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The impact of artificial intelligence on employment: the role of virtual agglomeration

Yang Shen [1]✉ & Xiuwu Zhang [1]

Sustainable Development Goal 8 proposes the promotion of full and productive employment for all. Intelligent production factors, such as robots, the Internet of Things, and extensive data analysis, are reshaping the dynamics of labour supply and demand. In China, which is a developing country with a large population and labour force, analysing the impact of artificial intelligence technology on the labour market is of particular importance. Based on panel data from 30 provinces in China from 2006 to 2020, a two-way fixed-effect model and the two-stage least squares method are used to analyse the impact of AI on employment and to assess its heterogeneity. The introduction and installation of artificial intelligence technology as represented by industrial robots in Chinese enterprises has increased the number of jobs. The results of some mechanism studies show that the increase of labour productivity, the deepening of capital and the refinement of the division of labour that has been introduced into industrial enterprises through the introduction of robotics have successfully mitigated the damaging impact of the adoption of robot technology on employment. Rather than the traditional perceptions of robotics crowding out labour jobs, the overall impact on the labour market has exerted a promotional effect. The positive effect of artificial intelligence on employment exhibits an inevitable heterogeneity, and it serves to relatively improves the job share of women and workers in labour-intensive industries. Mechanism research has shown that virtual agglomeration, which evolved from traditional industrial agglomeration in the era of the digital economy, is an important channel for increasing employment. The findings of this study contribute to the understanding of the impact of modern digital technologies on the well-being of people in developing countries. To give full play to the positive role of artificial intelligence technology in employment, we should improve the social security system, accelerate the process of developing high-end domestic robots and deepen the reform of the education and training system.

[1] Institute of Quantitative Economics, Huaqiao University, Xiamen 361021, China. ✉email: yangs996@foxmail.com

Introduction

Ensuring people's livelihood requires diligence, but diligence is not scarce. Diversification, technological upgrading, and innovation all contribute to achieving the Sustainable Development Goal of full and productive employment for all (SDGs 8). Since the outbreak of the industrial revolution, human society has undergone four rounds of technological revolution, and each technological change can be regarded as the deepening of automation technology. The conflict and subsequent rebalancing of efficiency and employment are constantly being repeated in the process of replacing people with machines (Liu 2018; Morgan 2019). When people realize the new wave of human economic and social development that is created by advanced technological innovation, they must also accept the "creative destruction" brought by the iterative renewal of new technologies (Michau 2013; Josifidis and Supic 2018; Forsythe et al. 2022). The questions of where technology will eventually lead humanity, to what extent artificial intelligence will change the relationship between humans and work, and whether advanced productivity will lead to large-scale structural unemployment have been hotly debated. China has entered a new stage of deep integration and development of the "new technology cluster" that is represented by the internet and the real economy. Physical space, cyberspace, and biological space have become fully integrated, and new industries, new models, and new forms of business continue to emerge. In the process of the vigorous development of digital technology, its characteristics in terms of employment, such as strong absorption capacity, flexible form, and diversified job demands are more prominent, and many new occupations have emerged. The new practice of digital survival that is represented by the platform economy, sharing economy, full-time economy, and gig economy, while adapting to, leading to, and innovating the transformation and development of the economy, has also led to significant changes in employment carriers, employment forms, and occupational skill requirements (Dunn 2020; Wong et al. 2020; Li et al. 2022).

Artificial intelligence (AI) is one of the core areas of the fourth industrial revolution, along with the transformation of the mechanical technology, electric power technology, and information technology, and it serves to promote the transformation and upgrading of the digital economy industry. Indeed, the rapid iteration and cross-border integration of general information technology in the era of the digital economy has made a significant contribution to the stabilization of employment and the promotion of growth, but this is due only to the "employment effect" caused by the ongoing development of the times and technological progress in the field of social production. Digital technology will inevitably replace some of the tasks that were once performed by human labour. In recent years, due to the influence of China's labour market and employment structure, some enterprises have needed help in recruiting workers. Driven by the rapid development of artificial intelligence technology, some enterprises have accelerated the pace of "machine replacement," resulting in repetitive and standardized jobs being performed by robots. Deep learning and AI enable machines and operating systems to perform more complex tasks, and the employment prospects of enterprise employees face new challenges in the digital age. According to the Future of Jobs 2020 report released by the World Economic Forum, the recession caused by the COVID-19 pandemic and the rapid development of automation technology are changing the job market much faster than expected, and automation and the new division of labour between humans and machines will disrupt 85 million jobs in 15 industries worldwide over the next five years. The demand for skilled jobs, such as data entry, accounting, and administrative services, has been hard hit. Thanks to the wave of industrial upgrading and the vigorous development of digitalization, the recruitment demand for AI, big data, and manufacturing industries in China has maintained high growth year-on-year under the premise of macroenvironmental uncertainty during the period ranging from 2019 to 2022, and the average annual growth rate of new jobs was close to 30%. However, this growth has also aggravated the sense of occupational crisis among white-collar workers. The research shows that the agriculture, forestry, animal husbandry, fishery, mining, manufacturing, and construction industries, which are expected to adopt a high level of intelligence, face a high risk of occupational substitution, and older and less educated workers are faced with a very high risk of substitution (Wang et al. 2022). Whether AI, big data, and intelligent manufacturing technology, as brand-new forms of digital productivity, will lead to significant changes in the organic composition of capital and effectively decrease labour employment has yet to reach consensus. As the "pearl at the top of the manufacturing crown," a robot is an essential carrier of intelligent manufacturing and AI technology as materialized in machinery and equipment, and it is also an important indicator for measuring a country's high-end manufacturing industry. Due to the large number of manufacturing employees in China, the challenge of "machine substitution" to the labour market is more severe than that in other countries, and the use of AI through robots is poised to exert a substantial impact on the job market (Xie et al. 2022). In essence, the primary purpose of the digital transformation of industrial enterprises is to improve quality and efficiency, but the relationship between machines and workers has been distorted in the actual application of digital technology. Industrial companies use robots as an entry point, and the study delves into the impact of AI on the labour market to provide experience and policy suggestions on the best ways of coordinating the relationship between enterprise intelligent transformation and labour participation and to help realize Chinese-style modernization.

As a new general technology, AI technology represents remarkable progress in productivity. Objectively analysing the dual effects of substitution and employment creation in the era of artificial intelligence to actively integrate change and adapt to development is essential to enhancing comprehensive competitiveness and better qualifying workers for current and future work. This research is organized according to a research framework from the published literature (Luo et al. 2023). In this study, we used data published by the International Federation of Robotics (IFR) and take the installed density of industrial robots in China as the main indicator of AI. Based on panel data from 30 provinces in China covering the period from 2006–2020, the impact of AI technology on employment in a developing country with a large population size is empirically examined. The issues that need to be solved in this study include the following: The first goal is to examine the impact of AI on China's labour market from the perspective of the economic behaviour of those enterprises that have adopted the use of industrial robots in production. The realistic question we expect to answer is whether the automated processing of daily tasks has led to unemployment in China during the past fifteen years. The second goal is to answer the question of how AI will continue to affect the employment market by increasing labour productivity, changing the technical composition of capital, and deepening the division of labour. The third goal is to examine how the transformation of industrial organization types in the digital economy era affects employment through digital industrial clusters or virtual clusters. The fourth goal is to test the role of AI in eliminating gender discrimination, especially in regard to whether it can improve the employment opportunities of female employees. Then, whether workers face different employment difficulties in different industry attributes is considered. The final goal is to provide some policy insights into how a developing country can achieve full employment in the face a new technological revolution in the context of a large population and many low-skilled workers.

