A Preliminary Study on Artificial Intelligence and Labour Productivity in China

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Abstract

Using the total number of patents as a proxy for artificial intelligence (AI), this study adds to the body of knowledge by analysing the relationship between AI applications and labour productivity in China's overall sector and concentrating on China's agriculture sector. Even though this study only employed ordinary least squares (OLS) estimation, the results could still provide a rough idea of the current stage of China's AI patent applications and their impact on enhancing labour productivity. Our findings demonstrated that the impact of AI patent applications statistically affects the labour productivity of China's overall sector but did not appear to be well supported by our research in the agriculture sector. Our findings suggest that China's agriculture sector has less frequent and lesser experience with patenting to fully exploit innovation activities due to a lack of skilled labour and employee participation in scientific research and innovation activity as a result of the agriculture sector's continued dominance by low-educated labour. To address these challenges, we recommend that the Chinese government continue to invest more in innovation and AI, conduct employee retraining programmes to improve their skills and knowledge, create rules and guidelines to protect the privacy of patents, and promote a climate of openness and accountability when deploying AI in the industry.

Keywords:

Artificial Intelligence, Labour Productivity, Patent Applications, Agriculture Sector

INTRODUCTION

The commencement of Artificial intelligence (AI) represents the fourth industrial revolution, as AI becomes the principal driving force behind the reform and development strategies of different countries (Acemoglu & Restrepo, 2018; Purdy & Davarzani, 2015). Technological advances tied to AI have led to disruptive changes in the way employment is generated because they raise productivity levels and promote economic growth (Aghion et al., 2018; Puaschunder, 2019). Nevertheless, the impact of AI on productivity is limited by factors such as the pace of its application and the extent to which it relates to the skill level of the workforce (Acemoglu & Restrepo, 2018). Around the world, there has been a significant decline in the capacity of capital investment and labour to propel economic progress (Purdy & Davarzani, 2015). The economy has deteriorated significantly as labour shortages and the capital crisis have disrupted traditional growth models and productivity has fallen.

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China is no exception. Despite increased investments in digital innovation, advancements in AI have not consistently resulted in significant productivity gains across businesses and regions. The current level of technological innovation has not been fully utilised, resulting in the decline of China's labour productivity growth rate (Purdy & Davarzani, 2015; Zhang, 2020). In 2020, China's productivity growth will have flattened to approximately 7%, which is low compared to other developing countries' 9.9% (Yang et al., 2010). In addition, the mismatch between industry and job structure has developed as a result of the rapid advancement of AI, which has created a gap between theoretical and practical applications of the technology. The number of people employed in China's agriculture sector will have declined by about 24% by 2020 as a result of this gap, which may have an impact on production levels. Therefore, it is still debatable whether AI will be able to increase China's labour productivity (Zhu & Li, 2018; Yang, 2022).

Thus, based on a brief time series of data, this study offers an initial assessment of the effect of AI on China's labour productivity in economic sectors. We are using the number of patents as a proxy to represent the current stage of AI development and application in the industry due to patents becoming a more significant factor in economic performance and innovation (OECD, 2004). Studies to quantitatively gauge the impacts of AI on economic outcomes such as firms' performance, labour productivity, and employment are needed, but such studies are impeded by the requirement for high-quality firm- and sectoral-level data (Furman & Seamans, 2019; Raj & Seamans, 2019). Therefore, the quantitative technique proposed in our study can enable us to determine the degree of an employee's innovative capabilities in AI patents based on the value of the labour productivity coefficient (Maher & Schaffelke, 2023; Yunus, 2023; Wu & Yang, 2022).

We also contribute to the body of knowledge by specifically examining the impact of AI on labour productivity in China's agriculture sector. Most studies concentrated on high-technology industries like manufacturing, ICT, software, and services sectors in China and often overlooked the agriculture sector, even though the agriculture sector is one of the key contributors to China's economic progress (Banerjee et al., 2018; Yang, 2022). Superior technology, as stated by most research, may be more pronounced for high- and medium-technology industries, which also tend to employ workers with higher skills and knowledge, evident through their capability to adopt new technology in the industries (Yunus & Abdullah, 2022a). It is essential to comprehend how AI may be applied and utilised in China's agricultural sectors since its effects can considerably increase production and efficiency, which would have an impact on China's overall economic performance. By addressing this research gap in the agriculture sector, the results of this study can inform China's policymakers to close the digital divide, encourage widespread access to relevant AI tools in this sector, and create knowledge-sharing platforms that focus on the unique requirements of rural communities to deliver education and assistance (Xie et al., 2021).

