RESEARCH-ARTICLE

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Abstract

In order to analyze the potential impact of artificial intelligence (AI) technology on future work, this paper collected 14 years of wages, employment and other indicators data from 16 industries in 31 provinces of China as samples. According to the time sequence of technology development and the law of industry development, this paper studied the impact of AI on wages, employment growth, and industry wage gap by stages. In terms of the technological development trajectory, AI has positively promoted employment and wage growth over the past 14 years. However, after 2016, this positive promotion effect declined significantly, especially the impact of AI on employment turned from positive to negative, and it had a widening effect on the industry wage gap, which aggravated the inequality of income. This shows that China's labor market is undergoing profound changes. In the face of these challenges, the government must act actively, invest the necessary capital and educational resources, provide short-term and long-term support for workers' technological transformation. Meanwhile, the government should also encourage enterprises and social institutions to carry out AI innovation and project applications, so as to create more jobs and help increase the average wage level of the industries.

CCS Concepts

• **Applied computing** → Enterprise computing; Service-oriented architectures.

Keywords

AI, Automation, Labor Market

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1 Introduction

With the leapfrog development of artificial intelligence technology (AI), it has a more and more extensive impact on the daily life of people all over the world. ChatGPT and DeepSeek, for example, continue to achieve breakthroughs across a range of rigorous benchmarks, from rudimentary speech recognition, image processing to automated decision making and intelligent perception, as AI increasingly takes on "human-like" characteristics. As can be seen from the 2024 MMMU, GPQA, and SW-Bench benchmarks, AI performance is amazing. They are increasingly demonstrating strong capabilities in areas such as learning, reasoning, and perception, and even trending to surpass humans in some areas. In the RE-Bench benchmark and evaluation, launched in 2024, the top AI system outperformed human experts when limiting the time horizon to two hours, the AI can provide faster results when it comes to writing specific types of code tasks. It can be seen that AI has caused an increasing impact on the order of human life. A central question of particular concern is: will AI create more jobs, or will it lead to mass unemployment? Will it lead to a double rise in efficiency and pay, or will it lead to a growing polarization of income and benefits?

Aiming at these problems, there have been many meaningful explorations worth learning from. Regarding the impact of AI on work, most studies have confirmed the "dual" impact of AI, that is, the negative substitution effect and the positive creative effect. But most agree that the substitute effect of AI is more significant at the current stage of development. (Autor and Salomons ,2018) conducted research on OECD countries, and (Bessen et al. ,2023) did research on the Netherlands, both confirmed that industrial robots and automation have a substitution effect on employment. (Acemoglu and Restrepo ,2019) , through the study of the American labor market, believed that the accelerated application of automation technology reduced the demand of the labor market, and the job substitution effect brought by automation is more than the creation effect. (Frey and Osborne ,2017) classified 702 occupations in the United States and used Gaussian classifier to measure the probability of different occupations being replaced by computers. They pointed out that the substitution probability of conventional occupations such as logistics transportation and administrative office was high, while the unconventional occupations was relatively low.(Autor et al. ,2022) further differentiated the classification of conventional and unconventional occupations based on the occupational changes in the United States from 1940 to 2018, and clearly pointed out that those unconventional occupations that could not be easily replaced by new technologies would continue to adjust with technological changes. For instance, with the promotion of autonomous driving technology, driver, which was once considered an unconventional occupation with certain technical content, has become an alternative conventional occupation(Autor et al. ,2022).

However, there are also studies that support the positive impact of AI on the labor market. When Graetz & Michaels studied the impact of robot application on workers' employment and income,

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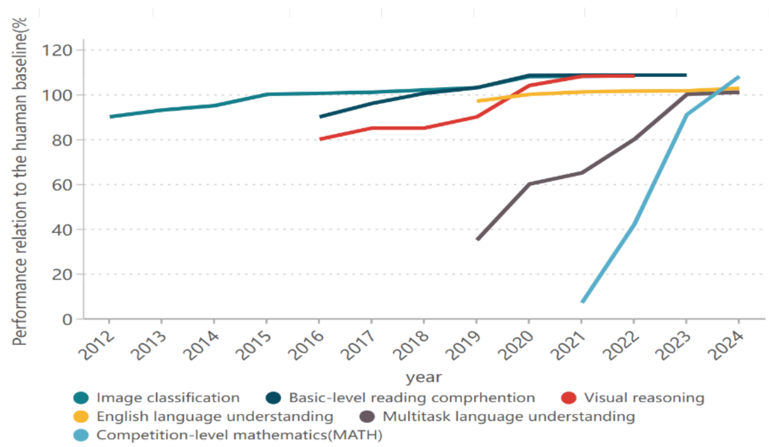

