Trends in Social Sciences and Humanities Research
Print ISSN: 2959-992X
Online ISSN: 2959-9938
DOI: https://doi.org/10.61784/tsshr3170

UNLOCKING THE POWER OF AI: HOW PEER EFFECTS AND INSTITUTIONAL ENVIRONMENT DRIVE PRODUCTION EFFICIENCY IN CHINA'S PUBLIC LISTED FIRMS

ShanShan Lin[1,2], XiaoHan Chen[3], Rong Huang[4*]
[1]School of Business Administration, Guangdong University of Finance, Guangzhou 510520, Guangdong, China.
[2]Center for Chinese Family Business, Sun Yat-sen University, Guangzhou 510275, Guangdong, China.
[3]Leliu Branch, Guangdong Shunde Rural Commercial Bank, Foshan 528300, Guangdong, China.
[4]Entrepreneurship Service Department, Guangdong Productivity Center, Guangzhou 510070, Guangdong, China.
Corresponding Author: Rong Huang, Email: 68771640@qq.com

Abstract: The rapid adoption of Artificial Intelligence (AI) has revolutionized productivity across various industries. However, the influence of peer effects—interactions between firms within the same industry—and external institutional factors on AI adoption remains insufficiently explored. This study examines how peer influence and institutional factors affect production efficiency in the adoption of AI technology. Using a sample of publicly listed Chinese firms from 2011 to 2022, the study finds that AI adoption by peer firms significantly increases the AI adoption by focal firms, creating a positive feedback loop that accelerates industry-wide innovation. Additionally, the results reveal a substitution effect between institutional factors and peer influences. Specifically, the impact of peer effects on production efficiency is constrained for firms in pilot cities with favorable AI-related policies. These findings highlight the importance of strategic networking and supportive policy frameworks in leveraging AI to gain a competitive edge. This study contributes to the literature on innovation diffusion and offers practical insights for policymakers and business leaders looking to foster a more efficient, technology-driven ecosystem.
Keywords: Peer effect; Institutional environment; Production efficiency, Artificial intelligence

1 INTRODUCTION

Artificial Intelligence (AI) is no longer just a buzzword—it's the driving force behind a revolution that is accelerating innovation, transforming industries, and redefining the global economy. Many countries like China are recognizing its potential, with AI being identified as a key component of economic strategies.

Research indicates that artificial intelligence (AI) can significantly boost productivity and foster innovation [1,2]. By automating routine tasks, streamlining workflows, and providing data-driven insights, AI empowers employees to focus on higher-value activities that require creativity and critical thinking. Furthermore, AI technologies can facilitate the development of new products and services by analyzing market trends and consumer behavior, enabling organizations to respond swiftly to changing demands.

However, little is known about how a firm's AI adoption decisions are influenced by its peers within an industry or how these decisions impact production efficiency. This study, therefore, aims to explore how peer effects—interactions between firms within the same industry—affect production efficiency when adopting AI technology. By examining these peer effects, this research seeks to expand the understanding of technological innovation diffusion and provide theoretical support for businesses in making AI-related innovation decisions. Furthermore, this study investigates whether these influences are shaped by institutional factors. By examining the interplay between firm behavior and the broader institutional context, the research aims to determine how external factors—such as industrial policies—moderate or amplify the impact of peer interactions. This nuanced approach seeks to offer a comprehensive understanding of how institutional frameworks can either facilitate or hinder the emergence of peer effects across different settings.

Theoretically, this study contributes existing research on technological innovation diffusion by incorporating peer effects into AI adoption, offering a new perspective on firm dynamics in technology diffusion [3]. It also enriches our understanding of production efficiency by integrating institutional factors into the framework. Practically, the study provides insights for businesses on how peer AI adoption impacts their technology investments and strategies, helping them avoid risks of either over- or under-adopting. This can improve AI adoption effectiveness, production efficiency, and market competitiveness. Additionally, the findings have policy implications, suggesting that governments and industry bodies can design targeted initiatives to promote AI adoption, optimize industrial structures, and enhance innovation and production efficiency.

2 LITERATURE REVIEW

2.1 AI Technology

Artificial Intelligence (AI) is a cutting-edge technology with profound implications, and its definition continues to evolve in line with technological advancements and ongoing research. At its core, it refers to systems that simulate human intelligence using computer technologies, including key fields such as machine learning, deep learning, natural language processing, and computer vision. These technologies enable computers to perform tasks such as image recognition, voice interaction, data analysis, and prediction—tasks that were once exclusive to human intelligence. As AI technology rapidly advances globally, scholars have begun to appreciate its implications from increasingly broad and deep perspectives. For instance, Ng suggests that AI encompasses not only traditional machine learning and deep learning algorithms but also emerging technologies like reinforcement learning and transfer learning [4]. The integration of these technologies allows computers to autonomously learn and optimize in complex environments, continuously enhancing their intelligence. From a practical standpoint, AI is transforming various industries by providing intelligent solutions that revolutionize traditional production and operational models, thereby creating significant value for both businesses and society.

