THE IMPACT OF ARTIFICIAL INTELLIGENCE ON LABOUR PRODUCTIVITY IN CHINA

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by

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AI_PATENT	Artificial intelligence patent application
SFA_INV_ITCS	Social fixed asset investment in information transmission, computer services and software industries
INV_SRF	Investment intensity of scientific research funds
HS	High-skilled occupation
MS	Medium-skilled occupation
LS	Low-skilled occupation
LP	Labour productivity
OLS	Ordinary Least Squares
QEDU	Share of education expenditure from total expenditure
TRAIN	Cost of Training Per Employee
RD	Research and Development Investment
GDP	The Gross Regional Product
TRADE	Trade openness as the proportion of total imports and exports to GDP
FDI	Foreign direct investment as share of foreign direct investment from GDP
K/L	Capital intensity is approximated by gross investments in fixed capital per worker
SYS- GMM	System Generalized Method of Moments
DIFF-GMM	Difference Generalized Method of Moments

KESAN KECERDASAN BUATAN TERHADAP

PRODUKTIVITI BURUH DI CHINA

ABSTRAK

Kajian ini meneliti kesan kecerdasan buatan (AI) terhadap produktiviti buruh di China dari tahun 2000 hingga 2020, menggunakan tiga proksi AI: pelaburan dalam aset tetap sosial untuk transmisi maklumat, perkhidmatan komputer dan industri perisian; intensiti pelaburan dana penyelidikan saintifik; dan aplikasi paten AI. Kajian menggunakan kaedah DIFF-GMM dan SYS-GMM untuk menyiasat kesan AI ke atas tiga kategori kemahiran pekerjaan (tinggi, sederhana, rendah).Hasil kajian mendapati bahawa pelaburan dana penyelidikan saintifik meningkatkan produktiviti pekerja berkemahiran tinggi sebanyak 41.6%, sementara aplikasi paten AI meningkatkan produktiviti sebanyak 39.3%. Namun, pelaburan aset tetap sosial tidak signifikan untuk pekerja berkemahiran tinggi. Sebaliknya, ia meningkatkan produktiviti pekerja berkemahiran sederhana sebanyak 18.5%. Untuk pekerja berkemahiran rendah, kedua-dua aplikasi paten AI dan pelaburan aset tetap sosial masing-masing meningkatkan produktiviti sebanyak 15.9% dan 32.2%. Kajian juga membandingkan kesan AI mengikut wilayah di China. Di wilayah autonomi, pelaburan dalam aset tetap sosial mempunyai kesan signifikan terhadap produktiviti semua kategori pekerja. Namun, di 23 wilayah utama, kesan AI adalah signifikan untuk semua kategori pekerja. Kesimpulannya, perbezaan kesan AI terhadap produktiviti di seluruh China dipengaruhi oleh jurang teknologi, tahap pembangunan ekonomi, dasar kerajaan, dan ketersediaan pekerja mahir. Kajian ini mencadangkan agar dasar memperkukuh pendidikan, latihan, penyelidikan, dan subsidi kerajaan untuk meningkatkan produktiviti melalui AI dalam semua kategori kemahiran pekerja.

THE IMPACT OF ARTIFICIAL INTELLIGENCE

ON LABOUR PRODUCTIVITY IN CHINA

ABSTRACT

This study examines the impact of Artificial Intelligence (AI) on labour productivity in China from 2000 to 2020, using three AI proxies: investment in fixed social assets for information transmission, computer services, and the software industry; intensity of scientific research fund investments; and AI patent applications. The study employs the DIFF-GMM and SYS-GMM methods to investigate the effects of AI on three labor skill categories (high, medium, and low-skilled occupations). The findings reveal that scientific research fund investment increases the productivity of high-skilled workers by 41.6%, while AI patent applications increase productivity by 39.3%. However, investment in fixed social assets is not statistically significant for high-skilled workers. In contrast, it increases the productivity of medium-skilled workers by 18.5%. For low-skilled workers, both AI patent applications and fixed social asset investments boost productivity by 15.9% and 32.2%, respectively. The study also compares the impact of AI across different regions in China. In autonomous regions, investment in fixed social assets significantly enhances productivity across all worker skill categories. However, in 23 major provinces, AI's effect is significant for all worker categories. In conclusion, the variation in AI's impact on productivity across China is influenced by the technological knowledge gap, levels of economic development, government policies, and the availability of skilled workers. The study suggests policies to strengthen

education, training, research, and government subsidies to improve productivity through AI across all labor skill categories.