Figure 1: The development level of AI in 2012-2024

they found that companies did have a negative impact on the income of low-skilled workers when they increased robot investment, but it did not significantly reduce the total number of employment as a whole(Graetz& Michaels,2018).Leigh et al. found that automation even promoted employment growth in the United States (Leigh&Kraft, 2020). Acemoglu & Restrepo also argued that the application of robots reduces traditional jobs on the one hand, and also derives some new jobs on the other hand, and in the long run, the "substitution effect" of automation and intelligent technology on the labor market is less than the "creation effect"(Acemoglu & Restrepo,2018)(Acemoglu & estrepo,2020).In addition, the study of Brynjolfsson et al. confirmed that the "creation effect" brought by AI on the labor market has not been fully estimated, and the "substitution effect" was often overestimated (Brynjolfsson et al.,2023) .

On the whole, the above studies fully demonstrate the "substitution effect" and "creation effect" brought by AI on the future work and clarify the types of occupations to be replaced and created. However, technological development has its stages and is bound to go through periods such as germination, growth, maturity and decline. At different stages, the impact and influence of new technology on existing work must also be significantly different. However, there are relatively few studies that analyze the different impacts of AI on future work scenarios from the perspective of the technological development stages. This paper takes this as the breakthrough point to analyze.

2 The development stage of artificial intelligence and the measurement of the development level

2.1 2.1 Stages of Artificial Intelligence Development

The impact of AI on the economy has gone through three distinct stages. The first stage can be traced back to Automation and Robotics in manufacturing in the 1990s. The second stage is the industrial robots after 2010, which can interact with the environment and perform more complex tasks. The third stage is the AI era that has been in full swing since 2016, with AI technology gradually expanding to data-driven Machine Learning and Large Language Model AI. According to the "Artificial Intelligence Index Report 2025" released by Stanford HAI, as shown in Figure 1, we can clearly see that 2016 is an important point for the development of artificial intelligence. Since 2016, AI has continuously outperformed humans in benchmarks tests such as visual reasoning, English comprehension, and image classification. In 2024, on SWE-bench, AI achieved a breakthrough in both its ability to solve coding problems and high-quality video generation

Looking back on the technological development process over the past 30-plus years, the progress of AI has evolved from "simple labor" that could only handle single tasks to "complex labor" capable of dealing with comprehensive problems, and gradually expanded from the initial single problem that can only solve "professional field" to the "general field" that can deal with complex processes. It develops from fragmented "augmentation" to partial process replacement or "whole process automation", and from the liberation of "hands" to the replacement of "brain". "According to the "law of accelerating returns" proposed by (Ray Kurzweil,2016), the "economic singularity" of AI is bound to come in the coming decades.

2.2 A measure of AI development

The methods to measure the development level of AI include the proxy variable method and the comprehensive index construction method. The common proxy variable method is to use a single variable such as computer, information technology, and industrial robots to represent the development level of AI. The construction indicators that comprehensively reflect the development level of AI from multiple dimensions include AI Occupation Exposure (AIOE), AI Firm Exposure (AIFE), and TF-IDF method. AIOE was constructed by(Felten et al. ,2018) based on the disaggregated information of work tasks or required abilities contained in each occupation provided by the U.S. Department of Labor and combined with the susceptibility of artificial intelligence technology to these tasks or abilities (Felten et al. ,2018). AIFE was calculated by (Acemoglu et al. ,2022) according to the task analysis theory, the proportion of all tasks of the enterprise performed by AI and then defined as the artificial intelligence penetration of the enterprise. The evaluation methods adopted by AIOE and AIFE objectively analyze the impact of AI on occupations from the perspective of technological development and human ability. TF-IDF is a method used by (Stanford University ,2022) to measure the penetration rate of artificial intelligence. Using this method, Stanford University measures the penetration rate of AI in various fields such as networks, manufacturing, software and IT, education, finance, and hardware in different countries to assess the development status of AI globally. Since the first release of the "Artificial Intelligence Index Report" in 2017, it has been continuously released for eight issues. It objectively reflects the impact of AI on economic and social development in different periods.