Therefore, in this study, AI technology is defined as an integrated system encompassing machine learning, deep learning, natural language processing, and computer vision. By utilizing data and algorithms to simulate human intelligence, AI forms a comprehensive platform for data processing, decision optimization, and intelligent task execution. Its impact on production efficiency is evident through process optimization, enhanced management, and product/service innovation. Additionally, AI drives information dissemination, technological imitation, and competitive pressure among peer companies, influencing their technology adoption decisions.

AI technology can improve production efficiency both directly and indirectly. Directly, AI enhances efficiency by streamlining production processes, increasing automation, and reducing the need for manual intervention. For instance, industrial robots can automate tasks, improving both speed and quality. Machine learning algorithms can analyze and predict production data, leading to optimized production schedules and resource allocation [5]. Indirectly, AI improves efficiency by developing advanced products and services, and enhancing management practices [6]. For example, through machine learning and data analysis, companies can gain deeper insights into market demand, target customers more effectively, and develop competitive products and services. AI can also improve management by optimizing human resource allocation and reducing administrative costs.

2.2 Peer Effect

Peer effects, also known as social learning or social contagion, refer to the influence exerted by interactions within a network of individuals who share common characteristics or are part of similar relationship groups. These interactions shape the decisions and actions of individuals within the group. In other words, a person’s behavior is influenced not only by their own attributes but also by the behavior of their peers. The concept of peer effects originated in social psychology, with Rhine being among the first to suggest that individual decisions could be influenced by the choices of others in the same peer group [7]. Over time, a consensus has developed in the academic community regarding the definition of a peer group: it is a social network comprising individuals of equal status [8]. Peer effects are identified when an individual’s behavior or outcomes are influenced—positively or negatively—by the decisions made by other group members. The essence of peer effects lies in the behavioral convergence resulting from social interactions among individuals, which can act as a powerful diffusion mechanism [9]. Small changes in initial behaviors within a group can be amplified and lead to a chain reaction through interactions among its members. Therefore, peer effects occur when an individual’s decision-making is influenced not only by their own characteristics but also by the behavior patterns of others within the same group [10].

Social learning theory and dynamic competition theory provide key theoretical foundations for understanding peer effects. Bandura, a leading figure in social learning theory, integrated cognitive and behavioral perspectives in his 1977 seminal work [11]. Bandura’s social learning theory asserts that individuals are boundedly rational, meaning their perceptions and decisions are influenced by the external environment, and that there is a dynamic relationship between individuals, their surroundings, and behavior. The theory identifies two core learning mechanisms: consequence learning (learning from one’s own actions) and observational learning (learning by observing others’ actions). This theory underscores the idea that human behavior is largely learned by observing others and understanding the consequences of their actions. Subsequent studies suggest that individuals form behavioral strategies and predict outcomes by observing and encoding information from others [12].

Weiss was among the first to apply social learning theory to organizational management, demonstrating that the extent to which followers imitate leaders’ behavior is positively correlated with their perception of the leader’s status and success [13,14]. This process is further moderated by followers’ self-esteem, with reward expectations playing a mediating role. Subsequent research confirmed that the effectiveness of followers’ learning from leaders depends on both the leader’s and follower’s characteristics [15]. In terms of research scope, the peer effect in this study generally involves two primary subjects: the core firm (the research focus) and the peer firms that serve as the source of influence. Peer firms can be defined in different ways, but the most common criterion is firms that operate within the same industry or share similar industry characteristics. Leary and Roberts found that peer firms play an important role in determining corporate capital structures and financial policies [16].

Turning to dynamic competition theory, this field has evolved significantly since Schumpeter’s initial concept of competitive dynamics [17]. Some studies further examined the interactive nature of competitive behavior [18], while Schumpeter refined his framework for dynamic competition, challenging the static view of perfect competition. He argued that competition is a dynamic process driving continuous economic evolution [19]. As a core theory for understanding competitive advantage in the post-Porter era, dynamic competition theory focuses on how the interactions between competitors shape firms' competitive advantages [20,21]. It posits that firms' cognitive abilities can be measured along three dimensions: organizational structure, complexity, and market dependence. For example, Smith et al. found that firms focused on production efficiency exhibit internal driving forces, whereas those that emphasize environmental analysis rely more on external information. Firms that are outward-looking tend to shorten response times and enhance their counterattack capabilities [22].

3 RESEARCH HYPOTHESES

3.1 The Existence of Peer Effect

Companies within the same industry often share similar technological trends, market demand characteristics, and development prospects, which fosters close competition among them. According to strategic ecology theory, a company's position as a "competitor" makes it highly sensitive to the strategic actions of other firms, especially in adopting AI technology. Consequently, companies tend to respond swiftly to these actions in an effort to maintain or enhance their competitive advantage [23].