LITERATURE REVIEW

There is no uniform definition around the concept and the actual scope of AI in academia, and the technical connotation of AI is still being expanded and deepened. At the nascent stage of development, McCorduck and Cfe (2004) defined AI as a "thinking machine" that has the ability to think and act like humans and which can surpass the corresponding human ability in the future. Bharadwaj et al. (1998) used the notion of organisational competence to describe

AI technology. Combining various organisational resources and functions with AI technology has a positive impact on labour productivity.

The literatures found that there is not enough evidence to accurately evaluate and gauge the AI advancement by using the right proxies because AI may be regarded a technology that has only recently drawn attention and applied in a wide range of studies (e.g: Chen et al., 2020; Damioli et al., 2021). We discovered that the number of industrial robots utilised in the sector is the method most frequently used to gauge the development of AI. For instance, Qiulin et.al (2019), concentrated on the density of robot installation, which is calculated by dividing the total number of intelligent robots installed in the domestic sector by the number of employees in that year to determine the industry's adoption of AI. Graetz and Michaels (2015), Acemoglu and Restrepouribe (2017) and Zhu and Li (2018) used the total sales of industrial robots in China to reflect the degree of AI application in the sector. They concluded that the relative supply of expert and unskilled labour will increase as AI develops and technical proficiency increases. This will improve the labour force's general quality and optimise the labour structure.

Empirically, robotics applications and patents in AI activities have increased recently. A study by Damioli et al. (2021) revealed that products based on AI technology may begin to influence the economy. A global sample of 5,257 businesses studied showed that these companies had filed at least one AI-related patent in their business between 2000 and 2016 to evaluate the hypothesis. After accounting for other patenting activities, the study's analysis revealed that AI patent filings have a greater impact on firms' labour productivity. The study, which was also conducted on small and medium enterprises and the service sector, showed that one of the main factors influencing the impact of AI so far is the ability to quickly adapt and implement AI-based applications in the production process.

A study by Acemoglu and Restrepo (2017) focused on the impact of the use of industrial robots on labour productivity in the United States in 722 regions and in 19 manufacturing industries between 1993 and 2007. Empirical results show that the widespread use of industrial robots has a significant negative impact on labour productivity. They came to the conclusion that the benefits of the invention outweighed the impact of robots on labour productivity. Their analysis also showed that between 1990 and 2007, the number of unemployed people in the manufacturing industry increased from 360,000 to 670,000 as a result of the use of industrial robots.

Meanwhile, at the industry-level, Cheng et al. (2019) examine the development of robots in Chinese manufacturing enterprises using data from the China Employer-Employee Survey (CEES). Their study's research paints a preliminary picture of some of the initial measures that need to be taken to comprehend the reasons for and effects of the growing usage of robots in China's manufacturing sector. They also demonstrated the importance of the government promoting the use of robot technology. Further research is recommended to examine the impact of the use of robots in the manufacturing sector on labour productivity, the existence of complementarity and substitution effects between humans and robots, and the impact on other segments of the labour market.

Singh et al. (2020) viewed AI as a technology that leads to increased use of capital in the industry. They emphasised that although the use of AI will increase labour productivity because it saves labour time, it will also lead to a reduction in the use of labour that will be gradually replaced by technology. They also reported that the technology composition of capital leads to a higher relative surplus value of capital by affecting its value composition. On the contrary, Muhanna and Stoel (2010) found that investment in AI technology will not lead to proliferated labour productivity. They opined that the impact of the actual results of such a rapid investment depends on factors unique to the business and the market. Expanding on this, Brynjolfsson and Mitchell (2017) further categorised AI-related problems into four factors: false expectations, wrong measurement, reallocation effect, and general technology implementation.

Considering empirical research by economic sectors, Trajtenberg (2018) predicted that by 2024, almost all new jobs will be concentrated in the service sector, especially in health care and social assistance services, when the industry begins to apply AI to the industry’s tasks and production. This prediction prompts workers to improve their social skills and related skills and shift their job choices, noting that socially intensive jobs in the United States grew by 24% from 1980 to 2012, with a 7.2% increase in the share of employment over the same period, and wages rose by 26.0%. Meanwhile, industry-level studies in China reported mixed evidence regarding the impact of AI on labour productivity. These studies concluded that AI escalates growth through the proper use of trade liberalisation, as it helps the economy be open and flexible to various free trade agreements. This openness facilitates technological advancement, opens up new markets for growth and expansion, especially AI, attracts and encourages foreign direct investment, which will cater for technology transfer and create new jobs and economic growth (Acemoglu et al., 2018; Ma et al., 2019).

