

# *A Review of Research on the Employment Effect of Artificial Intelligence Applications*

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**Abstract:** Based on the concept of artificial intelligence (AI) and the summary of existing research methods, this essay reviews the theoretical and empirical research into AI's impact on industrial distribution, jobs, wages and other aspects in the field of employment. The essay finds that AI technology accelerates job polarization in the labor market and causes wage inequality during this process while taking over some occupations and promoting the flow of labor among different industries. In the long run, the substitution and creation effects will coexist for the long term, and the creation effects will exercise increasingly obvious influence; wage inequality can be compensated by long-term social policies; job polarization will not last for long; and workers' flow between industries is essentially a result of matching labor skills with task needs after technological changes. More scholars believe that the impact of artificial intelligence on employment in the future is controllable, and the key is in the broad and effective human-computer cooperation facilitated by the improvement of labor's skill levels through education and training.

**Keywords:** artificial intelligence (AI), industrial structure, jobs and wages

In recent years, the impact of artificial intelligence (AI) has become an important subject in employment research. Researching the employment effects of the application of artificial intelligence in all aspects of production

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we can learn, at a macro level, the directional influence of artificial intelligence on the employment situation and meanwhile observe, at the micro level, the specific changes of existing work tasks and income distributions. Before discussing the impact of various aspects, it is necessary to clarify the concept and application of artificial intelligence and the existing main methods of research into employment effects. Scholars disagree about the concept of artificial intelligence. In its early stage, artificial intelligence was described as “machines that think” with the ability to think and act in a way that will surpass human beings (McCorduck, 1979). Others believed that the demonstration of such abilities requires specific carriers and external circumstances, for example, both Dreyfus’s (1972) classic criticism against artificial intelligence<sup>①</sup> and Searle’s (1992) “biological naturalism”<sup>②</sup> argued that the realization of human-like intelligence entails the physical embodiment, like a human, and certain social backgrounds. At present, a more comprehensive description of the concept of artificial intelligence comes from the research of MIT in the field of electrical engineering: artificial intelligence is an organic whole, an expression system for thinking, perception and action, which is established through models, taking the working-out of test methods as its basic operation mode, but this system faces certain constraints, which work through algorithms (programs or methods) (Finlayson et al., 2010).

Since artificial intelligence is entering and reshaping production and life in all aspects, the description should avoid both Luddism in epistemology and technological determinism to maintain an objective understanding of artificial intelligence technology (Zhang, 2018).<sup>③</sup> Therefore, this essay holds that artificial intelligence is a technology created for specific tasks and exhibiting similar levels of human abilities (cognition, thinking, or action), and that this technology needs to work with corresponding carriers (tools) and application environments. Under existing technological conditions, the application carrier of artificial intelligence is mainly computerized and automated equipment, and the application environments refer to circumstances required for the fulfillment of tasks.

At present, the research outside China on the impact of artificial intelligence upon employment is usually based on the task model approach. Autor et al. (2003) distinguished cognitive and manual tasks, and routine and non-routine tasks, and in doing so, they mainly intended to learn how computerization<sup>④</sup> changes the demands for job skills. From a “machine’s-eye” view, they disassembled specific work into different tasks, determined which could be executed by

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① Dreyfus’s (1972) critique of artificial intelligence involves four main assumptions of artificial intelligence research: “biology”, “psychology”, “epistemology”, and “ontology”. In the “biological” assumption, the brain is similar to computer hardware, and thinking is like software; the “psychological” assumption is that thinking works by performing calculations on symbols (in the form of algorithmic rules); “epistemological” assumption suggests that all activities can be implemented in the form of predictive rules; and the “ontological” assumption proposes that the reality consists entirely of a set of independent but inseparable facts.

② Searle (1992) argued that if you want to create a conscious existence, you will have to replicate any physical processes that the brain experiences, to mimic and awaken consciousness.

