EMPIRICAL ANALYSIS OF THE IMPACT OF AI ON THE EMPLOYMENT OF EMPLOYEES IN SERVICE ENTERPRISES

——Evidence from China

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Abstract

With the development of artificial intelligence technology, its replacement impact on occupation has been one of the hot topics of discussion, especially the breakthrough development of generative AI, which has caused people's further concern about "machine replacing human". As the service industry absorbs the largest employment population, whether and what impact the development and application of artificial intelligence technology will have on the employment of the service industry is an urgent question to be answered. Based on the data of listed enterprises in the service industry from 2014-2022, this study uses the difference-difference method to study the impact of the application of artificial intelligence technology on the number of employees, the skill structure of employees and the income of employees in the service industry from the enterprise level. The main conclusions of this study are as follows: First, although the high-risk occupations replaced by artificial intelligence are still mainly concentrated in the manufacturing industry, the risk of service occupations being replaced by artificial intelligence is gradually becoming prominent; Second, the application of artificial intelligence technology in service enterprises will increase the total number of employees and absorb more employment. Third, despite the increase in the number of employees, this demand is mainly reflected in the demand for high-skilled employees, and the demand for medium-low skilled employees is reduced, showing a trend of "degree-position" polarization; Finally, in terms of employee income, the application of artificial intelligence technology in service enterprises has caused a certain downward trend in employee income, which is also one of the negative effects of de-skills, leading to the decline of employees' bargaining ability on salary, resulting in income inequality.

Keywords: Artificial Intelligence; Occupation Substitution; Service Industry

1.Introduction

With the development of algorithms such as big data technology, machine learning and deep learning, artificial intelligence has made major breakthroughs and gradually been widely applied in various industries, although different industries and academic fields have different definitions of artificial intelligence. But AI is generally thought to refer to computer systems that can perform tasks that would normally require human intelligence, such as visual perception, speech recognition, decision-making, or translation. At the same time, with the continuous development of artificial intelligence technology, its impact on the labor market, especially the replacement of occupations, has been one of the hot topics.

2.Literature review

Previous research on AI job substitution has focused on manufacturing, focusing on the impact of automation technologies, such as industrial robots, on jobs. The study found that the traditional manufacturing production line repetitive mechanical operation jobs will be more easily replaced by artificial intelligence technology, automation and intelligent technology can meet the flexible production mode of automatic positioning, equipment, handling, automatic welding needs, and machine vision can achieve more rapid, efficient and accurate product quality inspection work than manual. He Qin et al. (2020) conducted empirical studies on the employment impact of manufacturing industries or enterprises, and the main results of these studies show that the application of artificial intelligence technology will lead to a decrease in the number of manufacturing jobs. Compared with the manufacturing industry, artificial intelligence technology pays less attention to the study of employment substitution in the service industry, because it is generally believed that artificial intelligence follows the substitution order from low skill to high skill for jobs, while the automation cost of service industry jobs is higher, and its demand for creativity and emotional understanding is difficult to meet by current artificial intelligence technology. However, in fact, intelligent customer service has been widely used in the service industry, and with the rapid development of generative AI such as Chat GPT and GPT4, it has been able to complete difficult and complex tasks based on cognitive and creative skills, and the generation of code, advertising copy, illustration and short videos can be easily completed by using ChatGPT. At the same time, a report released by Goldman Sachs in 2023 predicts that with major breakthroughs in generative artificial intelligence, artificial intelligence could replace the equivalent of 300 million full-time jobs worldwide in the future, with about two-thirds of jobs in the United States and Europe facing AI automation. These affected occupations are more involved in non-technical operations such as lawyers and administrators. It can be seen that artificial intelligence technology will have a huge impact on service industry employment, and what impact it will have is an urgent question to be answered.