In the context of the agriculture sector, Bannerjee et al. (2018) argued that AI applications do not have a significant impact on the number of farmers at this stage. They found AI technologies do transform the habits and methods of farmers' productive labour and strengthen the connection to the market. In terms of the farmer-market linkages, Lele et. al (2017) demonstrated that the speed and scope of smart, digital technological change at this stage are conducive to inclusive agricultural and rural development, truly bringing farmers and markets closer together at every stage of production and can indirectly increase farmers' incomes by providing higher levels of education, health care, financial, and market services.

Frey and Osborne (2017) found that the effects of AI have changed agricultural production methods, increasing production efficiency as well as increasing farmers' incomes, but AI has not had a significant substitution effect on farmers. This may be due to the fact that changes in the way production tasks are achieved during the transition from mechanisation to automation in agricultural production do not affect the demand of farmers in the agricultural production process or are far from the effects that occur when agricultural mechanisation and equipment are used. Vadlamudi (2019) also found that the effects of AI affect the agricultural production sector, while in the manufacturing sector, this study found that labour in this sector will gradually be transferred to the service sector due to the substitution effect of AI.

Based on our careful search in the literature, only a few studies used patent applications as a proxy to measure AI and study their impact on labour productivity (Damioli et al., 2021; Bannerjee et al., 2018; Yang, 2022). Their study provides suggestions and brief ideas for policy implications regarding the effectiveness of patent applications in the economic sector. These suggestions and ideas may be applicable in the context of the Chinese labour market, as the restructuring of labour supply and demand would help China respond to the industry’s demand and the speed of AI development across the world. While recent studies have found that there is increased awareness of the impact of AI patent applications due to their positive further impact on business profitability and that they serve as a source of forecasts for emerging technologies (Benson & Magee, 2015; Fankhauser et al., 2018), their impact on worker productivity is still insufficient (Damioli et al., 2021; Fujii & Managi, 2022; Yang, 2022).

DATA SOURCES AND THE DESCRIPTION OF VARIABLES

The present study uses the balanced data published by the China Macroeconomic Database and China Statistical Yearbook during the period of 2000–2019 to analyse the relationship between AI patent applications and labour productivity. To obtain the number of AI patent applications, the data is gathered from the National Industrial Information Security Development Research Centre and the Electronic Intellectual Property Centre of the Ministry of Industry and Information Technology, which released the 2020 Report of China Patent Artificial Intelligence.

The dependent variable in this study is labour productivity (*LAP*) for overall sectors in China. Labour productivity is measured as value added per worker in any specific sector (Acemoglu et al., 2018; Chen et al., 2020; Liu et al., 2001). A similar approach was applied for the calculation of labour productivity in China's agriculture sector.

We adopt the AI patent applications (*AI_PATENT*) as the independent variable of main interest, as it is rarely applied to study the relationship between AI and China's labour productivity in spite of China's emerging status as an innovator in AI as it progressed in filing AI patents and experimented with the most cutting-edge AI technology to drive applications in industry (Cheng & Zeng, 2022; Damioli et al., 2021; Yang, 2022). Patents are widely seen as initial indicators of innovation since patent applications are frequently filed before a product using the newly developed technology, method, or formulation is released into the market (Benson & Magee, 2015; Fankhauser et al., 2018). The proxy of AI patent applications, represented by the number of AI patents, might be a potential indicator of a company's investment in AI and R&D (Benson & Magee, 2015).

Other control variables are human capital, scientific research investment intensity, and foreign trade level. Consistent with the theory of endogenous economic growth and scholars such as Le et al. (2019) and Towse (2006), who have redefined 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, being a more important indicator to determine higher labour productivity growth, in this study, human capital is represented by two proxies, namely, education development level (*EDU*) and human capital level (*HUM*) (Cleeve et al., 2015; Yunus et al., 2014; Ramli et al., 2016; Yunus & Masron, 2020). Education development level is measured by the percentage of education fiscal expenditure from total fiscal expenditure in China (Luo et al., 2019; Maazouz, 2013). Human capital level is measured as the percentage of employees involved in science and technology activities out of the total number of employees.