③ Stanford University pointed out the artificial intelligence effect in its 2017 report, asserting that new technology will replace the previous technology through its popularization and turn into the “real” artificial intelligence in the public consciousness, although the previous technology still belongs to the category of artificial intelligence. Because of the existence of this effect, it is necessary to consider which technologies belong to the category of smart technology before learning about how the application of smart technology affects employment. Here it may involve both high-tech and the tools that we are used to.

④ Computer science is especially important for the realization of intelligent concepts. Intelligent computing, intelligent information processing, and computer science are basic dynamics for intelligent realization. This is also an important reason why this essay regards the technology of computerization and automation based on computerization as the embodiment of artificial intelligence.

a computer, and described four cases in which workers could be affected by computers in the workplace; substitution, mutual complementation, imperfect substitution, and conditional mutual complementation. Autor et al. believed that computers had become an alternative labor force for many daily tasks and had shown strong mutual complementarity with the workforce performing non-routine cognitive tasks. However, Autor et al. did not predict complementarity with any labor force performing non-routine manual tasks (non-routine physical labor) (Frey et al., 2017).<sup>①</sup>

### Impact on the Industrial Distribution of Employment

From the current research results, the agricultural production sector is less affected by artificial intelligence and the labor force in the manufacturing sector will gradually shift to the service sector due to the substitution effects of artificial intelligence (Autor et al., 2013), and Zhong Renyao et al. (2013) believed that this situation is related to the knowledge structure and adaptability of original practitioners. According to a study by the US Bureau of Labor Statistics, by 2024, almost all new jobs will be concentrated in services, especially in the areas of health care and social assistance services (Trajtenberg, 2018).

### Impact on Agriculture

Although the application of artificial intelligence at present imposes no significant impact on the number of farmers (Manyika et al., 2017; Frey et al., 2017), artificial intelligence technologies do transform farmers' habits and methods in production and strengthen their links with the market. First, from the perspective of agricultural production, Ampatzidis et al. (2017) pointed out that currently automation and robots can realize human-machine cooperation through the entire process of agricultural production, that is, from crop selection to sowing, disaster prevention, and finally to crop harvesting. Second, from the perspective of farmers' connection with the market, Lele et al. (2017) believed that the current transformation of intelligent and digital technology, in terms of the former's speed and scope, is conducive to the inclusive development of agriculture and rural areas, capable of truly realizing the close connection between farmers and the market in each production process, and able to indirectly increase farmers' incomes by providing higher levels of education, health care, finance and market services.

As existing research has shown, the impact of artificial intelligence on agricultural production is mainly concentrated on transforming agricultural production methods, improving production efficiency, and increasing farmers' income, but the substitution effect on farmers is not obvious. Possibly it is because during the transition from mechanization to automation in the process of agricultural production, the change of ways to accomplish production tasks do not affect the demand

<sup>①</sup> Frey et al. (2017) further redefined the task model in their research, subdividing the labor input of non-routine tasks into perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks. According to Arntz et al. (2016), this redefinition (extension) has exceeded the definition of routine and non-routine tasks proposed by Autor et al.

for farmers in the agricultural production process, or are far less comparable to the influence that agricultural mechanization once exerted.

### **Impact on Manufacturing**

Focused on the impact of industrial robots on the US labor market, Acemoglu et al. (2017) studied the relationships between the large-scale use of industrial robots in 19 industries (mainly manufacturing) and the employment rates and wages in 722 commuting zones from 1993 to 2007. They found that the large-scale application of industrial robots has a significant negative correlation with employment and wages, and concluded that the substitution effect of industrial robots on the labor market at present is greater than its creative effect, suggesting that each additional robot per one thousand workers reduces employment by about 0.18-0.34%, and wages by 0.25-0.5 percent. Thus, they deduce that the number of lost jobs from 1990 to 2007 due to the use of industrial robots in the industrial sector ranges between 360,000 to 670,000. At the same time, artificial intelligence also profoundly affects the production models and production systems within the manufacturing industry and changes the skill demands on workers within these systems. Yin et al. (2017) examined the changes in production systems during each industrial revolution and found that in comparison with the assembly line, Toyota production system (TPS), and cellular manufacturing created by the second industrial revolution, the flexible manufacturing system (FMS) and Seru<sup>①</sup> production system, which were fostered by the third industrial revolution and use computerization and industrial robots as their software and hardware bases, can better meet the demands of product markets for mass customization under industry 4.0 conditions. According to Yin et al., this will not only change the pattern of future manufacturing development but also impose further requirements for the improvement of workers' skills.

