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The role of AI in reshaping productivity: A skill-based analysis from China

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ABSTRACT

This study explores recent trends in artificial intelligence (AI) and labour economics by analysing how various AI applications affect labour productivity across different skill levels in China. Using data from 23 provinces between 2000 and 2020, the research employs three AI proxies: AI patent applications, investment in information transmission, computer services and software industries, and the intensity of scientific research funding. The study applies Ordinary Least Squares (OLS) estimation to assess the impact of these indicators on high-, medium-, and low-skilled occupations. Results show that all three AI proxies significantly and positively influence labour productivity across all skill groups. This challenges earlier research that largely focused on benefits to high-skilled workers, suggesting instead that AI-related investments also enhance productivity in medium- and low-skilled roles. These outcomes are likely driven by regional policy support and strategic investments in technology and innovation. The findings have important policy implications, particularly for designing targeted reskilling and upskilling programmes based on occupational skill levels. By identifying the specific AI investments that improve labour productivity, the study contributes valuable insights for fostering inclusive growth in an AI-driven economy, ensuring that technological benefits are distributed more equitably across the labour force.

Contribution/ Originality: This work contributes to the body of knowledge by examining recent trends in research and practice regarding how artificial intelligence (AI) affects labor productivity. It uniquely investigates the differentiated impact of AI using three distinct indicators: AI patent applications, investments in information transmission, computer services, and software industries, and scientific research investment intensity across 23 provinces in China. A key innovation of this study lies in its focus on labor skill composition, utilizing occupational classifications to distinguish between high-, medium-, and low-skilled workers.

1. INTRODUCTION

China's labour market is undergoing a profound transformation by 2025, driven by demographic shifts, technological advancements, and evolving workplace dynamics. China is also facing a shrinking working-age population, which is projected to decline by 6.83 million from 2022 to 2023, reaching 857.98 million (World Economic Forum, 2025). This decline is further compounded by an aging workforce, the average age of which has increased from 32.25 years in 1985 to 39.72 years in 2022, contributing to a decline in labor productivity (International Labour Organization, 2025). To address this problem, the application of artificial intelligence (AI) has been projected as a critical tool to offset this demographic pressure, thereby helping to increase productivity across sectors in China.

Despite the willingness of Chinese institutions to leverage AI to generate productivity gains, external barriers such as restrictions on technology transfer from Western countries have slowed the adoption of AI in the economy. However, AI technology especially generative AI is expected to contribute significantly to China's economic growth, potentially increasing GDP by over 6% by 2052. Nevertheless, the impact of AI on labor productivity by job classification remains inconclusive, particularly regarding the extent to which current skills can adapt to the application of AI in their work (Wang, Zhao, Cao, & Dong, 2024; Yunus & Zouya, 2025). This reflects the fact that most studies, whether in developed or developing countries, have primarily measured AI and labor productivity at the macro level (Borland & Coelli, 2017; Damioli, Van Roy, & Vertesy, 2021). There are only a few recent studies that have examined the impact of AI on productivity according to skill level, especially in China (Yunus & Zouya, 2024; Yunus & Zouya, 2025).

Therefore, this study aims to fill a critical gap in the existing literature by analyzing labour productivity across different skill levels and job classifications in 23 provinces of China. This study also contributes to the literature by using three different levels of AI variables to gauge which AI proxy potentially affects the labour productivity of workers with different skill sets in these provinces. Although most current research considers labour as a uniform input, the study's findings have the potential to introduce a different perspective by categorizing labour based on job skill levels, which can offer a more comprehensive understanding of the extent to which artificial intelligence applications affect productivity across various segments of the workforce in China's regions.

The importance of this study lies in its potential to inform both theoretical frameworks and policy decisions. The study contributes to the theoretical development of the field by proposing a framework that links AI adoption to labor productivity. Theoretically, it contributes to the literature by integrating AI adoption with labor economics, offering new insights into modeling productivity that accounts for skill heterogeneity. This theoretical framework helps to conceptualize how different types of AI investments influence productivity, considering both technological spillovers and regional capacity for technological absorption. Empirically, regional-level analysis allows policymakers to tailor AI and workforce development strategies to regional needs, promoting equitable and efficient labor market outcomes. As China continues to navigate its demographic and technological transitions, evidence-based insights are essential for designing adaptive labor policies and sustaining long-term economic growth.

