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Artificial Intelligence and Labour Productivity: Lessons from China

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Abstract

This study investigates the impact of artificial intelligence (AI) on labour productivity across China's manufacturing, services, and agriculture sectors by using the number of patented AI applications as a proxy for AI. The research spans the period from 2000 to 2019. Employing Ordinary Least Squares (OLS) regression analysis, our findings reveal that the influence of AI patent applications on labour productivity is more pronounced in the manufacturing sector compared to the services sector. In contrast, we observe insignificant results in the agriculture sector. Several factors contribute to these disparities, including the greater employment of highly skilled workers in China's manufacturing sector, while the services sector generates more jobs for less skilled employees due to lower AI utilisation. Nevertheless, we conclude that the effects of current AI patent applications on labour productivity in Chinese economic sectors are not immediate, only manifesting after several years. This lag can be attributed to the time required for patent processing and research and development (R&D) activities, along with the lag structure of labour productivity. Our results also underscore a notable gap in the rapid development of AI patent applications between agriculture and both the manufacturing and services sectors. This highlights the policy implications of the need to enhance coordination between industrial structures and employment structures across industries. Greater investments in patents, R&D, innovation activities, and workforce training should focus on industries with low AI adoption rates. Consequently, policymakers in China should prioritise augmenting the level of human capital by improving the technological skills of the labour force, enabling

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workers to assimilate AI, and increasing the number of AI patent applications across economic sectors.

Keywords: *AI patent applications, artificial intelligence, labour productivity.*

1. Introduction

Undoubtedly, technology-based artificial intelligence (AI) has played a major role in the digitization of the economy and society since its ability to collect, process, and analyse large amounts of data at a faster rate. Advances in AI have helped various industries create new technologies, improve business processes, and produce greater efficiency. AI is also considered a key driver of economic growth and is seen as a productivity-enhancing agent (Acemoglu et al., 2018). However, the slow economic growth experienced in developed countries also emphasises the extent to which AI can boost productivity. Data shows that 36 out of 37 developed economies experienced slower economic growth in 2006–2016 (1 per cent) compared to 1996–2006 (2.7 per cent), although AI applications have been widely used in developed countries (Furman and Seamans, 2019).

Slower economic growth in developed countries is still closely related to the decline in productivity, which is constrained by factors such as the difficulty workers face in learning new skills, the rate of AI adoption, and the extent to which AI interacts with the efficiency and knowledge of labour (Acemoglu and Restrepo, 2018). Likewise, the ability of labour and capital investment to drive economic progress has declined significantly globally (Purdy and Davarzani, 2015). The current level of technological progress that has not been fully utilised has led to structural changes that disrupt the composition of employment, and China is no exception to this situation. The increase in labour productivity in China could be affected if the emergence and development of AI are not fully utilised, which would lower both China's overall productivity and the trend of labour productivity. As evidenced in 2020, China's productivity is only about 7 per cent, which is low compared to 9.9 per cent in other developing countries (Yang et al., 2010). Meanwhile, China's labour productivity declined by 4.82 per cent year-over-year in December 2022, compared to growth of 9.05 per cent in the previous year.

A plausible reason for the declining trend of China's labour productivity may be attributed to the efforts of Chinese policymakers to make China a leader in the industrial revolution with a special focus on AI. The Chinese government has placed a specific emphasis on this goal in its national development policy by making significant capital investments in the high-tech industry based on AI technology (Sheehan, 2022). However, too much emphasis on AI development has raised concerns about potential drawbacks, such as the crowding out of R&D and productivity in sectors not strictly connected with AI, which tends to cause the development of other important economic sectors to be neglected (Arenal et al., 2020). As a result, the impact of AI on overall economic productivity becomes uncertain.

The emergence of AI has also created a discrepancy between China's employment structure and industrial structure, resulting in the country's low labour productivity (Zhang, 2020). The existing gap between the rapid development of AI and the practical application of AI has caused a mismatch between the transformations and the upgrading of China's industry and employment structure. This has further led to poor growth in the corresponding labour force across agriculture and service industries, resulting in low labour productivity. Therefore, it is debatable whether AI could improve labour productivity in China. Studies are required to quantify the effects of AI on economic outcomes like employment, productivity, growth, and labour productivity, but these studies are hampered by the requirement for accurate and excellent firm- and sectoral-level data (Furman and Seamans, 2019; Raj and Seamans, 2019).

This study provides a preliminary analysis based on the short-term series data regarding the impact of AI patent applications on China's labour productivity. In this study, we contribute to the innovation literature in two ways. First, we provide one of the earliest instances of how AI patent applications affect labour productivity at the sectoral level in China. Specifically, we investigate the impact of AI on labour productivity according to the technology intensity classification based on R&D intensity in China's economic sectors.[1] Most researchers and policymakers focused on high-technology industrial sectors such as ICT and manufacturing sectors, including in China, and often overlooked low-tech sectors like agriculture, despite the latter being one of the most important sectors contributing to China's economic development (Banerjee et al., 2018).