The scientific research investment intensity (*RDIF*) was also chosen as one of the control variables due to its crucial role in a country's technological progress and economic development, which ultimately influence labour productivity (Parham & Zheng, 2006). In this study, the RDIF variable refers to the research and development institution's research and experimental development spending as a proportion of gross domestic product (GDP). In the context of China, the effects of scientific research investment intensity on economic outcomes need to be investigated as the Chinese government expands funding for R&D initiatives in areas connected to AI (Yang, 2022). Adopting this proxy for labour productivity estimation, the study could gauge the effectiveness of investment in scientific research in relation to the workers' labour productivity, thus enabling firms to increase their technical capability and profitability. Meanwhile, foreign trade level (*TRA*), used as the index of an export-oriented economy, is measured as the total import and export volume (Acemoglu & Restrepo, 2018; Luo et al., 2019).

EMPIRICAL MODEL AND METHODOLOGY

The study's theoretical framework is based on a study by Damiole et al. (2021), while the empirical model specification is a combination of those proposed by Acemoglu and Restrepo (2018), Gollin et al. (2014) and Le et al. (2019). These are used to investigate the relationship between AI and labour productivity in China. The basic model in this study is presented as follows:

$$LAP_t = \beta_0 + \beta_1 AI\_PATENT + \beta_2 EDU + \beta_3 HUM + \beta_4 RDIF + \beta_5 TRA + \varepsilon_t \qquad (1)$$

where: *t* is time index. *LAP* is labour productivity for China's overall economic sector as the dependent variable. *AI_PATENT* is the number of AI patent applications for China during the period of 2000-2019. *EDU* is education development level (the percentage of education fiscal expenditure from total fiscal expenditure). *HUM* is measured as the percentage of employees involved in science and technology activities from the total number of employees. *RDIF* is the investment intensity of scientific research funds (the percentage of research and experimental development expenditure per GDP). *TRA* is the total import and export volume. ε_t is the error term.

When studying the impact of AI on labour productivity, endogenous issues are considered. To better solve this problem, we followed Baldwin and Okubo (2006) and Damioli et al. (2021) to lag the labour productivity variable with one period to provide a more robust analysis of the relationship between AI patents and labour productivity and improve the reliability and validity of the regression estimates (Maher & Schaffelke, 2023). The estimation model for labour productivity in China with the lag of labour productivity for China's overall economic sector is presented below:

$$LAP' = \beta_0 + \beta_1 LAP'_{t-1} + \beta_2 AI\_PATENT_t + \beta_3 EDU_{\ t} + \beta_4 RDIF_{\ t} + \beta_5 TRA_{\ t} + \varepsilon_t \qquad (2)$$

where: *LAP'* is labour productivity model for all economic sectors in China. $LAP'_{t-1}$is the lagged China's labour productivity for all sectors. This specification allows for gradual convergence in efficiency levels between firms, which has been observed as important in past empirical productivity studies, as lagging firms were able to improve their productivity faster (Blundell & Bond, 2000; Lokshin et al., 2008). We extend the Model (2) above to study the effect of AI on labour productivity in the agriculture sector. The labour productivity estimation model for agricultural (*LAP2*) are indicated as follows:

$$LAP2 = \beta_0 + \beta_1 LAP2_{i,t-1} + \beta_2 AI\_PATENT_{i,t} + \beta_3 EDU_{\ i,t} + \beta_4 RDIF_{\ i,t} + \beta_5 TRA_{\ i,t} + \varepsilon_t \qquad (3)$$

where: *i* and *t* refer to agriculture sector and their time index, respectively. *LAP2* is agriculture sector's labour productivity as dependent variable and $LAP2_{i,t-1}$ is the lagged agriculture sector's labour productivity.

The present study used ordinary least squares (OLS) estimators with robust standard errors to examine the effects of AI on labour productivity throughout the period 2000–2019 due to the lack of time series data (20 observations). Even with homoscedasticity, the robust standard errors were reasonable. Because some observations may have large residuals, leverage, or influence, the robust standard errors option in regression was also effective in addressing the minor normality issue (Hoechle, 2007). It also effectively captured any potential worries regarding the effects of serial correlation on the standard errors. Even though this study only employed OLS estimation, the results could still provide a preliminary picture of China's AI application and labour productivity. The combined role of AI, human capital, and research and experimental development expenditure in the labour productivity policy in China is relatively ignored (Damioli et al., 2021). Romer (1990) stressed that these complementary inputs could determine whether physical capital (investment in R&D expenditure and/or a combination of both internal and external knowledge, such as investment in education, job training, and technological progress via trade and FDI should be applied in the growth and productivity model.

RESULTS AND DISCUSSIONS

Correlation Results

In this study, the correlation results were performed as a validity test before we analysed the OLS estimation results in Table 1. We conducted the 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 test in the context of labour productivity (Yunus & Abdullah, 2022b). Thus, the validity results of the proxies were assessed on their correlation values. If the value between the independent variables indicates a positive value, then it is considered a good dependent variable (Yunus & Abdullah, 2022a).

