate that investment intensity in scientific research and the application of AI patents have a positive and significant impact on both high- and low-skilled workers in municipal provinces and do not significantly affect the productivity of middle-skilled workers. This may be attributed to the nature of middle-skilled jobs, which often involve more traditional tasks and are less focused on innovation (Damioli et al., 2021). As can be seen in Table 1, investment in research increased the productivity of high- and low-skilled workers by 52.2% and 39.2%, respectively. The main reason is that the application of AI patents requires highly educated and highly skilled personnel with innovative consciousness, and the development of AI will change the labour production mode and improve the efficiency of low-skill work. Based on the coefficient results, this study concludes that the demand for highly skilled workers to be involved in scientific research activities and AI patent activities is greater in line with the theoretical part which is that highly educated people have more technical knowledge and higher absorptive capacity, as seen by their ability to incorporate new technologies into their business activities. For low-skilled occupation groups, the results of this study may be related to the existence of more jobs created for low-skilled workers in China's urban areas that still require low skills in some patent activities. The literature supports the notion that municipal provinces that prioritise investment in scientific research and AI applications tend to create innovative ecosystems that stimulate economic growth. Such environments attract businesses, which in turn generate employment opportunities for both high- and low-skilled workers. As these municipalities become hubs of innovation, they also benefit from increased tax revenues, which can be reinvested into local education and training programmes, further enhancing the skill sets of the workforce (Yan & Chen, 2019).

The findings in our study can be interpreted through the lens of political economy and the concept of capability traps in China. Our results show that investment in intensity in scientific research and AI patent applications significantly improves the productivity of both high- and low-skilled workers in municipal provinces but has no statistically significant effect on middle-skilled workers. This uneven impact aligns with the argument by Andrews, Pritchett, and Woolcock (2017) that states may adopt the appearance of functional capacity while lacking the internal capabilities to deliver inclusive, broad-based outcomes—a phenomenon known as the "capability trap". In the context of China's political economy, innovation policies such as "Made in China 2025" prioritise advanced technologies and high-end R&D in urban centres (Naughton, 2018; Lewin et al., 2016), thereby creating concentrated gains for high-skilled elites and limited trickle-down benefits for other worker groups. The fact that low-skilled workers also benefit may be attributed to increased automation in routine sectors, which boosts efficiency without demanding complex reskilling (OECD, 2021). However, the lack of significant impact on middle-skilled workers suggests institutional and policy blind spots in equipping this segment with adaptive, mid-level technological capabilities.

Furthermore, this study suggests that the observed positive effect of social fixed asset investment in IT-related industries on medium and low-skilled workers, but not on high-skilled workers, suggests a policy focusing on foundational digital infrastructure, which raises productivity in less complex tasks but does not elevate higher-level innovation competencies. This finding supports the notion that improvements in physical and digital infrastructure may yield faster productivity gains in sectors relying on standardised tasks, while higher-skilled innovation takes longer to manifest due to the time-intensive nature of capability building (Andrews et al., 2017). The lag between policy implementation and its full impact also reflects the structural challenges in China's skills development and education systems, where vocational training has yet to fully align with the evolving demands of AI and digital industries (Chen & Qian, 2021; Zhou et al., 2020; Pritchett et al., 2013).

For other control variables, the overall results show that the effect of education expenditure, FDI, and trade performs a positive coefficient and is statistically significant in influencing both high and low-skilled workers' labour productivity. Several reasons can support these findings. First, municipal provinces may have established industries or sectors that require skilled labour and FDI due to their advanced technology or knowledge-intensive nature (Yang & Ai, 2023). Second, labour-intensive industries that rely on cost competitiveness to succeed may have a demand for low-skilled labour. For instance, in the case of FDI, municipal provincial policies and incentives to attract FDI may also focus on industries that employ highly skilled or low skilled workers (Wang & Dong, 2011).

The result in this study shows that trade and FDI have no significant effect on improving the productivity of middle-skilled workers in municipal provinces. This result may indicate that middle-skilled workers are not directly involved in export-oriented activities or are not benefiting from technology spillovers from foreign firms. At present, middle-skilled workers in various provinces in China are mainly engaged in electricians, welders, mechanics, waiters, tour guides, cooks, sales and marketing, etc. Because of their low foreign language level, middle-skilled workers rarely enter foreign trade companies to engage in export or foreign-trade-related work. Meanwhile, the effect of training has a significant impact on the labour productivity for low and medium-skilled occupations because of the combination of various forms of training that lead to an increase in the skills of low- and medium skilled workers in line with the needs of an enterprise.

Finally, we find that R&D investment only has a significant, but negative impact on the labour productivity for highly skilled occupations. This is consistent with the skills-biased technological change theory, which states that the impact of R&D investment on highly skilled labour productivity is related to industry characteristics such as technology and industry type. This study finds that a more highly skilled labour force is needed in R&D activities in China's Internet, hospitals, education, electronics, and other sectors (Cai, 2017). Nonetheless, the negative correlation found in this study implies that the lack of technological knowledge of skilled workers in certain economic sectors in China may prevent the firms from operating in high-value-added activities in their innovation and R&D activities.

Conclusion

This study directly addresses how artificial intelligence (AI) influences labor productivity across different skill levels by analyzing data from Chinese municipal regions between 2000 and 2020, using AI patent applications, scientific research investment, and IT-related fixed asset investment as proxies. The findings reveal that while AI investment enhances productivity for both high- and low-skilled workers, only IT sector investment significantly benefits medium-skilled workers engaged in routine tasks. This uneven impact underscores a growing skill-based polarization in labor demand and productivity, emphasizing the urgent need for targeted policy interventions. To address these disparities, the study recommends strengthening vocational training, lifelong learning, and curriculum reforms tailored to evolving technological demands, supported by stronger collaboration between government and industry to promote on-the-job training and apprenticeships. Recognizing limitations such as definitional ambiguities and integration barriers, future research should investigate medium-skilled workers' specific capabilities and training requirements, employing broader and more diverse datasets to ensure generalizable insights and support inclusive, innovation-driven productivity growth.

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