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# Article

# The impact of artificial intelligence on the labour market: Evidence from China

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#### Abstract

The rapid advancement of artificial intelligence (AI) technology has been the driving force behind the new wave of technological revolution. In this study, we examine the impact of AI technology on corporate employment decisions. Using a sample of Chinese listed firms from 2012 to 2021, we find that AI technology applications have a positive influence on the total number of corporate employees. In addition, we find that this positive relationship is more pronounced in non-state-owned enterprises and in asset-light companies. Furthermore, our mechanism analysis indicates that AI technology has positive effects on corporate employment by increasing sales revenue and attenuating financial constraints. In general, our findings highlight the importance of AI technology to the labour market and have several implications for corporate employment decisions.

Keywords: Artificial intelligence, patents, labour market, employees

JEL Classification: O3, G3, J0

#### Introduction

In the past decade, the rapid advancement of artificial intelligence (AI) technology has been the key catalyst for the latest surge in the technological revolution. Companies in various industries are increasingly introducing more AI technologies into their production and management processes (Crafts, 2021; Hilb, 2020; Pelau et al., 2021). Consequently, the

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Vol. 26 • No. 67 • August 2024



integration of AI technology into business activities has a significant impact on corporate operations and decisions. Some studies have documented some economic consequences of AI technology adopted in production and management in companies, such as facilitating product innovation (Rammer et al., 2022), improving the productivity of total factors (Zhai and Liu, 2023), and increasing sales and market valuation (Babina et al., 2024). However, there is limited empirical evidence on whether and how AI technology applications affect the labour market, especially at the firm level in developing countries. In this study, we aim to address this interesting and important issue in the Chinese setting, which has initiated a wide range of national-level artificial intelligence policies.

We follow the literature (Babina et al., 2024; Zhai and Liu, 2023) and focus on the AI patent applications and the number of AI patents to measure the application of AI technology. Using a sample of Chinese A-share listed firms from 2012 to 2021, we find a significant positive impact of AI technology application on the employment scale within companies, suggesting AI's contribution to employment growth. Furthermore, our study reveals that higher levels of AI are associated with increased company sales, thus promoting employment growth. Furthermore, higher levels of AI can alleviate financial constraints, thus expanding the scale of employment. Moreover, we observe that the positive relationship between AI technology applications and corporate employment is more pronounced in non-state-owned enterprises (non-SOEs) and asset-light type companies. We also conduct a series of robustness tests. Our results remain unchanged and show a robust outcome.

This study contributes to the literature on several important dimensions. First, it offers new empirical evidence at the company level amid the debate on the employment effects of AI, indicating that the application of AI technology is a positive factor driving company employment growth. Previous studies primarily discuss the effects of AI on employment at a macro level (Graetz and Michaels, 2017), noting its dual role in both fostering job growth and exacerbating technological unemployment (Acemoglu et al., 2022; Frey and Osborne, 2017). Additionally, we introduce a novel metric based on company AI patents to evaluate its influence on employment across different industries (Zhai and Liu, 2023), providing a more comprehensive assessment compared to traditional measures such as industrial robot counts. Furthermore, this study enriches the literature on microeconomic factors that affect employment at the enterprise level. Although existing research often focusses on government subsidies (Yu et al., 2020), financing constraints (Benmelech et al., 2021), and tax incentives (Cruces et al., 2010), our study examines the impact of technological progress of AI on enterprise employment. Finally, our study contributes to the literature on the economic implications of AI industry policies in emerging economies. Given the significant number of AI-related industrial policies implemented in China, our research explores the employment effects of AI technology adoption in Chinese companies, shedding light on the broader implications of AI policy interventions for emerging economies globally.

The rest of this study is organised as follows. Section 1 presents the related literature and lays out our hypotheses. Section 2 describes the sample and our research design. Section 3 reports the results of our baseline findings, mechanism analyses, heterogeneity analyses, and robustness checks. The final section includes our conclusions and discussion.

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# 1. Literatures Review and Hypothesis Development

#### 1.1. The impact of AI on firm employment

During the process of technological revolution driving economic development, the employment effects generated by technological progress have sparked widespread attention and discussion in the literature. Over the past decade, AI, as a highly pervasive general-purpose technology, has been deeply integrated into corporate operations, production, and management across various industries. In this emerging business paradigm that leverages AI technology, tasks traditionally handled by humans have been extensively supplanted by AI systems (Jarrahi, 2018; Pelau et al., 2021). Therefore, the literature pays close attention to the employment effects of AI, which are inherently complex.