In the research on the industrial distribution of artificial intelligence's impact upon employment, the manufacturing industry has been highlighted. This is not only because the manufacturing industry itself is vulnerable to industrial robots and automation, but also because the manufacturing industry absorbs a large amount of ordinary labor and its labor distribution is more concentrated than that of the agriculture and service industries. The impact of artificial intelligence on manufacturing is not limited to the number of jobs nor is it completely negative. The specific effects depend on the characteristics and attributes of the industry (Acemoglu et al., 2017); it is widely expected that the positive results of industrial robot applications are directly related to productivity, especially in industrial environments, where the use of industrial robots for specific tasks will reduce human workloads and possible dangers while saving labor time and increasing leisure. The primary consideration for negative influences is the impact of industrial robots on employment, and the accountability for accidents while using industrial robot applications.

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① Seru production is a production method that can change its own production content in accordance to the needs of different production tasks; it is suitable for multi-variety and small-batch market demand and has both efficiency and flexibility. Since its inception, Seru production has been rapidly popularized in the manufacturing industries in Japan, becoming an assemble system adopted by many Japanese electronics companies.

### Impact on the Service Industry

According to the research of Frey et al. (2017), many workers in the service industry are at risk of being replaced by computers while they must accept new colleagues from the manufacturing industries. Workers engaged in telemarketing, insurance underwriting, transportation services, photography, data maintenance, etc. are groups that are very likely to be replaced by computers. However, the creative effect of artificial intelligence has also led to an increase in the demand for labor in some occupations, those that have witnessed the fastest growth involve kindergarten (and primary school) teachers, accounting and finance staff, nurses, healthcare consultants, therapists and social information workers. For the growing amount of labor demand in the social information sector, Deming (2017) believed that the task requirements for social skills cannot yet be met by computerized and automated technologies, which will encourage workers to improve their social skills which will allow them to change their work choices. Moreover, he points out that from 1980 to 2012, jobs with high social skill intensity increased by 24% in the US, while the share of employment grew by 7.2% and wages rose by 26% in the same period.

### Impact on Jobs

From the existing literature, the impact of artificial intelligence on jobs not only involves changes in both the number of jobs and the nature of the tasks, namely, substitution and creation effects, but also causes job polarization and accelerates human-machine cooperation.

#### Job Polarization

The computer revolution in the 20th century and the rapid development of artificial intelligence technology in the 21st century have worked together to significantly impact jobs and a distinct sign of this is the reduced number of jobs with middle incomes and middle-skill requirements (Autor, 2013; Frey et al., 2017). Correspondingly, high-paid mental jobs (cognitive tasks) and low-paid physical labor occupations have increased, and the number of employed people has also changed accordingly. The labor market has shown the trend of polarization and affected workers' employment choices (Goos et al., 2007). As Autor et al. (2013) have noticed, the job-polarization trend in the US labor market is mainly reflected in the increased number of low-skill service jobs while in the routine labor-intensive market, the polarization of employment and wages is more obvious. At the same time, Jerbashian (2016) focused on single-technology fields using data from 10 European countries to prove that the fall of IT prices is related to a decline in the share of middle wage occupations and an increase in the share of high wage occupations, but its impact on the proportion of the lowest paid occupations is less, which is a proof that the intelligent technology represented by computerization has the distinct potential to cause further job polarization.

For the trend of polarization, Autor (2013) believed that it is difficult to ascertain the

complementarity in other areas and the countervailing effects of rising demands in labor markets were difficult to determine as job polarization would not continue indefinitely. Frey et al. (2017) pointed out that computerization was mainly limited to low-skill and low-wage occupations, the labor market polarization would stop expanding and its impact can be alleviated through corresponding measures, that is, low-skilled workers would be redistributed to tasks that are not affected by computerization, but workers must improve their creative thinking and social skills in order to win these opportunities.

