Quantifying the Impact of Artificial Intelligence Technology on High Quality Employment

Fu Xian

xianfu800@163.com

School of Digital Economics, Sichuan University Jinjiang College, Meishan, Sichuan, China

Abstract. The labor market has been particularly impacted by the rapid development of artificial intelligence technology. This impact on employment has a variety of characteristics that will not only cause changes in the quantity of employment but also open up opportunities to raise the quality of employment. This study, which is based on the current state of AI and China's employment development, focuses on the effect of the level of AI development on the quality of employment, uses a sample of China's provincial data from 2010 to 2019 and empirically investigates the relationship between the level of AI development and the quality of employment in China using multiple regression analysis. The findings demonstrate that the quality of employment is significantly positively impacted by the state of artificial intelligence development.

Keywords: Artificial intelligence technology, High quality employment

1 Introduction

The big language model ChatGPT was stunningly introduced in November 2022. Artificial intelligence application scenes and penetration fields continue to expand, and will significantly approach the artificial intelligence technology singularity. Artificial intelligence is the leading technology of the new round of science, technology, and industrial revolution. In recent years, innovation results continue to break through. The AI Innovation Index has long placed the United States and China in the top two places in the world, thanks to their impressive advancements in talent, education, patent output, and other areas of AI research. However, there is still room for improvement in the level of fundamental resource construction. The United States, which tops all three indices with a perfect score of 100 points, will continue to hold the position of global hegemony in the field of artificial intelligence in 2023. With several significant machine learning models, a broad variety of AI application fields and user groups, including smart healthcare, smart cities, and smart education, China continues to lead the world in AI innovation., as Fig. 1 below.

ICBBEM 2024, March 29-31, Wuhan, People's Republic of China

DOI 10.4108/eai.29-3-2024.2347436

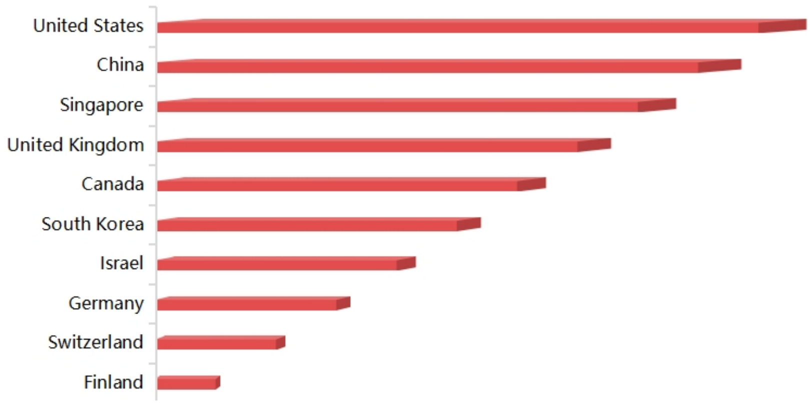

Fig. 1. Top 10 Global Artificial Intelligence Innovation Index Rankings in 2023.

The size of China's AI sector is predicted to reach 195.8 billion yuan in 2022 with an annual growth rate of 7.8% and overall steady progress with the assistance of authorities. The building of the Smart Computing Center, the demand for large-model training applications, and the market for conversational AI and intelligent robots, which are driven by the demand for contactless services, will all contribute to the company growth in 2022. The size of the AI industry as a whole might reach 612.2 billion dollars by 2027. Fig. 2 below illustrates it.

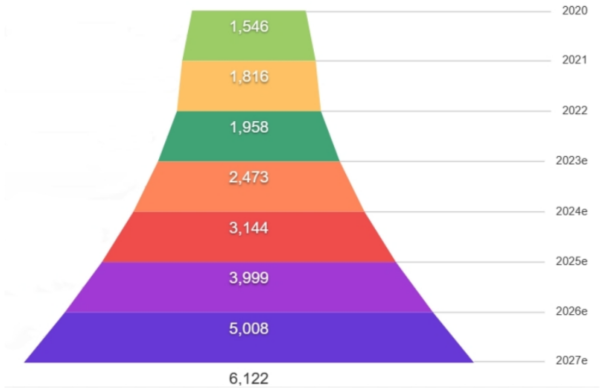

Fig. 2. Chinese artificial intelligence market size (in billions of Yuan).