Thus, we attempt to contribute to the literature by focusing on the impact of AI patent applications in both high-tech and low-tech industrial sectors in China due to the limited number of studies that make comparisons, particularly involving the agriculture sector (Sheng et al., 2020). Realising that China's agricultural sector is currently experiencing pressure due to rapid population growth, degradation of agricultural land, and the pressure of conflict between the population and agricultural resources, it is important to explore the impact of AI in the agricultural sector. We measure this through labour productivity, considering it one of the main indicators of the ability of workers to adopt AI technology given mastery in the application of AI has been shown to improve the quality and accuracy of the overall harvest, in line with the goal of the agricultural sector to reduce inputs (Elbasi et al., 2022; Sheng et al., 2020).

Additionally, this paper uses the number of AI patents to represent the application of AI technology in investigating the impact of AI patents on labour productivity in China's economic sectors. China is emerging as a leader in AI as it shows improvement in filing of AI patents and experimenting with the most recent AI technologies to power industrial applications (Cheng and Zeng, 2023). The literature has shown increasing attention to the evolution of AI patent applications due to their positive effect on companies' performance, but their impact on labour productivity is still inadequate, and there is no clear consensus on how AI patents might influence both firms' productivity and labour productivity (Fujii and Managi, 2018; Cockburn et al., 2019; Mátė et al., 2016; Yang, 2022).

To the best of our knowledge, only a study by Yang (2022) applied AI patents as a proxy to measure the effects of AI application in China's case, but the author's focus was on firms' productivity and employment and not specifically divided according to China's economic sector levels. The study provides suggestions and brief ideas for policy implications regarding the effectiveness of patent applications in the industry. These 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 for and the speed of AI development across the world. Therefore, our comparative examination between high-tech and low-tech sectors would show the level of employee productivity to be gained from the application of patented AI. The results of this study will also help China's economic sectors better understand its employees' capability to capture AI technology, which will have structural and scale implications for restructuring the labour market. This scale effect will aid businesses in deciding whether to raise labour demand, which will result in more jobs and higher salaries. At the same time, the structural impact would create a redistribution of tasks between humans and machines, which might result in a loss of tasks for humans (displacement effect) or an increase in new or changed job responsibilities (Damioli et al., 2021; Fossen et al., 2022).

Meanwhile, our findings may enhance managers' use of AI in connection with industry-related AI patent applications to boost market capitalization and enable businesses to have improved labour productivity (Máté et al., 2016; Yang, 2022). Since the lack of labour skills and AI talent has a direct impact on the application of AI in businesses, managers must be aware of these implications and work with their teams to develop more collaborative production models that actively involve both humans and machines. This is due to the fact that recently developed AI and robotics would eliminate jobs and cause irreparable harm to the labour market.

The remainder of the paper is organised as follows: Section 2 reviews the literature related to AI from theoretical and empirical perspectives. The methodology section, which includes the data sources, scope of the study, and variables used in this study, is explained in Section 3. Section 4 explains the empirical model. The findings of this study are discussed in Section 5. The conclusion and suggestions for policy implications are presented in Section 6.

2. Literature Review

The concept and application of AI in academics is not standardised, and its technical application is still being broadened. McCorduck and Cfe (2004) characterised AI as a "thinking machine" that can currently mimic human thought and behaviour and, in the future, may outperform it. The concept of organisational competence was used by Bharadwaj et al. (1998) to define AI technology. The productivity of the workforce can be increased by integrating AI technology with various organisational resources and tasks. According to Singh et al. (2020), AI is a technology that encourages industry to spend more capital. They stressed that despite the fact that utilising AI would boost labour productivity because it reduces labour time, it would also result in a decrease in the usage of labour that would eventually be replaced by technology. Additionally, they claimed that the value composition of capital is impacted by its technological composition, which raises the relative surplus value of capital. However, Muhanna and Stoel (2010) discovered that investing funds in AI technologies is unlikely to result in higher labour productivity. They contend that specific market and business-specific criteria determine the actual impact of such a fast investment. Brynjolfsson and Mitchell (2017) expanded on this by further classifying AI-related issues into four categories: misleading expectations, incorrect measurement, reorganisation effect, and general technology adoption.

Romer's (1990) model serves as the foundation for the theory of technological progress, which claims that the application of AI leads to productivity changes among industries. Thus, factors of production such as labour will be optimally allocated and directly or indirectly affect the share of employment and output value of each industry, i.e., industrial structural change. Romer's model also refers to the combined input productivity of all factors as total factor productivity (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. Based on Romer's analysis, AI may cause changes in the allocation of factors of production between industries, thus affecting labour productivity. Meanwhile, the endogenous growth theory contends that increases in productivity can be directly linked to more rapid innovation and greater investments in human capital from both the government and private sectors.

Given that AI may be regarded as a technology that has only recently gained attention and been applied in an extensive number of studies, the literature has shown that there is not enough evidence to accurately assess and gauge the development of AI by using appropriate proxies (e.g., Chen et al., 2020; Damioli et al., 2021; Purdy and Davarzani, 2015). However, most of the research indicates that the most prevalent approach to measuring the advancement of AI is the number of industrial robots utilised in the industry. For example, empirical studies include those by Graetz and Michaels (2015), Acemoglu and Restrepo (2018) in the United States, and Zhu and Li (2018) in China. These studies employed total sales of industrial robots to demonstrate the extent of AI application in the various economic sectors. They came to the conclusion that as AI advances and technical expertise rises, there will be an increase in the proportion of skilled and unskilled workers in the labour force. This will enhance the overall quality of the labour force and optimise the labour structure. Qiulin et al. (2019) focused on the degree of robot installation, which they determined by dividing the total number of intelligent robots installed in the domestic sector by the number of workers employed in that year as a measure of the industry's adoption of AI. According to a survey by the European Commission of the 3,000 manufacturing companies, the usage of industrial robots has contributed to achieving higher labour productivity (Jäger et al., 2015).