### **Replacement of Occupations**

The substitution effect of artificial intelligence is more obvious than the impact of any previous technological progress (Cao Jing & Zhou Yalin, 2018). According to a World Bank survey, 57% jobs in more than 50 countries in 2013 were affected by automation technology (Manyika et al., 2017). In the US, 47% of employment faces the high risk of substitution (computerization), the replacement rate is negatively correlated with the requirements of wage and occupational skill, and among the 702 occupations reviewed, workers engaging in transportation, logistics services, office clerks, and some production departments are at high risk of being replaced (Frey et al., 2017). Arntz et al. (2016) analyzed the extent to which jobs in 21 OECD countries could be automatically replaced and the result showed that 9% of jobs in the US are at high risks<sup>①</sup>. Likewise, David (2017) found that 55% of jobs in Japan are at “risk” and that workers in non-regular employment were more likely to be replaced. In 2016, the German Federal Ministry of Labour and Social Affairs (BMAS) calculated the probability of jobs replaced by machines in Germany, with a result of 13%. In comparison, Oschinski et al. (2017) surveyed the Canadian labor market and found that the jobs at risk to high automation account for only 1.7 percent of employment. Scholars differ in terms of the results of their calculations and this is possibly caused by disparities between statistical specifications, overestimated technological capabilities, lagging utilization levels, and the heterogeneity of workplaces (Arntz et al., 2016). In addition, substitution effects also vary due to differences between industries, and between time series. As Jiang Jinqiu and Du Yuhong (2015) have found, employment in different industries in short, medium and long terms has different responses to technological progress.

Regarding the development trend of occupation replacement, the traditional view represented by technological unemployment still has a strong voice. As Trajtenberg (2018) pointed out, some new “technology enthusiasts” believed that artificial intelligence would replace most people's jobs in a predictable period, releasing huge productive forces, and that subsequently there would occur negative influences on employment expectations and income distributions. In this regard, scholars hold different views. For example, Arntz et al. (2016) suggested that the existing substitution effects have been overstated and that the research results based on the distinguishing of tasks represented

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① Arntz et al. (2016) regard the automation substitution with probability more than 70% as high risk; the value that Oschinski et al. (2017) chose while considering the risk levels of automation approximates the former, and their calculation results for the proportion of the high-risk occupations from high to low are Austria and Germany (12%), Spain (11.5%), Slovak Republic (10.5%), United Kingdom, Norway, Netherlands, and Czech Republic (10%, respectively), Canada, Denmark, France, and the US (9%, respectively), Sweden, Poland, Japan, Finland, and Belgium (7%, respectively), Estonia (6.5%), and South Korea (6%).



merely the possibility of substitution, rather than the actual situation; Autor (2015) and Brynjolfsson et al. (2018) pointed out that most automation systems lack flexibility, and were unable to accommodate the demands of some non-routine tasks. Cao Jing and Zhou Yalin (2018) also believed that the risk of jobs being automated does not mean actual job losses. In addition, the more compromised view is that technological progress will benefit everyone in the long run. But in the short term, not everyone will be a winner (Cortes et al., 2014). Manyika et al. (2017) considered the impact of automation on jobs (occupations), and believed that the transformation at present is full of challenges, but by 2030 most workplaces will be able to provide sufficient jobs for full employment.<sup>①</sup>

### Job Creation

Although artificial intelligence applications (computerization and automation at present) have shown relatively obvious substitution effects, their creative effects still exist. Acemoglu (2017) proposed that automation would generate new employment opportunities by creating new job tasks while reducing employment. The newly created jobs will consist of two parts, one is the growth of labor demand that artificial intelligence applications bring about by increasing workloads; the other is the new types of jobs around artificial intelligence (algorithm development, AI-designer trainer, intelligent equipment maintenance, etc.). These two employment groups have something in common, i.e., both workers related to the emerging industry of general-purpose technology (GPT)<sup>②</sup> itself, and those relevant with the frontier fields in whose major application domains the general purpose technology is deployed, are characterized with youth and entrepreneurship, and meanwhile qualified with the technological knowledge reserve and skills required by the new general-purpose technology (Trajtenberg, 2018).