The relationship between AI technology applications and corporate employment decisions is ambiguous. On the one hand, the introduction of intelligent machines has narrowed the scope of human work, resulting in a substantial replacement of positions by AI and exacerbating technological unemployment (David, 2017; Frey and Osborne, 2017). AI technology can dismantle and replace a large number of job positions, thus leading to a reduction in the number of employees. One of the significant characteristics of artificial intelligence lies in its ability to autonomously perform tasks traditionally undertaken by humans (Jarrahi, 2018). The rapidly advancing AI technology integrated into corporate production and management activities improves productivity. Considering the automated nature of AI technology, this efficiency enhancement comes at the expense of technology-substituted labour (Acemoglu and Restrepo, 2018). This implies that AI technology will result in job displacement, exacerbating technological unemployment. Based on these arguments, academic research has provided some preliminary evidence of the negative relationship between AI technology and employment. These studies emphasise that AI technology can mimic human brain functions, leading to widespread replacement of workers in industries, resulting in significant technological unemployment (David, 2017; Frey and Osborne, 2017). In addition, articles that measure AI using the quantity of enterprise machinery find that AI hurts employment (Acemoglu and Restrepo, 2020). However, such studies primarily rely on the density of industrial robots as a proxy variable for AI in earlier empirical regressions. Given the extensive application of AI in industries beyond manufacturing, these studies fail to capture the creation of new job positions outside the manufacturing sector, thus neglecting the positive impact on employment. Furthermore, as research progresses in the microfield of AI's impact on the enterprise level, more studies use AI patent intensity at the enterprise level to represent the level of AI embedding (Babina et al., 2024; Yang, 2022; Zhai and Liu, 2023). This measure is considered a better measure of AI technology and can be applied to the literature on the influence of AI technology on corporate decisions (Babina et al., 2024; Parteka and Kordalska, 2023).

However, the expansion of employment due to AI lies in the enhancement of product innovation, the reduction of production costs, and the introduction of products that better align with consumer preferences facilitated by AI technology. An increase in production scale leads to the creation of more job opportunities, which is based on the intensity of AIskilled hiring (Babina et al., 2024). AI is the primary driving force behind the "fourth industrial revolution," profoundly impacting the production, management, and business operations across various industries. This influence yields a complex dual effect on employment, encompassing destructive and positive impacts. First, the application of AI

Vol. 26 • No. 67 • August 2024

technology can improve the efficiency of business operations by reducing production costs, fostering product innovation, and expanding the market. This expansion of market scale inherently leads to job creation, manifested in an increase in the number of job positions available (Babina et al., 2024). Second, although AI technology has shown a strong tendency to replace traditional job positions, it has also concurrently created new job positions that require human participation in the application of AI technology, thereby generating new types of job positions (Acemoglu and Restrepo, 2018). This creation of new forms and types of job positions reflects the effect of AI on employment creation (Acemoglu et al., 2022). Viewed from a societal perspective and considering the consumer surplus, AI technology improves productivity, leading to lower product prices. Reduced prices increase the surplus of consumers, stimulating companies to create more job opportunities and foster employment growth.

Based on the discussion above, we expect that the positive impact of the application of AI technology on firm employment outweighs the negative impact. Therefore, we propose the following hypothesis:

Hypothesis 1: The application of AI technology has a positive influence on corporate employment.

# 1.2. Mediating effect of sales revenue

As a general-purpose technology, AI exerts influence on enterprise activities in various specific contexts and significantly impacts numerous industries. Specifically, the application of AI technology achieves growth at the enterprise level by improving productivity and promoting product innovation across a wide range of industries (Agrawal et al., 2019; Lu, 2021). The impact of AI on firm employment manifests itself in two aspects. First, AI technology can replace certain human tasks, thus reducing production and management costs (Autor, 2015). Second, AI's predictive capabilities enhance operational efficiency and decrease operational costs. This impact fundamentally aims to reduce business expenses, helping enterprises achieve success in market competition. Furthermore, AI technology promotes product innovation and drives sales growth (Babina et al., 2024). At the same time, artificial intelligence can reduce the cost of product innovation, thus improving the quality of existing products (Hottman et al., 2016). For instance, AI algorithms can uncover patterns from big data, reducing research and development uncertainties, and enhancing innovation efficiency. Simultaneously, AI technology can more accurately discern customer demands, customise products, and expand sales markets (Foster et al., 2016). Therefore, the application of AI technology stimulates sales growth, contributing positively to the employment market. On the basis of the aforementioned analysis, we propose our second hypothesis.

Hypothesis 2: The positive impact of the application of AI technology on employment is achieved through the mediation of increased sales revenue.