Since patents are a significant driver of productivity development and firm performance, AI patent data is another body of literature that has been used extensively to measure AI. For instance, Van Roy et al. (2020) examined the economic outcomes of European companies that filed patents for AI (i.e., "AI creators") from 2000 to 2016. Using a keyword-based approach to find AI patents, they discovered a large increase in annual sales for AI developers with at least one granted patent, particularly SMEs, as compared to companies with only ungranted AI patent applications. A panel data set of German companies was used by Behrens and Trunschke (2020) to examine the impact of patents on the industry 4.0 revolution. According to this study, the marginal benefit of additional "4.0 patents" will boost company revenues by 8.3 per cent, with the marginal effect decreasing with business size.

The literature showed that there are only a small number of studies that expressly explore the impact of AI on labour productivity using patent information, namely Yang (2022), Cockburn et al. (2019), and Alderucci and Sicker (2019). However, their research still focused on studying the effects of AI on firm productivity, labour demand and employment. However, studies that specifically examine how AI patents affect worker labour productivity are still absent and require further study given the widespread concern and debate surrounding its potential repercussions in job losses and wage stagnation for most workers (Brynjolfsson and McAfee, 2015).

We discovered that only a few studies have examined the impact of AI on labour productivity using different AI proxies. For example, Damioli et al. (2021) investigated the impact of patent applications for AI on labour productivity using AI patents and robotics as their AI proxies. Using a global sample of 5,257 firms, they found that most companies were filing a minimum of one AI-related patent between 2000 and 2016. Their analysis showed that AI patent applications and robotics activities had a significant impact on firm labour productivity. They also found that the impact of AI and robotics applications in industry is highly dependent on the capacity of the SME sector and the service sector to quickly adopt AI-based technology to increase the effectiveness of the manufacturing process in the SME sector and productivity in the service sector.

Acemoglu and Restrepo (2018) examined how the adoption of industrial robots affects US labour productivity. They investigated in detail the impact of the large-scale use of robots on labour productivity in 19 manufacturing industries across 722 regions between 1993 and 2007. Overall, their findings show that the widespread use of robots in the manufacturing sector has a very negative impact on worker productivity because the impact of robots outweighs the creation advantage. The results of their study revealed that the use of industrial robots contributed to an increase in the number of unemployed workers in the manufacturing sector from 360,000 to 670,000 between 1990 and 2007. However, their findings raise concerns about the future of jobs, and wages are increasing as robots and technology provide other computer-aided replacements for labour-intensive tasks. According to their estimates, each additional robot increases the job-to-population ratio from 0.18 to 0.34 age points and increases the wage by 0.25 to 0.5 per cent per 1,000 workers. They also suggest that the use of robots in one shuttle zone could reduce production costs and, through trade, allow other industries to create jobs across the economy. The application of AI in the agricultural sector has recently been the centre of attention. Bannerjee et al. (2018) investigated the impact of AI on the agricultural sector. Their findings show that although the application of AI does not show a significant increase in the number of farmers interested in using AI in agricultural activities, but the application of AI technology has improved farmers' relationships with the market by changing their work habits and practices. Lele et al. (2017) also focused on the agricultural sector, showing that smart digital technology is beneficial to inclusive agricultural and rural development, is capable of bridging farmers and markets at every stage of production, and has indirectly increased farmers' incomes. Several schemes have been put in place to raise the standard of education, healthcare, finances, and market services for farmers in an effort to boost their income.

Other studies by Brogårdh (2007) and Bechar and Vigneault (2016) show that AI applications mean robots are now fully-equipped to maximise output in the agricultural sector, increase productivity and the standard of agricultural products. Spanaki et al. (2021) show that the use of data can improve farming practices and operations because agri-food businesses can create value from it, depending on the ability of AI to manage data sharing and access control. Therefore, AI can address the knowledge needs of farming businesses and improve their ability to identify diseases, monitor irrigation, reduce human effort, and maximise yield production. According to Spanaki et al. (2021), the use of data can improve agricultural processes and practices because agri-food enterprises can profit from it; however, it depends on the capacity of AI to oversee information sharing and accessibility. As a result, AI can help farming enterprises improve their ability to detect disease, track irrigation, save labour costs, and increase agricultural production.