The adoption of AI by companies within the same industry can significantly increase the likelihood of the focal company adopting AI as well. When a competitor successfully adopts AI, it can help the focal company overcome strategic shortsightedness. By boosting production automation and improving decision-making mechanisms, AI can enhance a company's market responsiveness and resource allocation efficiency, positioning it as a core strategic tool for gaining a competitive edge in a dynamic market [24]. As certain companies within the industry achieve a competitive advantage through AI and establish market barriers, other companies, seeking to avoid losing market share and weakening their competitive position, will become more motivated to adopt the technology. This drives them to develop more forward-looking strategies and strengthens their commitment to AI adoption.

Additionally, the application of AI by peers in the same industry helps mitigate the risk of failure for the focal company. AI adoption entails significant changes across multiple facets of a company's technology, business processes, and organizational management, all of which carry inherent risks and uncertainties. By observing and learning from the successful applications of AI within their industry, companies can absorb knowledge, adopt best practices, and emulate proven strategies, thereby increasing their own chances of success in AI implementation. Therefore, we propose the following hypothesis:

Hypothesis 1: There is an industry peer effect in the adoption of artificial intelligence technology. Specifically, the AI adoption by other firms within the same industry positively influences the AI adoption by the focal firm.

3.2 The Impact of AI Peer Effect on Production Efficiency

Production efficiency is a fundamental research topic in economics and management. It plays a pivotal role in assessing a company's performance. It depicts the relationship between input and output in a company's production process, thus serves as a key indicator reflecting the effective use of various resources, including human, material, financial, and technological assets [25].

Production efficiency is determined by both internal and external factors. Technological innovation drives productivity by improving resource utilization, streamlining production, and fostering long-term growth [26]. Effective management is also crucial, as it promotes collaboration, communication, and efficient decision-making, boosting both management and production efficiency. Additionally, high-quality human capital is essential for technological innovation and process improvements that impact productivity. Externally, market competition pressures firms to optimize production processes and quality to maintain competitiveness. The policy environment also plays a key role by offering tax incentives and financial subsidies to support R&D and technology adoption, creating favorable conditions for efficiency improvements [27]. Government policies can therefore act as catalysts for enhancing enterprise productivity.

The peer effect of artificial intelligence (AI) technology plays a crucial role in the improvement of production efficiency through several channels. First, the peer effect promotes collaborative development among companies in optimizing production processes. When companies in the same industry adopt AI to transform their production processes—such as implementing intelligent production scheduling systems or automated testing equipment—they create a positive learning environment for others in the industry. As these companies observe successful applications of AI in production, they can emulate best practices to streamline their own processes. Second, companies within the same industry can influence each other's human resource development. The successful application of AI requires specialized talent, and as companies invest in AI-related skill development—through internal training or partnerships with universities and research institutions—they create a skilled workforce that benefits the industry as a whole. This shared talent pool boosts the overall production efficiency of companies within the industry. Finally, the peer effect promotes synergies in market expansion and resource integration. As peer companies improve their use of AI, they can offer more competitive products and services, expanding their market share. Additionally, AI adoption enables better integration of resources across supply chains. For example, in supply chain management, AI can optimize supplier selection, inventory management, and logistics, thereby enhancing the overall efficiency of the supply chain. Therefore, we propose the following hypotheses:

Hypothesis 2: The peer effect of AI adoption is positively associated with the production efficiency of the focal firm.

3.3 The "Substitution" Effect of the Institutional Environment

The Chinese government has proactively responded by introducing a series of incentive policies to promote innovation in the AI field. On August 29, 2019, the Ministry of Science and Technology issued the "Guidelines for the Establishment of National Next-Generation Artificial Intelligence Innovation and Development Pilot Zones", proposing the establishment of a number of national next-generation AI innovation and development pilot zones across the country. To date, 18 cities have been approved as the pilot zones (Table 1). Leveraging policy support and resource allocation, these pilot zones are playing a pioneering role in promoting the practical application and industrialization of AI technology, as well as exploring distinctive governance tools.

As noted above, the peer effects will influence strategic decisions about AI adoption, and thus production efficiency. Typically, companies in the same industry observe and emulate each other's AI adoption, and this peer effect helps improve production efficiency. However, changes in the external policy environment, such as the establishment of national pilot zones for next-generation AI innovation and development, may alter the relationship between peer effects and production efficiency. Strong external policy pressures may lead companies to over-rely on policy resources, reducing their ability to learn from the successful experiences of their peers and weakening the role of peer effects in boosting production efficiency. Therefore, we propose the following hypotheses:

Hypothesis 3: The institutional environment for AI development negatively moderates the relationship between peer effect and production efficiency, which indicates there is a substitution effect between the institutional environment and peer effect.