In addition to the increase of jobs, Wang Jun and Yang Wei (2017) proposed that the progress of new technologies, including artificial intelligence, has an expansive impact on employment and is conducive to improving the quality of work. According to Kremer's (1993) O-ring model, the growth in task productivity increases the value of the remaining tasks in a production chain, while artificial intelligence helps increase the value of remaining manual labor production links when it improves the efficiency of routine physical labor. The first prerequisite for improvement is the complementarity between man and machine in the task process. From 1988 to 2004, ATMs caused a one-third decrease of bank tellers on average in the branches of US banks, but the number of branches throughout the US rose by more than 40%; at the same time, bank tellers were also liberated from the chores of routine cash-handling tasks: they gradually turned from their previous jobs towards sales, customer business, and each occupation thus created more value (Autor, 2015).

① Manyika et al. (2017) believed that theoretically half of activities in work at present can be accomplished through automation, but only a very small number (5%) can be fully automated. Despite of this, the impact of transformation still exists, for nearly one-third of the activities for nearly 60% of the occupations can be automated, which means that all workers are facing a lot of workplace transformation and changes (<https://www.mckinsey.com/featured-insights/future-of-organizations-and-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages>).

② At the NBER conference in early 2018, artificial intelligence was considered to have great potential for becoming a new general-purpose technology, and it was pointed out that in its constantly expanding application area, AI would bring about a wave of complementary innovations.

## **Job Cooperation**

The study of relationships between a worker on his job and artificial intelligence applications can be understood through the conflict between McCarthy and Douglas's core views, i.e., whether to employ an increasingly powerful combination of computer software and hardware to replace workers in the workplace, or to use the same tool to expand the capabilities of workers in terms of brains, society and the economy. There is no right or wrong position (or opinion) in this debate, only that a controversy about phenomena or trends would lead to a bias when debaters considered these two problems outside of the real situation (Markoff, 2015), and the practical application of technology might provide more inspiration for us instead.

The computer system devised by Douglas C. Engelbart opened a door to office automation, some jobs have been taken over by many artificial intelligence applications (programs, equipment, etc.), but workers accomplishing tasks still have partnerships with those on other jobs, and the difference lies in the added cooperation between workers and machines. Therefore, human-machine cooperation and human-computer interaction determine that we will regard the carriers of artificial intelligence as partners (Markoff, 2015), and to realize human-computer interaction and facilitate these carriers to play their roles in teamwork we need to be qualified with the necessary knowledge and skills concerning the task and other essential features including team knowledge, leadership, communication, monitoring, and feedback capabilities.

Since 2009, applied research oriented toward deep learning has yielded significant results. Changes in the process of artificial intelligence innovation have led to a sequence of key issues in policy and management areas (Cockburn et al., 2018). Specifically, machine learning can incorporate as many variables as possible, stripping out the influencing factors that traditional methods cannot approach (Camerer, 2018). With the development of machine learning, the artificial intelligence applications in the research on relationships between prediction and decision-making have enhanced their prediction ability and decreased their prediction cost under uncertainty, hence artificial intelligence thinking can be regarded as a supplement to human judgment (Agrawal et al., 2018). In reference to existing research, human-computer cooperation on a job will have a clear advantage in the future, therefore, learning how to cooperate with artificial intelligence is also an indispensable skill for future workers.

## **Impact on Wages**

Existing research emphasizes the impact of artificial intelligence and other technological progress on wages, not only because the theme of income inequality is important, but also because the evolution of wage distribution provides market value information on different types of skills (Acemoglu et al., 2011). In addition, the issue of inequality between workers in the workplace, which is caused by artificial intelligence, may be directly related to the impact of artificial intelligence applications on



wages (Chace, 2016).