CHAPTER 1
INTRODUCTION

1.1 Introduction

Artificial Intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence. These tasks include decision-making, problem-solving, learning, perception, and understanding natural language. AI systems can be categorised into two types: narrow AI, which is designed to perform a specific task, and general AI, which can theoretically perform any intellectual task that a human being can do. AI technologies are based on algorithms and models that allow machines to learn from data, improve their performance over time, and simulate cognitive functions such as reasoning and pattern recognition. AI has emerged as a transformative force across various industries, revolutionizing sectors such as healthcare, finance, manufacturing, and education. It enables the automation of complex processes, enhances decision-making capabilities, and fosters innovation by unlocking new possibilities for technological advancements. The rise of AI has been fueled by the increasing availability of big data, improvements in computing power, and advances in machine learning and deep learning techniques. However, alongside its benefits, AI also raises important ethical and social concerns, such as privacy, job displacement, and accountability in decision-making processes.

Based on the aforementioned issues, this study aims to examine the impact of AI on labour productivity in China between 2000 and 2020, focusing on three different AI proxies: investment in fixed social assets (information transmission, computer services, and the software industry), scientific research fund investments, and AI patent applications. By analysing these proxies across three occupational labour skill categories—high-skilled, medium-skilled, and low-skilled workers—the study seeks to understand the extent to which AI contributes to labour productivity in China. Moreover, this study attempts to explore provincial differences in AI's impact across 23 of China's provinces, autonomous regions, and municipalities, providing a comprehensive picture of how AI affects labour productivity across the China.

1.2 The Background of the Study

In the 21st century, AI and big data have played a leading role in in the current technological revolution. AI's influence is increasingly significant in our environment, lives and economy. Many consider AI as a productivity and economic growth driver. By analysing vast amounts of data, AI can greatly improve decision-making processes and increase efficiency (Acemoglu & Restrepo, 2018; Purdy & Davarzani, 2015; Fan& Zhen,2020). In addition, it can simulate the development of new markets, industries, and goods and services, increasing consumer demand and bringing in fresh sources of income.

According to China Reporting Network in 2023, AI could potentially double the annual global economic growth rate by 2035. Firstly, AI will be able to drive growth leading to a robust 40% increase in labour productivity through innovative technologies that enable more efficient workforce-related time management. Secondly, AI could create a virtual workforce described as 'intelligent automation', capable of problem-solving and self-learning. Thirdly, the economy will likely benefit from the spread of innovation, which will increase the flow of industry and economic growth. AI has the potential to create material wealth, avoid heavy physical labour, enhance social welfare and improve living standards.

However, the development of AI has also brought about challenges such as over-reliance on AI, leading to reduced productivity in some cases (Song, 2021). AI might, however, potentially have a very negative impact on society and the economy. Some fear that it would result in the development of super companies, which would be centres of expertise and wealth that would be harmful to the overall economy. Additionally, it might increase the skills gap between developed and developing countries and increase the need for workers with particular skills while marginalising others. These trends could have significant effects on the labour market, including the potential to raise inequality, drive down wages, and reduce the size of the tax base. Although these concerns remain valid, there is no solid understanding and evidence to assess whether and to what extent the risks associated with AI applications will have an impact on the labour market and this leads to the need for policies that need to be carefully designed to foster AI development while mitigating negative labour market impacts.

Nevertheless, to take advantage of the new round of technological change, many countries have introduced development strategies related to AI from various aspects. From the macro perspective of the industrial revolution by country, Germany introduced a development strategy that corresponds to the concept of Industry 4.0 to the development stage of the industrial revolution, to increase the intelligence and global competitiveness of German manufacturing (Dauth et al., 2017). Meanwhile, Canada was the first country to formulate an AI strategy explicitly, and in 2017, Canada implemented a Pan-Canadian AI Strategy, which is to invest $125 million to develop Canada's top technical talent in AI (Oschinski & Wyonch, 2017).

Studies showed that countries with relatively high levels of economic development in the West are beginning to develop their AI strategies to enhance their competitiveness. Developed nations consider the development of AI as a major strategy to improve competitiveness and national security and compete to increase investment in research and development of AI. Historically, research on AI in the US and UK has significantly influenced other countries. The US appears to be more mature in terms of AI ecosystem building, with AI start-ups such as Google and Microsoft already in place. Since 2013, the US has made several plans to help AI development, and in 2016 further paid more attention to its development and research efforts to accelerate the process. In the same year, the US government also releases several reports, including "Preparing for the Future of Artificial Intelligence", to promote the healthy development of the AI industry (Jorgenson, 2001).

Similarly, AI patent applications have increased worldwide with an average annual growth rate of 6% between 2010 and 2015, which is higher than the annual growth rate observed for other patents. During this period, Japan, South Korea and the United States accounted for almost two-thirds of AI-related patent applications. South Korea, China and Chinese Taipei have recorded a remarkable increase in the number of AI patents compared to their previous results. EU Member States accounted for 12% of the total AI-related inventions, a decrease from the 19% recorded in the previous decade.

