TWO STUDIES ON THE ARTIFICIAL INTELLIGENCE INVESTMENTS OF FIRMS, EFFICIENCY ENHANCEMENT AND SPILLOVER EFFECT IN SUPPLY CHAIN

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The Hong Kong Polytechnic University

2023

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Two Studies on the Artificial Intelligence Investments of Firms, Efficiency Enhancement and Spillover Effect in Supply Chain

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A thesis submitted in partial fulfilment of the requirements for the degree of Master of Philosophy
May 2023

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Abstract

The past decade has seen the rapid development of artificial intelligence (AI) along with related technologies such as machine learning, natural language processing, deep learning, and computer vision. AI becomes more powerful to directly impact the creation and development of a wide range of products and services, thereby transforming the entire economy and society. Particularly, AI has revolutionized the development of new manufacturing technologies and products that can be applied in a wide range of fields.

AI Investments have led the manufacturing industry toward intelligent manufacturing, which is constantly developing. Undoubtedly, the breakthroughs brought about by AI technology can significantly change the production methods of firms, thereby affecting their operational management. A recent report suggests that with the rapid growth of AI Investments, more and more firms have commercially implemented AI (from 20% in 2017 to 50% in 2022) (McKinsey, 2017, 2022). However, the actual return on AI Investments still needs to be determined. Only 10% of more than 3,000 firms in the survey reported that their AI investments have yielded significant benefits and mitigated relevant operational risks (Jeans, 2020). Therefore, it is crucial and topical to examine the true impact of AI on firms' operational efficiency.

In Study 1, I leverage a unique proprietary data set provided by Burning Glass Technologies (BGT) and use machine-generated keywords to identify AI specialist jobs. By matching AI talent recruitment information with Compustat's data and using the fixed effects panel models (FEM) and dynamic panel data (DPD) models, I can longitudinally estimate the impact of AI investments on firms. Specifically, I apply stochastic frontier analysis (SFA) and generalized method of moments (GMM) techniques to examine the impact of AI investments on the operational efficiency of firms and relevant moderators.

Study 2 is based on the findings of Study 1, and further examines the impact of focal firms' AI investments on suppliers' operational efficiency and relevant moderators. By introducing FactSet

Revere Supply Chain Relationship data, I illustrate the spillover effect of AI investments from the perspective of social network theory and provide valuable insights for improving the buyer-supplier relationship.

This research enables us to understand the real business value of AI and create new opportunities to explore the impact of AI at the firm level. It also provides valuable insights into the contextual factors that make firms' AI capability a more crucial asset in the era of the intelligent machine era.

Keywords: Artificial intelligence, operational efficiency, operational complexity, industry dynamism, spillover effect, dynamic panel data

Acknowledg(e)ments

Looking back my two-year MPhil study at The Hong Kong Polytechnic University, it's my great honor to receive encouragement, support, and help from many people which will become a precious treasure in my life. I would like to express my sincere gratitude to all people who have supported and encouraged me to fight for my dreams.

First of all, *one who could propagate the doctrine, impart professional knowledge, and resolve doubts*. My sincerest thanks must go to my chief supervisor, Prof. Andy C. L. YEUNG, for offering me the precious opportunity to study and carry on research under his guidance. Prof. YEUNG is not only an excellent scholar, but also an approachable advisor in my life. He led me to delve deeper into the field of operations management and provided me with many valuable guidance. I sincerely appreciate his support, encouragement, and understanding, which are of great significance to me.

Secondly, I would like to express my gratitude to the Board of Examiners: Prof. Zhou XU, Prof. Timon DU and Dr. Yuanzhu ZHAN. I sincerely appreciate that they can participate in my oral examination and provide me with constructive comments on improving the quality of my thesis.

Thirdly, I would like to express my special gratitude to all the academic staff, administrative staff, and research students in the Department of Logistics and Maritime Studies who support me in these two years.

Finally, and most importantly, *who says mine heart like a blade of grass, could repay her/his love's gentle beams of spring sun?* I'm deeply grateful to my parents and my grandmother. My parents have been strict with me since I was a child, and in the process of growing up, they not only fully considered my feelings on various issues, but always advised the direction for me at the right time. My grandmother, along with my parents, witnessed my success and cheered me on from setbacks. Without them, I could not have completed this thesis.

I would like to sincerely wish all of you a happy, long and healthy life.

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Chapter 1: Introduction

1.1 Research Background

1.1.1 Practical Background (Industry)

In the summer of 1956, Dartmouth College witnessed the proposition of the concept of "Artificial Intelligence (AI)" by many scientists, who made great contributions to the birth of AI. AI is an emergent technical science that can extend the theories, methods, technologies, and application systems of human intelligence (GSMA, 2019). In the past few decades, AI has become the decisive force driving humanity development. Many industries fully recognize the importance of AI technology in leading the transformation and rapidly carry out innovations in AI. In many countries, the development of AI is regarded as a major strategy to improve national competitiveness and maintain national security, striving to be in a leading position in international scientific and technological competition. Many large firms are increasing AI investments to get a head start in the global marketplace (Stanford, 2023).

With the further maturation of AI technology and increasing investments from government and industry, the scale of the global AI industry has entered a period of rapid growth, and the application of AI in **operations management (OM)** has flourished. According to the IBM Global AI Adoption Index (IBM, 2022), 35% firms report that they are currently using AI in their business, and another 42% are exploring AI. Meanwhile, McKinsey (2021) stated in its report titled '*The State of AI'* that 56% of respondents adopted AI in at least one function in 2021, up from 50% in 2020.

As a matter of course, implementation of AI is not an easy task, and other survey data show the downsides of AI. Research has increasingly focused on the true return of AI investments. A report from MIT's Sloan Management Review and Boston Consulting Group (BCG) found that in a survey of more than 3,000 firm managers on AI expenses, only 10% said their investments had yielded significant financial gains so far. Shervin Khodabandeh, who co-leads BCG's AI and Analytics business in North America, said that the gains from AI technology had not kept pace with the increasing adoption of AI (Jeans, 2020).