2. LITERATURE REVIEW

2.1. The Theory of Artificial Intelligence and Labour Productivity

This decoupling of technological progress and productivity is not new and has already been observed during the first wave of digitalization. In the 1980s, Nobel Prize winner Solow (1956) famously claimed that "computers can be seen everywhere except in the statistics" (David, 1990). According to Romer (1990), model of technological change, as the application of AI leads to productivity changes among industries, factors of production such as labor will be optimally allocated and directly or indirectly affect the share of employment and output value of each industry, i.e., industrial structural change. Based on the above analysis, AI may cause changes in the allocation of factors of production between industries, thus affecting labor productivity. The theory 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 criticize the shortcomings of neoclassical economic growth theory based on Schulz's theory of human capital. They no longer confined their inquiry to labor and capital but sought to analyze long-term economic development from a new perspective. In the process, the theory of endogenous economic growth was gradually developed. Scholars began to redefine labor as an investment in human capital, meaning that labor inputs include both the demographic size of the workforce and the quality of the workforce, with the quality (knowledge, skills) often being more important. The endogenous growth theory also argues that productivity improvements can be directly linked to faster innovation and increased investments in human capital from governments and private sector institutions.

Romer (1990) introduced the theory of technological progress. He argued that the accumulation of human capital provides an enduring engine for long-term economic growth. Romer's theory of economic growth states that, in addition to the basic factors of production, human capital and new ideas (knowledge) play important roles in promoting economic growth. Another aspect is the intrinsic effect, in which individual enterprises in society use knowledge of innovation to gain higher profits, which in turn encourages them to increase research and development of new products. As seen in the production process, knowledge accumulation not only generates economic benefits on its own but also increases the returns generated by capital and labor, thereby raising the overall level of returns.

2.2. The Empirical Research of Artificial Intelligence and Labour Productivity

Empirical studies on AI, robotics, and patent activity have provided mixed evidence regarding their effects on labour productivity. For instance, Damioli et al. (2021) found a positive relationship between AI-related patent applications and labour productivity, particularly in small and medium-sized enterprises (SMEs) and the service sector. Analyzing data from 5,257 firms across various countries between 2000 and 2016, their study highlights that firms benefit the most when AI applications are swiftly adopted and effectively integrated into operations.

In contrast, Acemoğlu and Restrepo (2017) present a more cautious view, focusing on the U.S. manufacturing sector. Their analysis of 19 industries from 1993 to 2007 indicates that the adoption of industrial robots led to job displacement and a net decline in labor productivity. They emphasize a critical trade-off between automation and employment, where productivity gains in some areas are offset by widespread job losses. Similarly, Graetz and Michaels (2015) found that while industrial robots boost overall productivity and wages, they reduce the demand for low-skilled workers. This trend aligns with Fu, Bao, Xie, and Fu (2021), who warn that although AI may initially impact low-skilled jobs, high-skilled occupations could also face long-term disruption as AI systems evolve.

However, the productivity benefits of AI investments are not universally accepted. Muhanna and Stoel (2010) argue that rapid investment in AI does not guarantee productivity improvements, as outcomes depend heavily on a firm's ability to integrate AI into its workflows. Brynjolfsson, Mitchell, and Rock (2018) highlight a "productivity paradox" where technological potential outpaces realized outcomes due to measurement limitations and implementation challenges. Furthermore, Brynjolfsson et al. (2018) suggest that the expected productivity gains from AI are often overstated, as many AI systems remain inflexible and unable to manage non-routine tasks. Echoing this view, Cao, Hao, Kou, Zhou, and Zou (2025) argue that automation alone is not sufficient for productivity growth, especially when systems are not adaptable to complex or dynamic labor demands.

The literature shows that only a few recent studies have examined the transformative impact of AI on labor skills, particularly in relation to evolving skill demands, but none of these findings directly relate to labor productivity. For example, Morandini et al. (2023) highlight how the use of AI is reshaping professional skills and workplace dynamics, emphasizing the importance of transversal skills such as adaptability, communication, and critical thinking central to navigating the changes brought about by AI. Their findings suggest that organizations must first map the transversal skills needed to address existing skills gaps and then develop strategies to upskill and reskill workers to support AI integration. Similarly, Colombo, Mercorio, and Mezzanzanica (2019) applied machine learning techniques to web-based job vacancies in the Italian labor market, developing a skills taxonomy based on the ESCO classification system. Their study provides a detailed analysis of the relevance and composition of soft and hard skills across occupations and regions, revealing that digital and soft skills significantly influence the probability of automation and can complement or replace traditional hard skills in various job roles.