1.2.1 The Artificial Intelligence Development in China

China, as one of the world's leading economies, has made substantial investments in AI, both at the national and regional levels. The government has prioritised AI development as part of its broader agenda to transition from labourintensive manufacturing to a knowledge-based economy. Despite this progress, the benefits of AI in terms of labour productivity have not been uniformly distributed across the country. There are stark differences in how AI technologies impact productivity based on skill levels and regional disparities in infrastructure, technological adoption, and workforce capabilities.

The development of AI presents a significant opportunity for China, playing a vital role in addressing challenges such as an ageing population and driving sustainable development. Although AI development in China began later than in other nations, gaining momentum only after 2000, the country has significantly increased support for AI-related R&D over the past decade. Initiatives such as the establishment of academic groups and the launch of the "New Generation Artificial Intelligence Strategic Plan" in 2017 have solidified AI as a national priority. By 2030, China aspires to become a global hub for AI innovation, with an AI industry valued at over $1 trillion and related industries surpassing $10 trillion. Investment in AI has grown exponentially, rising from 9.1 billion yuan in 2015 to 58.2 billion yuan in 2017, and AI industry revenue doubled between 2014 and 2016. China also surpassed the U.S. in AI patent applications by 2016. Despite a late start, China's AI industry has established a robust foundation and continues to expand as more sectors integrate AI technologies, reflecting the nation's strong prospects for industrial and technological advancement.

In China, AI research predominantly focuses on applied technologies, becoming a multidisciplinary system when combined with other fields for interdisciplinary research. According to the China's New Generation of Artificial Intelligence Technology Industry Development Report 2023*,* AI enterprises are largely concentrated in the tertiary sector, accounting for 75.79%, followed by 23.82% in the secondary sector, and only 0.39% in the primary sector. Within the tertiary sector, information transmission, software, and IT services lead at 28.46%, followed by scientific research and technical services at 22.17%, leasing and business services at 10.75%, and the financial industry at 10.68%. Other industries account for less than 10% each. China is home to hundreds of AI start-ups focusing on areas such as healthcare, image recognition, and finance, with notable examples like the intelligent robot "Jiajia" from the China University of Science and Technology and Alibaba's intelligent customer service system "Ali Xiaomi." As AI continues to integrate with various industries, the domestic market is poised for new product innovations and greater market potential. The AI industry is primarily driven by application-layer enterprises, which face more intense competition compared to the base and technology layers. Of the 2,200 leading AI companies, only 53 (2.41%) operate at the base layer, providing core hardware and data services, while 273 (12.41%) focus on technology development such as core algorithms. The majority, 85.18% (1,873 companies), work at the application layer, concentrating on the practical integration and use of AI technologies (Acharya & Arnold, 2019).

1.2.2 The Artificial Intelligence Development in China's Provinces

AI development in China is highly uneven across provinces, with distinct regional clusters leading AI applications due to differences in economic resources, talent pools, and industrial bases. Major AI hubs are concentrated in economically advanced provinces, particularly in the eastern and southern coastal regions. Beijing, for instance, stands out as a national leader in AI research and application, benefiting from its robust academic and research institutions, such as Tsinghua University, and its proximity to government policymakers. Beijing's AI applications are widespread in healthcare, smart cities, and autonomous driving technologies. Shanghai and Guangdong are other key provinces; Shanghai excels in financial technology (fintech) and industrial AI, leveraging its position as China's financial center, while Guangdong, home to tech giants like Huawei and Tencent, focuses on AI applications in telecommunications, manufacturing, and digital platforms.

Meanwhile, the provinces like Zhejiang, led by the city of Hangzhou, have also become AI powerhouses, particularly in e-commerce, logistics, and smart retail, driven by the presence of Alibaba. In contrast, western and inland provinces such as Gansu and Qinghai have fewer AI applications, as their economies are more resource-based and less technologically developed. However, these regions are beginning to explore AI in agriculture and energy management as part of broader national initiatives to promote AI adoption across all sectors and regions (Zhang et al., 2023). The regional disparities in AI application across China reflect broader trends in economic development, with leading provinces continuing to drive the country's AI innovation and implementation.

1.2.3 The Artificial Intelligence and Labour Productivity in China

The advent of AI signifies the onset of the fourth industrial revolution, positioning AI as a key driver in the reform and development strategies of various countries (Acemoglu & Restrepo, 2018; Purdy & Davarzani, 2015). Technological advances in AI have led to transformative changes in the way employment is generated, raising productivity levels and promoting 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). Consequently, there is an ongoing debate about whether AI can improve labour productivity. In the macroeconomic context, AI affects economic growth mainly through productivity. Early research argued that AI could perform manual labour at lower skill levels and improve labour productivity and efficiency through 'human-machine collaboration', thereby contributing to economic development. As industrial robots became the most common application of AI in the 21st century, the application of robots was widely used to measure the development of AI (Frey & Ostorne, 2017; David & Dorn, 2013).