Table 1 Cities approved as "National Next-Generation Artificial Intelligence Innovation and Development Pilot Zone"

Quantity	Name	Approval Time	Region
1	Beijing National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	February 20, 2019	Beijing
2	Shanghai National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	May 2, 2019	Shanghai
3	Tianjin National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	October 17, 2019	Tianjin
4	Shenzhen National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	October 17, 2019	Shenzhen
5	Hangzhou National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	October 17, 2019	Hangzhou
6	Hefei National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	October 17, 2019	Hefei
7	Deqing County National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	November 2, 2019	Deqing County
8	Chongqing National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	January 23, 2020	Chongqing
9	Chengdu National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	January 23, 2020	Chengdu
10	Xi'an National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	January 23, 2020	Xi'an
11	Jinan National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	January 23, 2020	Jinan
12	Guangzhou National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	September 3, 2020	Guangzhou
13	Wuhan National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	September 3, 2020	Wuhan
14	Suzhou National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	March 24, 2021	Suzhou
15	Changsha National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	March 24, 2021	Changsha
16	Zhengzhou National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	November 13, 2021	Zhengzhou
17	Shenyang National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	November 13, 2021	Shenyang
18	Harbin National New-Generation Artificial Intelligence Innovation and Development Pilot Zone	November 13, 2021	Harbin

Source: Letters issued by the Ministry of Science and Technology between 2019 and 2021 on "supporting local governments in establishing National New-Generation Artificial Intelligence Innovation and Development Pilot Zones".

4 RESEARCH DESIGN

4.1 Sample and Data

To test our hypotheses, we collected a sample of Chinese companies listed on Shanghai and Shenzhen stock exchanges from 2011 to 2022 from the China Stock Market and Accounting Research (CSMAR) database, which are widely used for previous research. Financial service companies, ST and *ST companies, and delisted companies were excluded. After removing observations with missing values on key variables, our final sample consisted of 17,040 firm-year observations.

4.2 Variable Measurement

4.2.1 Total factor productivity (TFP)

Previous research suggests that total factor productivity (TFP) is influenced not only by technological progress but also by various other factors, including the level of production knowledge, management effectiveness, the institutional environment, and measurement errors [28]. As a comprehensive indicator of overall productivity, TFP effectively captures the impact of AI technology applications on enterprise productivity. In this study, TFP is used as a proxy for measuring enterprise productivity. TFP is estimated using the Cobb-Douglas production function:

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

Where Y represents enterprise output, L is labor input, K is capital input, and A is the total factor productivity of the focal firm. By taking the logarithm of model (1), we can transform it into a linear form (2):

$$y_{i,t}=\alpha l_{i,t}+\beta k_{i,t}+\mu_{i,t} \tag{2}$$

Here, y, l and k represent the natural logarithms of output (Y), labor input (L) and capital input (K), respectively. The residual term includes the logarithm of total factor productivity (TFP). Given that the traditional OLS method may face issues such as simultaneity bias and sample selection bias, this study adopts the semiparametric estimation method proposed by Olley and Pakes [29]. Specific indicators are constructed as follows: the natural logarithm of total sales is used to measure firm output, the natural logarithm of the number of employees is used to represent labor input, and the natural logarithm of net fixed assets reflects capital investment. Additionally, these investment indicators are calculated based on the natural logarithm of cash payments made by firms to acquire assets (e.g., fixed assets, intangible assets, and other long-term assets). This approach helps improve the accuracy and reliability of the measurement results.

4.2.2 AI adoption of peer firms (AI_Peer)

Adopted from Grennan [30], we measure the AI adoption of peer firms by assessing the levels of AI technology adoption within other firms in the same industry. The process for constructing this measure is as follows: First, by referring various sources, including the Chinese translations of AI-related terms provided by Chen and Srinivasan [31], the "Science and Technology Innovation Board Series - Panorama of the AI Industry Chain" by Ping An Securities, the "2019 China Artificial Intelligence Industry Market Prospects Research Report" by the China Business Industry Research Institute, the "2019 Artificial Intelligence Industry Status and Development Trends Report" published by the Shenzhen Qianzhan Industry Research Institute, and the AI-related vocabulary provided by the World Intellectual Property Organization (WIPO), we constructed an AI dictionary consisting of 73 terms, as shown in Table 2.