Extending this discourse, Tolan et al. (2021) present a comprehensive framework for assessing the impact of AI on jobs by linking job tasks to cognitive abilities and AI benchmarks. This layered mapping offers insights into the abilities most vulnerable to AI exposure and highlights how emerging AI capabilities—particularly in visual, auditory, and sensorimotor functions could affect jobs previously considered resistant to automation. In line with this, Zarifhonarvar (2024) provides empirical evidence on the potential impact of generative AI tools such as ChatGPT, showing that 32.8% of jobs could be fully impacted, 36.5% partially impacted, and 30.7% remain unaffected. This categorization contributes to a broader understanding of the short- and long-term implications of AI for different jobs, underscoring the need for proactive workforce planning and ongoing skills development.

At the regional level, studies exploring the impact of technological progress on total factor productivity (TFP) in China suggest that AI's influence varies by location. Dai, Hu, Tian, and Jiang (2024) found that technological progress was the primary driver of TFP growth across China's provinces, with the eastern region showing the most significant gains. Chen, Guo, and Xu (2022) further add that intellectual capital plays a crucial role in enhancing labor productivity in China's IT sector, with human capital being the key factor for state-owned enterprises and structural capital for private firms. Together, these studies illustrate that while AI and automation hold promise for improving labor productivity, the effects are complex and highly context-dependent, varying by industry, region, and the capacity of firms to integrate AI technology effectively.

3. METHODOLOGY

The methodology section will begin by presenting the scope of the study. Next, the theoretical framework, which illustrates the interaction between AI and labor productivity, will be discussed in Section 3.2. This will be followed by model estimation and econometric specifications in Sections 3.3 and 3.4, respectively.

3.1. Scope of Study

Given the availability of AI-related data, this study focuses on 23 Chinese provinces over the period 2000 to 2020 (T = 21) to examine the impact of AI on labor productivity across different skill levels. These provinces are directly administered by the central government and often receive preferential treatment in terms of infrastructure investment, research funding, and policy support. As a result, they serve as strategic hubs for technological advancement, frequently hosting clusters of high-value industries, leading universities, and premier research institutions (Yang, 2022). This makes them ideal for analyzing the diffusion and impact of emerging technologies such as artificial intelligence on the labor market.

3.2. Theoretical Framework: Artificial Intelligence and Labour Productivity

The Cobb-Douglas production function, which is used in literature to measure the role of technological progress in economic growth, can also be applied to investigate the relationship between technological progress and productivity (Romer, 1990). Based on the characteristics of AI as presented in detail in Chapter 2, AI is considered part of technological progress. Therefore, in this study, the productivity theory has been utilized since the work of Tinbergen (1942) and followed by Solow (1957), and it can be applied to analyze the labor productivity function as well. The basic model to represent the Cobb-Douglas production function is expressed below:

$$Y_t = A_t K_t^{\alpha} L_t^{\beta} \qquad (1)$$

Where:

Y= Output (Value added).

L= Number of workers.

K= Capital stock.

A= TFP.

Adding the time figure in Equation 1 to represent the Solow model of economic growth model (Solow, 1957).

$$Y_t = A_t K_t^{\alpha} L_t^{\beta} \qquad (2)$$

Where: t represents the time index, α and β are the output elasticity of capital stock and number of workers respectively and $\alpha+\beta=1$.

The model assumes that under conditions of perfect competition in economic development, both labour and capital are remunerated by their marginal product. The two factors are interchangeable, the payoffs to scale of production are constant, and technological progress is Hicks-neutral. When technical progress is not taken into account, if both capital and labour inputs are expanded by a factor of *n*, the output will also be expanded by a factor of *n*.

$$nY = An^{\alpha}K^{\alpha}n^{\beta}L^{\beta} \qquad (3)$$

From Equation 3 it follows that $a + b = 1$, at which point Equation 3 can be written as:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \qquad (4)$$

Both ends of Equation 4 divided simultaneously by L give:

$$\frac{Y_t}{L_t} = A_t \left(\frac{K}{L}\right)_t^{\alpha} \qquad (5)$$

In Equation 5, y/L is the labour productivity, expressed as *P*. Then Equation 5 can be written as:

$$P_t = A_t \left(\frac{K}{L}\right)_t^{\alpha} \qquad (6)$$

Taking the logarithm of both sides gives

$$lnP_t = lnA_t + \alpha ln \left(\frac{K}{L}\right)_t \qquad (7)$$

The derivative of Equation 7 provides the rate of labor productivity growth.