China is no exception in this global trend. Despite increased investments in digital innovation, advancements in AI have not resulted in significant productivity gains across businesses and regions. The current level of technological innovation has not been fully utilised due to a lack of skills problems, resulting in the decline of China's labour productivity growth rate (Purdy & Davarzani, 2015; Zhang, 2020). In 2020, China's productivity growth slowed to approximately 7%, modest compared to the 9.9% seen in other developing countries (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 extended the gap between theoretical and practical applications of the technology. As the growth rate of China's working-age population slows down, China faces the pressure of a shortage of labour supply and rising labour costs, which provides impetus for promoting the development of AI technology in China (Cheng et al., 2019). Existing studies also show that the progress of AI significantly impacted China's labour market (Ford, 2015).

Based on Figure 1.1 below, the declining trend in labour productivity growth in China can be seen from 2001 to 2016 and decreased by 3.7% between 2019 and

2022. According to the IMF report in 2019, China's labour productivity has converged from 15% of the world frontier to only 30% over the past two decades.

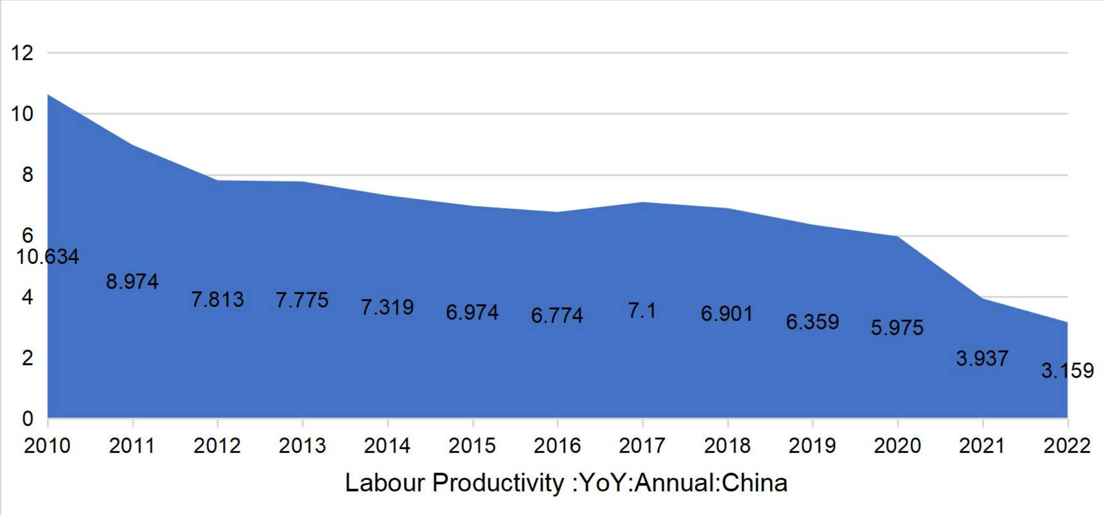

Figure 1.1 Labour Productivity Growth in China, 2010-2022

Source: World Bank Data, 2010-2022

One of the reasons for the decrease in China's labour productivity is due to the problem of skill shortage, lack of high-skilled labour and skill mismatch remains a major challenge (Yang, 2022; Purdy & Davarzani, 2015; Zhang, 2020).

1.3 Problem Statement

Theoretically, AI is considered to improve labour productivity through the combination of humans and machines, since technological progress will lead to disruptive changes in employment, and therefore the level of productivity must be increased to promote economic growth (Paskander, 2019). A plethora of empirical studies have supported the endogenous theory that showed an improvement in labour productivity linked to a faster pace of technological progress, innovation and investments in human capital and R&D (Ballot et al., 2001; Bassanini et al., 2005; Conti, 2005; Crespi & Zuniga, 2012; Hall et al., 2009; Pischke, 2005; Romer, 1990).