Early (2023) is even blunter in pointing out the possibility of considerable bubbles in AI investments and cautions firms to think carefully before making investments. A recent survey of 3,000 chief technology executives in 10 countries (McKinsey, 2017) suggests that only a small portion of firms have commercially implemented AI, and the actual return on AI investments is highly questionable. Evidently, the industry generally believes that obtaining returns that match AI investments is a significant challenge in the context of large-scale implementation of AI.

In summary, the complex and changeable market environment has triggered profound reflection, and it is necessary to explore whether AI investments can lead to the actual improvement of operational efficiency—a key factor in firms' operations management. In addition, it is important to understand the influence of potential factors on this effect. Research questions are listed in Section 1.2.

1.1.2 Theoretical Background (Academic)

"*Success in creating AI would be the biggest event in human history. … It would take off on its own and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn't compete, and would be superseded.*"

—Stephen Hawking, theoretical physicist

In investigating whether AI investments are effective, prior studies examined the relationship between generalized research and development (R&D) investments and financial performance (Hendricks et al., 2009; Lam, 2018; Yiu et al., 2020). Most of them found a positive relationship between R&D investments and financial performance. Firms who invest actively in R&D investments have concrete future development goals, leading to continuous improvement of operation processes, thus enhancing financial return.

However, no study has specifically focused on the impact of AI investments on operational efficiency. A plausible reason is that firms adopt AI investments merely to catch up with the hyped AI trend, while the actual implementation effect is highly questionable.

This research narrows the gap by examining the relationship between AI investments and operational efficiency to determine the validity of AI investments.

Research Gap 1: Existing studies have not reached a consensus about whether AI investments are effective in improving operational efficiency.

Previous studies mainly used surveys or secondary data to examine the relationship between R&D investments and operational performance when they face the problem of whether R&D investments are valuable. Guan et al. (2023) examined the relationship between R&D investment and firm performance during the COVID-19 pandemic. Results indicated that firms that invested more in R&D achieved stronger resistance during the pandemic. Zhang et al. (2022) found that absorptive capacity from customers, universities, and research institutes have significant mediating roles in the impact of R&D investment on firm innovativeness. Yiu et al. (2020) found that firms' financial returns on R&D investments improved greatly when they implemented Six Sigma and achieved the enhancement of operational efficiency.

At this moment, an important question is what circumstances will strengthen or weaken the impact of AI investments. This thesis narrows this gap by investigating the moderating factors in the relationship between AI investments and operational efficiency.

Research Gap 2: Because there is no consensus about whether AI investments have a moderating effect, more empirical studies are needed to examine the issue.

Suppose AI Investments can improve operational efficiency in the scope of focal firms, does the spillover effect of AI Investments exist in the supply chain network due to the close buyer-supplier relationships? In exploring the spillover effect in OM, previous studies have focused on information systems, the stock market, and accounting studies at the firm level. For example, Zambrana (2021) showed that there is a spillover effect between firms that own the best-performing funds and shares of the parent company. Financial institutions can benefit from operating asset management departments because they can bolster brand reputation and benefit from spillovers. Kim and Swink (2021) found that the impact of suppliers' relationships with key customers on performance depends on their own operational efficiency. Strong suppliers can gain a higher market share and lower profitability as relationships with key customers strengthen.

Only a few studies have investigated R&D investment's potential spillover effect, but no study has yet been conducted on the spillover effect of AI investments precisely. For example, Higon (2007) showed that R&D investments from the domestic manufacturing industry have a positive impact on industry productivity, but foreign R&D investments have no significant return. Ugur et al. (2020) explored the pros and cons of R&D investments. On the one hand, the potential benefits of R&D investments cannot be fully utilized, resulting in insufficient investment enthusiasm. On the other hand, R&D spillovers are a source of productivity gains. Therefore, investigating the spillover effect of AI investments on operational efficiency is needed to narrow this gap.

Research Gap 3: Previous studies have discussed spillover effects in many fields, such as information systems and accounting studies, but researchers have not yet examined how focal firms' AI investments influence suppliers' operational efficiency. Even fewer studies consider the factors from the perspective of the supply chain relationship.

1.2 Research Objectives

To narrow existing research gaps, this thesis investigates four research questions.

Research Question 1: What is the impact of artificial intelligence investments (AII) on operational efficiency (OE) in the U.S. manufacturing industry?

I address this question by matching Burning Glass Technologies' AI job postings with Compustat's financial data and using panel data models with fixed effects and dynamic panel data models.

Research Question 2: How could different contextual factors potentially strengthen or weaken this impact?

I address this question by considering firms' operational complexity, R&D intensity, and industry dynamism and applying generalized method of moments (GMM) techniques.

Research Question 3: What is the spillover effect of focal firms' AII on suppliers' OE in the U.S. manufacturing industry?

I address this question by matching Burning Glass Technologies' AI job postings with Compustat's financial data and FactSet Revere Supply Chain Relationship data and using FEM and DPD models.

Research Question 4: How this spillover effect could be potentially strengthened or weakened by different contextual factors?

I address this question from perspectives of complexity and connectedness factors and apply generalized method of moments (GMM) techniques.

1.3 Research Framework

Figure 1.1 illustrates this thesis's overall framework, comprising two related studies. The purpose of this thesis is to examine how focal firms' AI investments influence their operational efficiency and how focal firms' AI investments have a spillover effect on suppliers' operational efficiency.