3 Empirical test: AI development level, employment number, wage level and income gap

Looking at the development history of the previous three technological revolutions, from the technological revolution to the industrial revolution, from the laboratory to the factory workshop and then to the consumer products, the cycle had been very long. The more universal a technology is, the more extensive its potential application value will be, and the more far-reaching its impact will be. However, the time interval from its creation to its full applicability in the economy and society will also be longer. This is also known as the "Solow Paradox". At present, AI has been widely applied in various scenarios of human life. However, whether it is production robots or living robots, there is still a considerable distance to go before they can be scaled up, industrialized or scenario-based. In the following, we will take China as a sample and analyze the impact of AI on employment, wage growth and wage gap in the future of work in two stages, so as to provide reference for predicting the sustained impact of AI in the next stage.

3.1 Data source and processing

In order to study the impact of different development stages of AI on work from the perspective of technology evolution, 2016 is taken as a turning point here. The two time periods of 2010-2016 and 2017-2023 are selected respectively to analyze the impact of AI on work scenarios. Considering the accessibility and comparability of all variables, this paper selected 31 inter-provincial administrative regions in China from 2010 to 2023 as the research samples and obtained panel data of the 31 provinces for 14 years. The measurement indicators of all the research variables were obtained from "China Statistical Yearbook" and "China Urban Statistical Yearbook".

Drawing on the practice of Jeff and Michael, we choose "investment in fixed assets of the whole society in information transmission, computer services and software industry" to measure the development level of AI, and made standardized processing to convert it into AI development index. Meanwhile, we selected the number of employees in each province to measure the level of labor force employment, select the average wage of urban workers in each province to measure the wage level, and select the Theil index to measure the wage gap between industries (Twage).

The Thiel index was proposed by Thiel (1967) using the concept of entropy in information theory , which can measure income inequality. Its calculation formula is shown in Equation (1) :

$$Twage = \frac{1}{n}\sum_{i=1}^{n}(\frac{W_i}{\omega})\ln(\frac{W_i}{\omega}) \tag{1}$$

In Equation (1), n represents the number of industries, W_i represents the wage level of industry i [1] in a certain region, and ω represents the average wage level of all industries in a certain region. The calculated Theil index will vary between (0,1), with a larger Theil index indicating a more unequal income distribution. Therefore, the smaller the Twage value calculated based on Equation (1) is, the smaller the wage gap among industries is, and the income is relatively equal.

3.2 Model building

The panel regression model constructed in this paper is shown in Equation (2) :

$$Y_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_{it} + v_{it} + \varepsilon_{it} \tag{2}$$

In Equation (2), t represents the year, i represents the province, Y_{it} represents the number of employed people, average wage level and industry wage gap of a certain province in a certain year, AI_{it} represents the development level of artificial intelligence, X_{it} represents the control variable, μ_{it} and v_{it} respectively represent the individual effect and the time effect, and ε_{it} is the random error term. The direction and significance of regression coefficient β_1 are the focus of this paper. If $\beta_1 > 0$ and the significance test of 10% is passed, it indicates that the development of AI has a promoting effect on employment, wage growth and income gap. Otherwise, it has an inhibitory effect.

Referring to the research results of relevant scholars, this paper introduces seven variables to control the influence of the macroeconomic and social development conditions of each province on wages and employment. The specific indicators and interpretations are shown in Table 1.

The descriptive statistics of all variables in the model are shown in Table 2. Among them, the average wage level is measured in ten thousand yuan, the number of employed people is measured in thousands. The data of all variables are stable, within a reasonable range, and there are no outliers, which are suitable for regression analysis.

