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Artificial Intelligence, Workforce Skills and Enterprise Productive Efficiency

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Abstract: ***Artificial intelligence (AI) technology is important for achieving high-quality economic development. While most of the existing research put emphasis on the impact of AI on the macroeconomy, this paper examines from the enterprise level how AI technology affects production efficiency and workforce skill structure. In this paper, we analyse the text of annual reports and patents of listed companies to construct AI indicators at the enterprise level. The study finds that AI significantly enhances the productivity of listed companies in China, and this finding holds across a series of robustness tests. In respect of the impact mechanism, AI increases firms' productivity by less demand for routine low-skilled labour and more demand for non-routine high-skilled labour, which reflects the restructuring of their workforce force skills. This paper deepens the awareness and understanding of the role of AI in the production process at the micro-enterprise level, and provides recommendations for advancing AI technology.***

Keywords: Artificial Intelligence, Business Productivity, Workforce Skills

1. Introduction

Artificial intelligence (AI) has been developing at a rapid pace and has become an important engine for promoting scientific and technological development, upgrading industrial structure and increasing productivity. Many countries have taken AI as an essential strategy for boosting the competitiveness of their economic and industrial. At the micro enterprise level, the answers to the questions of to what degree the use of AI can boost productivity upgrading and how to adjust the workforce structure of firms to better play the efficiency enhancement effect of AI technology are not yet clear (Chen & Srinivasan, 2024). AI's influence on productivity in China has been widely studied from the micro perspective of firms and examines how firms can adjust their workforce force skill structure in response to AI, and the answers to these questions will help us understand how AI technology can play a role at the enterprise level.

However, the empirical examination of AI's influence on microenterprises is impeded by a dearth of AI-specific data. This shortfall in data limits our ability to assess the micro-level transformations that AI might be effecting within smaller business contexts. Despite the theoretical projections, concrete micro-level evidence, particularly concerning the adaptability and outcomes of AI integration in microenterprises, remains largely uncharted. Efforts to amalgamate more granular data are necessary to reveal the intricate ways AI could be reconfiguring the operational and competitive landscapes of these smaller firms.

2. Research Hypotheses

Considered as an essential engine of the 3rd round of technological revolution, there is great potential for AI to improve enterprise productivity and drive economic growth (Brynjolfsson et al.) The theoretical impacts of AI at the macro level have been predominantly discussed, utilizing models like dynamic general equilibrium models (Furman and Seamans, 2019).

Artificial Intelligence has produced huge changes in reality, but the academic world is more interested in exploring the micro-principles at a theoretical level - substituting for labour, complementing it or both. As AI continues to evolve, it is clear that its impact on the macroeconomic landscape and the nature of work will be profound and multifaceted.

For one thing, it is possible for AI technology to replace a portion of the labour force with smart machine systems to achieve intelligent production, which can reduce costs and improve efficiency. There are already more and more intelligent equipment or software to replace labour, thus reducing the labour demand of firms (Asimoglu & Restrepo, 2018b). At the same time, AI can facilitate the skill level of non-routine and creative work and raise productivity (Goldfarb et al.,2023).

H_1: Artificial intelligence is beneficial to improve the productivity of firms.

Based on the potential influence of AI on workforce skills, this paper classifies the workforce of an enterprise into routine low-skilled workforce (production, operations, marketing, and finance staff) and non-routine high-skilled workforce (technology and R&D staff). AI is mainly a substitute for the routine low-skilled labour force and a complement to the non-routine high-skilled labour force (Zhou et al., 2020).

H_2: The demand for routine low-skilled labour will be reduced and the demand for non-routine high-skilled labour will be increased, which in turn will promote the improvement of productivity.

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3. Research Design

3.1 Data collection

Based on A-share listed companies (Shanghai and Shenzhen), China, the data period is from 2007 to 2012. The annual reports used in this paper come from Xinlang Finance website (https://finance.sina.com.cn/); patent data come from IRPDB Intellectual Property Database (https://www.iprdb.com/); labour-related data come from RESSET database; basic information and financial data of firms come from the China-Taiwan Database (https://www.iprdb); and the data of the Chinese AI industry come from the China-Taiwan Database (https://www.iprdb). The enterprise basic information and financial data come from CSMAR. This paper process the data as follows: (1) excluding firms in the financial industry, for AI always been used; (2) Removing enterprises in the information delivery, software and technology services industry, because these industries themselves use AI , and it may not be possible to clearly determine the impact of the application of AI ; (4) Excluding samples with ST and *ST status in the current year; (5) Excluding samples with missing data. To mitigate the disturbance of extreme values, all continuous variables are winsorized at 1% level.