Although China's labour productivity has not shown a significant decline over the past 5 years, it is increasing at a diminishing rate (Cheng & Zeng, 2022; Guo & Shen,2024; Yang, 2022). The labour productivity growth decreased from 8.59% in 2000 to 6.47% in 2015 and continued to decrease by 3.63% in 2019 (IL0, 2021). An International Monetary Fund report in 2019 also showed that China's labour productivity has converged from 15% of the world frontier to only 30% over the past two decades (Singh & Bayoumi, 2019). According to China's Ministry of Human Resources and Social Security, the 2020 report stated that the diminishing rate of China's labour productivity growth is due to the shortage of skilled labour, and the problem of mismatch between demand and supply. Since 2016, the number of skilled workers in the Chinese labour market has been only about 19% of the total workforce, with high-skilled workers comprising only 5% (Morgan &Yuan,2016). The gap between supply and demand for skilled labour is widening and thus will affect labour productivity (Morgan &Yuan, 2016; Purdy et al., 2017).

Globally, there has been a marked decline in the ability of increases in capital investment and labour to propel economic progress (Purdy et al., 2017). Both investments are traditional drivers of production, yet they are no longer able to sustain the steady march of prosperity enjoyed in previous decades in many economies. China is no exception. The economy has deteriorated significantly, labour shortages and the capital crisis have disrupted old growth models, and productivity has declined. The data also showed that the expenditure on education in China decreased from 3.82% in 2015 to 3.542% in 2018, while investment in R&D only increased by 4.06% over the same period (ILO, 2021). Based on the declining trend of both investment in education and R&D, it is implied that the potential to achieve higher labour productivity needs to be associated with AI, as studies have shown AI has the potential to add as much as 1.6 % points to China's economic growth rate by 2035 (Acharya & Arnold, 2019; Purdy et al., 2017).

The emergence of AI has created a disparity between China's employment structure and its industrial structure, contributing to low labour productivity (Zhang, 2020). The gap between the rapid development of AI and its practical application has led to a mismatch in the transformation and upgrading of China's industries and employment structure, further exacerbating this issue. As a result, whether AI can significantly improve labour productivity in China remains a topic of debate (Chen & Zhang, 2020; Huang et al., 2021).

The rapid advancement of AI technologies has transformed labour markets globally, reshaping productivity patterns across various industries. In China, the integration of AI is particularly impactful, with significant variations in how it influences labour productivity across different regions and occupational skill levels. While AI has been shown to improve efficiency and performance in high-skilled occupations through automation and data-driven decision-making, its effects on medium- and low-skilled occupations are less clear and often debated. Some argue that AI may displace workers in lower-skilled roles, while others believe it can complement these jobs by automating repetitive tasks and enabling workers to focus on more complex activities (Acemoglu & Restrepo, 2019). This raises critical questions about the distributional impacts of AI across different labour segments, especially in a diverse economy like China's, where regional disparities and varying levels of economic development exist.

China's provinces differ significantly in their economic structure, technological adoption, and workforce skills, which could result in heterogeneous effects of AI on labour productivity. For instance, developed regions such as Beijing, Shanghai, and Guangdong may experience greater benefits from AI due to their higher concentrations of high-skilled workers and advanced infrastructure, while less developed areas may face challenges in adapting to AI-driven changes. Yet, there is limited research comparing how AI affects labour productivity across different occupational skill levels in key provinces. Understanding these regional differences is crucial for developing policies that mitigate potential inequalities and ensure that the benefits of AI are broadly shared across the country. Therefore, this study aims to analyse and compare the impact of AI on labour productivity across occupational skills in three main provinces in China, addressing the need for a nuanced understanding of AI's role in shaping regional labour markets (Chen & Zhang, 2020; Huang et al., 2021).

1.4 Research Objectives

The general objective of this study is to analyse the impact of AI on China's labour productivity during the period of 2000-2020. The specific objectives of this study are as follows:

i) To analyse the impact of AI on labour productivity across different occupational skill levels: high-skilled occupations, medium-skilled occupations, and low-skilled occupations.

ii) To compare the impact of AI on labour productivity across different occupational skills in three main provinces of China.

1.5 Research Question

Based on the problem statement above, this study seeks to answer the following research questions as follows：

i) How does AI affect labour productivity according to labour skills, i.e., highly- skilled occupations, medium- skilled occupations and low-skilled occupations in China?

ii) Why does the impact of AI on labour productivity differ across occupational skill levels in the three provinces of China?

1.6 Research Significance

Realising the lack of high-quality data and the lack of high-tech talent is one of the obstacles in the wider use of AI that also occurs in China, the findings from this study can give some insight into the strategies and policies that can be implemented by the government, industry, higher education institutions and individuals. This is important in ensuring that the application of AI can be used by all parties given that there is a mismatch between education and the demand for skills in the Chinese labour market, especially when it occurs during macroeconomic transformation and structural change in China's labour market.