The impact of artificial intelligence on employment is mainly divided into three aspects: first, the Deskilling effect brought by artificial intelligence; second, the impact of the application of artificial intelligence technology on the total employment; third, the impact of the application of artificial intelligence technology on the employment structure.

Deskilling Effects brought about by technological development have always been the focus of researchers' research. Deskilling is when workers' specialized skills are replaced by automation, or their jobs are downgraded to "low-skilled jobs that don't require complex thinking or special skills." This leads to reduced investment in human capital, cost savings, weakening the bargaining power of human capital, and resulting in income inequality. The research on De-skilling mainly focuses on the impact of technological development on employee skill structure and employee income. Research on the skill structure of employees shows that further subdivision of work as a result of technological advances leads employees to face a greater risk of Deskilling in terms of skill structure, thereby reducing their bargaining power and requiring them to learn new skills. Twenty years ago, Autor et al. (2003) analyzed the impact of computer technology on employees' skill structure, laying a foundation for today's research on the impact of new technologies such as artificial intelligence on employees' skill structure. In terms of employee income, the De-skilled effect will further exacerbate the problem of income inequality. Dong Zhiqing et al. (2014) found that skill-biased technological progress has a positive impact on the demand for highly skilled labor and the wage level. Jackson et al. (2023) found that the development of artificial intelligence would increase the demand for labor skills, thus widening the wage gap between high-skilled and low-skilled labor. However, some scholars also found that the application of artificial intelligence technology by enterprises would have a negative impact on labor wages as a whole.

In the research on the impact of artificial intelligence application on the number of jobs, there is no unified conclusion at present, and the current research mainly includes three schools: substitution effect, creation effect and comprehensive effect. The first type of research school, namely the school of substitution effect, believes that the application of new technologies such as artificial intelligence will have a huge impact on the social job market, and there will be a wave of layoffs. CAI Xiao (2022) studied the manufacturing industry and found that in most cases, artificial intelligence technology would inhibit manufacturing employment. Empirical studies on substitution effect in developed countries have also confirmed this view to some extent. Acemoglu and Restrepo (2018), through the analysis of employment data in the United States, found that if the number of robots per 1,000 people increases by 1, the employment population ratio in the United States will decrease by about 0.18-0.34 percentage points. The second school of research, the Creation effect school, is optimistic that the application of new technologies such as artificial intelligence will create new industries and new jobs, which will lead to an overall increase in employment. There have been many technological innovations throughout history that have revolutionized society and brought great shocks to the labor market. However, in general, the trend of increasing employment can be seen in countries all over the world, because new technologies have created new occupations. By studying the level of development and the different impacts of AI technology in different countries, Roy(2019) found that while AI may eliminate some jobs, it can also create new jobs, which can have an impact on the overall labor market. The third school of research, the comprehensive effect school, points out that the impact of AI application on the number of jobs is caused by both the substitution effect and the creation effect. Therefore, the impact of the application of artificial intelligence on the number of jobs needs to consider the size of the substitution effect and the creation effect, and the final result is thus determined. Wang Wen (2023) believes that technological change will trigger employment substitution effect and creation effect, and the relative magnitude of the two determines the increase or decrease of employment. Ace-moglu and Restrepo (2020) make a similar point, arguing that intelligence will shrink the share of employment and may even lead to lower wages, but the creation of new tasks will have the opposite effect.

The application of artificial intelligence technology will have an impact on the employment structure, such as the age structure and education level distribution of the employed population. For example, for the manufacturing industry, aging has brought about labor shortage, which is not conducive to the sustainable development of the manufacturing industry, but artificial intelligence can better cope with the negative impact of aging. Meng Hao et al. (2022) found that although artificial intelligence will increase the employment demand of high-skilled labor, it will also lead to a decrease in the number of jobs for medium-skilled labor. Another study analyzed how artificial intelligence will affect the distribution of employed population among various sectors of the national economy. For example, at present, there is a large number of surplus labor force in China's primary industry and its employment proportion is higher than the proportion of output value, but artificial intelligence has promoted the trend of "advanced" employment structure.