3.2 Variable measurement

3.2.1 AI

This paper adopts machine learning method to generate AI dictionaries, and then constructs enterprise AI indicators based on annual reports of listed companies and patent texts respectively (Sai et al., 2019).

First, the AI lexicon is generated. Referring to the research reports released by major brokerage firms and the AI glossary from the World Intellectual Property Organisation (WIPO), the terms ‘artificial intelligence’, ‘machine learning’, ‘Internet of Things ’, ‘cloud computing’ and other terms. Repeated words, words not related to AI, and words with too low word frequency are eliminated, and finally the AI dictionary is generated with 74 AI vocabularies on the basis of which to build (Chen & Srinivasan, 2024). Subsequently, the development of an AI metric is undertaken. For this purpose, the open-source Python library 'jieba' is employed to analyze the textual content. This library facilitates the lexical analysis and identification of text within these reports. The firm's AI metric is then derived from the natural logarithm of the count of AI-related keywords, incremented by one (Lnwords).

3.2.2 Enterprise productivity

In this paper, total factor productivity (TFP) is used as a measure of firm productivity, which is related to technological progress and also mirrors the knowledge and skills of material production, management mode, etc. (Lu and Lian, 2012). TFP is estimated based on the Cobb-Douglas production function.

$$Y_{it} = A_{i,t} L_{i,t}^{\alpha} K_{i,t}^{\beta} \tag{1}$$

where Y, L and K represent the firm's output, labour inputs and capital inputs respectively, and A is the firm's total factor productivity.

3.3 Model

To examine the productivity influence of AI, the following model is developed.

$$TFP_{it} = \alpha + \beta AI + \gamma Controls_{it} + \varepsilon_{it} \tag{2}$$

Where i and t represent firms and years, TFP is total factor productivity of firms, and AI is an artificial intelligence indicator. According to Hypothesis 1, this paper predicts that the β is significantly positive, and ε is the random error term. controls represent control variables. To mitigate the problem of inter-industry heteroskedasticity, the standard errors of the regression coefficients are clustered. The variables are defined in Table 1.

Table 1: Variables' Definition

Name	*Variable*	*Description*
Total Factor Productivity	TFP	Calculated according to the method of Orly and Parks (1996)
Annual Report Artificial Intelligence Keyword Word Frequency	Lnwords	Number of AI terms in annual reports of listed companies plus 1, in natural logarithms
Routine Low-Skilled Labour	Routine	Number of manufacturing, operations, sales, and accounting staff of the listed company / number of employees of the company
Unroutine High-Skilled Labour	Non_routine	Number of technical and R&D staff of listed companies / number of staff of the company
Firm Size	Size	Total number of staff, in natural logarithms
Firm Age	Age	Age of firm establishment, in natural logarithms
Firm Leverage	Leverage	Total liabilities / total assets
Growth	Growth	Growth rate of sales revenue, in natural logarithms
Board Size	BoardSize	Number of board members, in natural logarithms
Dual-Title	Dual	The chairman and manager of the board of directors in one time to take 1, otherwise take 0
Concentration of Employment Equity	Top1	Shareholding ratio of the largest shareholder

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4. Results

4.1 Descriptive Statistics

The descriptive statistics are shown in Table 2 & 3. Among them, about 39.37% of the annual reports between 2007 and 2022 disclosed AI-related information . According to Table 3, the mean of AI-related terms is 0.606, with a standard deviation of 0.985. This tells a wide variation in AI adoption among companies, as the standard deviation exceeds the mean. The frequency of the term 'Routine' ranges from 0.000 to 0.923, while 'Non-routine' varies from 0.0130 to 0.700. These ranges highlight the significant differences in the skill sets and operational approaches of the workforce across different companies. The disparity in AI-related content and the focus on routine versus non-routine activities in annual reports reflect the varied strategic priorities and adaptability of companies in the face of technological advancements.