$$\frac{\Delta P}{p} = \frac{\Delta A}{A} + \alpha \left(\frac{\Delta C}{C}\right) \qquad (8)$$

In Equation 8, $\Delta P/P$ is the average growth rate of labour productivity is the average rate of increase in the level of technology, denoted by *s*; *C* is the per capita capital stock, i.e., K/L; $\Delta c/C$ is the average annual growth rate of per capita capital stock, i.e., the rate of capital deepening, denoted by g. Then Equation 8 can be simplified to the following model.

$$r = s + aq \qquad (9)$$

Model (9) states that the change in labour productivity *(r)* is caused by two components: the growth rate of technological progress *(s)* and the growth rate of capital deepening *(aq)*. Under this model, the contributions of technical progress and capital deepening to labour productivity growth are respectively.

$$EA=\frac{s}{r}\times 100\%; \quad Ec=\frac{aq}{r}\times 100\% \qquad (10)$$

In Equation 10 *EA* and *Ec* are the contribution rates of technical progress and capital deepening to labour productivity growth, respectively.

3.3. Model Estimation

This study extends the labour productivity function to compare the impact of AI on labour productivity across different occupational skills in 23 provinces in China. It applies the basic approach of Hollanders and Ter Weel (2002), which constructs a model to estimate the impact of technological progress on labour productivity. However, the model in this study differs from theirs by representing technological progress using three different proxies of AI and by investigating 23 provinces and the classification of labour skills in China. Therefore, the basic model for labour productivity of high-skilled, medium-skilled, and low-skilled occupations across 23 provinces in China can be expressed as follows:

$$lnLP\_HS_{it=}\alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4\, ln\, TRAIN_{\,it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \qquad (11)$$

$$lnLP\_MS_{it} = \alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4\, ln\, TRAIN_{it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \quad (12)$$

$$lnLP\_LS_{it} = \alpha_o + B_1 ln\left(\frac{K}{L}\right)_{it} + B_2 lnAI_{it} + B_3 lnQEDU_{it} + B_4\, ln\, TRAIN_{it} + B_5 lnRD_{it} + B_6 lnGDP_{it} + B_7 lnTRADE_{it} + B_8 lnFDI_{it} + \varepsilon_{it} \quad (13)$$

Where i is the 23 provinces in China and t time index respectively. 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) workers respectively. $\frac{K}{L}$ ratio of capital to worker (K/L) or capital intensity is approximated by gross investments in fixed capital per worker (Corvers, 1997). *AI* is measured by three proxies which are social fixed asset investment in Information Transmission, Computer Services and Software Industries (*SFA_INV_ITCS*) (Borland & Coelli, 2017); investment intensity of scientific research funds (*INV_SRF*) (Yunus & Zouya, 2025) and AI patent applications (*AI_ PATENT*) (Damioli et al., 2021). *QEDU* is the education expenditure from total expenditure (Zhang & Liu, 2022). *TRAIN* refers to the cost of training per employee (Yunus, Said, & Siong Hook, 2015). Y_{it} represents other factors commonly considered in discussing labour productivity, namely, RD refers to research and development investment. *GDP* refers to the gross regional product, and *TRADE* is trade openness as the proportion of total imports and exports to GDP. *FDI* is foreign direct investment as a share of foreign direct investment from GDP (Yunus, 2023; Yunus & Abdullah, 2022). $\varepsilon_{it}$is an error term that captures the time-varying province-specific productivity shocks.

3.4. Econometric Specification

Ordinary Least Squares (OLS) estimators with robust standard errors are employed in this study to compare the effects of AI on labor productivity by labor skills across 23 provinces in China. This technique effectively addresses issues related to normality and heteroscedasticity, especially when some observations exhibit many residuals, leverage points, or influential effects, as well as the impact of sequence correlation on standard errors (Huber, 1992). With robust options, the coefficients of point estimation are preserved, but the standard errors account for heterogeneity and non-normality, as well as the fact that observations within regions are usually not independent. It is important to note that, although this study uses the OLS estimator to model labor productivity by labor skill level, the results are valuable as preliminary findings for identifying the level of labor suitability and the integration of AI in industries by job category.