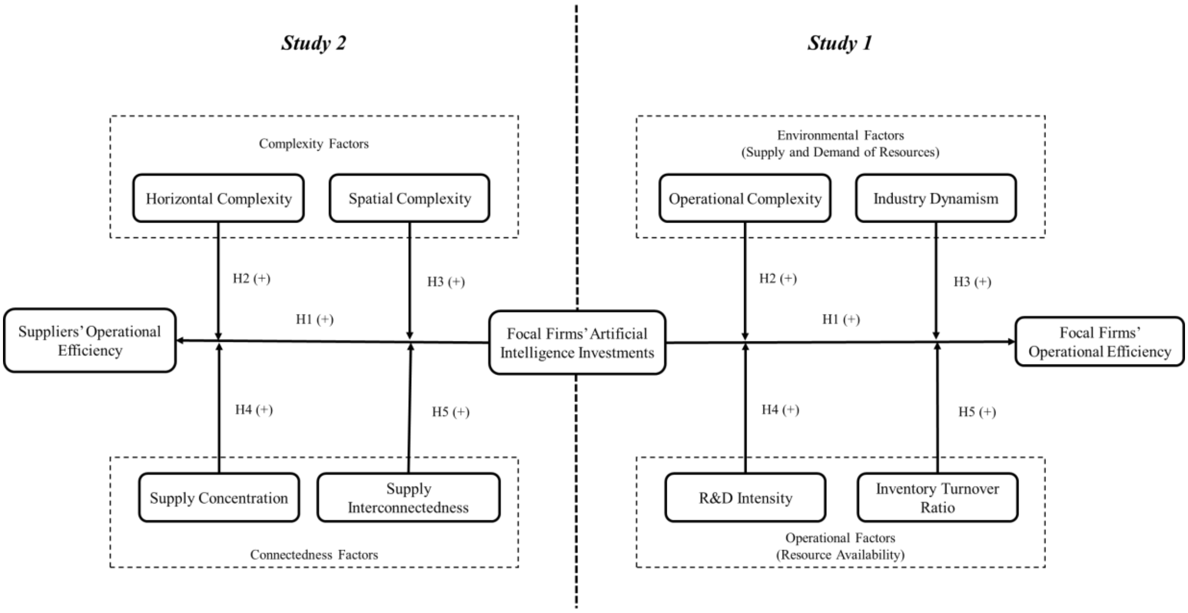


Figure 1.1 Overall Research Framework for the Thesis

In Study 1, I investigated the relationship between AI investments and operational efficiency at the focal firm level and the impact of different contextual factors in this relationship. In Study 2, I investigated the spillover effect of this impact at the buyer–supplier level and relevant moderators.

1.4 Research Significance

The significance of this thesis lay in its contributions to understanding the impact of AI investments on operational efficiency and the relevant spillover effect.

Firstly, this study adopts a novel perspective and provides a wealth of empirical evidence to answer the question of whether AI investments can bring true effects. Secondly, this study enriches knowledge about the moderating factors of environmental factors and operation factors. Third, this research expands on the spillover effect of AI investments, bridging the gap of technology management studies between focal firms and their collaborators. Finally, this research enriches empirical studies about U.S. manufacturing firms' AI investments.

1.5 Thesis Structure

This thesis consists of four chapters. Chapter 1 introduces the research background from both theoretical and practical perspectives, summarizes existing research gaps, and proposes research questions.

Chapter 2 presents Study 1 about the impact of AI investments on operational efficiency and the moderating effects of environmental and operational factors. The purpose of this study is to explore whether and when AI investments are effective in improving operational efficiency.

Chapter 3 presents an extended Study 2 on the impact of focal firms' AI investments on suppliers' operational efficiency and the moderating roles of complexity and concentration factors. The purpose of this study is to investigate whether and when it pays to adopt AI investments in the supply chain network. More specifically, this study applies social network theory and organizational learning theory to study the spillover effect of AI investments, which fills the gap in relevant studies.

Chapter 4 summarizes general conclusions, illustrates theoretical implications and managerial implications, and discusses the limitations and directions of future research.

Chapter 2 Study 1: The Impact of Focal Firms' Artificial Intelligence Investments on Focal Firms' Operational Efficiency

2.1 Introduction

2.1.1 Research Background

Artificial intelligence (AI) is a collective term for the capabilities enabled by machine learning and analytical systems, that are considered to have human-like intelligence. Typically, AI capabilities include natural language processing, image and speech recognition, and intelligent autonomous systems (IBM, 2022). We are currently living in an age of astonishing progress in machine learning technology.

The impact of technology on firms has always been one of the most important topics in **Operations Management (OM)**. The rapid development of new technologies often intensifies the business competition pattern, increasing market competitiveness and threatening the survival of some traditional industries. Today, firms are increasingly focusing on the competitive advantage brought by technological innovations, and AI is undoubtedly one of the most promising and fastest-growing technologies. In the manufacturing sector, AI is revolutionizing manufacturing operations and has great potential to improve production efficiency, demand forecast, product quality, and supply chain efficiency (Stanford, 2023).

There is no doubt that the breakthroughs brought about by AI technology can greatly change the production methods of firms, thereby affecting operational efficiency. Despite the global optimism about the future of AI, the actual return of AI Investments is still questionable. Only 10% of more than 3,000 firms in the survey reported that their AI investments had yielded significant benefits and mitigated relevant operational risks (Jeans, 2020). Most existing research focuses on the impact of AI on the labor market or economic growth (Aghion et al., 2018; Babina et al., 2020; Furman & Seamans, 2019; Korinek & Stiglitz, 2018; Varian, 2018). Few studies have been conducted to examine the impact of AI at the firm level, particularly from the OM perspective (Wamba-Taguimdje et al., 2020; Yang et al., 2020).

The debate over the actual value of AI investments is still ongoing among leading firms. There are widespread concerns that optimism about the potential value of AI is misplaced and unfounded and that the overall impact of AI on operations might be hyped up in the years ahead. From the institutional perspective, it is possible that firms adopt AI ostensibly without really improving performance. AI investments may be driven by global enthusiasm about recent technological innovations, leading to unrealistic expectations that cannot be met (Aghion et al., 2018; Cao et al., 2018). Therefore, there is an urgent need to explore AI's actual economic impact on individual firms' operational performances. However, so far, there has been little rigorous research examining the impact of AI on operational performance at the individual firm level.

The lack of empirical evidence from a large sample of individual firms is mainly due to the difficulty in obtaining firm-level AI usage data (Furman & Seamans, 2019). In this thesis, I overcome this problem by using a unique proprietary data set that covers a wealth of microdata of individual U.S. firms' recruitment information (Babina et al., 2020; Hershbein & Kahn, 2018). Driven by AI technologies' reliance on human capital rather than physical assets (Babina et al., 2020), I use a unique measurement of AI investments based on detailed firms' AI talent recruitment data. I implement a contingent dynamic capabilities (CDC) perspective on firms' AI investments to understand the most important conditions for AI investments.