At present, the impact of artificial intelligence on the labor market is becoming a global research focus, but the existing research has the following shortcomings: First, at present, most of the domestic and foreign research on the impact of artificial intelligence on employment focuses on the manufacturing industry, and there is no unified view on the impact of employment number, and there is a lack of relevant research on the impact of artificial intelligence on service industry employment; Second, most studies focus on employment at the macro level, while relevant studies based on firm level data are insufficient, especially those on employment structure. Finally, there is insufficient research on the degree to which service jobs are at risk of being displaced by AI. Based on this, this study raises the following research questions: How does the application of artificial intelligence technology affect the employment of service enterprises in terms of the number of employees, the skill structure of employees and the income of employees?

3.Empirical analysis of the employment impact of the service industry enterprise data

3.1Model construction

In this paper, taking "artificial intelligence" as the natural experiment, using the Difference-In-Difference method (for short, DID) is used to quantify the causal effect of AI technology in the number of employment, employment structure, employee income and other aspects. In this study, the enterprise sample is divided into two groups, namely, AI enterprises (process group)and non-AI enterprises (control group) in the scope of artificial intelligence. Set the variable *IsAIE* for proxy, that is, if the enterprise belongs to AI enterprises, the *IsAIE* value is 1, and otherwise is 0; The virtual variable *Istart* for whether the enterprise adopts the AI policy, if the enterprise adopted the artificial intelligence policy, namely the company's annual report and artificial intelligence related keywords frequency is greater than or equal to 10, this paper assumes that the company has had an AI policy since that year, the *Istart* in this year before the year value is 0, in this year and later year value is 1. In order to study the effect of AI policies in service enterprises on the relative demand of labor, this study divides the enterprise sample into AI enterprises and non-AI enterprises, explaining that the core variable is DID = IsAIE ×Istart, and its coefficient reflects the effect of policy on the relative demand of labor. If the coefficient is significantly negative, it means that the adoption of the policy significantly reduces the demand for workforce.

This section refers to the research of Dachs, Bai Jun and other scholars to build the following measurement models to test the effect of AI technology in service enterprises on the number of employees, employee skill structure and employee income:

$$InEMP_{it} = a_0 + a_1 DID_{it} + a_2 X_{it} + \lambda_i + \mu_i + \varepsilon_i \quad (1)$$

$$LOW_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + \lambda_i + \mu_i + \varepsilon_i \quad (2)$$

$$MID_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + \lambda_i + \mu_i + \varepsilon_i \quad (3)$$

$$HIGH_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + \lambda_i + \mu_i + \varepsilon_i \quad (4)$$

$$InEMPS_{it} = \gamma_0 + \gamma_1 DID_{it} + \gamma_2 \mathrm{X}_{it} + \varepsilon_i \quad (5)$$

This part uses multiple models to examine the effect of AI on the service industry. Model (1) tests the effect of using AI on the number of employees in service enterprises. $lnEMP_{it}$ is the total employees of the company in the year and takes the logarithmic, while model (2) - (4) respectively tests the effect of the AI on the skill structure of employees in service enterprises. Finally, the model (5) tests the effect of the AI on the wage in service enterprises. $lnEMPS_{it}$ takes the logarithm of employee compensation. The core explanatory variable DID_{it} is the cross term of the virtual variable, the variable X_{it} is a series of control variables, which will be explained in detail later; β_0, β_1 and β_2 are estimated parameters, μ_i is a fixed effect of the province where the enterprise is registered, λ_i is a fixed effect of year, and ε_i is a random interference term.

The above econometric model takes the quantity of workers in service enterprises, the skill structure of employees and the income of employees as explanatory variables. To reduce the heteroscedasticity in the regression equation, each variable was treated logarithmically except for the proportion category variable.