Regarding research that examines the impact of AI applications in the service sector, Trajtenberg (2018) shows that the impact of AI has increased the number of jobs in the socially intensive sector in the United States by 24 per cent, and wages increased by 26 per cent between 1980 and 2012. By 2024, the author predicts that as industry begins to use AI for its tasks and production, almost all new jobs will be concentrated in the sector, particularly in healthcare and social assistance services. Using the number of patents and trademarks as a proxy for AI, Máté et al. (2016) examined the effects of AI on labour productivity in the long run in several OECD countries. Additionally, they used dynamic panel regression models to look at the long-term effects of intellectual property rights on productivity to see if there is a connection between output per person and the number of patents and trademarks. Based on their findings, the increasing number of patents and trademarks may be inversely correlated with labour productivity growth in the context of knowledge-intensive (business) service industries between 1995 and 2011. Their research's conclusions accord with the conclusions made by Park (2005), who showed a negative effect of trademarks and no direct effect of intellectual property rights (IPR) on labour productivity in the manufacturing sector. The negative impact of trade and IPR on labour productivity was also confirmed by Chen and Puttitanun (2005), who stated that there is a U-shaped relationship between IPR and economic development due to the stronger incentives of developing countries to imitate the higher IPR protection of developed countries, while the high level of IPR can stimulate productivity growth. Inversely, to a certain extent, productivity decreases, which is consistent with the rise in IPR experienced by most OECD countries. Based on the literature presented above, the understanding of how the application of AI patents can improve labour productivity, especially in the economic sectors, is not comprehensive and is still in its early phase, which may be due to a lack of data. This situation shows that additional quantitative research and numerical analysis are still needed to fully understand how advancing the level of AI development and practical application by workers affects labour productivity (Damioli et al., 2021; Wu et al., 2020). As such, the study found that quantitative methods allow us to gauge the degree of workers' absorption capability based on the value of the labour productivity coefficient (Yunus, 2023; Wu and Yang, 2022; Zhang, 2020).

3. Methods

3.1 Data Sources and the Scope of Study

The data sources used to calculate labour productivity, which require the variables of value added and the number of employees in China's manufacturing, services, and agriculture sectors, were gathered from the China Macroeconomic Database. We obtained data from the National Industrial Information Security Development Research Centre and the Electronic Intellectual Property Centre of the Ministry of Industry and Information Technology for AI data, which is measured by the number of patented AI applications. These sources provide information about China's economic sectors and offer reports on China's patents related to AI technology. Additionally, we utilised the China Statistical Yearbook to obtain other variables, namely, fixed capital stock, the per centage number of employees involved in science and technology activities as part of the total workforce, fiscal education expenditure, research and experimental development expenditure, gross domestic product (GDP), and total import and export volume.

The sample size in this study is limited to 20 observations because our study covers the period 2000–2019, taking complete data into account. In the period 2000–2019, the number of AI patent applications has been large in accordance with the initiatives of the Chinese government to further expand R&D funds for AI, and the number of research projects in AI sponsored by the Chinese government has increased significantly since 2000 (Sheehan, 2022). During the period of investigation, China also consistently filed more AI patents than any other country. For instance, as of March 2019, there were 1,189 Chinese AI companies. Nonetheless, the coverage is constrained because finalised data for China's patented AI applications, including in the Chinese economic sectors, has not been released after 2019 (Barton et al., 2017).

3.2 Variables

The dependent variable in this study is labour productivity (LP), which is measured as value added per worker in specific sectors (Acemoglu et al., 2018; Chen et al., 2020; Liu et al., 2001; Yang, 2022). We applied a similar approach in our study to calculate labour productivity for China's manufacturing, services, and agriculture sectors. For the independent variable, we focus on the number of patented AI applications (*AI_PATENT*) because of its significant impact on labour productivity, as indicated in current literature on China's sectoral labour productivity (Damioli et al., 2021; Yang, 2022). Patent information serves as a practical source of data since firms have a strong motivation to patent their AI-related technology to prevent replication, hinder future competitors, and maximise commercial revenues (Yang, 2022). AI patents provide the best proxy for AI technology because the information contained in the process of AI patents embodies the components of invention, utility, and new design, which are associated with new technical solutions for products and processes. Patents are considered to have greater technological novelty and positively impact labour productivity. AI patent applications help capture changes in a firm's AI knowledge base (Damioli et al., 2021).

3.3 Control Variables

This study incorporates control variables known in the literature to impact labour productivity, namely, human capital, research and experimental development expenditure, and foreign trade level. For the human capital variable, two proxies were used, namely, education fiscal expenditure (*EXP_EDU*) and the number of employees involved in science and technology activities (*EMP_ST*) (Le et al., 2019; Towse, 2006). Education fiscal expenditure is measured as the per centage of education fiscal expenditure relative to total fiscal expenditure in China (Luo et al., 2019; Maazouz,2013; Wulandari et al., 2021). Both variables, which represent the human capital proxy, are well utilised in empirical studies to investigate their impact on labour productivity (e.g., Le et al., 2019; Towse, 2006; Yunus et al., 2014; Yunus, 2020). Both proxies are also compatible with the theory of endogenous economic growth, which redefines labour as an investment in human capital, emphasising both workforce size and quality (knowledge and skills) as important indicators to determine higher labour productivity growth.

Additionally, in the context of China, it is important to look at the impact of education expenditure on productivity so that adjustments to education and training policies can be implemented. This is particularly relevant considering the shortage of AI talent in China and the need to enhance technological capabilities in the production industry. The main obstacle to the spread of AI technology in China is the lack of AI talent (Liu et al., 2021).