### Impact on Individual Workers

Starting from the premise that workers have been replaced due to technological progress, Acemoglu et al. (2017) argued that the application of industrial robots in manufacturing industries has a strong negative impact on the wages of manufacturing workers. Korinek et al. (2017) classified the different impacts of artificial intelligence on wages and welfare. First, in the best scenario (perfect market where individuals invest in technological progress and carry out risk aversion), technological progress always makes everyone better off. Second, in the second-best case (perfect market, which is accompanied by costless redistribution), if redistribution is given a full play of its role, there will be a win-win situation between workers and technological progress, but when there is not enough redistribution capacity to make up for the workers' losses, it will inevitably lead to resistance, and in the case of excessive income disparity, the improvement of production by means of technological progress will be affected. Third, in a perfect market (with redistribution at a price), wages and welfare will be affected in the short term, but Pareto Improvement exists in the long run. When technological progress causes capital monopoly, it will realize relatively fair resource allocations through redistribution although this depends on the costs of redistribution. Fourth, in the imperfect market, a Pareto Improvement is difficult to achieve, and technological progress will have a great impact on workers' welfare.

From the perspective of workers' educational returns, Brown et al. (2002) argued that wage inequality based on educational returns will expand in the context of technological impact, and this is a result from the fact that the increased mutually complementary level of skills and capital leads to the rise in the demand for high-skilled workers. In the long run, however, unless the improvement of education levels and skills is restricted, the education returns of the higher-educated workers would gradually return to the market average. The resulting countermeasure is to strive for the second-best by means of measures including the development of intellectual property rights, and maximize the Pareto Improvement effect of artificial intelligence in the win-win form of facilitating the improvement of wages, welfare and expanding the application of intelligent technology. When it is impossible to create the second-best situation, it is necessary to facilitate the adjustment of resource allocations and provide support for those who are disadvantaged in the face of artificial intelligence. From the perspective of political economy, Trajtenberg (2018) believed that the realization of "human-enhancing innovations"<sup>①</sup> is a matter of orientation, in which government policies play a key role, and needs to place extra emphasis on education, labor training, and service professionalization.

① Trajtenberg (2018) held that technological innovation should aim at the improvement of the skill level of people rather than the substitution for the needs of human skills. He gives an example: AI data mining for electronic medical records can be used for the evaluation of subsequent drug efficacy, but does not replace doctors, rather, it enhances the combination of technology and doctors' ability, resulting in better doctors. Therefore, it belongs to "human-enhancing innovations" (HEI) instead of "human-replacing innovations" (HRI).

### **Impact on Industries as a Whole**

First, within the same industry, job polarization itself represents wage differences based on skill levels. With respect to the specific degree of differences, the rapid development of technological progress has led to growing gaps between the middle and bottom groups in the wage distribution process, and this trend will continue for the long term (Kearney et al., 2015). At the same time, in consideration of management and costs, enterprises with higher levels of artificial intelligence applications may possibly outsource low-skilled jobs to other enterprises, and give high wages to skilled workers who remain inside the outsourcing enterprises (Aghion et al., 2017); consequently, this also widens wage gaps.

Second, for different industries, the absolute value of comparative wages does not make much sense due to the difference in the nature of jobs. However, by comparing the changes in wages we can see different responses that industries make to technological progress. Taking the service industry as an example, Autor et al. (2013) found that in the past 25 years, the actual income and employment rates of workers in the majority of low-skilled occupations and of industries they belong to, have stagnated or declined, but employment and income in the service industry is an exception. From 1980 to 2005, employees without university degrees increased their working time in the service industry by more than 50%, but at the same time, their real hourly wages increased by about 11%, exceeding the wage growth of other low-skilled occupations and industries.