3.3 Analysis of empirical results

Through the Hausman test, this paper adopts the panel data fixed effect model and gradually adds the province and year fixed effects. The regression results are shown in Tables 3 and 4

By analyzing the regression results in Table 3, it can be seen that the level of AI development has a promotive effect on both wage growth and employment growth from 2010 to 2023, and the

[1] The industries here include 16 sectors: mining, manufacturing, production and supply of electricity, gas and water, construction, transportation, warehousing and postal services, information transmission, computer services and software, wholesale and retail trade, accommodation and catering services, finance, real estate, leasing and business services,Scientific research, technical services and geological exploration, water conservancy, environment and public facilities management, resident services and other services, education, health, social security and social welfare, culture, sports and entertainment.

Table 1: Control Variables and Their Definitions

Indicator identification	Index Name	Indicator Explanation
LNPGDP	Level of economic development	Per capita GDP of each province, log
FDI	Degree of foreign investment	The proportion of foreign investment in fixed assets of the whole society
FINA	Degree of financial development	Financial sector value added as a percentage of GDP
GOV	Strength of financial support	Public spending as a percentage of GDP
LNFRA	Level of infrastructure construction	Urban road area per capita, log
LNSCALE	Size of population	The total permanent population of each province at the end of the year, log
CITY	Ratio of urbanization	Proportion of urban population to total population

Table 2: Descriptive statistics of each variable

Indicators	Observations	Mean	Maximum	Minimum	Std. Dev.
AI	434	1.99	10.77	0.09	1.93
WAGE	434	7.32	22.93	2.77	3.25
EMPL	434	5.39	21.11	0.22	3.97
TWAGE	434	0.045	0.09	0.02	0.0145
LNPGDP	434	10.86	12.01	10.00	0.41
FDI	434	0.32	0.80	0.01	0.23
FINA	434	7.56	19.63	3.24	3.00
GOV	434	29.93	135.38	11.96	20.92
LNFRA	434	16.40	26.78	4.11	4.77
LNSCALE	434	8.13	9.44	5.76	0.84
CITY	434	0.59	0.90	0.24	0.13

correlation coefficients between them are generally positive and significant. In terms of stages, from 2010 to 2016, the positive impact of AI on wage growth was more significant, and its influence coefficient reached 0.693. After 2016, the correlation coefficient between the two weakens to 0.168, but the positive effect still passes the significance test at the 10% level. This indicates that as the level of AI improves, its effect on enhancing the average wage level in the labor market shows a decreasing trend. Meanwhile, the impact of AI on employment has changed from a positive 0.025 to negative 0.015, which indicates that the impact of AI on employment has shifted from positive promotion to negative substitution. Although the results of the negative impact did not pass the significance test, this changing trend is still worthy of warning.

In terms of control variables, the level of infrastructure construction, degree of financial development, and ratio of urbanization in a region all have a significantly positive impact on wage growth. This is in line with the expected results. It is worth noting that the population size has a negative impact on the employment growth, which may be related to the change of China's population structure.

From the regression results shown in Table 4, it can be seen that with the development of AI, the wage gap between industries in China is gradually widening. Before 2016, AI had a positive impact on the expansion of the wage gap, with a correlation coefficient of 0.011. After 2016, the development of AI further expanded the industry wage gap, and the correlation coefficient gradually increased to 0.013.

The control variable FDI (degree of foreign investment) has a significant impact on the reduction of TWAGE (the wage gap between industries), and the impact of CITY (ratio of urbanization) on TWAGE has changed from narrowing before 2016 to expanding, which is related to the formula we use to calculate the TWAGE. Since the indicator CITY is calculated as "Proportion of urban population to total population", the urbanization rate is getting higher and higher as the rural population migrates to different industries in the cities, the wage gap among workers in different industries in cities shows a widening trend.

4 Conclusions and Countermeasures

4.1 CONCLUSIONS

In order to analyze the impact of AI on future work, this paper chooses to start from the industrialization stage of technological evolution, selects China as a sample, and divides China's AI development into two stages to verify the impact of AI on wage growth, employment promotion and industrial wage gap respectively. Through empirical analysis, we have found that the overall progress of AI has had a positive impact on employment and wages from 2010 to 2023,. However, after 2016, the impacts on both have weakened. In particular, the impact of AI on employment has turned from positive to negative, and AI has a widening impact on the industry wage gap, which indicates that the shock effect of artificial intelligence on China's labor market at the current stage is