2.1.2 Research Objectives

To narrow existing research gaps, in Study 1, I investigate two research questions.

Research Question 1: What is the impact of artificial intelligence investments (AII) on operational efficiency (OE) in the U.S. manufacturing industry?

I address this question by matching Burning Glass Technologies' AI job postings with Compustat's financial data and using panel data models with fixed effects and dynamic panel data models.

Research Question 2: How could different contextual factors potentially strengthen or weaken this impact?

I address this question by considering firms' operational complexity, R&D intensity, and industry dynamism and applying generalized method of moments (GMM) techniques.

2.2 Literature Review and Hypotheses Development

2.2.1 Relationships Between AI Investments and Operational Efficiency

Instead of focusing on specific applications, the basic ideas of AI lay the foundation for many applications such as natural language processing, machine vision, and intelligent data retrieval. This is a broad term used to describe technologies with humanoid intelligence (Yang, 2022). The most popular AI technologies include machine learning

(ML), natural language processing (NLP), deep learning (DL), computer vision (CV), and others (Stanford, 2023).

The **traditional resource-based view (RBV)** emphasizes that firms gain a competitive advantage by possessing unique and heterogeneous capabilities derived from firms' existing resource base (Barney, 1991; Wernerfelt, 1984). Different from RBV, the dynamic capabilities view emphasizes firms' capacity to create, extend, or modify their current resource base (Helfat et al., 2007; Hitt et al., 2016). Applying the dynamic capabilities view allows us to discuss how ongoing AI investments might enable firms to regenerate their resource base and improve operational capabilities. Despite the popularity of the dynamic capabilities view, some scholars argue that a dynamic capability, like RBV, is context-incentive (Gunasekaran et al., 2017; Ling-yee, 2007). To complement this view, CDC perspective incorporates contingency theory into the analysis to explore conditions under which organizational resources or capabilities are more effective. According to **contingency theory,** adapting an organization's resources or capabilities to its internal and external environments allows these unique intangible resources or capabilities to be better utilized, and needs and contradictions at different levels of the organization can be better understood for decision-making (Balarezo & Nielsen, 2022; Volberda et al., 2012). Therefore, contingency theory provides a useful theoretical perspective for understanding how the impact of AI investments is affected by different internal (e.g., operational complexity and R&D intensity) and external (e.g., industry dynamism) operating environments.

Following the logic of dynamic capabilities, I argue that firms' investments in AI improve their information processing capability (Chatterjee et al., 2023; Srinivasan & Swink, 2018). The importance of this capability is that it allows managers to better combine information from different sources, types, and qualities, enabling firms to make more accurate forecasts and judgments. As a result, firms may improve production processes, enhance human–machine collaboration, and improve product quality, leading to higher operational efficiency. In addition, the information processing capability developed by AI investments will enable firms to integrate their existing resource bases better, strengthen supply chain coordination, improve operational strategy flexibility, and bring new opportunities for efficiency improvements (Duan et al., 2019; Kortmann et al., 2014). In this thesis, I examine the impact of AI investments on operational efficiency based on the CDC perspective, which enriches the dynamic capabilities theory by considering a contingency perspective (Lam et al., 2019; Schilke, 2014; Vergne & Durand, 2011). Hence, I propose the following main hypothesis:

HYPOTHESIS 1 (H1). *AI investments have a positive impact on operational efficiency.*

2.2.2 Role of Environmental Factors (Supply and Demand of Resources)

(1) Role of Operational Complexity

Operational complexity refers to the number of elements or subsystems and the degree of connectivity and interaction among these elements in organizational or operational systems (Wu et al., 2007). Operational complexity is also regarded as dynamic complexity (Dittfeld et al., 2018; Wu et al., 2007), which is related to uncertainty and has been defined as "the unpredictability of a system's response to a given set of inputs" (Bozarth et al., 2009). Uncertainty is related to time and randomness (Serdarasan, 2013), contradictions and ambiguities in processes, and demand and/or the geopolitical environment (Isik, 2010).

Researchers have stated that firms with more complex operations tend to have more creative discussions (Melero, 2011; Miller & Del Carmen Triana, 2009), enhance resource availability, which may help them deal with complex problems, and improve innovativeness. Thus, when operational complexity is high, similar to the logic of the value-in-diversity hypothesis (Cox & Blake, 1991), complexity can help firms gain a competitive advantage (Upadhyay & Triana, 2021).

In summary, operational complexity increases with the number of employees, product categories, business processes, and customer segmentations (Chand et al., 2022). The increase in operational complexity inevitably leads to more significant operational costs and less operational efficiency. Additionally, operational complexity often results in multiple conflicting requirements across organizational units, increasing operational problems and risks. In complex operating environments, firms are under constant pressure to streamline operations, improve workflows, and reduce risks, making AI-related advanced analytical and intelligent capabilities even more important. However, if a firm's operations are fairly straightforward, the full potential of AI may not be realized. Therefore, the more complex the operations, the more valuable AI investments are to individual firms. Hence, I propose the following hypothesis:

HYPOTHESIS 2 (H2). *Higher operational complexity will strengthen the positive impact of AI investments on operational efficiency.*

(2) Role of Industry Dynamism

Industry dynamism is defined as the level of instability (Boyd, 1990) which represents the frequency, degree, and unpredictability of changes in a firm's operating environment (Beard, 1984; Sabherwal et al., 2019; Starbuck, 1976). This core concept attracted much attention when scholars moved from closed-systems to open-systems models of organizations, which regarded the environment as having a greater role (Scott, 1998), and then from variance methods to models that more directly recognize the role of process and change (Chia, 2002; Van de Ven, 2007). This concept also exists in diverse research fields, such as executive turnover (Henderson et al., 2006), competitive advantage (Suarez & Lanzolla, 2007), dynamic capabilities (Eisenhardt & Martin, 2000), and decision-making (Mueller et al., 2007).