Table 2 Artificial Intelligence (AI) Dictionary

AI	Knowledge Graph	Smart Governance	Smart Elderly Care	Pattern Recognition
AI Product	Smart Banking	Autonomous Driving	Big Data Marketing	Edge Computing
AI Chips	Smart Insurance	Smart Transportation	Big Data Risk Control	Big Data Platform
Machine Translation	Human-Machine Collaboration	Convolutional Neural Networks	Big Data Analysis	Smart Computing
Machine Learning	Smart Regulation	Voiceprint Recognition	Big Data Processing	Smart Search
Computer Vision	Smart Education	Feature Extraction	Support Vector Machines (SVM)	Internet of Things
Human-Computer Interaction	Smart Customer Service	Self-driving Automobile	Long Short-Term Memory (LSTM)	Cloud Computing
Deep Learning	Smart Retail	Smart Home	Robotic Process Automation	Augmented Intelligence
Neural Network	Smart Agriculture	Question-Answer System	Natural Language Processing	Voice Interaction
Biometric Recognition	Smart Investment Advisors	Facial Recognition	Distributed Computing	Smart Environment Protection
Image Recognition	Augmented Reality	Business Intelligence	Knowledge Representation	Human-Machine Dialogue
Data Mining	Virtual Reality	Smart Finance	Smart Chips	Deep Neural Network
Feature Recognition	Smart Healthcare	Recurrent Neural Networks	Wearable Product	Big Data Operation
Speech Synthesis	Smart Speaker	Reinforcement Learning	Big Data Management	
Speech Recognition	Smart Voice	AI Agent	Smart Sensor	

Source: Various sources.

Next, we applied the widely used Python open-source "jieba" Chinese word segmentation module to segment the text from the annual reports of listed companies. The AI dictionary was incorporated as a preset proper noun dictionary in the "jieba" module to count the number of AI-related terms in these reports. Finally, we calculate the natural logarithm of the total number of AI-related words found in each report (plus 1) and use this as the indicator for AI adoption of each firm i during period t.

For each firm i, we calculate the AI adoption of its peers (other firms in the same industry, excluding the focal firm) in period t. Let n represents the number of companies in the same industry. The variable $AI_{j,k}$ denotes the level of AI technology usage by firm j in the same industry during period t. The AI adoption of its peers for each firm i during period t is calculated as follows:

$$AI\_Peer_{i,t}=\frac{1}{n\text{-}1}\sum_{\substack{j=1\\ j\neq i}}^{n} AI_{j,t} \tag{3}$$

4.2.3 Institutional environment (Policy)

To examine the impact of the institutional environment on the relationship between peer effects and production efficiency, we use a difference-in-differences approach. A policy dummy variable, (Treat × Post) is used to capture the implementation of the "National Next-Generation Artificial Intelligence Innovation and Development Pilot Zone" initiative. If a city is a pilot city, the Treat variable is set to 1; otherwise, it is 0. The Post variable is a year dummy, where it takes a value of 1 for cities approved in 2019, 2020, or 2021 and for subsequent years, and 0 otherwise. This policy dummy variable is thus used to identify whether city i was designated as a "National Next-Generation Artificial Intelligence Innovation and Development Pilot Zone" in year t.

We controlled for several variables that may influence the relationship between the peer effect of AI technology adoption and production efficiency. Firm size (SIZE) is measured as the natural logarithm of a company's total assets. Firm size is a proxy for a company's ability to acquire and allocate resources. Larger firms often have advantages in capital, technology, and human resources, which can enhance production efficiency and influence decision-making regarding AI adoption. Firm age (AGE) is calculated as the natural logarithm of the difference between the company's founding year and the current year. Firm age reflects accumulated experience and the company's stage of development. Companies at different stages may exhibit varying levels of technological innovation, management models, and market adaptability, all of which can influence the application of AI and its effect on production efficiency. Performance (Tobin_Q) is measured as the ratio of the market value to the book value of total assets. Companies with higher Tobin's Q values typically exhibit stronger performance, which enables them to invest more in AI research and development. Their superior performance provides the resources necessary for technological innovation, thereby enhancing their competitiveness and improving production efficiency. The level of institutional investor ownership (INST) is measured by the ratio of shares held by institutional investors to total outstanding shares. In terms of corporate governance, board size (BOARD) is measured as the natural logarithm of the number of board members. Larger boards may offer more diverse perspectives and more comprehensive decision-making, which could positively influence AI adoption and, in turn, production efficiency.

4.3 Model Setting

To examine whether there is a peer effect in the use of artificial intelligence technology by firms, we draw on the peer effect identification model proposed by Manski [32]. The model is specified as follows:

$$AI_{i,t}=\mu_0+\mu_1 AI\_Peer_{i,t}+\mu_2 Controls_{i,t}+\sum Year+\sum Province+\varepsilon_{i,t} \tag{4}$$

In this model, the dependent variable $AI_{i,t}$ represents the AI technology usage of the focal firm, while $AI\_Peer_{i,t}$ denotes the AI technology usage of peer firms in the same industry. Additionally, we control for year and province effects.