Table 1. Correlation results for overall China's sector and agriculture sector

Overall China's sector.							
	LP1	**LAGGED LP1-1**	**AI_PATENT**	**HUM**	**EDU**	**RDIF**	**TRA**
LP1	1.000						
LAGGED LP-1	0.332	1.000					
AI_PATENT	0.743	-0.410	1.000				
HUM	0.716	-0.601	0.701	1.000			
EDU	0.516	0.162	0.388	0.453	1.000		
RDIF	0.773	0.521	0.679	0.627	-0.324	1.000	
TRA	0.491	-0.322	0.667	0.380	0.417	0.735	1.000
Agriculture Sector							
	LP2	**LAGGED LP2-1**	**AI_PATENT**	**HUM**	**EDU**	**RDIF**	**TRA**
LP2	1.000						
LAGGED LP2-1	0.356	1.000					
AI_PATENT	0.781	0.422	1.000				
HUM	0.663	0.671	0.761	1.000			
EDU	0.572	0.227	0.375	-0.547	1.000		
RDIF	-0.634	0.591	0.675	0.631	-0.487	1.000	
TRA	-0.518	-0.345	0.639	0.411	0.396	0.783	1.000

Note: Natural log is used to transformed all variables.

As shown in Table 1, the positive correlation between labour productivity and the independent variables indicated clear signs that almost all industries in China have benefitted by exploiting the opportunities of a new degree of automation brought by AI technologies in their industries.

In the agriculture sector, the correlation results also reported a positive correlation between labour productivity and all independent variables, except showed negative correlation between investment intensity of scientific research funds (RDIF) and TRADE. The negative correlation suggests that the impact of investment in scientific research on labour productivity is associated with the sector's characteristics, such as the technology and type of sectors (Damioli et al. 2021). The results of the correlation analysis in this study also indicate a better picture than the segregated information. The correlation value for all variables was less than 0.8, proving that there was no existing multicollinearity in the model used in this study (Gujarati et al., 2012).

Regression Results

Table 2 presents the regression results for the two models investigating the effects of AI along with other influencers of labour productivity for China's overall economic sector and agriculture sector.

Table 2. Ordinary least square estimation on labour productivity for China's overall economic sector and China's agriculture sector

Dependent Variable: Labour productivity	Model (1) Overall Sector in China	Model (2) China's Agriculture Sector
Lagged labour Productivity	0.081 (0.061) ***	0.067 (0.070)*
AI Patent Applications (*AI_PATENT)*	0.309 (0.151) ***	-0.257 (0.195)
Education Development Level (*EDU*) - *Education fiscal expenditure*	0.177 (0.028)***	0.278 (0.050)**
Human capital Level (*HUM*) *–The number of employees involved actively in science and technology activities*	0.153 (0.072)***	0.045 (0.081) ***
Investment in Scientific Research Funds (*RDIF*)	-.0.265 (0.258)*	-0.109 (0.130)
Foreign Trade Level (*TRA*)	0.191(0.056)**	-0.167(0.240)
Observations	20	20
R-squared	0.896	0.876

Notes. The dependent variable is labour productivity for overall Sector in China (Model 1), Agriculture sector (Model 2. Standard errors are reported in parentheses. ***P<0.01, **p<0.05 and *p<0.1 indicate significance at the 1%, 5%, and 10% levels, respectively.

The analysis of Model (1) clearly showed that the patent applications in China had a significant positive impact on labour productivity for China's overall economic sector, as with every 1% application of a patent in China, labour productivity would increase by 30.9%. Nonetheless, we found the effects of patent applications in the agriculture sector were negative and did not significantly influence the sector's labour productivity. This is consistent with earlier studies that highlight the shortcomings of patents as a gauge of innovation and their poor capacity to predict business performance (Arora et al., 2008; Isa et.al, 2023). Our finding can also be supported by Damioli et al.'s (2021) conclusion that AI technology in the first period was still less mature, characterised by less frequent patenting and sectors probably having less experience fully exploiting it. In the case of the agriculture sector, our results suggest that firms require some time to adapt the new technologies to their production and sector routines.

Based on our results, this study revealed that one of the main difficulties in using AI in agriculture is likely to be due to a lack of skilled labour as well as a lack of labour participation in R&D activities because the sector is still dominated by low-educated labour. It can be proved that, as the value of this study shows, only 4.5% of employees are actively involved in science and technology activities in the agricultural sector, which contributes to an increase in labour productivity. Therefore, through skills training and the development of new job prospects in the agricultural sector, we suggest that attention be paid to helping farm workers make the transition to AI applications efficiently. Our findings concerning how patents affect the labour productivity of the agriculture sector not only refute traditional assumptions about the value of patents but also offer recommendations for policymakers as well as practitioners in developing strategies for maximising the returns on innovation and AI investments.