The remainder of the paper is organized as follows. In Section Literature Review, we summarize the literature on the impact of AI on the labour market and employment and classify it from three perspectives: pessimistic, negative, and neutral. Based on a literature review, we then summarize the marginal contribution of this study. In Section Theoretical mechanism and research hypothesis, we provide a theoretical analysis of AI's promotion of employment and present the research hypotheses to be tested. In Section Study design and data sources, we describe the data source, variable setting and econometric model. In Section Empirical analysis, we test Hypothesis 1 and conduct a robustness test and the causal identification of the conclusion. In Section Extensibility analysis, we test Hypothesis 2 and Hypothesis 3, as well as testing the heterogeneity of the baseline regression results. The heterogeneity test employee gender and industry attributes increase the relevance of the conclusions. Finally, Section Conclusions and policy implications concludes.

Literature review

The social effect of technological progress has the unique characteristics of the times and progresses through various stages, and there is variation in our understanding of its development and internal mechanism. A classic argument of labour sociology and labour economics is that technological upgrading objectively causes workers to lose their jobs, but the actual historical experience since the industrial revolution tells us that it does not cause large-scale structural unemployment (Zhang 2023a). While neoclassical liberals such as Adam Smith claimed that technological progress would not lead to unemployment, other scholars such as Sismondi were adamant that it would. David Ricardo endorsed the "Luddite fear" in his book On Machinery, and Marx argued that technological progress can increase labour productivity while also excluding labour participation, thus leaving workers in poverty. The worker being turned 'into a crippled monstrosity' by modern machinery. Technology is not used to reduce working hours and improve the quality of work, rather, it is used to extend working hours and speed up work (Spencer 2023). According to Schumpeter's innovation theory, within a unified complex system, the essence of technological innovation forms from the unity of positive and negative feedback and the oneness of opposites such as "revolutionary" and "destructive." Even a tiny technological impact can cause drastic consequences. The impact of AI on employment is different from the that of previous industrial revolutions, and it is exceptional in that "machines" are no longer straightforward mechanical tools but have assumed more of a "worker" role, just as people who can learn and think tend to do (Boyd and Holton 2018). AI-related technologies continue to advance, the industrialization and commercialization process continues to accelerate, and the industry continues to explore the application of AI across multiple fields. Since AI was first proposed at the Dartmouth Conference in 1956, discussions about "AI replacing human labor" and "AI defeating humans" have endlessly emerged. This dynamic has increased in intensity since the emergence of ChatGPT, which has aroused people's concerns about technology replacing the workforce. Summarizing the literature, we can find three main arguments concerning the relationship between AI and employment:

First, AI has the effect of creating and filling jobs. The intelligent manufacturing industry paradigm characterized by AI technology will assist in forming a high-quality "human–machine cooperation" employment mode. In an enlightened society, the social state of shared prosperity benefits the lowest class of people precisely because of the advanced productive forces and higher labour efficiency created through the refinement of the division of labour. By improving production efficiency, reducing the sales price of final products, and stimulating social consumption, technological progress exerts both price effects and income effects, which in turn drive related enterprises to expand their production scale, which, in turn, increases the demand for labour (Li et al. 2021; Ndubuisi et al. 2021; Yang 2022; Sharma and Mishra 2023; Li et al. 2022). People habitually regard robots as competitors for human beings, but this view only represents the materialistic view of traditional machinery. The coexistence of man and machine is not a zero-sum game. When the task evolves from "cooperation for all" to "cooperation between man and machine," it results in fewer production constraints and maximizes total factor productivity, thus creating more jobs and generating novel collaborative tasks (Balsmeier and Woerter 2019; Duan et al. 2023). At the same time, materialized AI technology can improve the total factor production efficiency in ways that are suitable for its factor endowment structure and improve the production efficiency between upstream and downstream enterprises in the industrial chain and the value chain. This increase in the efficiency of the entire market will subsequently drive the expansion of the production scale of enterprises and promote reproduction, and its synergy will promote the synchronous growth of the labour demand involving various skills, thus resulting in a creative effect (Liu et al. 2022). As an essential force in the fourth industrial revolution, AI inevitably affects the social status of humans and changes the structure of the labour force (Chen 2023). AI and machines increase labour productivity by automating routine tasks while expanding employee skills and increasing the value of work. As a result, in a machine-for-machine employment model, low-skilled jobs will disappear, while new and currently unrealized job roles will emerge (Polak 2021). We can even argue that digital technology, artificial intelligence, and robot encounters are helping to train skilled robots and raise their relative wages (Yoon 2023).

Second, AI has both a destructive effect and a substitution effect on employment. As soon as machines emerged as the means of labour, they immediately began to compete with the workers themselves. As a modern new technology, artificial intelligence is essentially humanly intelligent labour that condenses complex labour. Like the disruptive general-purpose technologies of early industrialization, automation technologies such as AI offer both promise and fear in regard to "machine replacement." Technological progress leads to an increase in the organic composition of capital and the relative surplus population. The additional capital formed in capital accumulation comes to absorb fewer and fewer workers compared to its quantity. At the same time, old capital, which is periodically reproduced according to the new composition, will begin to increasingly exclude the workers it previously employed, resulting in severe "technological unemployment." The development of productivity creates more free time, especially in industries such as health care, transportation, and production environment control, which have seen significant benefits from AI. In recent years, however, some industrialized countries have faced the dilemma of declining income from labour and the slow growth of total labour productivity while applying AI on a large scale (Autor 2019). Low-skilled and incapacitated workers enjoy a high probability of being replaced by automation (Ramos et al. 2022; Jetha et al. 2023). It is worth noting that with the in-depth development of digital technologies, such as deep learning and big data analysis, some complex, cognitive, and creative jobs that are currently considered irreplaceable in the traditional view will also be replaced by AI, which indicates that automation technology is not only a substitute for low-skilled labour (Zhao and Zhao 2017; Dixon et al. 2021; Novella et al. 2023; Nikitas et al. 2021). Among factors, AI and robotics exert a particularly significant impact on the manufacturing job market, and industry-related jobs will face a severe unemployment problem due to the disruptive effect of AI and robotics (Zhou and Chen 2022; Sun and Liu 2023). At this stage, most of the world's economies are facing the deep integration of the digital wave in their national economy, and any work, including high-level tasks, is being affected by digitalization and AI (Gardberg et al. 2020). The power of AI models is growing exponentially rather than linearly, and the rapid development and rapid diffusion of technology will undoubtedly have a devastating effect on knowledge workers, as did the industrial revolution (Liu and Peng 2023). In particular, the development and improvement of AI-generated content in recent years poses a more significant threat to higher-level workers, such as researchers, data analysts, and product managers, than to physical labourers. White collar workers are facing unprecedented anxiety and unease (Nam 2019; Fossen and Sorgner 2022; Wang et al. 2023). A classic study suggests that AI could replace 47% of the 702 job types in the United States within 20 years (Frey and Osborne 2017). Since the 2020 epidemic, digitization has accelerated, and online and digital resources have become a must for enterprises. Many occupations are gradually moving away from humans (Wu and Yang 2022; Männasoo et al. 2023). It is obvious that the intelligent robot arm on the factory assembly line is poised to allow factory assembly line workers to exit the stage and move into history. Career guides are being replaced by mobile phone navigation software.