The impact of AI on labour productivity is still at an infancy stage as more existing literature emphasises the context of developed countries and discusses relatively poorly the role of AI in the labour market in developing countries, most focusing on productivity and Total Factor Productivity (TFP) (Driffield et al., 2014; Elia et al., 2009; Liu et al., 2016; Yunus et al., 2015; Zhou et al., 2019). This study examines the extent to which the effects of AI can increase labour productivity in

China at a macro level study. Studies examining the effects of AI on labour productivity are relatively scarce. Only a few studies specifically explore the impact of AI in the context of China, yet their focus is on data at the industry level and economic sectors (Xie et al., 2021; Zhou et al., 2020; Liu et al., 2022). Only a recent study by Bonsay et al. (2021) explicitly investigates the impact of AI on labour productivity in China. Hence, this study will provide findings from AI as a benchmark at the micro level in China, thereby enabling to comparison with other countries' findings.

This study also bridges the gaps in the literature by investigating occupation which is divided into three categories: high-skilled occupations, medium-skilled occupations and low-skilled occupations. The effects of AI and other technological advances are less studied specifically on medium-skilled workers in terms of labour productivity (Xie et al., 2021). This may be due to the data and no standard definition of medium-skilled workers (OECD, 2021). This approach may provide good findings because a comparative analysis can be done instead of just focusing on high-skilled workers' productivity because of capital investment, where AI and other technological progress may be more pronounced for high-skilled workers (Yunus & Masron, 2020).

For industry stakeholders particularly in China, based on the findings from this study, the specific policies should be prioritized to maximize knowledge spillovers without hindering innovators' incentives and to adopt new frameworks that are more appropriate for measuring AI's contribution to productivity. This step is to ensure that managers become more familiar with the practical implications of AI to contribute to the reorganization of work, towards a model where AI machines and labour act as complements.

This study will also benefit in helping industry stakeholders, in evaluating employees' ability to adapt AI in their industries. Based on the value of labour productivity coefficient by occupation studied using provinces data, the findings of this study can act as an initial information channel to employers regarding the status of labour productivity which in turn helps employers to segregate workers according to productivity level. Segregation of employees according to occupation skills and mastery of AI technology can be done to ensure efficiency in the organization or firm and in turn this measure helps increase employee productivity (Dudnik et al., 2021). Similarly, the structure of wages paid according to employee skills is seen to be more transparent and will increase employee satisfaction as emphasized in sorting theory (Spence, 1973).

By examining the impact of AI on labour productivity in different provinces in China as the second objective of the study, this study will help formulate policies for coordinated regional development in China as the role of AI in regional coordinated development has not received much attention (Yang, 2022). At the same time, this research can help the government to establish reemployment training institutions in provinces to prevent labour force unemployment caused by AI. Retraining opportunities can be considered to provide for low-skilled workers to match talent cultivation with future labour demand to help them upgrade their skills and enter other occupations to offset the potential negative impact of falling wages, thus helping workers stay afloat.

Lastly, the findings of the study will also contribute to the development of the national education system and improve the education system in the era of AI particularly in China. Facing the rapid development of AI, China's colleges and universities should build a comprehensive and interdisciplinary curriculum system, pay attention to the cultivation of students' innovation ability and the development of integration skills, to realize the improvement of labour skills and comparative advantages from the supply side (Wang, 2021).

The findings of the study could contribute to improving the education system by highlighting the areas where workforce skills are either enhanced or undermined by AI. For instance, if the study reveals that AI significantly boosts productivity for high-skilled workers while displacing medium- or low-skilled occupations, it may inform policymakers and educators about the need to adapt educational curricula to prepare future workers for an AI-driven economy. By identifying gaps in skills and highlighting the importance of reskilling and upskilling programs, the study could indirectly influence reforms in the education system to better align with labor market demands, especially in provinces most affected by AI advancements.

1.7 Scope of Study

Taking into consideration the availability of AI data, for the first objective, this study employs the provinces panel data from three main provinces in China which cover 32 cities and spanning the period from 2000 to 2020 (T=21). For the second objective, this study specifically classified into 3 main provinces in China as shown in Table 1.1.

Table 1.1 Administrative Region in China

Municipalities (4)	Beijing, Tianjin, Shanghai, Chongqing
Autonomous Region (5)	Inner Mongolia, Guangxi, Xizang, Ningxia, Xinjiang
Provinces (23)	Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, H ubei, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Taiwan

Source: Central People's Government portal website (www.gov.cn)

This study focuses on the period from 2000 to 2020 because it encompasses significant advancements in AI technology and machine learning, marking a crucial transition in how these innovations began reshaping industries and labour dynamics (Brynjolfsson & McAfee, 2014; Xu & Huang, 2020). During this time, the Chinese government implemented various policies aimed at promoting technological adoption, which provides important context for understanding the changes in industrial practices and workforce skills (Wang et al., 2021). The study leverages comprehensive panel data from 32 cities, allowing for a robust regional analysis that can reveal long-term trends and causal relationships between AI adoption and productivity shifts (Li & Zhang, 2019; Yang et al., 2020). This research examines a 21-year period to understand how different provinces adapted to technological changes, providing insights into the impact of AI on various skill levels and regional economies.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Chapter 2 begins to discuss the concept and characteristics of artificial intelligence. Section 2.1 provides the basis for this study, including the definition of AI and its characteristics. Section 2.2 reviews the literature related to the first research objective, namely, the literature review on the impact of AI on labour productivity. Section 2.3 reviews studies related to the second research objective, namely the differences in the impact of AI on labour productivity in different provinces and cities in China.