#### **1.3. Mediating effect of financial constraints**

Financing constraints have a negative impact on employment at the enterprise level (Chodorow-Reich, 2014; Giroud and Mueller, 2017). Financial constraints are a critical

Amfiteatru Economic



factor that limits firms from increasing labour investment, as cash inflows generated by labour typically lag behind revenue. When firms face financial constraints and cannot generate sufficient cash flows to support the expansion of labour investments, they are unable to create additional job opportunities (Benmelech et al., 2021). However, the literature suggests that companies with higher levels of AI technology can secure more bank loans. thereby reducing the level of financial constraints faced by these firms (Shao et al., 2022). This is because the use of AI technology has brought competitive advantages and enhanced reputations to firms (Hirsch, 2018; Rammer et al., 2022), helping to reduce information asymmetry in lending decisions by financial institutions and providing the necessary funds to expand labour investment. From the perspective of banks, enterprises that integrate more AI technology into their product innovation and business processes can better showcase their commercial competitiveness, reduce information asymmetry, and thus improve their access to bank loans (He et al., 2024). It also implies that with the application of AI technology leading to sales growth, the funding requirements for expanding production scale are also alleviated due to the easing of financial constraints. Based on these analyses, we propose the following hypothesis:

Hypothesis 3: The positive impact of the application of AI technology on firm employment is achieved through mediation to alleviate financing constraints.

# 2. Research design

# 2.1 Data

Our initial data set comprises all companies listed as A shares on the Shanghai and Shenzhen Stock Exchanges in China from 2012 to 2021. We chose to begin our analysis from 2012, aligning with the pivotal advances in deep learning models and the subsequent rapid evolution of AI technology. Firms flagged with ST (Special Treatment) or \*ST by the China Securities Supervision and Management Committee are excluded from our sample due to their abnormal financial status, rendering their data incomparable to other listed firms. Similarly, companies operating in the financial industry are omitted from our analysis because their financial statements do not align with those of nonfinancial firms. Furthermore, observations with missing values in our primary variable are excluded. Consequently, our final dataset consists of 19,792 firm-year observations. Data on AI technology were sourced from the IncoPat database. To identify AI patents, we adopted the methodology outlined in previous literature (Yang, 2022; Zhai and Liu, 2023), leveraging the International Patent Classification (IPC) code along with the "Strategic Emerging Industries Classification and International Patent Classification Relationship Table (2021)" issued by the China National Intellectual Property Administration. Employee data are retrieved from the China Stock Market & Accounting Research (CSMAR) database, and additional financial data is obtained from both the CSMAR and Wind databases.

# 2.2 Variable definition

The primary dependent variable in this study is the number of employees within the company at the end of the year (*EmpScale*), which is measured as the natural logarithm of one plus the total number of employees, following the approach of Popov and Rocholl (2018).

Vol. 26 • No. 67 • August 2024

Furthermore, consistent with the methodologies of the prior literature (Babina et al., 2024; Zhai and Liu, 2023), we use two variables to gauge AI technology adoption. *AIpatentD* is a binary variable coded as one if the firm files at least one AI patent application within the year, and zero otherwise. *AIpatentN* represents the natural logarithm of one plus the total count of AI patents.

In addition, we incorporate several control variables that are known to potentially influence the number of employees. These variables include *Size*, *LEV*, *ROA*, *PPE*, *Growth*, *Board*, *InDirector*, *Duality*, *TOP*, and *RDintensity*. The rationale for selecting these variables has been widely discussed in previous studies (Babina et al., 2024; Benmelech et al., 2021; Popov and Rocholl, 2018). For example, a larger size (size) and the proportion of fixed assets (*PPE*) indicate a larger number of employees. The leverage ratio (*LEV*) and the profitability (*ROA*) also affect the scale of employees through the cash flow constraints faced by labour investment. In addition, the expansion of company sales revenue (*Growth*) and the intensity of R&D investment (*RDintensity*) are closely related to the scale of employees. Meanwhile, a better governance structure can increase the number of employees by enhancing corporate profitability and promoting sales expansion. Thus, we control for a series of corporate governance variables, such as *Board*, *InDirector*, *Duality*, and *TOP*. All variables are defined in Table 1. Continuous variables are subjected to winsorization at the 1st and 99th percentiles to minimise the impact of outliers.