Table 2: AI Variable Descriptive Statistics

Year	*Number of Listed Company*	*Number of Listed Companies Disclosing Artificial Intelligence in Their Annual Reports*
2007	1539	27
2008	1598	34
2009	1746	80
2010	1975	171
2011	2205	283
2012	2282	347
2013	2358	462
2014	2497	628
2015	2620	885
2016	2933	1177
2017	3471	1660
2018	3573	1865
2019	3778	2136
2020	4266	2509
2021	4668	2837
2022	5106	3255

Table 3: Controls Descriptive Statistics

Variable	*N*	*mean*	*sd*	*min*	*max*
TFP	32,288	7.790	0.957	5.822	10.35
Lnwords	32,288	0.606	0.985	0	4.025
Routine	32,288	0.546	0.290	0	0.923
Non_routine	27,016	0.187	0.137	0.0130	0.708
Size	32,288	22.26	1.299	19.95	26.28
Age	32,288	2.887	0.345	1.792	3.526
Leverage	32,288	0.440	0.202	0.0601	0.892
Growth	32,288	0.169	0.394	-0.551	2.439
BoardSize	32,288	2.134	0.199	1.609	2.708
Dual	32,288	0.255	0.436	0	1
Top1	32,288	35.25	14.80	9.272	74.89
Lnallpats	32,288	2.703	1.801	0	7.056

4.2 Productivity effects of AI

Table 4 analyzes the influence of AI on productivity. Column (1) indicates that AI's presence, as measured by the natural logarithm of AI-related words (Ln-words), has a regression coefficient of 0.075, significant at 1% level, which suggests a positive correlation. Moving to Column (2), the addition of control variables does not diminish the significance of AI's influence; the coefficient remains positive and significant. Economically, for every standard deviation increase in AI-related content (Lnwords), total factor productivity (TFP) is predicted to rise by 2.96%. This is calculated as the product of the standard deviation of AI mentions (0.985) and the regression coefficient (0.030), indicating a substantial economic impact. This finding underscores the potential of AI to enhance productivity when its integration is effectively communicated in corporate reports. The above results show that, other things being equal, AI can significantly increase the TFP of an enterprise, which to a certain extent denies the ‘productivity paradox’ of Solow (1987), and Hypothesis 1 is verified. The regression results for control variables, for example, show that firms with larger size, higher gearing, better growth capacity and higher equity concentration are more productive.

Table 4: Regression Results

Variable	*(1)* *No controls*	*(2)* *With controls*	*(3)* *PSM*
Lnwords	0.075*** (6.728)	0.030* (1.446)	0.012** (1.599)
Size		0.514*** (33.875)	0.491*** (25.277)
Age		0.288*** (3.022)	0.466*** (2.941)
Leverage		-0.072* (-1.132)	-0.013** (-0.153)
Growth		0.220*** (21.544)	0.241*** (18.706)
BoardSize		0.005* (0.141)	-0.008* (-0.171)
Dual		-0.019** (-1.498)	-0.022* (-1.266)
Top1		0.001** (1.234)	0.001** (0.674)
Lnallpats		-0.008* (-1.496)	-0.007* (-0.801)
Constant	7.690*** (1,026.459)	-4.580*** (-9.442)	-4.595*** (-6.505)
Observations	35,182	35,182	14,791
Adjusted R^2	0.834	0.896	0.917

*Note: ***, **, * indicate significant at the 1 %, 5 % and 10 % level.*

4.3 Robustness Checks

The firms' decision to integrate AI is not haphazard but is influenced by internal factors such as human capital, management strategies, and the level of technological advancement, as well as external environmental factors. This can introduce self-selection bias in empirical analyses. To counteract this, the paper utilizes Propensity Score Matching (PSM) to undermine endogeneity issues (Zhong et al.,2024). The methodology involves segmenting the sample into experimental and control groups. The matching process uses the control variables from model (3) and employs a 1:1 nearest neighbour matching method with replacement to ensure a balanced comparison.

Before conducting the PSM regression, a balance test is essential. The balance test results are promising, showing a substantial reduction in the absolute values of standard errors for corporate characteristics between the experimental and control groups, with a decrease ranging from 59.9% to 97.9%. The standardized deviation for most covariates post-matching is less than 5%, indicating a high degree of balance. The t-test results support that the initial differences in group characteristics have been largely neutralized.

The robustness of the paper's findings to self-selection bias is confirmed by the matched sample test results, as depicted in column (3) of Table 4. These results reaffirm the study's conclusions, demonstrating that the integration of AI has a significantly positive impact on TFP, even when accounting for potential self-selection bias.