4. RESULTS AND DISCUSSIONS

Table 1 presents the regression analysis results for the impact of AI on labor productivity in 23 provinces in China. The findings in this study indicate that increased investment in social fixed assets within information transmission, computer services, and software industries as well as higher funding intensity in scientific research and AI patent applications have substantial positive effects on labor productivity. Specifically, in response to increased investment in these sectors, productivity rose by 42.8% for high-skilled, 36.3% for medium-skilled, and 27.3% for low-skilled occupations. These provinces, with their industrial diversity and strong integration into global supply chains, benefit from AI and IT investments across multiple sectors, including manufacturing, logistics, and services. Consequently, AI and IT innovations improve efficiency not only in high-skilled roles, such as research and technical positions, but also in medium- and low-skilled roles by automating repetitive tasks.

The significant positive impact of AI on productivity across skill levels in these provinces can be attributed to their prioritization of economic modernization and technology adoption, in alignment with China's "Made in China 2025" initiative, which promotes advanced manufacturing and technological progress. Investment in information transmission, computer services, and scientific research reflects a coordinated effort to improve digital infrastructure and enhance productivity across all skill levels. Furthermore, local government policies emphasize innovation-driven growth by offering subsidies, tax incentives, and grants to encourage AI and research investments. This support fosters a robust ecosystem where both high- and low-skilled workers benefit from advanced productivity tools, maximizing AI's overall impact on productivity across these provinces.

Table 1. Labour productivity by occupational skills in 23 provinces.

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**
KL	0.014	(0.092)*	-0.142	(0.045)**	-0.306	(0.074)***
Artificial intelligence proxies						
SFA_INV_ITCS	0.428	(0.081)***	0.363	(0.039)***	0.273	(0.064)***
INV_SRF	0.300	(0.055)***	0.081	(0.027)**	0.205	(0.044)***
AI_ PATENT	0.156	(0.038)***	0.162	(0.018)***	0.192	(0.030)***
Other control variables						
GDP	0.797	(0.196)**	0.653	(0.579)***	0.628	(0.055)***
TRAIN_EMP	-0.206	(0.054)**	-0.253	(0.026)***	-0.793	(0.043)***
QEDUEXP	-0.428	(0.115)***	0.104	(0.056)	0.111	(0.092)
RD	-0.423	(0.033)***	-0.298	(0.016)***	-0.243	(0.026)***
TRADE	-0.020	(0.028)	0.029	(0.014)**	0.038	(0.022)
FDI	-0.098	(0.017)***	-0.091	(0.008)***	-0.045	(0.014)***
Number of obs	483		483		483	
R-squared	0.884		0.827		0.813	
Prob > F	0.000		0.000		0.000	

Note: Table 1 presents the regression results of labour productivity for workers by occupational skills, which consist of high-skilled (LP_HS), middle-skilled (LP_MS), and low-skilled (LP_LS) in 23 provinces.
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.

This study suggests that variations in the availability of a skilled workforce across China's provinces and cities contribute to the diverse impacts of AI on labor productivity. In the 23 provinces with higher concentrations of skilled workers, such as Guangdong, Jiangsu, Fujian, and Zhejiang, the adoption of AI is better supported, enhancing productivity across skill levels (Geissmann & Zhang, 2018). Jiangsu, for example, hosts institutions like Nanjing University that collaborate with local industries on algorithmic research, creating an ecosystem of AI-focused labs and platforms in areas such as industrial robotics and smart chips. This concentrated talent and infrastructure allow the region to leverage AI more effectively, resulting in greater productivity gains.

Government policies further influence the productivity impact of AI. Provinces such as Guangdong, Shandong, and Jiangsu have implemented policies to promote AI development, including increased investment in information transmission and software industries, along with tax incentives for AI companies. For example, the Shandong Tax Bureau's R&D tax deductions and VAT refund initiatives in Qingdao have enabled firms to reinvest over 2.5 million yuan into innovation from 2020 to 2022, fostering a cycle of technological advancement. Cultural factors also play a role; while some regions like Jiangsu and Zhejiang embrace AI, others, such as Shanxi and Qinghai, adhere more to traditional work practices. In Qinghai, limited innovation capacity and a smaller economic base hinder AI development, further constraining productivity improvements in those areas.