2.1.1 The Concept and the Definition of Artificial Intelligence

At present, there is no uniform definition of the concept and scope of AI in academia, and the technical connotation of AI is still being expanded and deepened. At the early stage of development, McCorduck and Cfe (2004) describe AI as a "thinking machine" that has the ability to think and act like humans and can surpass the corresponding human ability in the future. Dreyfus' (1992) classical critique of AI and Searle's (1992) "biological naturalism" state that achieving human-like intelligence requires social context and human-like physical embodiment. Based on a more comprehensive description of the concept of AI from MIT Electrical Engineering, Finlayson et al. (2010) describe AI as an organic whole, an expressive system of thinking, perceiving, and acting through models, with generative testing as the basic mode of operation, a system with certain constraints, and algorithms (programs or methods) to achieve the role of constraint conditions.

In terms of the technological development of AI, Cockburn. Henderson and Stern (2019) summarized AI as "symbolic systems - robotics - neural networks". Typical applications are computer board games, industrial robots, and autonomous driving, respectively. Neural network technology breaks through the limitations of machine learning in terms of training and learning from quantitative data sets, and enhances the perception and decision-making capabilities of machines, ultimately giving them the property of "intelligence". From the technical aspect of AI, Taddy (2019) explains that it involves a "domain knowledge structure + data generation + generalized machine learning", so, machine learning can efficiently complete the learning of large unstructured data such as speech, images and videos, thus enabling AI to break through the previous technical limitations, and data is the core element of AI.

Zhang et al. (2020) define AI as a technology created to achieve a specific task goal that can exhibit a similar level of human ability (cognition, thinking, or action) and the technology needs to function with the help of the corresponding tools (tools) and application environment. Under the existing technical conditions, the application carriers of AI are mainly computerised and automated devices, which are mainly manifested as substitutes for human beings, but with a wider range of applications, such as automatic driving, artistic creation, emotional companionship, and others.

2.1.2 The Proxy of Artificial Intelligence

(i) The number of industrial robots

Regarding the accuracy of proxy variables to measure AI to represent the level of AI development, there is no sufficient data on AI development as the new generation of AI technology has just emerged and has been developed and applied for a relatively short period. Due to the wide range of social applications of AI covering all aspects of life, the available research does not yet have particularly good data to fully measure AI. Furthermore, due to the lack of statistical data on AI, the choice of this indicator is not yet conclusive.

Among them, the most widespread practice is to measure the level of industrial intelligence by the number of industrial robots applied. Some scholars, such as Graetz and Michaels (2015), and Acemoglu and Restrepouribe (2017), mainly use the development of industrial robots (e.g., sales, installations, density) to measure the level of AI development in their empirical analysis. Most of the indicators that measure the annual amount of change in industrial robots are the old devices of annual sales and the annual import and export of industrial robots. These two indicators reflect the level of development of industrial robots from different perspectives and are used as independent variables to analyse the relationship with changes in the workforce. The sales volume data provides a more intuitive picture of the incremental growth of industrial robots in China and facilitates comparative studies with indicators from different countries. Reports on robotics statistics are mainly from the International Federation of Robotics (IFR). The IFR provides information on the number of industrial robots installed and held at the national level as well as at the industry level in each country, as applied by Acemoglu and Restrepo (2020) using the number of industrial robot applications.

Zhu (2012) measured the current development of AI in China by the annual shipments of industrial robots in China. Zhu (2012) used this index to measure the absolute impact of AI on the change of industrial structure deviation by selecting data from 2005 to 2017. Zhu and Li (2018) use the development level of industrial robots to measure the development and application of AI in China and quantify the sales volume of industrial robots in China. They concluded that the development of AI and the improvement of the technical level would increase the relative supply of skilled labour and unskilled labour, which would help improve the overall quality of the labour force and optimize the labour structure.

Wang and Li (2020) used the imported data agent robots in China to evaluate the comprehensive development level of AI in China. Lu and Meng (2021) chose the application density of industrial robots to measure the development level of the new generation of AI and calculated the industrial robot density data of 52 countries from 2005 to 2017 (the annual industrial robot stock in each country divided by the annual manufacturing employment in each country). They empirically examined the impact of industrial robot application density on the adjustment of the job market structure and the development of foreign service trade.