In our study, research and experimental development expenditure (RDE) 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 and Zheng, 2006). In addition, RDE expenditure is measured as a per centage of GDP. In the context of China, the effects of research and experimental development expenditure on economic outcomes need to be investigated as the Chinese government increases support for R&D projects in AI-related fields. The government has also established academic groups such as the Professional Committee on Pattern Recognition and Machine Intelligence of the Chinese Society of Automation and the Chinese Society of Artificial Intelligence (Roberts et al., 2021). Adopting this proxy for labour productivity estimation, the study aims to assess the effectiveness of investment in scientific research in relation to workers' labour productivity, thereby enabling firms to enhance their technical capability and profitability. Meanwhile, foreign trade level (*TRADE*) is used as the index of an export-oriented economy, measuring it as the total import and export volume (Acemoglu and Restrepo, 2018; Luo et al., 2019). Foreign trade level reflects the degree of China's openness to the outside world, which can significantly impact China's total labour productivity.

4. Empirical Model

Given that studies on AI and labour productivity in China are still in their early stages, this study also paves the way for future studies on how AI, through the patented AI applications in China, could potentially enhance labour productivity in the economic sectors (Alderucci and Sicker, 2019; Damioli et al., 2021). The combined role of AI, human capital, RDE, and foreign trade level in the labour productivity policy in China has received relatively little attention (Yang, 2022). 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. Hence, this study attempts to contribute to the literature by re-estimating the labour productivity function for China's manufacturing, services and agriculture sectors based on the combination of the independent variables.

The theoretical framework in our study follows the research by Damioli et al. (2021) and Banerjee et al. (2018), which investigated the effects of AI on labour productivity. They measure AI using robotics and patented AI applications as proxies. In our study, due to limited sectoral data availability, we excluded the robotics variable and considered AI patent applications as the best proxy, consistent with the empirical model specification used by Fujii and Managi (2018) and Cockburn et al.(2019). The combined other independent variables, namely, human capital, research and experimental development expenditure, and foreign trade level, which were suggested by Acemoglu and Restrepo (2018), Gollin et al. (2014), Yunus et al. (2015), and Le et al. (2019) were applied in our model estimation. The basic model in this study, based on the Cobb-Douglas model for investigating the effects of AI combined with independent variables on labour productivity in China's economic sectors, is presented as follows:

$$LP_{i,t} = \beta_0 + \beta_1 K/L_{\ i,t} + \beta_2 AI\_PATENT_{\ i,t} + \beta_3 EXP\_EDU_{\ i,t} + \beta_4 EMP\_ST_{\ i,t} + \beta_5 RDE_{\ i,t} + \beta_6 TRADE_{\ i,t} + \varepsilon_{i,t} \quad (1)$$

where: *i* refers to China's economic sectors respectively for manufacturing, services and agriculture sectors; *t* is the time index; *LP* is labour productivity according to China's economic sectors as the dependent variable; *K/L* is physical capital labour ratio;[2] *AI_PATENT* is the number of patented AI applications; *EXP_EDU* is the per centage of education fiscal expenditure from total fiscal expenditure; *EMP_ST* is measured as the per centage of employees involved in science and technology activities from the total number of employees; *RDE* is the per centage of research and experimental development expenditure per GDP; *TRADE* 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 Damioli et al. (2021) to lag the period of the dependent variable with one lag period. The estimation model for labour productivity in China with the lag of labour productivity according to economic sectors is presented below:

$$LP_{i,t} = \beta_0 + \beta_1 LP'_{i,t-1} + \beta_2 K/L_{\ i,t} + \beta_3 AI\_PATENT_{\ i,t} + \beta_4 EXP\_EDU_{\ i,t} + \beta_5 EMP\_ST_{\ i,t} + \beta_6 RDE_{\ i,t} + \beta_7 TRADE_{\ i,t} + \varepsilon_{i,t} \quad (2)$$

where: $LAP'_{t\text{-}1}$ is the lagged China's labour productivity according to economic sectors. This specification allows for gradual convergence in efficiency levels between sectors, which has been observed as important in past empirical productivity studies to improve their productivity faster (Blundell and Bond, 2000; Damioli et al., 2021; Klette and Johansen, 2000; Lokshin et al., 2008).

With the limitation of time series data (20 observations), the present study employed an OLS estimator with robust standard errors to analyse the impact of AI patent applications on labour productivity during the period from 2000 to 2019.[3] The robust standard errors option in regression was also efficient in dealing with the minor normality problem because some observations might exhibit large residuals, leverage, or influence, as well as to capture the possible concerns about the effects of serial correlation on the standard errors (Hoechle, 2007). Even though this study only employed OLS estimation for a small sample, the results could still provide a preliminary picture of China's patented AI applications and labour productivity in China's economic sectors.

5. Findings

This section discusses the OLS regression results by narrowing the impact of patented AI applications on China's manufacturing, services and agriculture sectors.

5.1 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 and Abdullah, 2022b). Consequently, the validity results of the proxies were assessed based on their correlation values. If the correlation coefficient between the independent variables indicates a positive value, it is interpreted as an indicator of a strong relationship with the dependent variable (Yunus, 2023). As shown in Table 5.1, the positive coefficient obtained from these correlation analyses provides compelling evidence that nearly all the variables used in this study can be considered influential factors affecting labour productivity within China's economic sectors. Furthermore, the positive correlation observed between labour productivity and the independent variables also suggests a clear trend within most sectors in China that have benefited from exploiting the opportunities of a new degree of automation brought by AI technologies in their industries.