The dynamic industrial environment is characterized by fluctuating market demands, unpredictable technology trends, and ambiguous regulatory environments (Anand & Ward, 2004; Dale Stoel & Muhanna, 2009; J. G. Wang et al., 2021). A high level of dynamism usually heralds the obsolescence of current knowledge and a new phase of industry development, which requires new ideas, strategies, and business models (Larrañeta et al., 2014). In this case, dynamism may reduce the relevance of the founders' prior shared knowledge. Applying machine learning techniques and intelligent algorithms, AI enables firms to substantially improve their operational capability in a turbulent and uncertain environment. Therefore, under higher industry dynamism, the impact of AI investments on firms' operational efficiency is likely to be more significant (Li et al., 2022). Hence, I propose a further hypothesis as follows:

HYPOTHESIS 3 (H3). *Higher industry dynamism will strengthen the positive impact of AI investments on operational efficiency.*

2.2.3 Role of Operational Factors (Resource Availability)

(1) Role of R&D Intensity

Firms' R&D intensity refers to their accumulated innovation capabilities enabled by their current and past product-invention and process-invention knowledge and activities. R&D intensity is usually measured by the ratio of a firm's R&D expenditures to its sales income (percentage of revenue reinvested in R&D) in 1 year (Chao & Kavadias, 2013). Numerous studies have shown that R&D investments boost firms' operational performance (productivity), but productivity growth is clearly positive only after a certain amount of knowledge has been accumulated. There are significant intersectoral differences in R&D investments. Firms that invest in high-tech research activities will benefit more. For example, R&D investments can more effectively improve the operational performance of multinational firms facing complex operating environments, and the improved operating performance can feed back into R&D investments (Kwon et al., 2022; Peters et al., 2022).

The higher a firm's R&D intensity, the stronger its innovation capability and the better it will integrate AI technology to more efficiently transform AI investments into improving operational efficiency (Guarascio & Tamagni, 2019; Lu et al., 2022). When suffering from external negative shocks, firms with higher R&D intensity can effectively resist adverse effects and ensure their operational performance stays within a controllable range by virtue of the unique advantages conferred by technological innovation (Coad et al., 2016; Krieger et al., 2022). However, suppose a firm's R&D intensity is limited. In that case, it will be difficult for it to integrate AI capabilities into its overall technology configuration, and it will be more difficult for its AI investments to achieve the desired effects (Tse et al., 2020). Hence, I develop a further hypothesis as follows:

HYPOTHESIS 4 (H4). *Higher R&D intensity will strengthen the positive impact of AI investments on operational efficiency.*

(2) Role of Inventory Turnover Ratio

The inventory turnover ratio is the ratio of the operating cost (cost of goods sold) of a firm to the average inventory balance in a certain period (Modi & Cantor, 2021). It is used to reflect whether the liquidity of inventory and the proportion of inventory funds are reasonable to promote firms' efficiency in applying capital and enhance their short-term solvency while ensuring sustainable operations. The inventory turnover ratio is a comprehensive indicator that measures firms' input into production, inventory management level, and sales recovery ability.

The inventory turnover ratio reflects firms' sales efficiency and inventory utilization efficiency. The higher the inventory turnover rate of a firm, the stronger its sales ability, the higher its liquidity, and the less capital is occupied in its inventory. This ratio is the embodiment of the necessary core competence of firms. Firms can invest more capital into AI, and under the same level of AI investments, they can create higher value and improve operational efficiency.

The inventory turnover ratio of firms varies greatly across industries. For example, fast-moving consumer goods (FMCG) are consumer goods with short service lives and fast consumption rates, including packaged food, personal hygiene products, tobacco, alcohol, and other beverages (Guan et al., 2023). Consequently, FMCGs have a faster iteration speed, and customer demands change more rapidly compared to heavy industrial products, such as excavators and heavy trucks. Therefore, given these characteristics, AI investments can play a more significant role and improve operational efficiency more effectively in the FMCG industry than in other industries. Finally, the last hypothesis is proposed as follows:

HYPOTHESIS 5 (H5). *Higher inventory turnover ratios will strengthen the positive impact of AI investments on operational efficiency.*

The full theoretical framework is shown in Figure 2.1.