Qiulin et al. (2019) focus on the installation density of robots (the cumulative number of intelligent robots installed in domestic industry divided by the number of employees in that year). The substitution relationship between technological progress and employment and the machine installation data in the constructed IFR database.

(ii) The level of information technology

Apart from the robot proxies, this study found that some literature applied the level of information technology to represent the application of AI in the industry. For instance, Michaels et al. (2014) used data from 1980 to 2004 to investigate the effect of improvements in information and communication technology on labour market polarisation for the US, Japan, and nine European nations. According to their research, industries with stronger ICT growth have transferred demand from workers with a medium level of education to those with a high level of education, which is consistent with ICT-based polarisation. They also demonstrate that trade openness is linked to the polarisation of the labour market, but not to R&D activities. In line with the speed of ICT applications, they discovered that the need for highly educated workers has surged by more than a quarter.

Xue et al. (2022) utilised a panel dataset with more than 1,300 publicly traded enterprises in China from 2007 to 2018 to estimate the extent of development of AI technology using "software and information technology service income that will affect the labour structures of businesses and workers with and without formal college education. According to their study, AI applications were favourably related to both total employment and non-academically trained people without college degrees who were employed at the firm level. In contrast to the manufacturing sector, these associations were more significant in the service industry. Meanwhile, Chen et al. (2022) used the amount of social fixed asset investment in the information transmission, computer services, and software industry as a proxy of AI application to investigate the impact of AI on green total factor productivity and its decomposition indicators for the manufacturing sector in China's provinces from 2003 to 2017. The results showed that using AI to boost green total factor productivity in China's manufacturing industry is beneficial. This improvement is mostly the result of technological development, but the impact of technical efficacy on the manufacturing sector is minimal. Further research revealed that AI increased the manufacturing industry in China's pure technical efficiency.

Feng (2019) uses "software and information technology service income" to measure the development level of AI technology and studies the impact of AI on employment skill structure. The results show that the influence of the early stage of

AI development on the structure of employment skills is characteristic of AI development. Zhou and Chen (2022) measure the current development of AI in China using the amount of social fixed asset investment in the information transmission, computer services and software industry to measure the impact of AI on green total factor productivity in the manufacturing sector in China's provinces from 2003-2017. They found that AI helps to promote the improvement of green total factor productivity in China's manufacturing sector due to the improvement in technical efficiency. Rongjie lu (2018) uses the method of Jeff and Michael (2017) to measure the level of AI development through fixed asset investment across information transmission, computer services and software industries and panel data from 31 provinces in China and they found that the provinces with higher GDP have higher levels of AI development.

(iii) AI patent applications

Another study increases attention to using patent applications for AI proxy. According to Hu et al. (2021), the number of AI patent applications represents the application level of AI, and the research finds that the impact of patent applications on labour productivity increases first and then decreases. They showed that moderate application of AI is conducive to improving labour productivity, but excessive application will cause labour productivity loss due to human-machine mismatch.

Considering the degree of innovation in AI, Meng and Chen (2019) chose to analyse AI using panel data of patent applications related to AI in 31 states. This study found that the application of AI will promote the optimization and upgrading of the labour structure of manufacturing enterprises, that is, the proportion of high-skilled employees increases, while the proportion of low-skilled employees decreases.

The labour structure has a positive intermediary effect between the application of AI and the performance of manufacturing enterprises.

Li (2019) used the high-tech industry's new product sales revenue, high-tech industry patent applications, and technology market turnover to measure the three indicators representing AI. The results show that although China has a low technological starting point, in recent years, the growth rate of China's labour supply lags behind the growth rate of technological development.

Based on the available patent data that examines the impact of patent applications, Chen et al. (2019) made a comparative study on the development of the AI industry in China and the United States. This study shows the impact of patent applications showing that the AI industry in China and the United States is in a synchronized development stage. In terms of the development process, the United States' AI industry started faster than China's, but the future development potential of AI in China is expected to be greater. Third, from the perspective of the main body of innovation, the United States is dominated by enterprises, while China is dominated by universities.

Zhao et al. (2019) took patent data as the agent of AI and patent US5963940-A, which ranked first in citation frequency, as an example to analyse the citation frequency, citation object and multi-level citation network of this patent over the years. The results show that patent US5963940-A has been cited by subsequent patent technologies for 21 consecutive years from 1994 to 2015 and has received continuous attention from patent applicants in this field. The main citation objects of the patent include Google, JumpTap, IBM, VoiceBox, Microsoft and other enterprises, and there is a competitive relationship; The patent's network of primary