Variable Name	Definition
EmpScale	The natural logarithm of one plus the total number of employees.
A las art and D	A dummy variable that codes as 1 if the firm has at least one AI
AlpatentD	patent application in the year, and zero otherwise.
AIpatentN	The natural logarithm of one plus the total number of AI patents.
Revenue	The natural logarithm of one plus the total amount of sales.
FC	Financial constraints index, following the method proposed by Whited and Wu (2006).
Non-SOE	A dummy variable that codes as 1 if the firm is a non-state-owned enterprise and zero otherwise.
Light	A dummy variable that coded as on if the ratio of property, plant, and equipment (PPE) to total assets is smaller than the annual media value, and zero otherwise.
Size	The natural logarithm of total assets.
LEV	The ratio of total liabilities to total assets.
ROA	Return on assets, measured as the net income scaled by total assets.
PPE	The ratio of PPE to total assets.
Growth	The annual growth rate of total sales.
Board	Board size, measured as the natural logarithm of one plus the total number of directors on the board.
InDirector	The ratio of the total number of independent directors to the total number of directors on the board.
Duality	A dummy variable that codes as one if chairman and CEO are the same person, and zero otherwise.
ТОР	The percentage of shares held by the largest stockholder.
RDintensity	The ratio of the total amount of R&D input to total sales.

Table no. 1: Variable definitions

**Amfiteatru Economic** 

872

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# 2.3 Empirical specification

To examine the impact of AI technologies on corporate employment decisions, we construct a model using multiple regression analysis, drawing on the model design of Benmelech et al. (2021). Our original contribution lies in examining the impact of AI technologies on employment by using a standardised company employee scale as the dependent variable and using AI patent intensity as the independent variable. This study uses data from China, a developing country, to investigate this research question, providing direct evidence to evaluate the impact of AI on the labour market in emerging economies. The specific model is as follows.

$$EmpScale_{i,t} = \beta_0 + \beta_1 A I_{i,t} + Control_{i,t} + \varepsilon_{i,t}$$
(1)

where  $EmpScale_{i,t}$  is our dependent variable, measured as the natural logarithm of one plus the total number of employees of firm *i* in year *t*.  $AI_{i,t}$  is the variable of our interests. It includes two variables,  $AipatentD_{i,t}$  and  $AipatentN_{i,t}$ .  $Control_{i,t}$  includes several control variables that may affect corporate employment decisions, as mentioned above. We also include both industry fixed effects, year fixed effects, and province fixed effects in our estimations. Province fixed effects are based on the location of corporate headquarters at the province level. Robust t-statistics clustered by the firm level are reported in our estimations.

To provide empirical evidence for our proposed channels, we use the mediating analysis approach proposed by Baron and Kenny (1986) and include the following specifications:

$$Med_{i,t} = \beta_0 + \beta_1 A I_{i,t} + Control_{i,t} + \varepsilon_{i,t}$$
<sup>(2)</sup>

$$EmpScale_{i,t} = \beta_0 + \beta_1 A I_{i,t} + \beta_2 Med_{i,t} + Control_{i,t} + \varepsilon_{i,t}$$
(3)

where  $Med_{i,t}$  includes two mediating variables, *Revenue* and *FC*. In this approach, the relationship between our key independent variable (*AI*) and mediating variables is examined in equation (2). In addition, we combine the mediating variables and our independent variables into one equation. The mediating effects of *Revenue* and *FC* can be validated if we can find that  $\beta_I$  in both equations (2) and (3) is significant in statistics. Similarly, industry fixed effects, year fixed effects, and province fixed effects are included in both equations. Robust t-statistics clustered by the firm level are used in both equations as well.

# 3. Empirical Results

# 3.1 Descriptive statistics and univariate analysis

The descriptive statistics of our key variables are presented in Panel A of Table 2. The mean and standard deviation of *EmpScale* are 7.815 and 1.222, respectively, indicating sufficient variability in this variable to investigate the determinants of corporate employment. Furthermore, the mean value of *AIpatentD* is 0.250, with a median value of 0, suggesting that most of the listed firms in our sample do not have AI patent applications. The mean value of *AIpatentN* is 0.392, with a minimum of 0 and a maximum of 6.806, indicating a wide variation in AI technology between the listed firms in our sample.

Given that one of our key independent variables, *AIpatentD*, is a binary variable, we performed a univariate analysis to offer preliminary evidence supporting our hypothesis. The results are reported in Panel B of Table 2. The mean value of *EmpScale* in the first group (*AIpatentD*=1) is 8.172, while in the second group (*AIpatentD*=0), it is 7.697. According to

Vol. 26 • No. 67 • August 2024

the t-test, the mean difference between the two groups is significant at the 1% level, suggesting a positive influence of AI technology on corporate employment.