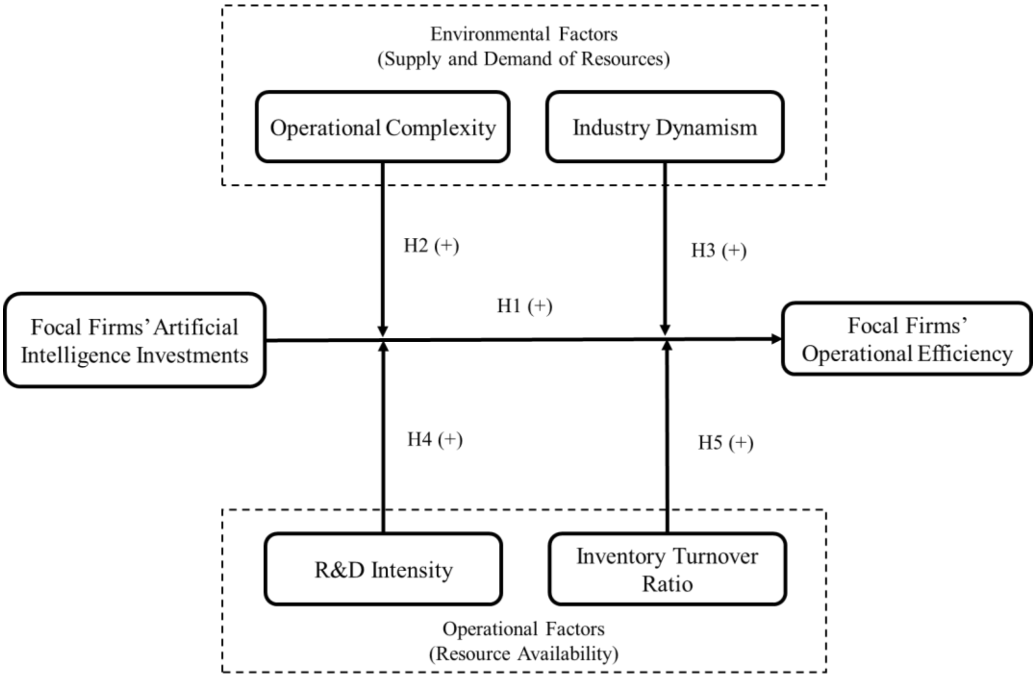


Figure 2.1 Theoretical Framework of Study 1

2.3 Research Methodology

2.3.1 Data Collection

Table 2.1 illustrates the data-cleaning process. I collected longitudinal data from multiple sources to develop my measurements. Specifically, I used a unique proprietary data set developed by Burning Glass Technologies (BGT) that covers over 180 million firm-level recruitment data in the United States from 2010 to 2021. BGT is an employment analytical firm that examines more than 40,000 posting sources and firm websites to combine and organize job vacancies into a systematic and machine-readable form. The key advantage of BGT data is the broad coverage and detailed job information. The data set captures a massive number of jobs and covers nearly all the vacancies posted in the United States, either online or offline. In addition, the BGT data contain details for each job, such as job title, occupation, geography, employer name, and most importantly for my research, the specific skills required. Using machine-generated keywords to identify AI specialist jobs, I examined individual firms' recruitment information on AI talent specifically from the massive BGT database.

I matched firms' job postings to Standard and Poor's Compustat firms to assemble firm-level job recruitments and merged them with other variables. After removing common endings in firm data (e.g., "Inc" and "L.P."), I fuzzy-matched firm names in BGT and Compustat by developing a computer program. As mentioned above, I focused on U.S.-listed manufacturing firms (SIC codes: 2000-3999) and recruitment information from 2010 to 2021. Table 2.2 shows the sample industry distribution across SIC sectors.

Table 2.1 Data Cleaning Process

Panel A: Data Development for Selection Model				
Steps	**Data Screening Steps**	**Reduction in the Number of Firms**	**Number of Firms**	**Database Used**
1	Start with firms with available data between 2010 and 2021	N/A	12,100	Compustat
2	Remove firms in service industries with few or no physical products	3,000	9,210	Compustat
3	Remove firms without	3,000	6210	Compustat

	inventory and employee data			
4	Remove firms not headquartered in the United States	10	6,200	Compustat
5	Remove firms with no job posting data sources in BGT database	3,692	2,508	BGT

Table 2.2 Sample Industry Distribution according to SIC Sectors

SIC	Description	Freq.	Percent (%)	Cumulation (%)
20	Food & Kindred Products	504	5.18	5.18
21	Tobacco Products	17	0.17	5.35
22	Textile Mill Products	45	0.46	5.81
23	Apparel & Textile Products	196	2.01	7.83
24	Lumber & Wood Products	82	0.84	8.67
25	Furniture & Fixtures	170	1.75	10.42
26	Paper & Allied Products	204	2.10	12.51
27	Printing & Publishing	158	1.62	14.14
28	Chemicals & Allied Products	2,389	24.54	38.68
29	Petroleum & Coal Products	137	1.41	40.09
30	Rubber & Misc. Plastic Products	161	1.65	41.74
31	Leather & Leather Products	84	0.86	42.60
32	Stone, Clay, Glass, & Concrete Products	83	0.85	43.46
33	Primary Metal Industries	220	2.26	45.72
34	Fabricated Metal Products	323	3.32	49.03

35	Industrial Machines & Computer Equipment	1,218	12.51	61.55
36	Electronic & Electrical Equipment	1,592	16.36	77.90
37	Transportation Equipment	611	6.28	84.18
38	Instruments & Related Products	1,398	14.36	98.54
39	Miscellaneous Manufacturing Industries	142	1.46	100.00
	Total	9,734	100.00	

2.3.2 Sample and Variables

(1) Measurement of AI Investments

Following the latest methodology (Babina et al., 2020, 2021; Babina et al., 2023), I adopted a new data-driven measure of AI investments based on detailed job recruitment data from BGT.

Previous research relied on a predetermined list of key terms (Hershbein & Kahn, 2018). Given the randomness of the keyword list, Type I errors (mistakenly marking unrelated workers as AI-related) and Type II errors (lacking core AI skills) may appear in the list at the same time. These errors are particularly needed to be addressed in areas with rapid development, such as AI, because new emerging skills can be easily overlooked. My approach circumvented these issues by learning the AI relevance of each of the nearly 15,000 unique skills from the job posting data directly, which are based on their symbiosis with clear core AI skills (the job postings' required skill list). Then, I summarized the skill-level measurement to the job-level by creating continuous AI-related measures for every position, from which I could distinguish employees between AI-skilled employees and non-AI-skilled employees.

I first determined whether the job recruitment was related to AI through machine-generated keywords, which were developed based on machine learning algorithms. Specifically, to identify whether a job was related to AI, I first considered five core AI concepts: artificial intelligence (AI), machine learning (ML), natural language processing (NLP), deep learning (DL), and computer vision (CV). Then, for each skill ω, I defined a metric that reflects the relatedness of that skill to the five core AI technologies (Babina et al., 2020; Babina et al., 2023; Hershbein & Kahn, 2018). This measure captures how "closely" each skill s is related to the core AI skills by estimating the overlap between the skill and core AI concepts:

$$w_s^{All\ AI} = \frac{\#\ \text{of jobs requiring skill}\ s\ \text{and (ML, NLP, DL, CV or AI in required skills or in job title)}}{\#\ \text{of jobs requiring skill}\ s}$$

Table A1 shows the top-10 skills with high AI-relatedness measure. For example, the value of the skill "*Kernel Methods*" is 0.979, which indicates that 97.9% of job postings with "Kernel Methods" as a demanded skill also need at least one core AI skills in the job title. Therefore, having a "Kernel Methods" requirement in the job posting is a strong indication that the position is related to AI.