3.2Selection of indicators

Artificial intelligence is a very complex and wide range of fields, the definition of AI is also very vague, and no consistent and authoritative definition standard has been formed. Therefore, when selecting and determining AI related indicators, it is necessary to fully consider different application fields and purposes, follow the principles of science, system, comprehensive and reasonable, and incorporate with the current circumstances and growth trend, flexibly select and combine different keywords and indicators to fully reflect all aspects and levels of AI, so as to comprehend better and evaluate the application and impact of AI. In view of this problem, this paper summarizes and selects the appropriate key words related to AI according to the AI's definition and the literature released by researchers.The rapid development of AI, some agencies issued reports, such as tsinghua university released the development of AI report 2011-2020, the report chose the 13 key areas of AI, and explains the evolution of each technology, it summarizes the development status in the AI field , trend and future outlook, emphasized the important influence of AI on social economy, and the necessity of strengthening personnel training and international cooperation. In addition, this paper also refers to foreign reports and literature, such as AI Index Report 2021 published by Stanford University and papers published by Acemoglu. These literature and reports cover the core technologies, products, applications and implementation foundations involved in the AI industry, providing a theoretical basis for the 53 AI field features selected in this study (see the attached table for details). Finally, this study sorts out the annual reports of listed service companies from 2014 to 2022, finds out the keywords related to AI in the annual report, and counts its word frequency, and whether enterprises are involved in artificial intelligence or have major technological breakthroughs, and then determines the starting year of enterprises adopting artificial intelligence technology.

Core explanatory variables

Artificial intelligence enterprise (IsAIE): Through the 2014-2022 services listed companies annual report search, obtain the use of artificial intelligence related features frequency, determine whether the enterprise belongs to AI application enterprise, if adopted the strategy of artificial intelligence, and artificial intelligence related features word use frequency is greater than 10, the enterprise belongs to the AI enterprise, the IsAIE value is 1, otherwise 0.

Artificial intelligence Policy (Istart): If a company does not show intelligent behavior or no intelligent preconditions by 2022, it is defined as a non-intelligent company, and from 2014 to 2022, the value of the Istart variable is set to 0. If the frequency of enterprise AI-related feature words is greater than 10 between 2014-2022, the value of the Istart variable is set to 1 from that year and 0 before that year.

IsAIE×Istart(DID)：The focus of this chapter is that the dummy variable cross-item DID=IsAIE×Istart, which is set to determine whether the adoption of AI policies by service enterprises will have effect on their relative demand for labor. When this coefficient is significantly negative, it indicates that the service enterprise will significantly reduce the relative demand for labor; otherwise, when this coefficient is significantly positive, the relative demand for labor will increase significantly.

Explained Variable

Total employees in service enterprises (*lnEMP$_{it}$*): the total employees in the year.

Proportion of highly skilled employed (HIGHit): The number of highly skilled workforce as a proportion of the total employment of the company. Base on the predecessors's methods and uses the proportion of people employed in the service industry with college degree or above as the proportion of highly skilled workforce.

Proportion of middle skilled employed (MIDit): The proportion of medium-skilled workforce in the total employment of the company. This paper uses the ratio of service employment in high school and secondary school education as the proportion of medium-skilled workforce..

Ratio of low-skilled employment (LOWit): The number of low-skilled workers accounts as a percentage of the company's total employment.

Employee compensation (lnEMPSit): According to the ILO definition, labor costs are the costs paid by an enterprise to hire workers. Since the income of senior executives of listed companies is a large part of the remuneration payable, this study intends to use the method of Wang Lei to determine the income of senior employees ("remuneration payable" of listed companies-Total compensation for senior managerstotal remuneration) / total number of employees, which is recorded as EMPS (Employee salary).