Regarding the role of education fiscal expenditure, our results showed that China's labour productivity was positive and statistically significant across China's economic sectors. The result showed that a 1% increase in education fiscal expenditure would increase the overall sector's labour productivity by 17.7% and 27.8%, respectively. This result supports the theory of human capital and empirical studies, stating that human capital and R&D determine the capacity to innovate and absorb new technology and are seen as a source of continuous innovation and higher productivity growth (Nelson & Phelps, 1966; Romer, 1990; Yunus & Abdullah, 2022b). This finding also implies that the strong national investment in new technology and the rapid development of AI technology, particularly during the period of 2015 to 2020, in line with China's national policy related to AI development, are being carried out steadily to equip young people with the necessary skills and to encourage the involvement of workers in scientific research. Moreover, the policy is aimed at helping workers thrive in a rapidly changing labour market and to ensure the new digital technology can be adopted by workers, thus resulting in greater labour productivity in their workplace (McGivney & Winthrop, 2016; Purdy et.al, 2015).

The effect of investment in scientific research on labour productivity was insignificant for the agriculture sector. This finding could be due to the crowding-out effect (Yunus & Masron, 2020; Yunus & Abdullah 2022a; 2022b). The effect of crowding tends to occur because investment in scientific research funds is concentrated in some high industries. Industries receiving higher investment in scientific research, such as China's manufacturing and services sectors, will enjoy better technology and lower production cost, hence increasing their labour productivity.

Lastly, the effects of the import-export activity on labour productivity in China's agriculture sectors is performed negative implying that in the case of China, the overwhelming number of unskilled workers at various production stages in the agriculture sector and the local firms’ low absorptive capacity impede the sector’s ability to imitate the imported intermediate inputs, particularly technological knowledge. This could cause a crowding-out effect, ultimately inducing a specialisation in the unskilled intensive segments of each industry, which hinders firms from achieving higher productivity (Rambeli & Povinsky, 2014).

CONCLUSION AND RECOMMENDATIONS

This study adopted total patent application as a proxy for AI, along with additional explanatory variables that were rarely used in the literature, to analyse its effects on labour productivity in China’s overall economic sector, with a focus on China’s agriculture sector. Using short-term series data from 2000 until 2019, the OLS estimation results confirm that AI has a significant positive impact on the overall sector of China’s labour productivity but found insignificant results in increasing the agriculture sector’s labour productivity. These results indicate that agriculture's service sector remains characterised by low-skilled labour, which contributes to the lower level of absorption of patent applications in their production, hence leading to the sector’s lower labour productivity.

Our results also suggest that a sharp technological improvement in AI may depend on the time interval required by the AI revolution to allow AI applications to become complementary and grow in the agriculture sector. The industry also needs to reorganise workers' skills and provide training in assimilating AI technology in the agriculture sector, and this situation has led to low productivity growth even in recent years (Brynjolfsson &Mitchell, 2017; Yang, 2022). To increase agriculture’s labour productivity, the Chinese government’s focus should be on the application of AI systems to help improve the overall harvest quality and accuracy, particularly in the digital transformation of small-scale farms. Also, AI technology helps in disease detection and deciding which herbicides to apply, especially by utilising AI sensors that can detect and target weeds.

Based on the overall findings of this study, we recommend to policymakers the necessity for focused actions to support the advancement of AI, raise levels of education and human capital, and encourage international trade alliances. The positive correlation between AI patent applications and labour productivity in the overall Chinese economic sector highlights how critical it is to encourage and promote AI research and innovation. To ensure that the workforce has the skills necessary to properly use AI technologies, policy initiatives should concentrate on bolstering the educational system and increasing human capital development.

Our study shows that data privacy and security issues should be considered in the agricultural sector when improving the ability of AI applications to increase labour productivity. This aims to maintain farmers' trust in the AI system depending on the extent to which the AI system is able to protect their personal information and prevent unauthorised access to their data. Strong data security mechanisms, encryption methods, and compliance with data privacy legislation are required to keep farmers' information safe and prevent its exploitation. The confidence needed to use AI in agriculture can be strengthened by fostering openness and providing clear norms for data ownership and use. In addition, a comprehensive database needs to be developed to collect and analyse a large amount of data, such as farm management records, weather patterns, and crop health records, which is important for the successful use of artificial intelligence technology in agriculture (Alreshidi, 2019).