Panel A: Descriptive stasitics						
VarName	Obs	Mean	SD	Min	Median	Max
EmpScale	19792	7.815	1.222	3.584	7.721	13.165
AlpatentD	19792	0.250	0.433	0.000	0.000	1.000
AIpatentN	19792	0.391	0.809	0.000	0.000	6.806
Revenue	19792	21.613	1.466	14.993	21.456	28.592
FC	19792	-1.032	0.271	-24.340	-1.021	-0.721
Asset-light	19792	0.575	0.494	0.000	1.000	1.000
Private	19792	0.919	0.273	0.000	1.000	1.000
Size	19792	22.263	1.320	17.806	22.081	28.857
LEV	19792	0.426	0.247	0.008	0.412	11.386
ROA	19792	0.031	0.152	-7.700	0.039	7.446
PPE	19792	0.199	0.142	0.000	0.173	0.876
Growth	19792	0.369	6.998	-0.992	0.116	665.540
Board	19792	2.114	0.198	1.099	2.197	2.890
InDirector	19792	0.377	0.055	0.143	0.364	0.800
Duality	19792	0.323	0.467	0.000	0.000	1.000
TOP	19792	33.963	14.710	2.197	31.700	94.150
RDintensity	19792	4.797	5.812	0.000	3.640	307.720
Panel B: Univariate analysis						
	AipatentD = 1		AipatentD = 0		Di	ff.
Obs		4940		14582		
EmpScale		8.172		7.697		0.475***

Table no. 2: Descriptive statistics and univariate analysis

#### 3.2 Baseline findings

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The findings of our primary analyses are summarised in Table 3. Columns (1) and (3) present the results without industry fixed effects, year fixed effects, and province fixed effects. Subsequently, we introduce three fixed effects into our estimation, and the corresponding results are displayed in columns (2) and (4). In columns (1) and (2), we observe that the coefficients in AlpatentD are 0.258 and 0.167, respectively, and both are statistically significant at the 1% level. For the economic importance according to the estimated coefficients, it suggests that a one decile change in AlpatentD translates in an increase in employee scale, relative to its mean of 3.301% (0.258/7.815, 7.815 is the mean of EmpScale) and 2.137% (0.167/7.815) respectively. These results indicate that the implementation of AI technology is associated with an increase in corporate employment, aligning with our initial hypothesis. Furthermore, in Column (3), we find that the coefficient on *AlpatentN* is 0.160, also significant at the 1% level. Similarly, in column (4), the positive and statistically significant coefficient in AlpatentN suggests a propensity for firms with greater integration of AI technology to expand their workforce. The economic significance is such that a one decile change in AlpatentN translates into an increase in employee scale, relative to its mean of 2.047%% (0.160/7.815) and 1.331% (0.104/7.815) respectively. In general, the results presented in Table 3 corroborate our hypotheses, thus validating our H1. Our findings are different from some studies (Acemoglu and Restrepo, 2018; Frey and Osborne, 2017), which suggest that AI has a negative impact on corporate employment decisions. These studies

**Amfiteatru Economic** 

Notes: \*, \*\* and \*\*\* indicate that the regression coefficients are significant at levels of 10%, 5%, and 1%, respectively.

#### Artificial Intelligence in Enterprises: How Staff Competencies Requirements of Business Organisations Are Evolving Through the Integration of Artificial Intelligence



mainly involve qualitative analysis and use industry robots to measure the effect of AI technology. However, our findings are consistent with the findings in Acemoglu et al. (2022). This study focusses on the United States, a developed country, and derives its conclusions from data on AI job demand from online recruitment websites. Our study uses a new measure of AI technology based on the recent literature (Babina et al., 2024; Yang, 2022; Zhai and Liu, 2023) and explores the research question in a developing country.

Variables	(1)	(2)	(3)	(4)
	EmpScale	EmpScale	EmpScale	EmpScale
A las art and D	0.258***	0.167***		
AlpatentD	(11.776)	(8.973)		
AIngtontN			$0.160^{***}$	$0.104^{***}$
Alpaienin			(11.611)	(8.550)
Size	$0.677^{***}$	$0.771^{***}$	$0.668^{***}$	0.763***
Size	(57.490)	(69.736)	(57.257)	(68.849)
IEV	$0.107^{*}$	0.163***	$0.111^{*}$	0.165***
LEV	(1.682)	(2.703)	(1.738)	(2.724)
POA	0.379***	0.303***	$0.374^{***}$	0.302***
KOA	(3.324)	(3.225)	(3.314)	(3.222)
DDE	1.128***	1.266***	$1.142^{***}$	$1.280^{***}$
FFE	(10.270)	(12.456)	(10.351)	(12.569)
Growth	< 0.001	-0.001	< 0.001	-0.001
Growin	(0.053)	(-0.773)	(0.106)	(-0.732)
Roard	0.320***	$0.220^{***}$	0.313***	0.215***
Doura	(4.313)	(3.457)	(4.212)	(3.363)
InDirector	$0.578^{**}$	0.154	$0.550^{**}$	0.130
mDirector	(2.450)	(0.726)	(2.317)	(0.610)
Duality	-0.017	-0.041**	-0.020	-0.043**
Duality	(-0.714)	(-2.032)	(-0.865)	(-2.118)
ΤΟΡ	$0.004^{***}$	$0.004^{***}$	$0.004^{***}$	$0.004^{***}$
101	(3.928)	(4.974)	(3.931)	(4.961)
RDintonsity	< 0.001	$-0.004^{*}$	<-0.001	$-0.004^{*}$
KDimensity	(0.159)	(-1.843)	(-0.107)	(-1.927)
Intercent	-8.615***	$-10.148^{***}$	-8.380***	-9.951***
шегеерг	(-27.059)	(-24.247)	(-26.359)	(-23.666)
Industry	NO	YES	NO	YES
Year	NO	YES	NO	YES
Province	NO	YES	NO	YES
$\mathbb{R}^2$	0.645	0.733	0.648	0.734
N	19792	19792	19792	19792