Controlled Variable

Degree of capital deepening (LnKLratio): In recent years, the phenomenon of capital deepening is widespread in enterprises. This phenomena has two primary causes: the first isScientific and technological innovation, more and more enterprises use capital instead of labor. Secondly, With a rise in the number of highly skilled personnel, enterprises are more likely to adopt highly skilled employees to replace low-skilled employees, so as to improve production efficiency and competitiveness and realize the survival of the fittest. This trend allows companies to reduce employee count under the same production target. This paper references Yang Zhihai's research using the net fixed asset to employee count ratio as a proxy.

R&D investment intensity (TYratio): The number and intensity indicators of R&D projects reflect businesses' technological strength, while the expenditure of R&D projects reflects the importance and support of enterprises for technological innovation activities. This paper uses the ratio of R&D spending to operational income serves as a proxy.

The number of years the business has been in existence (lnage): The time of a company is an important indicator of its existence. The existence period of the enterprise will affect the efficiency of operation, the speed of development and the effectiveness of management.

Enterprise size (size): Since different business sizes have different technical requirements for the labor force, so the enterprise size have impact on the overall skill structure of the workforce; this section uses the logarithm of total assets as the company size proxy.

GDP (PrvGDP) of the province where the enterprise is located: It also has a certain effect on the number and skill structure of the employees, his paper uses the logarithm of the GDP of the province where the enterprise is located as the agent variable, and the unit is 100 million RMB.

3.3.Regression analysis

3.3.1.Descriptive analysis

The data utilized in this chapter is entirely from the wind database, and the identification of AI enterprises comes from the text mining of enterprise annual reports. In the identification of service enterprises, we select according to the industries of listed enterprises, and all enterprises belong to 14 subindustries of the service industry.Furthermore, to ensure the integrity of the data, ST, ST * and delisted enterprises are excluded in this chapter.

Table1

Descriptive statistics of the variables

Variable	Sample number	Average Value	Standard Deviation	Minimum Value	Maximal Value
IsAIE	531	0.36	0.48	0	1
LOW	531	34.122	26.326	0	100
MID	531	22.077	16.428	0	98.81
HIGH	531	40.246	27.554	0	100
LnKLratio	531	12.203	1.485	4.127	19.543
PrvGDP	531	10.412	0.644	7.566	11.619
lnage	531	2.446	0.749	0	3.434
size	531	22.871	1.949	14.942	31.138
TYratio	531	7.086	9.128	0	98.39

The data collected in the sample were from enterprises from 2014 to 2022, which indicated that 531 enterprises were included in the sample, including 191 enterprises in the experimental group and 360 in the control group. From the perspective of labor skill type, the average proportion of high-skilled (HIGH), medium-skilled (MID) and low-skilled labor force (LOW) in the total employees is 34.12%, 22.07% and 40.24% respectively, it shows that the low-skilled and highly-skilled workforce in the listed service enterprises is the main personnel composition of Chinese listed enterprises at this stage.

3.3.2. Multiple collinearity test

VIF (variance inflation factor) is a measure of multicollinearity. It is an indicator used to check whether there is multicollinearity between the independent variables in the regression model. In the multiple linear regression analysis, if there is multicollinearity between the independent variables, the parameter estimates will be unstable, and the reliability and accuracy of the regression results will be affected. The larger the VIF value is, The stronger the relationship between this independent variable and the other independent variables, that is, the more obvious the multicollinearity is. Generally speaking, if the VIF of an independent variable and the value is greater than 10, you can consider a serious multicollinearity problem between the independent variable and other independent variables. VIF test results of this chapter are present in Table 2, and the mean VIF value is 1.3, so the results can be considered more reliable.

Table2

Multiple ollinearity analysis

variable	VIF	1/VIF
Size	1.570	0.639
Lnage	1.380	0.722
TYratio	1.360	0.737
LnKLratio	1.310	0.765
DID	1.170	0.856
PrvGDP	1.040	0.958
Mean VIF	1.300	

3.3.3.The effect of AI on the number of employees in service firm

First, the impact of AI application in service enterprises on the number of employees is analyzed. This section text mining of listed service industry businesses' annual reports from 2014 to 2022 is done using Python, and the starting year of artificial intelligence in 2014-2022 (Istart) is divided into experimental groups and control groups according to whether they have artificial intelligence characteristics (IsAIE). Multiple models were regressions with Stata,and Table3 shows the particular results .