In addition to the limitations and lack of a precise and widely accepted definition of AI, our study emphasises the difficulties and challenges that businesses face when integrating AI into their operations as well as the potential time needed for AI applications to become complementary and contribute to productivity growth. As a result, we recommend that future research broaden its scope to investigate the possibilities of merging data from various sources, such as combining data from several cities or areas within a province. To assure data consistency and representativeness, this strategy would need to be carefully considered.

REFERENCES

Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. *The Economics of Artificial Intelligence: An agenda* (pp. 197-236). University of Chicago Press.

Aghion, P., Jones, B. F., & Jones, C. I. (2018). Artificial intelligence and economic growth. *The Economics of Artificial Intelligence: An agenda* (pp. 237-282). University of Chicago Press.

Alreshidi, E. (2019). Smart sustainable agriculture (SSA) solution underpinned by internet of things (IoT) and artificial intelligence (AI). *arXiv preprint arXiv:1906.03106*.

Arora, A., Ceccagnoli, M., & Cohen, W. M. (2008). R&D and the patent premium. *International Journal of Industrial Organization*, *26*(5), 1153-1179.

Baldwin, R. E., & Okubo, T. (2006). Heterogeneous firms, agglomeration and economic geography: Spatial selection and sorting. *Journal of Economic Geography, 6(3), 323-346.*

Bannerjee, G., Sarkar, U., Das, S., & Ghosh, I. (2018). Artificial intelligence in agriculture: A literature survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies*, *7*(3), 1-6.

Benson, C. L., & Magee, C. L. (2015). Quantitative determination of technological improvement from patent data. *PloS one*. 10(4), e0121635.

Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews*, *19*(3), 321-340.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530-1534.

Chen, L., Cai, W., & Ma, M. (2020). Decoupling or delusion? Mapping carbon emission per capita based on the human development index in Southwest China. *Science of the Total Environment*, *741*, *138722.*

Cleeve, E. A., Debrah, Y., & Yiheyis, Z. (2015). Human capital and FDI inflow: An assessment of the African case. *World Development,74,* 1-14.

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, *11*(1), 1-25.

Fankhauser, M., Moser, C. & Nyfeler, T. (2018). Patents as early indicators of technology and investment trends: Analyzing the microbiome space as a case study. *Frontiers in Bioengineering and Biotechnology*, 6(84), doi: 10.3389/fbioe.2018.00084.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological Forecasting and Social Change*, *114*, 254-280.

Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation Policy and the Economy*, *19*(1), 161-191.

Gollin, D., Lagakos, D., & Waugh, M. E. (2014). The agricultural productivity gaps. *The Quarterly Journal of Economics*, *129*(2), 939-993.

Gujarati, D.N., & Porter, D.C. (2012). *Basic Econometrics* (5th ed.). New York: McGraw-Hill Education.

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, *2*, 1–31. Available at: https://doi.org/10.1177/1536867x0700700301.

Isa, S. F. M., & Yasin, M. A. I. (2023). Exploring effective negotiations on copyright transfer: A qualitative study of business communication in the creative industries. *International Business Education Journal*, *16*(1), 33-49.

Lele, U., Goswami, S., & Nico, G. (2017). Structural transformation and the transition from concessional assistance to commercial flows: The past and possible future contributions of the World Bank. *Agriculture and Rural Development in a Globalizing World* (pp. 325-352). Routledge.

Liu, X., Parker, D., Vaidya, K., & Wei, Y. (2001). The impact of foreign direct investment on labour productivity in the Chinese electronics industry. *International Business Review*, *10*(4), 421–439.

Lokshin, B., Belderbos, R., & Carree, M. (2008). The productivity effects of internal and external R&D: Evidence from a dynamic panel data model. *Oxford bulletin of Economics and Statistics*, *70*(3), 399-413.

Luo, Z., Hu, X., Tian, X., Luo, C., Xu, H., Li, Q., & Chu, J. (2019). Structure-property relationships in graphene-based strain and pressure sensors for potential artificial intelligence applications. *Sensors, 19(5), 1250*.

Maazouz, M. (2013). Return to investment in human capital and policy of labour market: Empirical analysis of developing countries. *Procedia Economics and Finance, 5*, 524-531.

Maher, T., & Schaffelke, N. (2023). *Unlocking the AI advantage: Investigating the impact of ai patents on firm earnings and industry dynamics: A comprehensive investigation of the influence of AI patent ownership on corporate financial performance* (Master

Dissertation, Umeå University). Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-210295

McCorduck, P., & Cfe, C. (2004). *Machines who think: A personal inquiry into the history and prospects of artificial intelligence*. CRC Press.