Table 5.1 Correlation Results for China's Manufacturing, Agriculture, and Services Sectors

Manufacturing								
	LP	LP'-1	K/L	AI_PATENT	EMP_ST	EXP_EDU	RDE	TRADE
LP	1.000							
LP'-1	0.212	1.000						
K/L	0.453	0.417	1.000					
AI_PATENT	0.621	-0.410	0.512	1.000				
EMP_ST	0.678	-0.601	0.423	0.632	1.000			
EXP_EDU	0.572	0.162	0.224	0.357	0.424	1.000		
RDE	0.681	0.521	0.235	0.665	0.731	-0.335	1.000	
TRADE	0.325	-0.322	-0.254	0.719	0.350	0.408	0.717	1.000
Services								
	LP	LP'-1	K/L	AI_PATENT	EMP_ST	EXP_EDU	RDE	TRADE
LP	1.000							
LP'-1	0.324	1.000						
K/L	0.412	0.362	1.000					
AI_PATENT	0.425	0.403	-0.213	1.000				
EMP_ST	0.215	0.612	0.456	0.661	1.000			
EXP_EDU	0.472	0.296	0.314	0.479	0.524	1.000		
RDE	-0.616	0.524	0.436	0.637	0.624	-0.318	1.000	
TRADE	-0.532	0.415	-0.242	-0.671	-0.391	0.346	-0.739	1.000

Agriculture								
	LP	LP'-1	K/L	AI_PATENT	EMP_ST	EXP_EDU	RDE	TRADE
LP	1.000							
LP'-1	0.342	1.000						
K/L	0.388	0.317	1.000					
AI_PATENT	0.727	0.392	0.453	1.000				
EMP_ST	0.648	0.518	0.251	0.759	1.000			
EXP_EDU	0.591	0.392	0.312	0.318	-0.542	1.000		
RDE	-0.642	0.5912	0.502	0.665	0.721	-0.449	1.000	
TRADE	-0.501	-0.357	-0.245	0.719	0.416	0.412	0.724	1.000

Note: All variables are transformed into natural log

To ensure firms are equipped to assimilate the latest technology, investment in education, R&D, and scientific research activities should be increased. This would ultimately enhance the overall productivity of the sector.

We also found a negative correlation between the coefficient of RDE and trade and labour productivity in both the agriculture and services sectors. This finding 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 sector (Damioli et al., 2021; Yang, 2022; Zouya and Yunus, 2024). The results of the correlation analysis in this study provide a more accurate picture than the individual data points. Notably, all variables' correlation coefficients were less than 0.8, demonstrating the absence of multicollinearity in the study's model (Gujarati and Porter, 2012).

5.2 Regression Results

Table 5.2 presents the results for the three models investigating the impacts of AI along with other influencers of labour productivity in China's manufacturing, agriculture, and services sectors. We utilised lagged variables of labour productivity to address time series persistence and endogeneity problems. Our findings reveal a positive and statistically significant effect of lagged labour productivity influencing labour productivity in China's economic sectors throughout the model.

Next, we shift our focus to the variable of interest in our study to seek the impact of AI patent applications on labour productivity. Our results in models (1) and (2) show that the application of patented AI in firm processes, product development, and monitoring has a significant positive impact on labour productivity for both China's manufacturing and services sectors. These results imply that by increasing innovation efforts by filing more patents for AI, labour productivity will increase by 31.8 per cent and 18.2 per cent, respectively, in the manufacturing and service sectors. These results are supported by Alderucci and Sicker (2019) and Damioli et al. (2021), all of whom report that the use of patented AI is positively associated with sales growth, labour market outcomes, and enhanced labour productivity within companies.

The higher coefficient of AI patent activity in the manufacturing sector compared to the service sector found in this study implies that the manufacturing sector in China may have more intensive patent applications and stronger patent laws than other sectors (Hu et al.,2012). The hiring of a higher number of highly skilled and talented workers in the manufacturing than in the services sectors may have different effects on labour productivity, in line with the skill-biased technological change (SBTC) theory. This statement can be supported by our results from model (2), which indicated that the per centage of employees involved in science and technology activities in manufacturing sectors is positive and significant, influencing labour productivity by more than 20 per cent.

A previous study by Xue et al. (2022) provides a comparison of AI applications between the manufacturing and services sectors in China, which may support the different results found in our study. Their results showed that in China's services sector, there is still more employment that needs to be maintained and more jobs created for less skilled employees due to a lower automation level, which still requires some level of human intervention or interaction. The deskilling effect of the automation technology used makes the occupations simpler and enables fewer qualified individuals to complete them in the services sector. Although the tasks in some manufacturing sectors are repetitive, standardised, and mostly free of human touch, a significant degree of customisation and the involvement of highly skilled workers are necessary in the manufacturing process, which contributes to the higher productivity of the manufacturing sector. As a result of the different characteristics between China's economic sectors, it leads to greater adoption of AI applications in the manufacturing sector compared to the service sector.