The regression results present that the estimated coefficient of the AI application level of the core explanatory variable is positive at the 10% significance level, that is, AI technology will raise the total number of workers in service enterprises. This shows that for the development of service enterprises, the adoption of AI can improve the production efficiency of employees, expand the scale of enterprises, increase corporate profits, and foster the growth of businesses.

Table3

the impact of AI on the number of employees in service enterprises

variable	(1) Mixed regression	(2) stochastic effect	(3) fixed effect	(4) Two-way fixation effect
AI	.42***	.162***	.12***	.102***
	(.01)	(.017)	(.017)	(.022)
PGDP	-.81***	.121**	.195***	-.041
	(.106)	(.06)	(.057)	(.062)
TRA	-.012	.045	.052	.031
	(.078)	(.07)	(.068)	(.023)
EDU	.063	.011	.019	.064*
	(.042)	(.024)	(.023)	(.034)
INF	-.013***	-.008***	-.005***	-.008***
	(.003)	(.002)	(.002)	(.002)
AFI	-.009**	-.004	-.002	-.012
	(.004)	(.003)	(.003)	(.017)
EZB	3.197***	.292	-.169	.31***
	(.267)	(.268)	(.261)	(.053)
constant term	12.24***	4.659***	3.999***	4.122***
	(.733)	(.563)	(.539)	(.634)
Observational quantity	300	300	300	300
R-squared	.797	.z	.693	.991

*Note: Steady standard error in brackets: *, **and *** represent significant at the statistical levels of 10%, 5% and 1% respectively*

3.3.4.The effect of AI on the skill structure of employees in service enterprises

According to the above econometric model, and two-way fixed effect regression is used. In Table4, The regression findings indicate that the influence of the core explanatory variable AI (DID) on the employment of high, medium-low-skilled levels has passed the significance level of 1%, indicating that the influence of enterprises adopting AI on the employment structure is significant. Regarding employment proportion of highly skilled workforce, the regression coefficient of DID is 13.795, indicating that for each unit increase by the AI index, the proportion of highly-skilled workforce will increase by an average of 13.795 units. Then the medium-low-skilled workforce, the regression coefficient of DID is-2.8 and-10.755, indicating that the proportion of DID will decrease by 2.8 and 10.755 units. In general, the need for highly-skilled labor rises as a result of service businesses implementing AI technology, whereas the need for medium-low-skilled labor significantly declines. This may be because, on the one hand, the enterprises studied in this section are all listed enterprises, with high digital and intelligent development, and have certain economic strength to invest in the creation and study of novel technologies, so that they eliminate an abundance of low-medium-skilled labor; On the other hand, because the explanatory variable of skill structure in this paper is proportional type, the number of medium-low-skilled labor force of enterprises may not decrease, but the growth rate is slower than that of highly skilled labor force, the adoption of AI makes its employee structure develop towards high quality.

From control variables, capital deepening (LnKLratio) reduces the demand for highly skilled workforce with a regression coefficient of -2.923; increases the need for medium-low-skilled workforce. This may be because, a large number of low-skilled labor has shifted to services, where the "last mile" problem has been difficult to solve with lower-priced technologies, so companies are more likely to hire cheaper low-skilled labor.