Table 3: The Impact of AI on Wage and Employment

	Wage			*Employment*		
	2010-2023	2010-2016	2017-2023	2010-2023	2010-2016	2017-2023
Cons.	702.41***	569.882	804.137***	562.941***	577.209**	557.052**
	(51.321)	(60.987)	(4.546)	(147.936)	(185.381)	(129.218)
AI	0.575***	0.693***	0.168*	0.037**	0.025**	-0.015
	(2.803)	(3.211)	(1.671)	(2.425)	(4.563)	(-0.629)
LNSCALE	-0.141	0.962	-2.472	-0.652*	-4.083***	-5.064*
	(-0.087)	(0.314)	(-1.206)	(-1.428)	(-5.075)	(-1.765)
LNPGDP	0.690	0.473	0.343	1.077***	0.831*	0.502
	(1.050)	(0.713)	(0.513)	(5.225)	(1.628)	(1.371)
INFRA	0.112***	0.114***	0.094***	0.007	0.003	0.103***
	(8.555)	(8.674)	(11.026)	(0.966)	(0.169)	(2.899)
GOV	0.015	0.023	0.022	0.008*	0.044***	0.012
	(0.540)	(1.139)	(0.940)	(1.457)	(3.845)	(0.532)
FINA	0.297***	0.386***	0.281***	0.007	0.033	0.012
	(11.853)	(9.782)	(6.568)	(0.975)	(0.638)	(0.259)
FDI	0.058	-0.827	-0.727	0.065	-1.919***	0.413*
	(0.059)	(-0.956)	(-0.731)	(0.288)	(-5.448)	(1.272)
CITY	17.967***	17.172***	20.883***	0.598	6.076**	2.655*
	(7.072)	(4.725)	(6.139)	(0.610)	(2.003)	(1.169)
Adjusted R^2	0.957	0.853	0.879	0.993	0.998	0.993
F-statistic	145.93***	74.636***	163.271.***	885.163***	2047.905***	686.712***

Note: a. Standard errors in parentheses. b. $p < 0.05$, $p < 0.01$, $p < 0.001$.

Table 4: Impact of AI Development Level on Twage

	2010-2023	2010-2016	2017-2023
Cons.	0.044**	0.043***	0.044***
	(67.779)	(57.801)	(55.597)
AI	0.012*	0.011***	0.013***
	(15.056)	(12.534)	(11.705)
LNSCALE	-4.095***	-3.321***	1.786
	(-4.478)	(-4.615)	(0.825)
LNPGDP	-0.914*	-0.094	-0.604
	(-1.834)	(-0.688)	(-1.284)
INFRA	0.003	0.054***	-0.083***
	(0.185)	(2.786)	(-3.204)
GOV	-0.045***	-0.041***	0.012
	(-3.158)	(-6.050)	(0.320)
FINA	-0.030	-0.134***	0.414***
	(-0.429)	(-13.501)	(30.629)
FDI	-1.976***	-1.166***	-1.604***
	(-4.238)	(-17.593)	(-6.341)
CITY	6.052***	-2.608***	17.271***
	(2.870)	(-12.921)	(5.869)
AdjustedR^2	0.818	0.921	0.829
F-statistic	30.347***	43.159***	22.395***

Note: a. Standard errors in parentheses. b. $p < 0.05$, $p < 0.01$, $p < 0.001$.

still ongoing. The substitution effect of AI on employment exceeds the creation effect, and the situation of income inequality has been strengthened.

4.2 Countermeasures

In the face of the accelerating development trend of AI, it has become an undeniable fact that a large number of repetitive and standardized jobs are replaced by intelligent robots and automated production lines. On the one hand, it directly leads to a significant reduction in employment opportunities for workers in related positions and a continuous widening of income gaps among different groups. On the other hand, it is also creating new jobs, enhancing labor productivity and reducing labor costs. To address the problems in development in a targeted manner, it is necessary for the government to provide financial support, enrich the investment in educational resources, and carry out targeted training programs for low-skilled workers, enabling them to adapt to the demands of emerging positions. Meanwhile, the government should also encourage enterprises and social institutions to actively carry out AI innovation and project applications, so as to create more jobs and raise the average wage level of the industries.

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