Third, the effect of AI on employment is uncertain, and its impact on human work does not fall into a simple "utopian" or "dystopian" scene, but rather leads to a combination of "utopia" and "dystopia" (Kolade and Owoseni 2022). The job-creation effects of robotics and the emergence of new jobs that result from technological change coexist at the enterprise level (Ni and Obashi 2021). Adopting a suitable AI operation mode can adjust for the misallocation of resources by the market, enterprises, and individuals to labour-intensive tasks, reverse the nondirectional allocation of robots in the labour sector, and promote their reallocation in the manufacturing and service industries. The size of the impact on employment through the whole society is uncertain (Fabo et al. 2017; Huang and Rust 2018; Berkers et al. 2020; Tschang and Almirall 2021; Reljic et al. 2021). For example, Oschinski and Wyonch (2017) claimed that those jobs that are easily replaced by AI technology in Canada account for only 1.7% of the total labour market, and they have yet to find evidence that automation technology will cause mass unemployment in the short term. Wang et al. (2022) posited that the impact of industrial robots on labour demand in the short term is mainly negative, but in the long run, its impact on employment is mainly that of job creation. Kirov and Malamin (2022) claimed that the pessimism underlying the idea that AI will destroy the jobs and quality of language workers on a large scale is unjustified. Although some jobs will be eliminated as such technology evolves, many more will be created in the long run.

In the view that modern information technology and digital technology increase employment, the literature holds that foreign direct investment (Fokam et al. 2023), economic systems (Bouattour et al. 2023), labour skills and structure (Yang 2022), industrial technological intensity (Graf and Mohamed 2024), and the easing of information friction (Jin et al. 2023) are important mechanisms. The research on whether AI technology crowds out jobs is voluminous, but the conclusions are inconsistent (Filippi et al. 2023). This paper is focused on the influence of AI on the employment scale of the manufacturing industry, examines the job creation effect of technological progress from the perspectives of capital deepening, labour refinement, and labour productivity, and systematically examines the heterogeneous impact of the adoption of industrial robots on employment demand, structure, and different industries. The marginal contributions of this paper are as follows: first, the installation density of industrial robots is used as an indicator to measure AI, and the question of whether AI has had negative effects on employment in the manufacturing sector from the perspective of machine replacement is examined. The second contribution is the analysis of the heterogeneity of AI's employment creation effect from the perspective of gender and industry attributes and the claim that women and the employees of labour-intensive enterprises are more able to obtain additional work benefits in the digital era. Most importantly, in contrast to the literature, this paper innovatively introduces virtual agglomeration into the path mechanism of the effect of robots on employment and holds that information technologies such as the internet, big data, and the industrial Internet of Things, which rely upon AI, have reshaped the management mode and organizational structure of enterprises. Online and offline integration work together, and information, knowledge, and technology are interconnected. In the past, the job matching mode of one person, one post, and specific individuals has changed into a multiple faceted set of tasks involving one person, many posts, and many types of people. The internet platform spawned by digital technology frees the employment mode of enterprises from being limited to single enterprises and specific gathering areas. Traditional industrial geographical agglomeration has gradually evolved into virtual agglomeration, which geometrically enlarges the agglomeration effect and mechanism and enhances the spillover effect. In the online world, individual practitioners and entrepreneurs can obtain orders, receive training, connect resources and employment needs more widely and efficiently, and they can achieve higher-quality self-employment. Virtual agglomeration has become a new path by which AI affects employment. Another literature contribution is that this study used the linear regression model of the machine learning model in the robustness test part, which verified the employment creation effect of AI from the perspective of positive contribution proportion. In causal identification, this study innovatively uses the industrial feed-in price as a tool variable to analyse the causal path of AI promoting employment.

Theoretical mechanism and research hypothesis

The direct influence of AI on employment. With advances in machine learning, big data, artificial intelligence, and other technologies, a new generation of intelligent robots that can perform routine, repetitive, and regular production tasks requiring human judgement, problem-solving, and analytical skills has emerged. Robotic process automation technology can learn and imitate the way that workers perform repeated new tasks regarding the collecting of data, running of reports, copying of data, checking of data integrity, reading, processing, and the sending of emails, and it can play an essential role in processing large amounts of data (Alan 2023). In the context of an informatics- and technology-oriented economy, companies are asking employees to transition into creative jobs. According to the theory of the combined task framework, the most significant advantage of the productivity effect produced by intelligent technology is creation of new demands, that is, the creation of new tasks (Acemoglu and Restrepo 2018). These new task packages update the existing tasks and create new task combinations with more complex technical difficulties. Although intelligent technology is widely used in various industries, it may have a substitution effect on workers and lead to technical unemployment. However, with the rise of a new round of technological innovation and revolution, high efficiency leads to the development and growth of a series of emerging industries and exerts job creation effects. Technological progress has the effect of creating new jobs. That is, such progress creates new jobs that are more in line with the needs of social development and thus increases the demand for labour (Borland and Coelli 2017). Therefore, the intelligent development of enterprises will come to replace their initial programmed tasks and produce more complex new tasks, and human workers in nonprogrammed positions, such as technology and knowledge, will have more comparative advantages.

Generally, the "new technology-economy" paradigm that is derived from automation machine and AI technology is affecting the breadth and depth of employment, which is manifested as follows:

1. It reduces the demand for coded jobs in enterprises while increasing the demand for nonprogrammed complex labour.
2. The development of digital technology has deepened and refined the division of labour, accelerated the service trend of the manufacturing industry, increased the employment share of the modern service industry and created many emerging jobs.
3. Advanced productive forces give workers higher autonomy and increased efficiency in their work, improving their job satisfaction and employment quality. As described in Das Kapital, "Although machines actually crowd out and potentially replace a large number of workers, with the development of machines themselves (which is manifested by the increase in the number of the same kind of factories or the expansion of the scale of existing factories), the number of factory workers may eventually be more than the number of handicraft workers in the workshops or handicrafts that they crowd out… It can be seen that the relative reduction and absolute increase of employed workers go hand in hand" (Li and Zhang 2022).
4. Internet information technology reduces the distance between countries in both time and space, promotes the transnational flow of production factors, and deepens the international division of labour. The emergence of AI technology leads to the decline of a country's traditional industries and departments. Under the new changes to the division of labour, these industries and departments may develop in late-developing countries and serve to increase their employment through international labour export.

From a long-term perspective, AI will create more jobs through the continuous expansion of the social production scale, the continuous improvement of production efficiency, and the more detailed industrial categories that it engenders. With the accumulation of human capital under the internet era, practitioners are gradually becoming liberated from heavy and dangerous work, and workers' skills and job adaptability will undergo continuous improvement. The employment creation and compensation effects caused by technological and industrial changes are more significant than the substitution effects (Han et al. 2022). Accordingly, the article proposes the following two research hypotheses:

Hypothesis 1 (H1): AI increases employment.