Table4

the effect of AI application on the skill structure of employees in service enterprises

variable	(1) LOW	(2) MID	(3) HIGH
DID	-10.755***	-2.87***	13.795***
	(.966)	(.756)	(.997)
LnKLratio	1.382***	1.661***	-2.923***
	(.341)	(.267)	(.352)
lnage	5.891***	-1.357**	-5.167***
	(.679)	(.532)	(.701)
size	-.247	-1.838***	2.042***
	(.354)	(.277)	(.365)
PrvGDP	5.132***	2.035***	-7.053***
	(.774)	(.606)	(.799)
RDSpendSumRatio	-.642***	-.2***	.868***
	(.053)	(.042)	(.055)
_cons	-44.029***	28.384***	114.523***
	(11.725)	(9.176)	(12.1)
Observations	2168	2168	2168
R-squared	.288	.066	.364

*Note: Steady standard error in brackets: *, **and *** represent significant at the statistical levels of 10%, 5% and 1% respectively*

Corporate age（lnage) increases the need for low-skilled workforce, and decreases the need for medium-skilled, highly skilled workforce. This may be the earlier the company is founded, It is more likely to be engaged in traditional service industries, which have higher intelligence costs but lower labor costs, so companies will hire more low-skilled labor.

The need for highly-skilled labor is higher in larger enterprises, the need for medium-skilled personnel is lower, and the influence on the need for low-skilled labor is ambiguous.This is because large enterprises need to introduce intelligent technologies to assist management. In order to effectively use these technologies, the participation of an abundance of highly-skilled labour is needed.

Regional economic level (PrvGDP) has raised the percentage of laborers with low to medium skill levels and reduced the proportion of highly skilled workers. This may be because China's service industry is currently in a stage of continuous expansion, absorbing a great quantity of low-skilled workforce.

R&D investment intensity (RDSpendSumRatio) has decreased the percentage of low-and medium-skilled workforce and raised the percentage of highly skilled individuals. This is consistent with what is true. Businesses that implement AI might replace a significant portion of the low- and medium-skilled work population, and the need to be recruited because the use of AI requires a great quantity of highly-skilled workforce.

3.3.5The effect of AI on the income of employees in service enterprises

Table5

the impact of AI application on employee income of service enterprises.

variable	Employee income
DID	-.098**
	(.049)
LnKLratio	-.174***
	(.023)
RDSpendSumRatio	-.001
	(.003)
lnage	.329***
	(.066)
size	.79***
	(.038)
PrvGDP	-.662***
	(.237)
cons	8.174***
	(2.817)
Observations	1715
R-squared	.927

*Note: Steady standard error in brackets: *, and * * * represent significant at the statistical levels of 10%, 5% and 1% respectively*

According to the above econometric model, the effect of the AI policy on employee wage is empirically tested, and the two-way fixed effect regression is used. The regression results are present in Table5.

The core explanatory variable AI (DID) has a significant impact on employee income. Specifically, the adoption of AI in service companies has slightly reduced employee income levels. This may be because AI can undertake more human skills, and companies can choose to use AI to replace workers. The relative cost of AI technology has decreased , making the cost advantage of artificial intelligence technology more obvious. In this case, employees may be reluctant to ask for a big pay increase because of the fear that companies will replace their jobs with AI.

From the perspective of control variables, capital deepening (LnKLratio) reduces the income of employees, This may be owing to the enterprise's limited capital and the growth in fixed-asset investment, which will reduce the compensation and benefits of employees. The age and size of the enterprise have a positive impact on employee income, and the regression coefficients of 0.329 and 0.79 respectively, and both of them passed the test at the 1% significance level, it indicates that the longer the enterprise history and the larger the enterprise, the better and more perfect the size of the employee welfare.

In this chapter, a multi-period DID method was used. Regarding the choice of methods to test robustness, although the time trend chart itself is a relatively simple method to test parallel trends, it is difficult to draw the time trend map because of the variable implementation time of the AI policy in each organization.Therefore, the event study method (Event Study) was used to examine the parallel trend of multiphase DID. There are two ways to test the hypothesis that the results match parallel trends: first, compare the time trend of the mean of the dependent variable between groups; second, and add the interaction term between dummy variables and policy variable at each time point to the tested regression. In this dissertation, the second method is used for the parallel trend test and some of the data for the parallel trend test is presented Table6.