Table	no.3	Baseline	finding
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Notes: Robsut t-statistics clusted by the firm level are reported in parentheses. \*, \*\* and \*\*\* indicate that the regression coefficients are significant at levels of 10%, 5% and 1%, respectively. It is the same in the following tables in this paper.

Vol. 26 • No. 67 • August 2024

# 3.3 Empirical evidence for proposed channels

# 3.3.1 Revenue channel

As discussed previously, we hypothesise that the application of AI technology can enhance corporate employment by boosting sales revenue. To empirically test this hypothesis, we introduce a new variable, *Revenue*, defined as the natural logarithm of the total sales amount. Following a mediating analysis approach, we initially investigated the impact of AI technology on corporate sales. The results are presented in columns (1) and (3) of Table 4. We observe that the coefficients of *AIpatentD* and *AIpatentN* are both positive and statistically significant at the 1% level, indicating that AI technology can indeed boost corporate sales. Subsequently, we integrate *Revenue* with *AIpatentD/AIpatentN* into a single specification. Consistent with previous research, we find a positive association between corporate sales and the number of employees within the firm. Furthermore, the positive and statistically significant impact of AI technology on corporate employment persists. Consequently, the results presented in Table 4 provide supporting evidence for our H2 hypothesis.

Table 10.4 Results for revenue channel					
	(1)	(2)	(3)	(4)	
Variables	Revenue	EmpScale	Revenue	EmpScale	
A Im a tour tD	0.119***	$0.101^{***}$			
AlpaleniD	(8.496)	(6.076)			
A Im a tom th			$0.084^{***}$	$0.057^{***}$	
Alpaienin			(10.055)	(5.103)	
Davanua		$0.558^{***}$		0.555***	
Kevenue		(26.448)		(26.193)	
Controls	YES	YES	YES	YES	
Industry	YES	YES	YES	YES	
Year	YES	YES	YES	YES	
Province	YES	YES	YES	YES	
R <sup>2</sup>	0.882	0.786	0.883	0.786	
Ν	19792	19792	19792	19792	

Table no.4 Results for revenue channel

# 3.3.2 Financial constraints channel

We also investigate whether the mitigation of financial constraints serves as a pathway through which AI technology influences corporate employment. To construct a proxy for financial constraints (FC), we adopt the method proposed by Whited and Wu (2006), commonly referred to as the WW index.

The regression results are reported in Table 5. Columns (1) and (3) indicate a negative association between AI technology and financial constraints. However, when both AI technology and financial constraints are simultaneously included in the estimate, we find that AI technology remains positively related to corporate employment, in line with our expectations. In general, the results in Table 5 validate our argument in H3, suggesting that AI technology can increase the number of employees by alleviating financial constraints.

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Variables	(1)	(2)	(3)	(4)
	FC	EmpScale	FC	EmpScale
A In a tout D	-0.005***	0.157***		
AlpaleniD	(-7.731)	(7.945)		
A In a tout N			-0.003***	$0.098^{***}$
Alpalenti			(-7.394)	(7.554)
EC		-1.574***		-1.558***
гC		(-5.866)		(-5.806)
Controls	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Province	YES	YES	YES	YES
$\mathbb{R}^2$	0.989	0.736	0.989	0.737
Ν	19792	19792	19792	19792

Table no.5 Results fo	r financial	constraints	channel
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#### **3.4 Heterogeneity analyses**

To further validate our primary conclusions, we perform two heterogeneity analyses to explore whether the positive relationship between AI technology and employment varies depending on the type of assets and government ownership.