To examine the impact of peer effects in AI technology adoption on enterprise production efficiency, the following model is specified:

$$TFP_{i,t}=\lambda_0+\lambda_1 AI\_Peer_{i,t\text{-}1}+\lambda_2 Controls_{i,t\text{-}1}+\sum Year+\sum Province+\varepsilon_{i,t} \tag{5}$$

In this model, the dependent variable $TFP_{i,t}$ represents the production efficiency of the focal firm, while $AI\_Peer_{i,t}$ refers to the AI technology usage of peer firms in the same industry. Additionally, we control for year and province fixed effects. Since the peer effect of AI technology use has a lag effect on the productivity of focal enterprises, the explanatory variables are lagged by one period.

5 EMPIRICAL RESULTS

5.1 Descriptive Statistics and Correlation Analysis

Tables 3 and 4 present the descriptive statistics and correlation analysis of the variables, respectively. Regarding productivity efficiency (measured by Total Factor Productivity, TFP), the number of observations was 17,040, with a mean of 6.739, a standard deviation of 0.921, a minimum of 3.039, and a maximum of 11.45. These statistics suggest some variation in productivity among the sample, with certain firms demonstrating relatively high efficiency, while others show lower efficiency. This variation also indicates a degree of dispersion in the indicators related to the use of artificial intelligence technology across different companies, reflecting diverse levels of AI adoption. The correlation analysis revealed that the correlation coefficients between the main variables were mostly below 0.3. In general, no strong correlations were found between the variables, which provides a useful basis for the selection of variables and the construction of models in the subsequent regression analysis.

Table 3 Descriptive Statistics

Variable	Obs	Mean	SD	Min	Max
TFP	17,040	6.739	0.921	3.039	11.45
AI_Peer	17,040	0.118	0.0711	0	0.778
AI	17,040	0.117	0.259	0	2.061
Policy	17,040	0.224	0.417	0	1
SIZE	17,040	22.28	1.374	15.58	28.61
AGE	17,040	2.972	0.319	1.099	4.025
Tobin_Q	17,040	2.034	2.567	0.625	259.1
INST	17,040	0.372	0.240	0	1.568
BOARD	17,040	2.115	0.198	1.386	2.890

Table 4 Correlation Analysis

	TFP	AI_Peer	AI	Policy	SIZE	AGE	Tobin_Q	INST	BOARD
TFP	1.000								
AI_Peer	0.134***	1.000							
AI	0.043***	0.240***	1.000						
Policy	0.065***	0.422***	0.115***	1.000					
SIZE	0.222***	0.109***	0.062***	0.088***	1.000				
AGE	0.137***	0.354***	0.113***	0.147***	0.160***	1.000			
Tobin_Q	-0.036***	-0.023**	-0.007	0.007	-0.241***	0.002	1.000		
INST	0.147***	-0.008	0.009	0.026***	0.495***	0.142***	0.020**	1.000	
BOARD	0.067***	-0.103***	-0.010	-0.052***	0.267***	0.046***	-0.089***	0.221***	1.000

Notes: * $p<0.05$; ** $p<0.01$; *** $p<0.001$ (two-tailed test).

5.2 Regression Analysis

The results in Table 5 demonstrate the existence of a peer effect in the use of artificial intelligence (AI) technology. Model 1 serves as the baseline model, including only control variables, while Model 2 is the main effect model, which incorporates the independent variables. In Model 2, “AI_Peer” represents the AI technology usage by peer firms within the same industry. The regression coefficient for this variable is 0.707 ($p < 0.001$), which indicates the AI adoption by companies in the same industry is positively associated with the AI adoption of the focal firm, after controlling for other factors. Therefore, Hypothesis 1 is supported.

Table 5 Regression Results: The Existence of Peer Effect

	(1)	(2)
VARIABLES	Model 1	Model 2
AI_Peer		0.707***
		(0.047)
SIZE	0.028***	0.016***
	(0.004)	(0.004)
AGE	0.233***	0.086***
	(0.014)	(0.013)
Tobin_Q	0.000	0.001
	(0.000)	(0.000)
INST	0.003	0.011
	(0.015)	(0.014)
BOARD	-0.054**	-0.026
	(0.019)	(0.019)

Constant	-1.047***	-0.504***
	(0.105)	(0.103)
Observations	17,040	17,040

Notes: Year dummy and province dummy variables are included, but not reported here. Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed test).

The results in Table 6 show the impact of the peer effect of artificial intelligence technology on production efficiency. Model 3 represents the baseline model containing only control variables, while Model 4 is the main effects model after including the independent variables. The variable "AI_Peer" serves as the key measure of the peer effect of AI usage, and production efficiency is assessed using TFP. In Model 4, the regression coefficient for "AI_Peer" which captures the peer effect of AI technology adoption, is 1.457 ($p < 0.001$). This suggests that after controlling for various factors, the peer effect of AI adoption is positively associated with production efficiency. In other words, as the peer effect of AI adoption increases, there is a significant improvement in production efficiency. Therefore, the regression results support Hypothesis 2.