4.4 Mechanistic Study

Artificial intelligence technology has a substitution effect on repetitive labour jobs, and a complementary effect on non-routine and non-repetitive labour jobs, so firms will make use of the productivity effect of artificial intelligence by reducingroutine low-skilled labour and increasing non-routine high-skilled labour. We refer to the classic mediation effect model of Barron and Kenny (1986) and conduct an empirical test based on the mechanism of 'labour force skill restructuring'.

$$TFP_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \gamma Controls_{it} + \varepsilon_{it} \tag{2}$$

$$Labor_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \delta Controls_{it} + \varepsilon_{it} \tag{3}$$

$$TFP_{i,t} = \theta_0 + \theta_1 AI_{i,t} + \gamma Controls_{it} + \varepsilon_{it} \tag{4}$$

Among them, Labor is the enterprise labour force indicator, referring to Ott et al. (2003), including regular low-skilled labour force (Routine) and non-routine high-skilled labour force (Non-routine), in which regular low-skilled labour force is measured by dividing the number of production, operation, marketing and finance personnel by the number of enterprise employees, and non-regular high-skilled labour force is measured by dividing the number of technical and R&D personnel. AI is an artificial intelligence indicator measured by the frequency of AI keywords (Lnwords). ε is a random error term. The control variables Controls are the same as those described in the previous section.

Table 5: Mechanistic Study Results-1

variable	*(1)* *TFP*	*(2)* *Routine*	*(3)* *TFP*
Lnwords	0.030** (1.446)	-0.021*** (-4.215)	0.008* (1.489)
Routine		0.514*** (33.875)	0.008*** (0.222)
Constant	-4.580*** (-9.442)	0.596*** (6.134)	-4.584*** (-9.437)
Controls FE	YES	YES	YES

Table 6: Mechanistic Study Results-2

variable	*(1)* *TFP*	*(2)* *Routine*	*(3)* *TFP*
Lnwords	0.030** (1.446)	0.008*** (5.474)	0.007** (1.412)
Non_Routin e			0.078*** (1.010)
Constant	-4.580*** (-9.442)	0.141* (1.724)	-4.502*** (-10.896)
Controls FE	YES	YES	YES

The coefficient γ_1 of AI in model (2) reflects the total influence of AI on productivity. The coefficient δ_1 of AI in model (3) reflects the effect of AI technology on different types of labour (routine low-skilled labour and unroutine high-skilled labour) in firms. Based on the theoretical analysis, when the explanatory variable is routine low-skilled labour, the δ_1 is expected to be significantly negative, indicating that AI replaces the routine low-skilled labour of the enterprise; when the explanatory variable is non-routine high-skilled labour, the δ_1 is expected to be significantly positive, indicating that the AI technology increases the demand for non-routine high-skilled labour of the enterprise. Model (4) adds Labor as an indicator of labour force on the basis of model (2), in which the coefficient of AI θ_1 represents the direct effect of AI on enterprise's productivity, while the coefficient of Labor θ_2 represents the effect of different types of labour force on enterprise's productivity after controlling for AI.

The stepwise regression results of the mediated effects model are shown above. Column (1) of Table 5 shows that AI significantly contributes to firms' productivity and the total effect of AI on firms' productivity is 0.030. Column (2) shows that AI reduces firms' demand for routine low-skilled labour, i.e., AI replaces routine low-skilled labour. In column (3), the coefficient of Lnwords is significantly positive and the Routine coefficient is notably negative. As shown in Table 6, the Lnwords coefficient in Column (2) is significantly positive, suggesting that AI markedly boosts the demand for non-traditional high-skilled labor. The Lnwords coefficient in Column (3) also exhibits a significant positive trend, as does the Non-routine coefficient, indicating the presence of a partial mediating effect.

5. Conclusion

As a key driver of the new technological revolution and industrial change, artificial intelligence has significant potential to increase firms' productivity and drive economic growth. However, due to data bottlenecks, there are no clear conclusions on how AI affects productivity at the firm level and how the skill structure of the firm's labour force changes in the process. In this paper, we collect textual data from annual reports and patents of listed companies, and use machine learning to generate an AI vocabulary, and then construct firm-level AI indicators. Through descriptive statistics and empirical research, this paper draws the following conclusions: (1) The level of AI among listed companies in China varies greatly. (2) Artificial intelligence significantly improves the productivity of listed companies. (3) Mechanism analysis shows that the use of AI technology will lead firms to adjust the skill structure of their labour force,

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which is manifested in the reduction of the demand for routine labour and the increase of the demand for non-routine labour.

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