Hypothesis 2 (H2): AI promotes employment by improving labour productivity, deepening capital, and refining the division of labour.

Role of virtual agglomeration. The research on economic geography and "new" economic geography agglomeration theory focuses on industrial agglomeration in the traditional sense. This model is a geographical agglomeration model that depends on spatial proximity from a geographical perspective. Assessing the role of externalities requires a particular geographical scope, as it has both physical and scope limitations. Virtual agglomeration transcends Marshall's theory of economies of scale, which is not limited to geographical agglomeration from the perspective of natural territory but rather takes on more complex and multidimensional forms (such as virtual clusters, high-tech industrial clusters, and virtual business circles). Under the influence of a new generation of digital technology that is characterized by big data, the Internet of Things, and the industrial internet, the digital, intelligent, and platform transformation trend is prominent in some industries and enterprises, and industrial digitalization and digital industrialization jointly promote industrial upgrading. The innovation of information technology leads to "distance death" (Schultz 1998). With the further materialization of digital and networked services of enterprises, the trading mode of digital knowledge and services, such as professional knowledge, information combination, cultural products, and consulting services, has transitioned from offline to digital trade, and the original geographical space gathering mode between enterprises has gradually evolved into a virtual network gathering that places the real-time exchange of data and information as its core (Wang et al. 2018). Tan and Xia (2022) stated that virtual agglomeration geometrically magnifies the social impact of industrial agglomeration mechanisms and agglomeration effects, and enterprises in the same industry and their upstream and downstream affiliated enterprises can realize low-cost long-distance transactions, services, and collaborative production through digital trade, resulting in large-scale zero-distance agglomeration along with neighbourhood-style production, service, circulation, and consumption. First, the knowledge and information underlying the production, design, research and development, organization, and trading of all kinds of enterprises are increasingly being completed by digital technology. The tacit knowledge that used to require face-to-face communication has become codable, transmissible, and reproducible under digital technology. Tacit knowledge has gradually become explicit, and knowledge spillover and technology diffusion have become more pronounced, which further leads to an increase in the demand for unconventional task labour (Zhang and Li 2022). Second, the cloud platform causes the labour pool effect of traditional geographical agglomeration to evolve into the labour "conservation land" of virtual agglomeration, and employment is no longer limited to the internal organization or constrained within a particular regional scope. Digital technology allows enterprises to hire "ghost workers" for lower wages to compensate for the possibility of AI's "last mile." Information technology and network platforms seek connections with all social nodes, promoting the time and space for work in a way that transcends standardized fixed frameworks. At the same time, joining or quitting work tasks, indirectly increasing the temporary and transitional nature of work and forming a decentralized management organization model of supplementary cooperation, social networks, industry experts, and skilled labour all become more convenient for workers (Wen and Liu 2021). With a mobile phone and a computer, labourers worldwide can create value for enterprises or customers, and the forms of labour are becoming more flexible and diverse. Workers can provide digital real-time services to employers far away from their residence, and they can also obtain flexible employment information and improve their digital skills through the leveraging of digital resources, resulting in the odd-job economy, crowdsourcing economy, sharing economy, and other economic forms. Finally, the network virtual space can accommodate almost unlimited enterprises simultaneously. In the commercial background of digital trade, while any enterprise can obtain any intermediate supply in the online market, its final product output can instantly become the intermediate input of other enterprises. Therefore, enterprises' raw material supply and product sales rely on the whole market. At this time, the market scale effect of intermediate inputs can be infinitely amplified, as it is no longer confined to the limited space of geographical agglomeration (Duan and Zhang 2023). Accordingly, the following research hypothesis is proposed:

Hypothesis 3 (H3): AI promotes employment by improving the VA of enterprises.

Study design and data sources

Variable setting

Explained variable. Employment scale (ES). Compared with the agriculture and service industry, the industrial sector accommodates more labour, and robot technology is mainly applied in the industrial sector, which has the greatest demand shock effect on manufacturing jobs. In this paper, we select the number of employees in manufacturing cities and towns as the proxy variable for employment scale.

Core explanatory variable. Artificial intelligence (AI). Emerging technologies endow industrial robots with more complete technical attributes, which increases their ability to act as human beings in many work projects, enabling them to either independently complete production tasks or to assist humans in completing such tasks. This represents an important form of AI technology embedded into machinery and equipment. In this paper, the installation density of industrial robots is selected as the proxy variable for AI. Robot data mainly come from the number of robots installed in various industries at various national levels as published by the International Federation of Robotics (IFR). Because the dataset published by the IFR provides the dataset at the national-industry level and its industry classification standards are significantly different from those in China, the first lessons for this paper are drawn from the practices of Yan et al. (2020), who matches the 14 manufacturing categories published by the IFR with the subsectors in China's manufacturing sector, and then uses the mobile share method to merge and sort out the employment numbers of various industries in various provinces. First, the national subsector data provided by the IFR are matched with the second National Economic Census data. Next, the share of employment in different industries to the total employment in the province is used to develop weights and decompose the industry-level robot data into the local "provincial-level industry" level. Finally, the application of robots in various industries at the provincial level is summarized. The Bartik shift-share instrumental variable is now widely used to measure robot installation density at the city (province) level (Wu 2023; Yang and Shen, 2023; Shen and Yang 2023). The calculation process is as follows:

$$Robot_{it} = \sum_{j=1}^{N} \frac{employ_{ij,t=2006}}{employ_{i,t=2006}} \times \frac{Robot_{jt}}{employ_{j,t=2006}} \tag{1}$$

In Eq. (1), N is a collection of manufacturing industries, Robot_{it} is the robot installation density of province i in year t, $\mathrm{employ}_{ij,t=2006}$ is the number of employees in industry j of province i in 2006, $\mathrm{employ}_{i,t=2006}$ is the total number of employees in province i in 2006, and $\mathrm{Robot}_{jt}/\mathrm{employ}_{i,t=2006}$ represents the robot installation density of each year and industry level.

Mediating variables. Labour productivity (LP). According to the definition and measurement method proposed by Marx's labour theory of value, labour productivity is measured by the balance of the total social product minus the intermediate goods and the amount of labour consumed by the pure production sector. The specific calculation process is $AL = Y - k/l$, where Y represents GDP, l represents employment, k represents capital depreciation, and AL represents labour productivity. Capital deepening (CD). The per capita fixed capital stock of industrial enterprises above a designated size is used in this study as a proxy variable for capital deepening. The division of labour refinement (DLR) is refined and measured by the number of employees in producer services. Virtual agglomeration (VA) is mainly a continuation of the location entropy method in the traditional industrial agglomeration measurement idea, and weights are assigned according to the proportion of the number of internet access ports in the country. Because of the dependence of virtual agglomeration on digital technology and network information platforms, the industrial agglomeration degree of each region is first calculated in this paper by using the number of information transmissions, computer services, and software practitioners and then multiplying that number by the internet port weight. The specific expression is $Agg_{it} = (M_{it}/M_t)/(E_{it}/E_t) \times (Net_{it}/Net_t)$, where M_{it} represents the number of information transmissions, computer services and software practitioners in region i in year t, M_t represents the total number of national employees in this industry, E_{it} represents the total number of employees in region i, E_t represents the total number of national employees, Net_{it} represents the number of internet broadband access ports in region i, and Net_t represents the total number of internet broadband access ports in the country. VA represents the degree of virtual agglomeration.