First, we distinguish between two types of listed firms: state-owned enterprises (SOEs) and non-SOEs, both pivotal drivers of economic growth in China. SOEs often dominate large-scale utilities and traditional industries, whereas non-SOEs are spearheading technological innovation in emerging industries, driving China's technological advancement. Non-SOEs, particularly supported by AI industry policies, are at the forefront of AI technology development in the nation (Zeng, 2021). Consequently, we anticipate that the impact of AI technology on corporate employment is more pronounced in non-SOEs compared to SOEs.

Second, AI technology, as a general-purpose technology, significantly impacts companies in all sectors, including both asset-heavy and asset-light firms. In asset-heavy companies, the widespread adoption of AI technology in intelligent devices often results in the substantial replacement of labour-intensive roles, potentially offsetting the employment-promoting effects of production scale expansion. In contrast, in asset-light companies, AI technology is applied primarily to areas such as product innovation and customer demand identification. In this context, AI technology predominantly acts as a tool to enhance human capabilities and streamline corporate operations, thus fostering job creation. Consequently, we anticipate that the influence of AI technology on corporate employment decisions will be more pronounced in asset-light companies.

To test our conjecture, we construct two dummy variables: *Non-SOE* and *Light*. *Non-SOE* is a dummy variable indicating whether the firm is a non-state-owned enterprise (1 for non-SOEs, 0 otherwise), while *Light* is a dummy variable denoting whether the ratio of property, plant, and equipment (PPE) to total assets is smaller than the annual median value (1 for asset-light firms, 0 otherwise). We include interaction terms between *AI* and *non-SOE* (*light*) in our analysis.

The results are presented in Table 6. In columns (1)-(2), the coefficients on the interaction terms, *AIpatentD×Non-SOE* and *AIpatentN×Non-SOE*, are both positive and statistically

Vol. 26 • No. 67 • August 2024

significant at the 1% level. This suggests that the positive association between AI technology and employment is more pronounced in non-SOEs compared to SOEs, consistent with our hypothesis. In columns (3)-(4), the coefficients on the interaction terms, *AIpatentD×Light* and *AIpatentN×Light*, are 0.0084 and 0.040, respectively, and are statistically significant. This indicates that the impact of AI technology on corporate employment is amplified for asset-light firms. In general, the results in Table 6 provide supporting evidence for our heterogeneity analyses and reinforce our main conclusions.

Variables	(1)	(2)	(3)	(4)
	EmpScale	EmpScale	EmpScale	EmpScale
AIngtontD	-0.005		0.131***	
AlpaleniD	(-0.083)		(4.685)	
AIngtontN		0.012		$0.086^{***}$
Alpalentiv		(0.374)		(4.019)
Ale stant Dy Man SOF	$0.188^{***}$			
AlpaleniD×Non-SOE	(3.148)			
		0.103***		
Alpatentiv×ivon-SOE		(3.272)		
			$0.084^{**}$	
AlpatentD×Light			(2.443)	
				$0.040^{*}$
AlpatentN×Light				(1.779)
N. COL	-0.091***	-0.089***		
Non-SOE	(-2.659)	(-2.596)		
T • 1,			-0.128***	-0.123***
Light			(-4.782)	(-4.606)
Controls	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Province	YES	YES	YES	YES
R <sup>2</sup>	0.734	0.735	0.726	0.727
Ν	19792	19792	19792	19792

Table no 6	Results	for	heterogeneity	analyses
1 abic 110.0	<b>I</b> CSUILS	101	neter ogenenty	analyses

#### 3.5 Robustness checks

#### 3.5.1 An exogenous shock to the impact of AI technology

A potential concern besetting our analysis is that the documented effect of AI technology on corporate employment could spuriously reflect endogeneity. To address this issue, we treat the Guiding Opinion of the State Council on Actively Promoting the 'Internet Plus' Action issued by the State Council in China as an exogenous shock to the impact of AI technology. Specifically, in May 2015, the Chinese State Council first proposed vigorous development of the new artificial intelligence industry and stated that artificial intelligence would be the main direction for the following development. In July 2015, the State Council issued the Guiding Opinions and encouraged the development of AI technology. As a result of these Guiding Opinions, listed firms are actively developing AI technology, and the influence of AI technology has been strengthened. Importantly, this Guided Opinion does not have any

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direct effect on corporate employee decisions. Therefore, it provides an ideal shock to examine the importance of AI technology for corporate employment decisions.

To capture the immediate impact of the exogenous shock, we focus on the three years before (2012-2014) and the three years after (2016-2018) the issuance of the Guidance Opinion. We exclude the year when the Opinion was issued to mitigate potential confounding effects. We create a new variable, *Post*, which equals one if the year falls within the period from 2016 to 2018, and zero if the year falls within the period from 2012 to 2014. Additionally, we construct a dummy variable, *Treat*, which equals one if the firm holds an AI patent in the year, and zero otherwise. The interaction term of *Treat* and *Post* is the variable of interest.