Table 6 Regression Results: Productivity Efficiency

	(3)	(4)	(5)
VARIABLES	Model 3	Model 4	Model 5
AI_Peer		1.457***	1.548***
		(0.150)	(0.160)
Policy	0.009	-0.035	0.123*
	(0.018)	(0.019)	(0.049)
AI_Peer × Policy			-0.948***
			(0.281)
AI	0.079**	0.038	0.036
	(0.027)	(0.027)	(0.027)
SIZE	0.072***	0.052***	0.051***
	(0.014)	(0.014)	(0.014)
AGE	0.750***	0.413***	0.398***
	(0.046)	(0.048)	(0.048)
Tobin_Q	0.003**	0.004**	0.004**
	(0.001)	(0.001)	(0.001)
BOARD	0.024	0.040	0.039
	(0.033)	(0.033)	(0.033)
INST	-0.122***	-0.087	-0.086
	(0.050)	(0.050)	(0.050)
Constant	3.081***	4.277***	4.340***
	(0.313)	(0.317)	(0.319)
Observations	17,040	17,040	17,040

Notes: Year dummy and province dummy variables are included, but not reported here. Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed test).

To examine the relationship between the institutional environment and the peer effect, Model 5 includes an interaction term "AI_Peer × Policy". As shown in Table 6, the regression coefficient for "AI_Peer × Policy" is -0.948 ($p < 0.001$). This suggests that the peer effect on the productivity gains from AI technology adoption is more pronounced before the initiative of pilot zones. In other words, within the policy environment of non-pilot cities, increased AI adoption by peer companies has a stronger impact on the focal company's productivity gains. These findings support Hypothesis 3, which posits that the institutional environment and peer effects have a "substitution" effect, indicating that the policy of the National New-Generation Artificial Intelligence Innovation Development Pilot Zone" may alter the strength of the peer effect in driving productivity improvements.

6 CONCLUSIONS

First, there is a significant industry peer effect in AI technology adoption. The regression results in Table 5 show that after controlling for variables such as firm size, firm age, and Tobin's Q, the regression coefficient for "AI_Peer" (representing AI technology adoption by firms within the same industry) is significantly positive, indicating that AI adoption by firms in the same industry significantly promotes AI adoption by the focal firm. This result supports Hypothesis 1. Furthermore, the peer effect of AI technology adoption contributes to improved production efficiency. As shown in Table 6, the regression coefficient for for "AI_Peer" is significantly positive, which suggests after controlling for other variables, an increase in peer effects significantly improves production efficiency (measured by TFP), thus supporting Hypothesis 2. Finally, by incorporating an interaction term of "AI_Peer × Policy", we observe a "substitution" effect between the institutional environment and the AI peer effect. Specifically, the institutional environment appears to negatively moderate the relationship between the peer effect and firm production efficiency, supporting Hypothesis 3.

7 IMPLICATIONS

For companies, it is crucial to actively learn from the experiences of their peers. Companies should prioritize the peer effect and closely monitor AI adoption trends within their industry. By studying the successful AI applications of peer companies, they can more efficiently innovate and implement AI technology, avoid potential pitfalls, reduce risks associated with technology adoption, and ultimately enhance their production efficiency. For instance, companies can engage in technical exchanges with peers to share practical insights on AI applications in areas such as production process optimization and product innovation. Additionally, companies must respond proactively to changes in the institutional environment. They should closely monitor AI-related policy changes, especially those impacting the region where they are located. When a region is designated as a pilot zone, companies should fully leverage the available policy resources without becoming overly reliant on them, as this could divert attention from learning from peer experiences. With policy support, companies should maintain their own initiative and drive innovation in AI applications, continuously improving production efficiency. For example, while benefiting from policy-driven R&D funding, companies should also actively collaborate with peers to explore more effective ways of applying AI technology.

For the government, it is essential to optimize both the formulation and implementation of AI-related policies. When designing AI policies, the government should carefully consider their impact on peer effects. Policies should not only encourage AI adoption but also foster a competitive and collaborative environment among businesses. Overly interventionist policies should be avoided, as they may undermine the positive impact of peer effects. For instance, the government could design policies that promote technological exchange and collaboration between firms, thereby strengthening the peer effect and driving industry-wide development. Furthermore, the government should enhance policy guidance and provide more tailored services to businesses, such as building platforms for AI technology sharing and organizing industry-wide training sessions to help businesses gain valuable knowledge and experience. Differentiated policies should be developed based on the specific characteristics of businesses in different regions to guide them in effectively applying AI, improving production efficiency, and supporting coordinated regional economic development.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This research is supported by funding from the National Natural Science Foundation of China (No. 71602196; No. 71810107002), Institute of Regional Openness and Cooperation of Sun Yat-sen University and the 14th Five-Year Plan for the Development of Philosophy and Social Sciences of Guangzhou City (2023JDGJO8).

REFERENCES

[1] Liu J, Chang H, Forrest J Y L, et al. Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. Technological Forecasting and Social Change, 2020, 158: 120142.