Control variables. To avoid endogeneity problems caused by unobserved variables and to obtain more accurate estimation results, seven control variables were also selected. Road accessibility (RA) is measured by the actual road area at the end of the year. Industrial structure (IS) is measured by the proportion of the tertiary industry's added value and the secondary industry's added value. The full-time equivalent of R&D personnel is used to measure R&D investment (RD). Wage cost (WC) is calculated using city average salary as a proxy variable; Marketization (MK) is determined using Fan Gang marketization index as a proxy variable; Urbanization (UR) is measured by the proportion of the urban population to the total population at the end of the year; and the proportion of general budget expenditure to GDP is used to measure Macrocontrol (MC).

Econometric model. To investigate the impact of AI on employment, based on the selection and definition of the variables detailed above and by mapping the research ideas to an empirical model, the following linear regression model is constructed:

$$ES_{it} = \delta_0 + a_1 AI_{it} + a_2 \sum_{m=1}^{7} Control_{itm} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

In Eq. (2), ES represents the scale of manufacturing employment, AI represents artificial intelligence, and subscripts t, i and m represent time t, individual i and the $\mathrm{m_{th}}$ control variable, respectively. μ_i, ν_t and ε_{it} represent the individual effect, time effect and random disturbance terms, respectively. δ_0 is the constant term, a is the parameter to be fitted, and Control represents a series of control variables. To further test whether there is a mediating effect of mechanism variables in the process of AI affecting employment, only the influence of AI on mechanism variables is tested in the empirical part according to the modelling process and operational suggestions of the intermediary effects as proposed by Jiang (2022) to overcome the inherent defects of the intermediary effects. On the basis of Eq. (2), the following econometric model is constructed:

$$Media_{it} = \delta_0 + \beta_1 AI_{it} + \beta_2 \sum_{m=1}^{7} Control_{itm} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

In Eq. (3), Media represents the mechanism variable. β_1 represents the degree of influence of AI on mechanism variables, and its significance and symbolic direction still need to be emphasized. The meanings of the remaining symbols are consistent with those of Eq. (2).

Data sources. Following the principle of data availability, the panel data of 30 provinces (municipalities and autonomous regions) in China from 2006 to 2020 (samples from Tibet and Hong Kong, Macao, and Taiwan were excluded due to data availability) were used as statistical investigation samples. The raw data on the installed density of industrial robots and the number of workers in the manufacturing industry come from the International Federation of Robotics and the China Labour Statistics Yearbook. The original data for the remaining indicators came from the China Statistical Yearbook, China Population and Employment Statistical Yearbook, China's Marketization Index Report by Province (2021), the provincial and municipal Bureau of Statistics, and the global statistical data analysis platform of the Economy Prediction System (EPS). The few missing values are supplemented through linear interpolation. It should be noted that although the IFR has yet to release the number of robots installed at the country-industry level in 2020, it has published the overall growth rate of new robot installations, which is used to calculate the robot stock in 2020 for this study. The descriptive statistical analysis of relevant variables is shown in Table 1.

Table 1 Descriptive statistics of the variables.

Variable	Code	Mean	Std. Dev.	Min.	Max.
Employment scale	ES	13.648	1.055	11.114	16.138
Artificial intelligence	AI	−4.292	1.707	−9.209	−0.046
Road accessibility	RA	9.653	0.851	6.918	11.535
R&D	RD	10.995	1.194	7.867	13.361
Wage cost	WC	10.770	0.515	9.654	12.128
Industrial structure	IS	1.105	0.641	0.499	5.297
Virtual agglomeration	VA	0.722	0.966	−1.499	2.824
Marketization	MK	1.849	0.314	0.846	2.485
Macrocontrol	MC	−1.549	0.398	−2.481	−0.442
Urbanization	UR	3.991	0.243	3.313	4.495
Capital deepening	CD	4.114	0.651	2.628	5.851
Division of labour refinement	DLR	13.548	0.804	11.463	15.472
Labour productivity	LP	12.604	0.411	11.428	13.467

Empirical analysis

Result. To reduce the volatility of the data and address the possible heteroscedasticity problem, all the variables are located. The results of the Hausmann test and F test both reject the null hypothesis at the 1% level, indicating that the fixed effect model is the best-fitting model. Table 2 reports the fitting results of the baseline regression.

As shown in Table 2, the results of the two-way fixed-effect (TWFE) model displayed in Column (5) show that the fitting coefficient of AI on employment is 0.989 and is significant at the 1% level. At the same time, the fitting results of other models show that the impact of AI on employment is significantly positive. The results confirm that the effect of AI on employment is positive and the effect of job creation is greater than the effect of destruction, and these conclusions are robust, thus verifying the employment creation mechanism of technological progress. Research Hypothesis 1 (H1) is supported. The new round of scientific and technological revolution represented by artificial intelligence involves the upgrading of traditional industries, the promotion of major changes in the economy and society, the driving of rapid development of the "unmanned economy," the spawning a large number of new products, new technologies, new formats, and new models, and the provision of more possibilities for promoting greater and higher quality employment. Classical and neoclassical economics view the market mechanism as a process of automatic correction that can offset the job losses caused by labour-saving technological innovation. Under the premise of the "employment compensation" theory, the new products, new models, and new industrial sectors created by the progress of AI technology can directly promote employment. At the same time, the scale effect caused by advanced productivity results in lower product prices and higher worker incomes, which drives increased demand and economic growth, increasing output growth and employment (Ge and Zhao 2023). In conjunction with the empirical results of this paper, we have reason to believe that enterprises adopt the strategy of "machine replacement" to replace procedural and repetitive labour positions in the pursuit of high efficiency and high profits. However, AI improves not only enterprises' production efficiency but also their production capacity and scale economy. To occupy a favourable share of market competition, enterprises expand the scale of reproduction. At this point, new and more complex tasks continue to emerge, eventually leading companies to hire more labour. At this stage, robot technology and application in developing countries are still in their infancy. Whether regarding the application scenario or the application scope of robots, the automation technology represented by industrial robots has not yet been widely promoted, which increases the time required for the automation technology to completely replace manual tasks, so the destruction effect of automation technology on jobs is not apparent. The fundamental market situation of the low cost of China's labour market drives enterprises to pay more attention to technology upgrading and efficiency improvement when introducing industrial robots. The implementation of the machine replacement strategy is mainly caused by the labour shortage

Table 2 The results of the baseline regression.

Variable	(1)	(2)	(3)	(4)	(5)
AI	0.368*** (17.16)	0.287*** (10.01)	0.003* (1.77)	0.439*** (7.94)	0.989*** (33.30)
Control variables	No	Yes	No	Yes	Yes
Individual effect	No	No	Yes	Yes	Yes
Time effect	No	No	No	No	Yes
R-square	0.3536	0.9551	0.0441	0.6762	0.9660

Note:- *** and * are significant at the 10% and 1% levels, respectively, and t statistics are displayed in parentheses.

Table 3 Robustness and endogeneity.