McGivney, E., & Winthrop, R. (2016). Education's impact on economic growth and productivity. *Washington, DC: Brookings Institution, July*.

Muhanna, W. A., & Stoel, M. D. (2010). How do investors value IT? An empirical investigation of the value relevance of IT capability and IT spending across industries. *Journal of Information Systems*, *24*(1), 43-66.

Nelson, R. R., & Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, *56*(1/2), 69-75.

Organisation for Economic Co-operation and Development (OECD). (2004). *Patents and innovation: Trends and policy challenges*. OECD Publishing.

Parham, D., & Zheng, S. (2006). Aggregate and industry productivity estimates for Australia. *Australian Economic Review*, *39*(2), 216-226.

Puaschunder, J. M. (2019). Artificial Intelligence market disruption. *In Proceedings of the International RAIS Conference on Social Sciences and Humanities organized by Research Association for Interdisciplinary Studies (RAIS) at Johns Hopkins University*, Montgomery County Campus, Rockville, MD, United States, 1-8.

Purdy, M., & Davarzani, L. (2015). The growth game-changer. How the industrial internet of things can drive progress and prosperity. *Accenture*.

Qiulin, C., Duo, X., & Yi, Z. (2019). AI's Effects on Economic Growth in Aging Society: Induced

Ramli, N. R., Hashim, E., & Marikan, D. A. A. (2016). Relationship between education expenditure, capital, labor force and economic growth in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, *6*(12), 459-468.

Rambeli, N., & Povinsky, J. M. (2014). A study of exogeneity tests on export-led growth hypothesis the empirical evidences on post-crisis exchange rate regime in Malaysia. *International Business Education Journal*, *7*, 1-15.

Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(1), 1-14.

Romer, P. M. (1990). Capital, labor, and productivity. *Brookings papers on economic activity. Microeconomics, 1990, 337-367.*

Singh, S. K., Rathore, S., & Park, J. H. (2020). Blockiot intelligence: A blockchain-enabled intelligent IoT architecture with artificial intelligence. *Future Generation Computer Systems*, *110*, 721- 743.

Towse, R. (2006). Human capital and artists' labour markets. *Handbook of the Economics of Art and Culture*, *1, 865-894.*

Trajtenberg, M. (2018). Artificial intelligence as the next GPT: A political-economy perspective. *The Economics of Artificial Intelligence: An Agenda* (pp. 175-186). University of Chicago Press.

Vadlamudi, S. (2019). How artificial intelligence improves agricultural productivity and sustainability: a global thematic analysis. *Asia Pacific Journal of Energy and Environment*, *6*(2), 91-100.

Wu, B., & Yang, W. (2022). Empirical Test of the Impact of the Digital Economy on China's Employment Structure. *Finance Research Letters*, 103047.

Yang, D. T., Chen, V. W., & Monarch, R. (2010). Rising wages: Has China lost its global labor advantage? *Pacific Economic Review*, *15*(4), 482-504.

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

Yunus, N. M. (2023). Absorptive Capacity and Technology Spillovers: A Quantile Regression Approach. *Institutions and Economies*, 1-27.

Yunus, N. M., & Abdullah, N. (2022a). A Quantile Regression Analysis of Absorptive Capacity in the Malaysian Manufacturing Industry. *Malaysian Journal of Economic Studies*, *59*(1), 153-170.

Yunus, N. M., & Abdullah, N. (2022b). The effect of foreign direct investment on labour productivity: Evidence from five investor countries in Malaysia's manufacturing industries. *Malaysian Management Journal*, 26(July), 55-86. https://doi.org/10.32890/mmj2022.26.3

Yunus, N. M., & Masron, T. A. (2020). Spillover effects of inward foreign direct investment on labour productivity: An analysis on skill composition in manufacturing industry. *International Journal of Asian Social Science*, *10*(10), 593-611.

Yunus, N. M., Said, R., & Siong Hook, L. (2014). Do cost of training, education level and R&D investment matter towards influencing labour productivity? *Jurnal Ekonomi Malaysia*, *48*(1), 133–142.

Zhang, Y. (2020). The impact of artificial intelligence on China's labor legislation. *International Journal of Frontiers in Sociology*, 2(3), 25-39.

Zhu, Q., & Li, M. (2018). Research on countermeasures for artificial intelligence, technological progress and labor structure optimization. *Science and Technology Progress and Countermeasures*, *35*(6), 36-41.