People's welfare and quality of life must continue to be improved by modernisation in the Chinese way. According to the most recent statistics, AI big model ranks first among the top 10 industries with the greatest annual growth in new job openings for the class of 2023, with an annual growth rate of 172.53%; new energy and new materials are in second and third place, respectively, with annual growth rates of 93.90% and 30.05%. Intelligent manufacturing, AIGC, and AI large model were placed the top three in terms of the average annual pay of recent graduates hired in these top 10 high-tech businesses, with salaries of 332,200 yuan, 303,600 yuan, and 279,900 yuan, respectively (see Fig. 3).

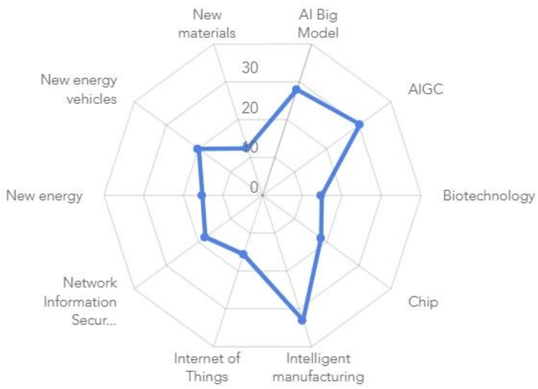

Fig. 3. Top 10 sectors with the highest freshmen average yearly income in 2023 (10,000 yuan).

On the one hand, the application of emerging technologies using capital as a carrier to change the initial allocation of factors of production in enterprises, lowering the remuneration of labor [1], and indirectly encouraging the labor force, whose incomes have been affected by the impact, to change jobs are manifestations of the impact of emerging technologies such as artificial intelligence on the labor market. On the other hand, it manifests in the replacement of labor-intensive traditional manufacturing tasks and the direct replacement of corresponding occupations [2], forcing the labor force to switch jobs and move about in pursuit of new employment [3]. Existing research indicates that the "replacement of machines with people" [4] that occurs as a result of the rapid development and application of artificial intelligence technology, including robots, can have a significant impact on labor income, industrial organization, and other economic behaviors. In actuality, the direct influence of artificial intelligence technology is more visible in the impact on the job market [5], and this impact does not equate to the labor market but rather displays blatant heterogeneity. Accordingly, the high-end manufacturing sector is more affected by the job creation impact of AI technology than the low-skill occupations are by the work replacement impact [6], which leads to changes in the employment scale and structure.

2 Models Materials and Methods

Artificial intelligence has emerged as the most notable theme of the present with the growth of the fourth industrial revolution based on artificial intelligence technology and the advent of the digital economy age, which will have a stronger influence on people's production mode and lifestyle. Therefore, there are scientific issues that need to be resolved, such as how to precisely grasp the impact of the trend of intelligence in enterprises on the quality of employment of workers; how to deeply comprehend the impact of the application of AI on the dimensions of workers' salaries, work efficiency, and subjective satisfaction. Investigating in depth how the use of artificial intelligence affects the employment quality of workers in the manufacturing industry and looking for practical solutions to raise that quality are important practical considerations.

2.1 Model Construction

The following model is created to examine the effect of industrial robots on employment quality:

$$Y_{it} = \partial_0 + \partial_1 AI_{it} + \sum_j \partial_j C_{it} + \mu_{it} + \theta_{it} + \xi_{it} \tag{1}$$

Where the explanatory variables are i and t, which stand for the area and year, respectively. AI stands for artificial intelligence, while Y stands for the quality of employment. Urbanization rate, foreign direct investment (FDI), economic openness, degree of human capital, and industrial structure are examples of control variables. μ stands for the random error term, θ for temporal fixed effects, and ε for individual fixed effects.

2.2 Variable Description

Quality of employment (Y): Currently, single, composite, and multidimensional indicators make up the three primary categories used to assess the quality of employment. Wages or job satisfaction [7] are just two indicators of the quality of an employment relationship. Comprehensive indicators primarily refer to the classification of employment quality into several first-level indicators, such as the work environment, skill level required for the job, job security, compensation, and labor relations, etc. A number of second-level indications are separated under each first-level indicator, and their weights are established using either the expert scoring technique or the weight method before being composited into an index. From a macro viewpoint, the level of social security (40%) is chosen as the characterizing variable, and from a micro perspective, the pay level (60%) is chosen as the characterizing variable. The weighting of the assignment is then used to produce the index of job quality. The employment quality of the region as a whole is used as a measuring indicator in this article due to the complicated way the labor market is segmented in China. In this work, Wang Jun's method of building China's employment quality index from two perspectives—macro and micro—is used to construct China's employment quality index [8]. Based on the current state of China's national conditions, wage income and social security are the important criteria to assess the quality of employment. This is the precise calculating formula:

$$Y = \alpha * (\chi * \mathrm{uw} + \delta * \mathrm{fw}) + \beta * \mathrm{fe} \tag{2}$$

Where Y stands for the employment quality index, uw is the average salary earned by urban workers, fw is the average wage earned by farmers, and fe stands for the fiscal expenditure on social security and employment. The analysis shown above yields a value of 0.6 for α and χ and a value of 0.4 for β and δ [8].