We defined the job-level AI-relatedness measure for a certain job as the mean (skill-level) measure across all skills required for that job. Following the formula (Babina et al., 2020, 2021; Babina et al., 2023) and letting N denotes the number of required skills listed for job j, the job-level AI-relatedness measure is as follows:

$$\omega_j^{All\ AI} = \frac{1}{N}\sum_{i=1}^{N} \omega_i^{All\ AI}$$

To further refine the measure and to eliminate general skills (e.g., computer programming), I categorized 700 skills that have an AI-relatedness measure above a certain threshold 0.05 and are required in at least 50 job postings into narrow AI skills (e.g., human language data, facial recognition, motion detection, long short-term memory [LSTM], TensorFlow) and skills more broadly related to AI (e.g., statistics, general programming) (Babina et al., 2020). The threshold of 0.05 is set sufficiently low to ensure that I do not miss any ex-ante important AI-skill. Accordingly, the measure $\omega_j^{All\ AI}$ can be decomposed into three components:

$$\omega_j^{All\ AI} = \omega_j^{Narrow\ AI} + \omega_j^{General\ AI} + \omega_j^{\omega < Threhold}$$

Finally, I used $\omega_j^{Narrow\ AI}$ as the primary continuous measure of AI-relatedness of jobs. I transformed this continuous measure into a discrete indicator by defining each job j as AI-related if and only if the measure $\omega_j^{Narrow\ AI}$ was higher than a certain threshold 0.1 (Babina et al., 2020). 0.1 becomes a threshold value that can capture all technical jobs related to AI to achieve the minimization of false positives based on manual data checks. Compared with previous studies that used a bag-of-words method with job posting data, the use of machine-generated keywords does not require researchers to specify a list of AI-related keywords in advance, but the system learns the most related terms from the data instead. For example, my initial search of AI-related jobs showed that knowledge of LSTM networks was likely to be a commonly required skill in AI jobs. So, depending on the final data set, "LSTM" could be a keyword for identifying AI jobs. After determining the number of AI-related recruitments in a certain firm in a certain year, I divided the sum scores of AI-related job recruitments J by the total number of job positions N released by firm i in year t to estimate the firm-year level AI investments ($AI\ Investments_{it}$).

$$AI\ Investments_{it} = \frac{\text{AI related job recruitments}_{it}}{Total\ number\ of\ jobs_{it}} = \frac{\left(\sum_{j=1}^{J} \omega_j^{Narrow\ AI}\right)_{it}}{N_{it}}$$

(2) Measurement of Operational Efficiency

Following prior studies on operational efficiency (Chen et al., 2015; Chuang et al., 2019; Dutta et al., 2005; Lam et al., 2016; Li et al., 2010), I applied stochastic frontier estimation (SFE) to compute firms' operational efficiency. SFE allows us to measure the relative efficiency of a firm in transforming various operational resources into operational output, which is in line with the input–output transformation model used in the OM literature. To implement SFE, I first developed a production function to model the relationships between a firm's operational inputs (i.e., cost of goods sold, number of employees, and capital expenditures) and its operational outcomes (i.e., operating income as output) as follows:

$$
\begin{aligned}
\ln\,(Operating\ Income)_{ijt} &= \alpha_0 + \alpha_1 \ln\,(Number\ of\ Employees)_{ijt} \\
&+ \alpha_2 \ln\,(Cost\ of\ Goods\ Sod)_{ijt} + \alpha_3 \ln\,(Capital\ Expenditure)_{ijt} \\
&+ \varepsilon_{ijt} - \eta_{ijt}
\end{aligned}
$$

where ε_{ijt} is the stochastic random error term and η_{ijt} denotes the operational inefficiency of firm i in industry j in year t. η_{ijt} ranges from 0 to 1, with 0 as the zero-level of inefficiency (i.e., the full efficiency frontier). Accordingly, the operational efficiency of firm i in industry j in year t can be calculated as follows:

$$Operational\ Efficiency_{ijt} = 1 - \widehat{\eta_{ijt}}$$

To ensure meaningful comparisons within a narrowly defined industry, I adopted a four-digit SIC code. This is important because the relative performance of operational efficiency is likely to deviate significantly across different sectors.

(3) Measurement of Operational Complexity

Consistent with previous OM studies (Hendricks et al., 2009; Lam, 2018; Yiu et al., 2020), I measured operational complexity from the perspective of labor intensity and geographical diversity. Generally, firms find it more challenging and difficult to coordinate many employees and manage widely distributed customers (Yiu et al., 2020). Specifically, I used the number of employees divided by sales to measure a firm's labor intensity, and I used sales distribution of different countries to measure its geographical diversity. After normalizing labor intensity and geographical diversity based on the industry mean and standard deviation (based on the four-digit SIC code), I used the arithmetic mean of labor intensity and geographical diversity to measure a firm's operational complexity.

The geographic Herfindahl index (G_{Hrf}) is calculated by the square summation of the ratio of the individual geographic segment's annual sales to the firm's total sales (Johnson et al., 2023):

$$G_{Hrf} = \sum_{i=1}^{N} (\frac{S_i}{S})^2$$

S_i is the annual sales of the i th geographic segment; S is the firm's total annual sales; N is the number of geographic segments reported in Compustat (Yiu et al., 2020). I measured geographic diversification G_{Diver} as 1 - G_{Hrf}. G_{Hrf} is equal to 1 for firms operating in a single geographic segment. If firms operate in multiple geographic segments, G_{Hrf} is less than 1, and G_{Diver} is between 0 and 1. Firms that have a high degree of geographic diversification will have low values of G_{Hrf} and high values of G_{Diver}.

(4) Measurement of Industry Dynamism

I followed the existing literature (Keats & Hitt, 1988; Sabherwal et al., 2019; Xue et al., 2011) to measure industry dynamism by calculating **the volatility of industry sales**. Specifically, for each firm, I regressed the natural logarithm of the total sales of a particular firm's four-digit SIC industry code against an index variable of years, over a period of five years (t-4, t). Then, I used the antilog of the standard error of the regression coefficient to measure the sales volatility, which acts as the proxy for a firm's industry dynamism. The standard error of the regression coefficient is an estimate of the unpredictability of the sales growth rate (Xue et al., 2011).

(5) Measurement of *R&D Intensity*

Following prior studies on technology management (Bloom et al., 2013; Cao et al., 2018; Jacobs & Singhal, 2017; Jaffe, 1986), I measured firms' R&D intensity by using their R&D expenditure divided by total sales in 1 year. To guarantee the validity of the results, I deleted R&D intensities with outliers, such as those negative values.