Table 5.2 Ordinary Least Square Estimation on Labour Productivity for China's Manufacturing, Agriculture, and Services Sectors

Dependent Variable: Labour productivity	**Model (1) Manufacturing**	**Model (2) Services**	**Model (3) Agriculture**
LP'-1	0.024(0.059) ***	0.057(0.087) **	0.064(0.071) *
Physical capital stock/ labour ratio (K/L)	0.032(0.163) *	0.254(0.205) **	-0.256(0.192) *
The number of patented AI applications (*AI_PATENT*)	0.318(0.151) ***	0.182(0.136)*	-0.256(0.195)
the per centage of education fiscal expenditure (*EXP_EDU*)	0.195(0.028) ***	0.143(0.043) *	0.268(0.050) **
the per centage number of employees involved in science and technology activities (*EMP_ST*)	0.213(0.072) ***	-0.278(0.079) ***	0.215(0.081)
Research and experimental development expenditure (*RDE*)	0.255(0.158) *	-0.237(0.173) *	-0.108(0.130)
Foreign Trade Level (*TRADE*) total import and export volume	0.181(0.056) ***	0.212(0.094) *	0.165(0.240)
Observation	20	20	20
R-squared	0.886	0.827	0.871

*Notes. The dependent variable is labour productivity for manufacturing sector (Model 1), services sector (Model 2) and agriculture sector in China (Model 3). All variables are transformed into natural log. Huber/white robust 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 impact of applying patented AI in the agriculture sector, however, was negative and did not significantly influence the agriculture sector's labour productivity. In the case of China's agriculture sector, our results suggest that firms require some time to adapt to the new technologies in their production and sectors' routines, which may be due to the lack of expertise and talent among the farmers to utilize the application of patent-based AI by agriculture sectors, since the integration of AI requires extensive cognitive computing, deep learning, and image recognition. This statement can be supported by our results in column (2), which showed that the number of workers involved in scientific research in the agriculture sector is not significant and is seen as one of the constraints to increasing agriculture's labour productivity. This result suggests that an insufficient number of farmers are directly accessing digital agriculture due to a lack of qualified farmland.

A previous study by Xie et al. (2021) demonstrated that rural Chinese labour is frequently undereducated and that present output is heavily reliant on experience. Urbanisation has led to the continuous inflow of young and strong labour into cities, resulting in an increasing proportion of older farmers in rural areas. Most farmers have not realised the value of digital agriculture, and they are not willing to invest in or unable to apply technology-based AI. These concerns, however, are not addressed in our current research due to the limitation of time series data on the issues. Therefore, the employees' involvement in scientific research aimed at increasing their absorptive capacity to exploit and assimilate patent applications in agriculture should be encouraged, as farmers need a certain skill set as AI is a complex system. The Chinese government should also increase their investment in AI and R&D in order to fully promote the digital transformation of agricultural production and operation, including planting information and the quality and safety control of food. China's investment in digital agriculture is lower than developed countries. Despite this, it has created a firm foundation in digital technology and economic development (Xie et al., 2021). The decision to increase the hiring and training of highly specialised AI talent can enable the agriculture sector to enter the productivity boom phase.

Another study showed that the differences in results between economic sectors may be due to the AI technology in the first period still being less mature, characterized by less frequent patenting, and that sectors probably had less experience fully exploiting it as digital agriculture is a technology-based industry. Similarly, the different results of the effect of patented AI on labour productivity between economic sectors might imply that the productivity of one sector also depends on the patent investment from other industries, as the knowledge may not have been originally contributed by their own investments in artificial intelligence and R&D. Instead, it may be affected by the knowledge of other firms or sectors through borrowing or even stealing (Damioli et al., 2021).

Lastly, we provide the results on the effects of control variables that affect labour productivity in China's economic sectors. At first glance, the effects of both human capital variables positively affect labour productivity across sectors. For instance, our results in model (1) showed that a one per cent increase in education fiscal expenditure and the number of employees involved actively in science and technology activities would increase the manufacturing sector's labour productivity by 19.5 per cent and 21.3 per cent, respectively. This result is supported by other empirical studies that found that involvement of educated and skilled workers in R&D activity and investment in education have a significant impact on labour productivity (e.g., Yunus et al., 2014; Afrooz et al., 2010; Goedhuys et al., 2006). Our findings may be in line with the efforts of the Chinese government, which continues to boost investment in new technologies in response to the need to provide young people with knowledge and skills and to promote employees' participation in scientific research, which is complementary to the use of AI-based technology in industry. These initiatives also seek to ensure that workers can adopt new digital technologies, increasing labour efficiency in their workplaces and enabling them to prosper in a labour market that is rapidly evolving (McGivney and Winthrop, 2016).

Regarding the effect of research and experimental development expenditure on labour productivity in China's economic sectors, our results found a significant and positive correlation for the manufacturing sector but a negative correlation with labour productivity in the service sector. This finding could be due to the crowding-out effect (Yunus et al., 2015; Yunus and Abdullah, 2022b). The effect of crowding tends to occur because investment in R&D is concentrated in some selected industries. Industries receiving higher investment in scientific research, such as China's manufacturing sector, will enjoy better technology and lower production costs, thereby increasing their labour productivity.

The effects of trade via import-export activity on labour productivity in the agriculture sector differ from the results found in China's manufacturing and services sectors. The distinction between sectoral and factoral dimensions in industries leads to different kinds of skills, as outlined in the Heckscher-Ohlin theory and the Stolper-Samuelson theorem (HOS) (Wood, 1994). As a result, in the case of China, the agriculture sector is hindered from replicating the imported intermediate inputs, particularly technological knowledge, due to the excessive number of untrained workers at numerous production phases and the limited capacity absorption of local enterprises. This could eventually result in specialisation in the intensive use of unskilled workers due to a crowding-out effect.