[2] Yang C H. How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan Region. Research Policy, 2022, 51(6): 104536.

[3] Robertson M, Swan J, Newell S. The role of networks in the diffusion of technological innovation. Journal of management studies, 1996, 33(3): 333-359.

[4] Ng A. Machine learning yearning: Technical strategy for ai engineers in the era of deep learning. 2019. https://www. mlyearning.org.

[5] Waltersmann L, Kiemel S, Stuhlsatz J, et al. Artificial intelligence applications for increasing resource efficiency in manufacturing companies—a comprehensive review. Sustainability, 2021, 13(12): 6689.

[6] Alonge E O, Dudu O F, Alao O B. Utilizing advanced data analytics to boost revenue growth and operational efficiency in technology firms. International Journal of Frontiers in Science and Technology Research, 2024, 7(2): 039-059.

[7] Rhine R J. The effect of peer group influence upon concept-attitude development and change. The Journal of Social Psychology, 1960, 51(1): 173-179.

[8] Winston G, Zimmerman D. Peer effects in higher education. College choices: The economics of where to go, when to go, and how to pay for it. University of Chicago Press, 2004, 395-424. DOI: https://doi.org/10.7208/chicago/9780226355375.003.0010.

[9] Glaeser E L, Sacerdote B I, Scheinkman J A. The social multiplier. Journal of the European Economic Association, 2003, 1(2-3): 345-353.

[10] Ding W, Lehrer S F. Do peers affect student achievement in China's secondary schools?. The Review of Economics and Statistics, 2007, 89(2): 300-312.

[11] Bandura A. Self-efficacy: toward a unifying theory of behavioral change. Psychological review, 1977, 84(2): 191.

[12] Wexley K N, Latham G P. Developing and training human resources in organizations. 1991.

[13] Weiss H M. Subordinate imitation of supervisor behavior: The role of modeling in organizational socialization. Organizational behavior and human performance, 1977, 19(1): 89-105.

[14] Weiss H M. Social learning of work values in organizations. Journal of applied psychology, 1978, 63(6): 711.

[15] Latham G P, Saari L M. Application of social-learning theory to training supervisors through behavioral modeling. Journal of Applied Psychology, 1979, 64(3): 239.

[16] Leary M T, Roberts M R. Do peer firms affect corporate financial policy?. The Journal of Finance, 2014, 69(1): 139-178.

[17] Becker M C, Knudsen T, Swedberg R. Schumpeter's Theory of Economic Development: 100 years of development. Journal of Evolutionary Economics, 2012, 22(5): 917-933.

[18] Bettis R A, Weeks D. Financial returns and strategic interaction: The case of instant photography. Strategic Management Journal, 1987, 8(6): 549-563.

[19] Schumpeter J A. Capitalism, socialism and democracy. Routledge, 2013.

[20] Chen M J, Miller D. Reconceptualizing competitive dynamics: A multidimensional framework. Strategic management journal, 2015, 36(5): 758-775.

[21] Chen M J, Michel J G, Lin W. Worlds apart? Connecting competitive dynamics and the resource-based view of the firm. Journal of Management, 2021, 47(7): 1820-1840.

[22] Smith K G, Ferrier W J, Ndofor H. Competitive dynamics research: Critique and future directions. The Blackwell handbook of strategic management, 2005, 309-354.

[23] Mithas S, Tafti A, Mitchell W. How a firm's competitive environment and digital strategic posture influence digital business strategy. MIS quarterly, 2013, 511-536.

[24] Gans J S. Artificial intelligence adoption in a competitive market. Economica, 2023, 90(358): 690-705.

[25] Farrell M J. The measurement of productive efficiency. Journal of the royal statistical society series a: statistics in society, 1957, 120(3): 253-281.

[26] Yi Z, Ayangbah S. The impact of ai innovation management on organizational productivity and economic growth: an analytical study. International Journal of Business Management and Economic Review, 2024, 7(3): 61-84.

[27] Song L, Wen Y. Financial subsidies, tax incentives and technological innovation in China's integrated circuit industry. Journal of Innovation & Knowledge, 2023, 8(3): 100406.

[28] Del Gatto M, Di Liberto A, Petraglia C. Measuring productivity. Journal of Economic Surveys, 2011, 25(5): 952-1008.

[29] Olley G S, Pake A. The dynamics of productivity in the telecommunications equipment industry. Econometrica, 1996, 64(6): 1263–1297.

[30] Grennan J. Dividend payments as a response to peer influence. Journal of Financial Economics, 2019, 131(3): 549-570.

[31] Chen W, Srinivasan S. Going Digital: Implications for Firm Value and Performance. Harvard Business School Working Paper, 2020, 19-117.

[32] Manski C F. Identification of endogenous social effects: The reflection problem. The review of economic studies, 1993, 60(3): 531-542.