### **Conclusion and Evaluation**

The current research consists of three main aspects; phenomenon description, detail analysis and trend prediction. It involves theoretical and empirical investigations and presents both positive and negative views. These views differ simply due to their different research perspectives and contents and involve nothing about right or wrong. Artificial intelligence has shown some negative effects on employment at present, and its destruction mechanisms, including substitution effects, the reduction of job numbers, and the widening of wage gaps, have also been recognized by many scholars, but the rapid progress of artificial intelligence cannot really play its role without the corresponding upgrading of other industries, and we need to continue observing whether these negative effects still exist after society, industries or organizations are correspondingly adjusted. However, it is still possible to grasp the future trends. The fact that artificial intelligence and its carriers used in the production sector are still under the background of computerization and automation (Acemoglu et al., 2018; Frey et al., 2017), the main considerations in the future should be the improvement of workers' skill levels conditioned on artificial intelligence applications and the demands for employing education and training to help them adapt to technological progress (Arntz et al., 2016). For the realization of effective human-computer cooperation, the 2018 report of : The Age of Artificial Intelligence: Towards a European Strategy for Human-Centric Machines issued by the European Political

Strategy Center<sup>①</sup> suggests that some workers will indeed be unemployed because of the application of artificial intelligence and other technologies, but the future focus is on facilitating the transition and improvement of skills on the basis of providing support and security to high-risk workers and we should attach importance to the development of a symbiosis between humans and machines to realize the improvement of workers' abilities and value, in lockstep with the development levels of artificial intelligence.

At present, the research into the impact of artificial intelligence on employment is primarily about achievements, but by reviewing the literature, we can find that there are still some problems in terms of research direction, interdisciplinary cooperation, and research objectives.

First, existing research is mostly focused on the substitution and creation effects of artificial intelligence on employment, paying more attention to the changes of employment quantity, but less to what economic and social significance the changes of industries, professions and occupations behind those two may have. Ma Hong et al. (2013) believed that employment quantity is only one aspect of employment structure, the creation and disappearance of large numbers of jobs simultaneously exist behind the changes in numbers, and have totally different meanings to the labor market. In addition, no research at present can accurately quantify the impact of artificial intelligence development on employment prospects. Therefore, while examining the changes of employment quantity, future research should pay more attention to the impact on the labor market and the economic society, which is represented by quantitative changes, and thus displays what significance the investigation into employment effects has in practice.

Second, existing research lacks cooperation with researchers in artificial intelligence technology. The biggest difference between the application of artificial intelligence and that of other technologies is that artificial intelligence is combined with jobs more deeply and more complicatedly. Economists and sociologists can finish the division and weight distribution of work tasks, but do not know whether a task can be independently accomplished by artificial intelligence, or if it must involve human participation. Arntz et al. (2016) argued that existing research tends to overestimate the capabilities of artificial intelligence technology and ignore backward application levels<sup>②</sup>. So, the cooperation with technological researchers is required to achieve an accurate match of tasks and technologies which will improve the relevance and accuracy of the analytical results.

Third, current research in China mostly focuses on status quo description and trend forecasting and lacks empirical research into the specific impacts of artificial intelligence on employment. This is possibly because the current insufficient statistics for labor market data in China cannot support the micro-level study of employment effects. It involves the particularity of computer capital and

① The Center acknowledges the positive role of artificial intelligence, but also argues that artificial intelligence can have an unstable impact on economic and social life, and analyzes in this report the opportunities and challenges brought by artificial intelligence([https://ec.europa.eu/epsc/publications/strategic-notes/age-artificial-intelligence\\_en](https://ec.europa.eu/epsc/publications/strategic-notes/age-artificial-intelligence_en)).

② According to a monitoring report released by the Federal Ministry of Economic Affairs and Energy in 2015, the digitization of the German manufacturing sector is still in a rather low degree, and will remain in the state of slow advancement until 2020 due to the restriction of technological conditions (Arntz et al., 2016).

technology investment that Autor et al. (2003) mentioned in their task model, and also the factors that are difficult to investigate within the current application scope of artificial intelligence in China, especially the situation where the ranges and levels of automation and computerized equipment applications in manufacturing enterprises are uneven and in lack of practical basis for shaping representative research. Therefore, as China is paying increasing attention to artificial intelligence and the field of application continues to expand, more data at sector or industry levels, and at the national level or regional levels will be needed in the future to consolidate the data base of empirical research in this area.

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