The analysis of other control variables affecting labour productivity in 23 Chinese provinces reveals several insights. Firstly, the results show that training costs, R&D investment, and foreign direct investment (FDI) have a significant negative impact on skilled labour productivity in these provinces. This negative correlation suggests that increased investments in training, R&D, and FDI do not always translate directly into productivity gains for skilled workers. It is possible that the allocation of these investments does not fully align with the needs of the skilled labour market, or that the productivity gains from these investments are not immediately realized (Yunus et al., 2015).

Additionally, the study highlights that GDP, as a reflection of the economic strength of regions, positively influences labour productivity. Higher income and wealth levels enable regions to improve production technology, management, vocational skills, and overall workforce quality, thus driving productivity improvements from 2000 to 2020. Education, however, has a mixed impact: it negatively affects the productivity of high-skilled occupations but shows no significant effect on middle- and low-skilled roles. This may indicate a skill mismatch where educational qualifications do not align well with industry demands, leading to lower motivation and productivity (Hu, Wang, & Zhao, 2021). Furthermore, trade has a positive effect on the productivity of low- and medium-skilled workers, likely due to the nature of industries in these regions and the outsourcing potential of tasks suited for medium skills, especially in the services and technology sectors (Shi, 2024). Provinces with strong foreign trade sectors, such as Guangdong, Zhejiang, Jiangsu, and Anhui, benefit from increased access to resources and advanced technology, which boosts productivity for medium-skilled workers, particularly in sectors focused on exporting low- and medium-technology goods (Zhang, Gan, & Fan, 2023).

5. CONCLUSION AND POLICY IMPLICATION

This study contributes to the existing body of knowledge on the relationship between AI and labor productivity, providing useful implications for policymakers, businesses, and researchers interested in enhancing productivity within the context of AI and labor skills in China at the provincial level. Using balanced panel data from 2000 to 2020, three proxies for AI are employed in this study: investments in information transmission, computer services, and software industries; AI patent applications; and the investment intensity of scientific research funds. The study also includes several factors that are rarely used as independent variables in the literature to influence labor productivity, considering different occupational skills and provinces in China. These variables are lagged labor productivity, capital-labor intensity, R&D, GDP, trade openness, and FDI.

The findings of this study can assist policymakers and industry leaders in identifying the training and development initiatives needed to improve workforce adaptability. It also offers valuable insights for future research on the relationship between skills, productivity, and the integration of artificial intelligence (AI) across different sectors. Specifically, the study can help employers determine the types of targeted training and skills most relevant to various AI applications. Additionally, it can inform education and workforce development policies by highlighting the sectors and regions that require the most support to help workers adapt to AI-driven changes over time.

The OLS estimation results conducted across 23 provinces indicate that the effects of social fixed asset investment in information transmission, computer services, and software industries, as well as the investment intensity of scientific research funds and AI patent applications, are significantly and positively associated with increased labor productivity in high-, medium-, and low-skilled occupations. The positive impact of AI on labor productivity across all skill levels in China's 23 provinces can be attributed to strategic investments and regional development policies that prioritize technological advancement. These provinces have allocated substantial funds to information technology, computer services, and software industries, alongside AI and scientific research, creating a well-supported environment for productivity improvements.

Furthermore, these provinces are economically diverse and integrated, allowing AI to drive productivity in various industries, from manufacturing to services. Workforce upskilling initiatives and training programs ensure that workers across all skill levels can effectively interact with AI-driven tools, which improves efficiency in high-skilled roles while simplifying tasks for medium- and low-skilled positions. The combined influence of targeted policy support, broad-based technology adoption, and diverse industry applications enables AI to have a comprehensive positive impact on labour productivity across different occupational levels in these regions.

To make AI a sustainable growth engine for China in the long term, the Chinese government is proposing to improve the diversity of data available to support the development of AI by creating several industry-specific data sets to reveal new government policies as well as open space for the public to access data related to AI development, the economy, health, recreation, public services, and more, as practiced in New York. This step needs to be implemented in China since AI is not yet a strategic priority for more than 40 percent of companies in traditional industries there. As a result, many of them have yet to capture the data they need to support future AI deployments. This situation is noticeable in firms and the agricultural industry; top management hardly ever keeps detailed records on topics like planting schedules or how the weather affects output, but this is the kind of data that AI systems can use to uncover insightful patterns and improve efficiency. In comparison, the United Kingdom, the United States, and Japan have implemented nationwide information systems to capture such data and apply advanced analysis to modern agricultural management.

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