If the sample is "treatment group" and "period j before policy implementation", d_j, value 1, otherwise 0. From the table we can conclude that the regression coefficient of d_j is not significant and that the coefficients are not significantly different from those in the baseline period, confirming the assumption of parallel trends.

3.4 Robustness test

Table6

Robustness test of the impact of AI on the employment of service enterprises

变量	(1) EMP	(2) LOW	(3) MID	(4) HIGH	(5) EMPS
d_1	-.029	.263	-1.202	1.528	-.178
	(.055)	(1.582)	(1.4)	(1.532)	(.139)
d_2	.036	-1.596	2.262	.091	.103
	(.072)	(1.815)	(2.104)	(2.483)	(.144)
d_3	.08	-.366	-.752	1.895	.119
	(.079)	(2.243)	(1.943)	(2.262)	(.179)
d_4	.016	-2.295	-.136	2.699	-.181
	(.126)	(2.365)	(1.506)	(2.176)	(.183)
d_5	.062	-1.814	-1.412	2.647	.045
	(.143)	(2.852)	(2.648)	(2.345)	(.232)
d_6	.12	1.816	-2.154	1.137	0
	(.173)	(3.445)	(2.669)	(2.737)	(.277)
d_7	-.004	2.51	.615	-2.423	-.164
	(.154)	(4.657)	(4.421)	(3.347)	(.15)
d_8	-.017	-.618	.082	.441	-.06
	(.16)	(4.716)	(4.841)	(3.082)	(.166)
d_9	-.437***	-4.486	.303	2.808	-.163
	(.149)	(4.008)	(3.223)	(4.212)	(.231)

*Note: Steady standard error in brackets: *, and * * * represent significant at the statistical levels of 10%, 5% and 1% respectively*

4. Research conclusions

The impact of the development of artificial intelligence technology on job substitution has become a hot research issue, but most of the current relevant studies focus on the manufacturing industry, and there is a lack of relevant research on the service industry, and secondly, there is insufficient research on the enterprise-level data. Based on the data of listed enterprises in the service industry from 2014-2022, this study uses the difference-difference method to study the impact of the application of artificial intelligence technology on the number of employees, the skill structure of employees and the income of employees in the service industry from the enterprise level. The main research conclusions of this paper are as follows: Empirical analysis of enterprise-level data shows that listed enterprises in the service sector adopting artificial intelligence technology will expand the demand for labor, that is, hire more employees, but there is heterogeneity in labor demand for different skill levels. Specifically, enterprises increase the demand for high-skilled employees, but reduce the demand for low - and medium-skilled employees. In addition, the application of AI technology will have a negative impact on the income of employees in service enterprises.

5. Policy Suggestions

Based on the above findings, this study puts forward the following policy recommendations:

(1) The occupation replacement of artificial intelligence will impact more industries, and the service industry, as the industry that absorbs the most employment population, faces great challenges, especially the middle and low skilled labor force faces challenges such as repositioning, career conversion and retraining. On the one hand, the government should pay attention to it and provide adequate social security policies. At the same time, it also needs to guide enterprises to carry out various forms of retraining and job transfer plans, such as providing online learning platforms, organizing internal training courses and cooperating with educational institutions, and formulating relevant subsidy policies to support the training of enterprises.

(2) While exacerbating the polarization trend of "education degree-position", artificial intelligence may further reduce employees' income. This study finds that the crowding of labor elements by artificial intelligence makes the average salary of employees in service enterprises drop significantly. Therefore, in the context of the new "human-machine collaboration" and "human-machine symbiosis", how to protect the rights and interests of workers in salary bargaining is also the content that relevant government departments need to consider, so as to achieve human-machine win-win and avoid ineffective competition brought about by the application of new technologies.

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