6. Conclusion and Policy Implications

This study adopted the number of patented AI applications as a main proxy for AI, along with a set of other explanatory variables have rarely been used in literature, to analyse its impacts on labour productivity in China's manufacturing, agriculture, and services sectors. The advantage of using AI patents as a proxy is the ability to measure changes in the knowledge of firms in the field of AI and their ability to track and analyse the adoption and spread of AI technologies in the economy over a period of time and space. The OLS estimation results from 2000 to 2019 confirm that the use of AI patents has a significant positive impact on the manufacturing and service sectors' labour productivity. This is consistent with the growth of AI adoption, which has been aided by supportive legislation, ample funding, and likely high government encouragement from China for the high-tech sector to utilise AI patents. Our results indicate that China's manufacturing sector is characterised by a high number of skilled workers as compared to the services sector, contributing to the higher level of absorption of patented AI applications in their production activities and firm routines, hence leading to the sector's higher labour productivity.

In the agriculture sector, however, we observed that the effects of applying AI patents are not statistically significant in increasing the agriculture sector's labour productivity. The contrasting findings between high- and low-tech sectors suggest that firms may face possible lags in determining future R&D and patent productivity. The lag could be attributed to firms needing time to decide whether to use or produce a successfully completed patent application in AI, as well as an R&D project. This study also shows that a significant technological improvement in AI could vary depending on the time period required for the AI revolution to allow AI applications to become complementary and grow within an industry.

As the study's findings favour AI, to mitigate the dual negative effects of the country's falling working-age population the Chinese government needs to take further measures to boost labour productivity by promoting AI development. At present, AI in the new era is mainly applied to manufacturing and service sectors, resulting in a bottleneck in the development of China's agriculture sector. As a result, the agriculture sector's growth in labour productivity is slow or even declining. The government's focus, therefore, should be the integration of AI in the agricultural sector, especially in the conversion of small farms to digital agriculture, despite the fact that digital agriculture technology is better suited for larger farms.

The Chinese government is recommended to enhance the wide range of data accessible for AI development in order to make AI a viable development engine for China over time. This may be achievable by creating several industry-specific datasets, introducing new policies, and opening access to the public for data related to AI development, the economy, public services, recreation, and health, as practiced in New York. This action needs to be taken in China, since more than 40 per cent of businesses in China's conventional industries do not yet consider AI to be a strategic imperative. As a result, many of them have yet to capture the information required to support upcoming AI installations. This situation is noticeable in agricultural industry firms, where top management rarely keeps detailed records on topics like planting schedules or how weather affects output. However, this is the kind of data that AI systems can use to uncover insightful patterns and improve efficiency. Comparatively, the United States, the United Kingdom, and Japan have put in place national information systems to gather such data and use cutting-edge analysis for contemporary agricultural management.

To promote the adoption of AI patents in the industry, our study suggests that policymakers should focus on helping the economics sector overcome problems such as the lack of awareness about the use of AI, financial problems, and a lack of technical skills in AI. Some of these problems can be solved using conventional economic instruments like tax breaks and subsidies. The government may additionally consider leading the way in implementing AI systems in all bureaucracies. By building up technical expertise and talent, this endeavour will eventually lower the cost of AI adoption by stimulating the market and supporting government suppliers.

In the meantime, industry stakeholders should give priority to established policies in order to take advantage of the knowledge spillovers from AI technology and boost the adoption of new frameworks that are better suited for gauging AI's impact on labour productivity. This endeavour aims to ensure that managers are better knowledgeable about the real-world effects of AI to enable them to reorganise work in a way that complements labour and AI robots.

Lastly, although the results of our study on a small sample suggest that patent applications can influence higher labour productivity in the manufacturing industry compared to other sectors in China, we observe that a longer period is needed to analyse whether the growth and adoption of AI technology would lead to productivity increases for both big and small manufacturing companies. This would require future studies to address. As our study is limited in terms of the time period investigated, the differences in the methodological approach employed, heterogeneity in data, and the absence of a clear and agreed definition of AI, it may have produced different study results from previous research. Thus, future studies could expand their context across countries and time. Future research models could also include other proxies that measure the application of AI patents, such as invention variables protected by other formal (e.g., software copyright) and informal intellectual property rights (e.g., confidentiality), to encompass the whole range of cutting-edge AI advancements.

Notes

1 Based on the International Standard Industrial Classification of All Economic Activities (ISIC), manufacturing and services sectors are classified as high-tech industrial sectors and agriculture as a low-tech sector.

2 We adopt the perpetual inventory method (PIM) to measure physical capital as suggested by Griliches (1980).

3 It is crucial to emphasise that before choosing OLS as the preferred method for analysing the study's data, a few model selection tests, including the Autoregressive Distributed Lag (ARDL) and Vector Error Correction Model (VECM) models, were conducted. Regrettably, these alternative approaches failed to yield optimal results. The number of observations (N) must be more than 30 in order to conduct both estimations (Maitra, 2019).

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