Variable	Robustness			Endogenous	
	Method 1	Method 2	Method 3	First stage	Second stage
AI	0.535*** (8.31)	0.978*** (32.18)	0.843		0.239*** (5.03)
IV				10.701*** (12.88)	
Control variables	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes

*** is significant at the level of 1%, and t statistics are reported in parentheses.

driven by high work intensity, high risk, simple process repetition, and poor working conditions. The intelligent transformation of enterprises points to more than the simple saving of labour costs (Dixon et al. 2021).

Robustness test. The above results show that the effect of AI on job creation is greater than the effect of substitution and the overall promotion of enterprises for the enhancement of employment demand. To verify the robustness of the benchmark results, the following three means of verifying the results are adopted in this study. First, we replace the explained variables. In addition to industrial manufacturing, robots are widely used in service industries, such as medical care, finance, catering, and education. To reflect the dynamic change relationship between the employment share of the manufacturing sector and the employment number of all sectors, the absolute number of manufacturing employees is replaced by the ratio of the manufacturing industry to all employment numbers. The second means is increasing the missing variables. Since many factors affect employment, this paper considers the living cots, human capital, population density, and union power in the basic regression model. The impact of these variables on employment is noticeable; for example, the existence of trade unions improves employee welfare and the working environment but raises the entry barrier for workers in the external market. The new missing variables are the average selling price of commercial and residential buildings, urban population density (person/square kilometre), nominal human capital stock, and the number of grassroots trade union organizations in the *China Human Capital Report 2021* issued by Central University of Finance and Economics, which are used as proxy variables. The third means involves the use of linear regression (the gradient descent method) in machine learning regression to calculate the importance of AI to the increase in employment size. The machine learning model has a higher goodness of fit and fitting effect on the predicted data, and its mean square error and mean absolute error are more minor (Wang Y et al. 2022).

As seen from the robustness part of Table 3, the results of Method 1 show that AI exerts a positive impact on the employment share in the manufacturing industry; that is, AI can increase the proportion of employment in the manufacturing industry, the use of AI creates more derivative jobs for the manufacturing industry, and the demand for the labour force of enterprises further increases. The results of method 2 show that after increasing the number of control variables, the influence of robots on employment remains significantly positive, indicating no social phenomenon of "machine replacement." The results of method 3 show that the weight of AI is 84.3%, indicating that AI can explain most of the increase in the manufacturing employment scale and has a positive promoting effect. The above three methods confirm the robustness of the baseline regression results.

Endogenous problem. Although further control variables are used to alleviate the endogeneity problem caused by missing variables to the greatest extent possible, the bidirectional causal relationship between labour demand and robot installation (for example, enterprises tend to passively adopt the machine replacement strategy in the case of labour shortages and recruitment difficulties) still threatens the accuracy of the statistical inference results in this paper. To eliminate the potential endogeneity problem of the model, the two-stage least squares method (2SLS) was applied. In general, the cost factor that enterprises need to consider when introducing industrial robots is not only the comparative advantage between the efficiency cost of machinery and the costs of equipment and labour wages but also the cost of electricity to maintain the efficient operation of machinery and equipment. Changes in industrial electricity prices indicate that the dynamic conditions between installing robots and hiring workers have changed, and decision-makers need to reweigh the costs and profits of intelligent transformation. Changes in industrial electricity prices can impact the demand for labour by enterprises; this path does not directly affect the labour market but is rather based on the power consumption, work efficiency, and equipment prices of robots. Therefore, industrial electricity prices are exogenous relative to employment, and the demand for robots is correlated.

Electricity production and operation can be divided into power generation, transmission, distribution, and sales. China has realized the integration of exports and distribution, so there are two critical prices in practice: on-grid and sales tariffs (Yu and Liu 2017). The government determines the on-grid tariff according to different cost-plus models, and its regulatory policy has roughly proceeded from that of principal and interest repayment, through operating period pricing, to benchmark pricing. The sales price (also known as the catalogue price) is the price of electric energy sold by power grid operators to end users, and its price structure is formed based on the "electric heating price" that was implemented in 1976. There is differentiated pricing between industrial and agricultural electricity. Generally, government departments formulate on-grid tariffs, integrating the interests of power plants, grid enterprises, and end users. As China's thermal power installed capacity accounts for more than 70% of the installed capacity of generators, the price of coal becomes an essential factor affecting the price of industrial internet access. The pricing strategy for electricity sales is not determined by market-oriented transmission and distribution electricity price, on-grid electricity price, or tax but rather by the goal of "stable growth and ensuring people's livelihood" (Tang and Yang 2014). The externality of the feed-in price is more robust, so the paper chooses the feed-in price as an instrumental variable.

It can be seen from Table 3 that the instrumental variables in the first stage positively affect the robot installation density at the level of 1%. Meanwhile, the results of the validity test of the instrumental variables show that there are no weak instrumental

Table 4 Mechanism test results.

Variable	Male	Female	LI	CI	TI
AI	0.966*** (32.47)	1.032*** (20.99)	0.054*** (3.48)	0.039*** (3.67)	0.026*** (4.91)
Control variable	Yes	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes

*** is significant at the 1% level, and t statistics are reported in parentheses.

Table 5 The results of the mechanism test.

Variable	CD	LP	DLR	VA
AI	0.052*** (3.59)	0.071*** (3.31)	0.302*** (4.93)	0.141** (2.63)
Control variable	Yes	Yes	Yes	Yes
Individual effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes

*** and ** are significant at the 1% and 5% levels, respectively, and t statistics are reported in parentheses.

variables or unidentifiable problems with this variable, thus satisfying the principle of correlation and exclusivity. The second-stage results show that robots still positively affect the demand for labour at the 1% level, but the fitting coefficient is smaller than that of the benchmark regression model. In summary, the results of fitting the calculation with the causal inference paradigm still support the conclusion that robots create more jobs and increase the labour demand of enterprises.

Extensibility analysis

Robot adoption and gender bias. The quantity and quality of labour needed by various industries in the manufacturing sector vary greatly, and labour-intensive and capital-intensive industries have different labour needs. Over the past few decades, the demand for female employees has grown. Female employees obtain more job opportunities and better salaries today (Zhang et al. 2023). Female employees may benefit from reducing the content of manual labour jobs, meaning that further study of AI heterogeneity from the perspective of gender bias may be needed. As seen from Table 4, AI has a significant positive impact on the employment of both male and female practitioners, indicating that AI technology does not have a heterogeneous effect on the dynamic gender structure. By comparing the coefficients of the two (the estimated results for men and those for women), it can be found that robots have a more significant promotion effect on female employees. AI has significantly improved the working environment of front-line workers, reduced the level of labour intensity, enabled people to free themselves of dirty and heavy work tasks, and indirectly improved the job adaptability of female workers. Intellectualization increases the flexibility of the time, place, and manner of work for workers, correspondingly improves the working freedom of female workers, and alleviates the imbalance in the choice between family and career for women to a certain extent (Lu et al. 2023). At the same time, women are born with the comparative advantage of cognitive skills that allow them to pay more nuanced attention to work details. By introducing automated technology, companies are increasing the demand for cognitive skills such as mental labour and sentiment analysis, thus increasing the benefits for female workers (Wang and Zhang 2022). Flexible employment forms, such as online car hailing, community e-commerce, and online live broadcasting, provide a broader stage for women's entrepreneurship and employment. According to the "Didi Digital Platform and Female Ecology Research Report", the number of newly registered female online taxi drivers in China has exceeded 265,000 since 2020, and approximately 60 percent of the heads of the e-commerce platform, Orange Heart, are women.