Artificial Intelligence (AI): We use data on imported robots in China as a proxy variable for China's usage of industrial robots since the number of self-produced industrial robots in China is relatively low and more than 70% of domestic industrial robot use originates from imported industrial robots.

Urbanization rate (Ur): Since the main characteristic of urbanization is the concentration of people in towns and cities, the percentage of urban residents in a region's resident population is used to measure the degree of urbanization.

Foreign Direct Investment (FDI): Foreign variables also have an impact on the quality of employment in the nation, in addition to elements that are domestically connected. Studies already conducted demonstrate that foreign direct investment significantly affects the standard of employment in China. Therefore, foreign direct investment is used as a control variable to study how foreign influences affect the standard of employment in China. Additionally, this article selects the average annual growth rate of FDI to quantify foreign direct investment due to the uniformity of data quality.

Economic openness (Tr): The level of economic openness indicates the level of marketization of an area, and marketization has an impact on the labor market's information flow and resource allocation, which has an impact on the quality of employment for employees. The ratio of total regional import and export to GDP is used to measure economic openness because the indicator of foreign trade dependency may accurately indicate the degree of regional economic openness.

Level of human capital (Hu): The main definition of human capital is the knowledge, skills, and health status of workers. Since it is challenging to find a comprehensive indicator that considers both aspects, human capital is measured in terms of the population's average number of years spent in school, as is frequently done in the literature currently in use . The percentage of the population with various levels of education and the number of years of education they have received are weighted in the yearly population sample surveys of each province over the sample period to provide the indicator of the average number of years of education of the population.

Industrial structure (Is): The quality of employment will be significantly impacted by changes in the industrial structure, and this article chooses the value added ratio of the tertiary sector to the secondary industry as a measure of the industrial structure.

The data for the independent variable artificial intelligence are taken from the China Electronic Information Industry Statistical Yearbook, China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China Information Society Development Report. This study uses 30 provinces (autonomous regions and municipalities directly under the central government) in China from 2010 to 2019 as its research sample. The China Statistical Yearbook and the China Employment Statistics Yearbook provided the information for the dependent variable, employment quality. The China Statistical Yearbook and the China Employment Statistics Yearbook provide the statistics for each moderating variable. Through the structure of the data, the study determines that there are hardly any missing data in the sample. The data were made up to reflect the actual situation since it was determined that the associated indicators did not exhibit large-scale variations during the sample period and that the missing data indicators had the same growth rate in the next years.

All variables in this study are logarithmized concurrently. The variables' descriptive statistics are presented in Table 1.

Table1. Descriptive statistics of main variables.

Variable	Variable Symbol	Observed value	Min	Max	Mean	Std
Quality of employment	Y	300	0.200	0.98	0.246	0.177
Artificial Intelligence	AI	300	7.1983	21.283	16.1302	4.3057
Urbanization rate	Ur	300	33.81	94.14	57.09	12.63
Foreign Direct Investment	FDI	300	9.565	20.199	16.375	2.29
Economic openness	Tr	300	1.20	146.86	28.47	30.89
Level of human capital	Hu	300	7.32	12.68	9.15	0.89
Industrial structure	Is	300	0.500	4.237	1.088	0.639

3 Results & Discussion

The regression of equation (1) is first performed. Table 2's columns (1) and (2), respectively, present the baseline regression findings before and after the introduction of control variables. The coefficient of AI is statistically positive at the 1% level whether or not control factors are included, demonstrating that AI greatly improves the quality of employment in China. The overall correlation coefficient between the level of AI and the quality of employment in each region is 0.052, which is a highly significant positive correlation and shows that AI development promotes employment quality, i.e., the higher the level of AI development in a region, the higher the quality of employment correspondingly. Additionally, there is a strong correlation between employment quality and every control variable, including the extent of regional urbanization, foreign direct investment, openness, human capital, and industrial structure. Urbanization level and employment quality have a significant positive correlation of 0.213; foreign direct investment and employment quality have a significant positive correlation of 0.390; economic openness and employment quality have a significant positive correlation of 0.423; and human capital and employment quality have a significant positive correlation of 0.423. Industrial structure and job quality have a considerable positive link, as indicated by the correlation value of 0.722.