The regression results are presented in Table 7. We observe that the coefficients on the interaction term are positive and statistically significant at the 1% level, indicating that firms in the treatment group have more employees after the implementation of the guiding opinion. This finding aligns with our expectations and provides additional evidence to support the causality of our primary conclusions.

Variables	(1)	(2)
	EmpScale	EmpScale
Treat	$0.258^{***}$	0.151***
Treat	(5.978)	(3.752)
True man De ma	$0.089^{***}$	$0.087^{***}$
Treat×Post	(2.605)	(2.752)
Post	-0.178***	-0.230***
POSI	(-7.597)	(-8.808)
Controls	YES	YES
Industry	YES	YES
Year	YES	YES
Province	YES	YES
R <sup>2</sup>	0.656	0.742
N	8482	8482

Table no.7 Results for an exogenous shock

# 3.5.2 Matched sample regression

Given the potential concern regarding systematic differences between firms with AI patent applications (treatment group) and those without (control group) due to the smaller sample size of the treatment group, we address this issue by reestimating our basic specification using a matched sample from propensity score matching (PSM) approach. Specifically, we employ nearest-neighbor matching, matching one observation in the treatment group with one observation in the control group. In the PSM approach, *AIpatentD* is employed as the dependent variable, while all control variables are utilised as covariates. For brevity, these results are untabulated. We find that the coefficients of *AIpatentD* and *AIpatentN* remain positive and statistically significant at the 1% level. This suggests that our main conclusions continue to hold even after addressing concerns about potential sample selection bias.

# 3.5.3 Heckman two-stage regression

Another concern is self-selection bias. Some factors that affect firms' decisions to apply for AI patents may be related to corporate employment decisions. To address this concern, we

Vol. 26 • No. 67 • August 2024

performed a two-stage Heckman regression. In the first stage regression, *AIpatentD* is used as our dependent variable and all control variables are used as an independent variable. Next, we use the inverse mill ratio (IMR) estimated from the first-stage regression as an additional control variable in the second-stage regression. The results are not reported for the sake of brevity. We continue to find supportive evidence for our baseline findings.

# 3.5.4 Other robustness checks

Finally, we conduct two additional tests to verify the robustness of our main findings. These results are not tabulated for brevity. First, to mitigate reverse causality, we construct our independent variable lagged one year. Additionally, we construct an alternative measure of our dependent variable, *Emp/Asset*, measured as the total number of employees scaled by total assets. Our findings continue to hold and show a robust outcome.

# 4. Conclusions

Artificial intelligence stands out as one of the most disruptive technologies of the century, fundamentally altering business organisations and societies in unforeseen ways. Although the consequences of the application of AI technology in corporate decisions have attracted a great deal of attention, this study expands the current literature by examining the relationship between AI technology adoption and corporate employment decisions. We find that firms with AI patents are associated with more employees. This positive association is more pronounced in non-SOEs and in asset-light type companies. In addition, we find that increasing the revenue and alleviating the financial constraints would be two potential channels to account for this relationship. In general, our findings highlight the importance of AI technology for the labour market, especially for employment decisions at the firm level. It has several practical implications for both developed and developing countries.

This study contributes to the economic theory on the impact of technological progress on the employment level. Furthermore, from the perspective of originality and novelty, this paper uses AI patents to evaluate the application of AI technology in enterprises, providing a more comprehensive assessment of the extent of AI use. Furthermore, based on the Chinese context, this study offers evidence of the impact of AI on employment in emerging economies. For practical implications, we suggest that companies should actively invest in AI technology to enhance their competitiveness, and that the government should introduce appropriate policies to encourage the development of AI technology, without the fear of technological unemployment.

This study also has some limitations. Due to the data availability, our study does not encompass some AI tools, such as ChatGPT and Gemini, and textual analysis of AI technology. These tools have been considered an important part of AI technologies since 2023. These AI technologies are supposed to influence corporate employment decisions. Therefore, future research can incorporate these AI technologies and provide a better measurement of the intensity of corporate AI technology. Furthermore, while our study focusses only on the number of employees, future studies can explore the impact of AI technology on employment demands, employee structures across industries, and employee salaries.

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Vol. 26 • No. 67 • August 2024

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#### Artificial Intelligence in Enterprises: How Staff Competencies Requirements of Business Organisations Are Evolving Through the Integration of Artificial Intelligence



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Vol. 26 • No. 67 • August 2024