Industry heterogeneity. Given the significant differences in the combination of factors across the different industries in China's manufacturing sector, there is also a significant gap in the installation density of robots; even compared to AI density, in industries with different production characteristics, indicating that there may be an opposite employment phenomenon at play. According to the number of employees and their salary level, capital stock, R&D investment, and patent technology, the manufacturing industry is divided into labour-intensive (LI), capital-intensive (CI), and technology-intensive (TI) industries.

As seen from the industry-specific test results displayed in Table 4, the impact of AI on employment in the three attribute industries is significantly positive, which is consistent with the results of Beier et al. (2022). In contrast, labour-intensive industries can absorb more workers, and industry practitioners are better able to share digital dividends from these new workers, which is generally in line with expectations (in the labour-intensive case, the regression coefficient of AI on employment is 0.054, which is significantly larger than the regression coefficient of the other two industries). This conclusion shows that enterprises use AI to replace the labour force of procedural and process-based positions in pursuit of cost-effective performance. However, the scale effect generated by improving enterprise production efficiency leads to increased labour demand, namely, productivity and compensation effects. For example, AGV-handling robots are used to replace porters in monotonous and repetitive high-intensity work, thus realizing the uncrewed operation of storage links and the automatic handling of goods, semifinished products, and raw materials in the production process. This reduces the cost of goods storage while improving the efficiency of logistics handling, increasing the capital investment of enterprises in the expansion of market share and extension of the industrial chain.

Mechanism test. To reveal the path mechanism through which AI affects employment, in combination with H2 and H3 and the intermediary effect model constructed with Eq. (3), the TWFE model was used to fit the results shown in Table 5.

It can be seen from Table 5 that the fitting coefficients of AI for capital deepening, labour productivity, and division of labour are 0.052, 0.071, and 0.302, respectively, and are all significant at the 1% level, indicating that AI can promote employment through the above three mechanisms, and thus research Hypothesis 2 (H2) is supported. Compared with the workshop and handicraft industry, machine production has driven incomparably broad development in the social division of labour. Intelligent transformation helps to open up the internal and external data chain, improve the combination of production factors, reduce costs and increase efficiency to enable the high-quality development of enterprises. At the macro level, the impact of robotics on social productivity, industrial structure, and product prices affects the labour demand of enterprises. At the micro level, robot technology changes the employment carrier, skill requirements, and employment form of labour and impacts the matching of labour supply and demand. The combination of the price and income effects can drive the impact of technological progress on employment creation. While improving labour productivity, AI technology reduces product production costs. In the case of constant nominal income, the market increases the demand for the product, which in turn drives the expansion of the industrial scale and increases output, resulting in an increase in the demand for labour. At the same time, the emergence of robotics has refined the division of labour. Most importantly, the development of AI technology results in productivity improvements that cannot be matched by pure labour input, which not only enables 24 h automation but also reduces error rates, improves precision, and accelerates production speeds.

Table 5 also shows that the fitting coefficient of AI to virtual agglomeration is 0.141 and significant at the 5% level, indicating that AI and digital technology can promote employment by promoting the agglomeration degree of enterprises in the cloud and network. Research Hypothesis 3 is thus supported. Industrial internet, AI, collaborative robots, and optical fidelity information transmission technology are necessary for the future of the manufacturing industry, and smart factories will become the ultimate direction of manufacturing. Under the intelligent manufacturing model, by leveraging cloud links, industrial robots, and the technological depth needed to achieve autonomous management, the proximity advantage of geographic spatial agglomeration gradually begins to fade. The panconnective features of digital technology break through the situational constraints of work, reshaping the static, linear, and demarcated organizational structure and management modes of the industrial era and increasingly facilitates dynamic, network-based, borderless organizational forms, despite the fact that traditional work tasks can be carried out on a broader network platform employing online office platforms and online meetings. While promoting cost reduction and efficiency increase, such connectivity also creates new occupations that rely on this network to achieve efficient virtual agglomeration. On the other hand, robot technology has also broken the fixed connection between people and jobs, and the previous post matching mode of one person and one specific individual has gradually evolved into an organizational structure involving multiple posts and multiple people, thus providing more diverse and inclusive jobs for different groups.

Conclusions and policy implications

Research conclusion. The decisive impact of digitization and automation on the functioning of all society's social subsystems is indisputable. Technological progress alone does not impart any purpose to technology, and its value (consciousness) can only be defined by its application in the social context in which it emerges (Rakowski et al. 2021). The recent launch of the intelligent chatbot ChatGPT by the US artificial intelligence company OpenAI, with its powerful word processing capabilities and human-computer interaction, has once again sparked global concerns about its potential impact on employment in related industries. Automation technology represented by intelligent manufacturing profoundly affects the labour supply and demand map and significantly impacts economic and social development. The application of industrial robots is a concrete reflection of the integration of AI technology and industry, and its widespread promotion and popularization in the manufacturing field have resulted in changes in production methods and exerted impacts on the labour market. In this paper, the internal mechanism of AI's impact on employment is first delineated and then empirical tests based on panel data from 30 provinces (municipalities and autonomous regions, excluding Hong Kong, Macao, Taiwan, and Xizang) in China from 2006 to 2020 are subsequently conducted. As mentioned in relation to the theory of "employment compensation," the research described in this paper shows that the overall impact of AI on employment is positive, revealing a pronounced job creation effect, and the impact of automation technology on the labour market is mainly positively manifested as "icing on the cake." Our conclusion is consistent with the literature (Sharma and Mishra 2023; Feng et al. 2024). This conclusion remains after replacing variables, adding missing variables, and controlling for endogeneity problems. The positive role of AI in promoting employment does not have exert opposite effects resulting from gender and industry differences. However, it brings greater digital welfare to female practitioners and workers in labour-intensive industries while relatively reducing the overall proportion of male practitioners in the manufacturing industry. Mechanism analysis shows that AI drives employment through mechanisms that promote capital deepening, the division of labour, and increased labour productivity. The digital trade derived from digital technology and internet platforms has promoted the transformation of traditional industrial agglomeration into virtual agglomeration, the constructed network flow space system is more prone to the free spillover of knowledge, technology, and creativity, and the agglomeration effect and agglomeration mechanism are amplified by geometric multiples. Industrial virtual agglomeration has become a new mechanism and an essential channel through which AI promotes employment, which helps to enhance labour autonomy, improve job suitability and encourage enterprises to share the welfare of labour among "cultivation areas."

Policy implications. Technology is neutral, and its key lies in its use. Artificial intelligence technology, as an open new general technology, represents significant progress in productivity and is an essential driving force with the potential to boost economic development. However, it also inevitably poses many potential risks and social problems. This study helps to clarify the argument that technology replaces jobs by revealing the impact of automation technology on China's labour market at the present stage, and its findings alleviate the social anxiety caused by the fear of machine replacement. According to the above research conclusions, the following valuable implications can be obtained.