Table 2. Results of the baseline regression.

Variable	(1)	(2)
AI	0.052***	0.031***
	(4.72)	(3.45)
Ur		0.213***
		(3.94)
FDI		0.390***
		(4.25)
Tr		0.423***
		(0.53)
Hu		0.273***
		(2.40)
Is		0.722**

		(0.27)
Individual effect	controlled	controlled
Time effect	controlled	controlled
Observed value	300	300
R2	0.781	0.813

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Equation (1) is re-estimated using panel quantile regression using the number of AI firms as a proxy variable for the regression results of AI in order to guarantee the validity of the results and further exclude the interference of outliers in the benchmark regression results of AI for employment quality. The estimation results for the 10%, 25%, 50%, 75%, and 90% quantiles are shown in Columns (1) through (5) of Table 3. Table 3 displays the test results:

Table 3. The results of quantile estimation.

Variable	(1)	(2)	(3)	(4)	(5)
AI	0.102*** (7.23)	0.089*** (10.39)	0.072*** (4.39)	0.048*** (4.53)	0.130*** (4.08)
Other control variables	Contained	Contained	Contained	Contained	Contained
Individual effect	Controlled	Controlled	Controlled	Controlled	Controlled
Time effect	Controlled	Controlled	Controlled	Controlled	Controlled
Observed value	300	300	300	300	300

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

The effect of AI on promoting employment quality is considerable for provinces with varied degrees of employment quality, as shown in Table 3, where all coefficients of AI are statistically positive at the 1% level. This further supports the findings of the benchmark regression.

4 Conclusions

How to properly use artificial intelligence and then support the improvement of job quality has been a societal issue given the growing growth of artificial intelligence and the environment of low employment quality in China. Based on this, this essay investigates how the level of artificial intelligence development influences the standard of work, or how employment quality is affected by the growth of AI. The influence of artificial intelligence development level on employment quality is experimentally examined by multiple regression analysis using the province panel data of China from 2010 to 2019. The empirical test's findings demonstrate that artificial intelligence significantly improves employment quality, and this conclusion suggests that the degree of AI development may successfully encourage this improvement. The development of artificial intelligence has prompted the labor force to improve the flexibility, complexity, interpersonal, and other aspects of the improvement of the secondary labor force employment, which in turn will promote the "wild goose" effect, which to some extent expands the size of the primary labor market. Since the quality of employment may be improved, the development of artificial intelligence is a significant factor in this direction.

Acknowledgment. Ministry of Education Industry-University Cooperation Collaborative Education Program 2022 Second Batch (22097029295812).

References

[1] Wang Mingliang. Research on Technological Progress and Optimization of Labor Capital Relations [J]. Business Research, (9): 21-25 (2012).
[2] Christian L V. Labor market polarization, the decision of route work, and technical change: a quantitative analysis [J]. Journal of Monetary Economics, (110) (2020).
[3] Kong Gaowen, Liu Shasha, Kong Dongmin: Robotics and Employment - Exploratory Analysis Based on Industry and Regional Heterogeneity [J]. China Industrial Economy, (8): 80-98 (2020).
[4] Graetz G, Michaels G. Robots at Work [J]. Review of Economics and Statistics,100(5): 753-768 (2018).
[5] Acemoglu D, Restrepo P. Robots and Jobs: Evidence from US Labor Markets [J]. Journal of Political Economics, 128 (6): 2188-2244 (2020).
[6] Manyika J, Lund S, Chui M, etal. Jobs Lost, Jobs Gained: Workforce Transitions in A Time of Automation [R]. New York: McKinsey Global Institute (2017).
[7] Wang Yingying. The Employment Effect of Spatial Agglomeration of Labor Force in China: From the Perspective of Individual Employment Quality [J]. Population and Economy, (04): 53-62 (2018).
[8] Wang Jun, Zhan Yunqiu. The Employment Effect of Consumption Upgrading and Industrial Structure Adjustment: A Double Inspection of Quality and Quantity [J]. East China Economic Management, 32 (01): 46-52 (2018).