1. Investment in AI research and development should be increased, and the high-end development of domestic robots should be accelerated. The development of AI has not only resulted in the improvement of production efficiency but has also triggered a change in industrial structure and labour structure, and it has also generated new jobs as it has replaced human labour. Currently, the impact of AI on employment in China is positive and helps

to stabilize employment. Speeding up the development of the information infrastructure, accelerating the intelligent upgrade of the traditional physical infrastructure, and realizing the inclusive promotion of intelligent infrastructure are necessary to ensure efficient development. 5G technology and the development dividend of the digital economy can be used to increase the level of investment in new infrastructure such as cloud computing, the Internet of Things, blockchain, and the industrial internet and to improve the level of intelligent application across the industry. We need to implement the intelligent transformation of old infrastructure, upgrade traditional old infrastructure to smart new infrastructure, and digitally transform traditional forms of infrastructure such as power, reservoirs, rivers, and urban sewer pipes through the employment of sensors and access algorithms to solve infrastructure problems more intelligently. Second, the diversification and agglomeration of industrial lines are facilitated through the transformation of industrial intelligence and automation. At the same time, it is necessary to speed up the process of industrial intelligence and cultivate the prospects of emerging industries and employment carriers, particularly in regard to the development and growth of emerging producer services. The development of domestic robots should be task-oriented and application-oriented, should adhere to the effective transformation of scientific and technological achievements under the guidance of the development of the service economy. A "1 + 2 + N" collaborative innovation ecosystem should be constructed with a focus on cultivating, incubating, and supporting critical technological innovation in each subindustry of the manufacturing industry, optimizing the layout, and forming a matrix multilevel achievement transformation service. We need to improve the mechanisms used for complementing research and production, such as technology investment and authorization. To move beyond standard robot system development technology, the research and development of bionic perception and knowledge, as well as other cutting-edge technologies need to be developed to overcome the core technology "bottleneck" problem.

2. It is suggested that government departments improve the social security system and stabilize employment through multiple channels. The first channel is the evaluation and monitoring of the potential destruction of the low-end labour force by AI, enabled through the cooperation of the government and enterprises, to build relevant information platforms, improve the transparency of the labour market information, and reasonably anticipate structural unemployment. Big data should be fully leveraged, a sound national employment information monitoring platform should be built, real-time monitoring of the dynamic changes in employment in critical regions, fundamental groups, and key positions should be implemented, employment status information should be released, and employment early warning, forecasting, and prediction should be provided. Second, the backstop role of public service, including human resources departments and social security departments at all levels, should improve the relevant social security system in a timely manner. A mixed-guarantee model can be adopted for the potential unemployed and laws and regulations to protect the legitimate rights and interests of entrepreneurs and temporary employees should be improved. We can gradually expand the coverage of unemployment insurance and basic living allowances. For the extremely poor, unemployed or extreme labour shortage groups, public welfare jobs or special subsidies can be used to stabilize their basic lifestyles. The second is to understand the working conditions of the bottom workers at the grassroots level in greater depth, strengthen the statistical investigation and professional evaluation of AI technology and related jobs, provide skills training, employment assistance, and unemployment subsidies for workers who are unemployed due to the use of AI, and encourage unemployed groups to participate in vocational skills training to improve their applicable skillsets. Workers should be encouraged to use their fragmented time to participate in the gig and sharing economies and achieve flexible employment according to dominant conditions. Finally, a focus should be established on the impact of AI on the changing demand for jobs in specific industries, especially transportation equipment manufacturing and communications equipment, computers, and other electronic equipment manufacturing.
3. It is suggested that education departments promote the reform of the education and training system and deepen the coordinated development of industry-university research. Big data, the Internet of Things, and AI, as new digital production factors, have penetrated daily economic activities, driving industrial changes and changes in the supply and demand dynamics of the job market. Heterogeneity analysis results confirmed that AI imparts a high level of digital welfare for women and workers in labour-intensive industrial enterprises, but to stimulate the spillover of technology dividends in the whole society, it is necessary to dynamically optimize human capital and improve the adaptability of man-machine collaborative work; otherwise, the disruptive effect of intelligent technology on low-end, routine and programmable work will be obscured. AI has a creativity promoting effect on irregular, creative, and stylized technical positions. Hence, the contradiction between supply and demand in the labour market and the slow transformation of the labour skill structure requires attention. The relevant administrative departments of the state should take the lead in increasing investment in basic research and forming a scientific research division system in which enterprises increase their levels of investment in experimental development and multiple subjects participate in R&D. Relevant departments should clarify the urgent need for talent in the digital economy era, deepen the reform of the education system as a guide, encourage all kinds of colleges and universities to add related majors around AI and big data analysis, accelerate the research on the skill needs of new careers and jobs, and establish a lifelong learning and employment training system that meets the needs of the innovative economy and intelligent society. We need to strengthen the training of innovative, technical, and professional technical personnel, focus on cultivating interdisciplinary talent and AI-related professionals to improve worker adaptability to new industries and technologies, deepen the adjustment of the educational structure, increase the skills and knowledge of perceptual, creative, and social abilities of the workforce, and cultivate the skills needed to perform complex jobs in the future that are difficult to replace by AI. The lifelong education and training system should be improved, and enterprise employees should be encouraged to participate in vocational skills training and cultural knowledge learning through activities such as vocational and technical schools, enterprise universities, and personnel exchanges.

Research limitations. The study used panel data from 30 provinces in China from 2006 to 2020 to examine the impact of AI on employment using econometric models. Therefore, the conclusions obtained in this study are only applicable to the economic reality in China during the sample period. There are three shortcomings in this study. First, only the effect and mechanism of AI in promoting employment from a macro level are investigated in this study, which is limited by the large data particles and small sample data that are factors that reduce the reliability and validity of statistical inference. The digital economy has grown rapidly in the wake of the COVID-19 pandemic, and the related industrial structures and job types have been affected by sudden public events. An examination of the impact of AI on employment based on nearly three years of micro-data (particularly the data obtained from field research) is urgent. When conducting empirical analysis, combining case studies of enterprises that are undergoing digital transformation is very helpful. Second, although the two-way fixed effect model and instrumental variable method can reveal conclusions regarding causality to a certain extent, these conclusions are not causal inference in the strict sense. Due to the lack of good policy pilots regarding industrial robots and digital parks, the topic cannot be thoroughly evaluated for determining policy and calculating resident welfare. In future research, researchers can look for policies and systems such as big data pilot zones, intelligent industrial parks, and digital economy demonstration zones to perform policy evaluations through quasi-natural experiments. The use of difference in differences (DID), regression discontinuity (RD), and synthetic control method (SCM) to perform regression is beneficial. In addition, the diffusion effect caused by introducing and installing industrial robots leads to the flow of labour between regions, resulting in a potential spatial spillover effect. Although the spatial econometric model is used above, it is mainly used as a robustness test, and the direct effect is considered. This paper has yet to discuss the spatial effect from the perspective of the spatial spillover effect. Last, it is important to note that the digital infrastructure, workforce, and industrial structure differ from country to country. The study focused on a sample of data from China, making the findings only partially applicable to other countries. Therefore, the sample size of countries should be expanded in future studies, and the possible heterogeneity of AI should be explored and compared by classifying different countries according to their stage of development.

Data availability

The data generated during and/or analyzed during the current study are provided in Supplementary File "database".

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Correspondence and requests for materials should be addressed to Yang Shen.