(6) Measurement of Inventory Turnover Ratio

I followed the existing literature (Xie et al., 2020) to measure the inventory turnover ratio by dividing the cost of goods sold (beginning inventories + cost of goods manufactured in a firm – ending inventories for a particular period) by the average inventory ([beginning inventories + ending inventories] / 2) for the same period of time as follows:

$$Inventory\ Turnover\ Ratio_{it} = \frac{Cost\ of\ goods\ sold_{it}}{Average\ Inventories_{it}}$$

A summary of inventory turnover ratios divided by two-digit SIC codes is listed in Table 2.3. The inventory turnover ratio of the FMCG industry (e.g., printing and publishing, chemicals and allied products) is significantly higher than that of heavy industries (e.g., leather and leather products, instruments, and related products).

Table 2.3 Average Inventory Turnover Ratio Across SIC Sectors

SIC Code	Description	Mean	Standard Error	Freq.	Percent	Cum.
20	Food & Kindred Products	7.156406	.2701236	504	5.18	5.18
21	Tobacco Products	3.728054	.106676	17	0.17	5.35
22	Textile Mill Products	3.81713	.1212534	45	0.46	5.81
23	Apparel & Textile Products	3.226851	.0918251	196	2.01	7.83
24	Lumber & Wood Products	9.79885	.4651006	82	0.84	8.67
25	Furniture & Fixtures	7.160437	.3405163	170	1.75	10.42
26	Paper & Allied Products	6.418883	.1356198	204	2.10	12.51
27	Printing & Publishing	23.53932	1.952585	158	1.62	14.14
28	Chemicals & Allied Products	67.93336	14.41017	2,389	24.54	38.68
29	Petroleum & Coal Products	13.79204	.5529557	137	1.41	40.09
30	Rubber & Misc. Plastic Products	5.422538	.1880734	161	1.65	41.74
31	Leather & Leather Products	3.478846	.2602273	84	0.86	42.60
32	Stone, Clay, Glass, & Concrete Products	5.613483	.253476	83	0.85	43.46
33	Primary Metal Industries	4.921989	.1559578	220	2.26	45.72
34	Fabricated Metal Products	5.292861	.1757022	323	3.32	49.03
35	Industrial Mach. & Computer Equip.	5.684675	.4102143	1,218	12.51	61.55
36	Electronic & Electrical Equipment	7.39923	.7273377	1,592	16.36	77.90
37	Transportation Equipment	6.962571	.2148149	611	6.28	84.18
38	Instruments & Related Products	3.573666	.1330814	1,398	14.36	98.54
39	Miscellaneous Manufacturing Industries	4.787394	.1324745	142	1.46	100.00
	Total	/	/	9,734	100.00	/

(7) Measurement of Reasonable *Control Variables*

Consistent with prior studies, I included a set of variables in my analysis to control for various factors that may influence firms' operational efficiency.

I included five control variables in my study that are likely to be associated with operational efficiency, namely firm size (*Size*), firm age (*Age*), firm profitability (*ROA*), property, plant and equipment (*ppegt*), book-to-market ratio (*bm*) (Kortmann et al., 2014; Lam et al., 2016; Wu et al., 2010). I measured firm size as the natural logarithm of a firm's sales (Bardhan et al., 2013; Hendricks et al., 2009); firm age as the natural logarithm of the number of years since a firm's initial public offering year (Bellamy et al., 2014; Vandaie & Zaheer, 2015); firm profitability as a firm's return on assets (*ROA*), which is widely applied in prior literature (Chizema et al., 2015; Mukherji et al., 2011; Wang & Qian, 2011); property, plant, and equipment as the cost/valuation of tangible fixed assets used in the production of revenue (Hendricks et al., 2009), book to market ratio as firm's market value of equity divided by book value of equity (Li et al., 2022). I also included year and industry dummies in my research for any unobserved trends, industrial characteristics, and geographic variations to eliminate persistent time-specific and industry-specific effects. Table 2.4 summarizes the definition of variables.

Table 2.4 Definition of Variable Measurements

Variables	**Measures**	**Data Source**	**References**
AI Investments	BGT's job posting data, as illustrated in Section 2.3.2	BGT	(Babina et al., 2020); Babina et al. (2021)
Operational Efficiency	Transformed operational inputs into operational outputs based on SFE	Compustat Number of employees ： Compustat Annual – EMP	Lam et al. (2016)

		Costs of goods sold : Compustat Annual – COGS Capital expenditure : Compustat Annual – CAPX	
Operational Complexity	The arithmetic mean of labor intensity and geographical diversity	Compustat Labor Intensity Geographical Diversity	Yiu et al. (2020)
Industry Dynamism	The level of instability, which represents the frequency, degree, and unpredictability of changes in a firm's operating environment	Compustat Volatility of industry sales	Sabherwal et al. (2019)
R&D Intensity	Total expenditure on R&D divided by total sales	Compustat	(Bloom et al., 2013; Hu et al., 2023)
Inventory Turnover Ratio	An efficiency ratio that measures how efficiently inventory is managed	Compustat	Xie et al. (2020)
Firm Size	A firm's total assets based on a logarithmic transformation	COMPUSTAT	Yiu et al. (2020)

Firm Age	A firm's age is based on the natural logarithm of the current year minus the IPO year.	Compustat – Compustat Annual – IPODATE	Yang (2022)
Firm Profitability	A firm's ROA is calculated from quarter/annual data (ROA measures a firm's short-term profitability)	Compustat – North America – Financial Ratios Firm Level by WRDS (Beta)	Lu and Shang (2017); Mackelprang et al. (2015)
Property, Plant, and Equipment	A firm's cost/valuation of tangible fixed assets used in the production of revenue	Compustat	Hendricks and Singhal (2009)
Book-to-Market Ratio	A firm's market value of equity divided by the book value of equity	Compustat	Li et al. (2022)

2.3.3 Model Specifications

(1) Static Panel Data Model with Fixed Effects

To investigate the impact of AI investments on operational efficiency, this thesis first establishes the following econometric model:

$$
\begin{aligned}
&Operational\ Efficiency_{i(t+1)} \\
&\quad = \beta_0 + \beta_1 AI\ Investments_{it} + \beta_2 AI\ Investments_{it} \\
&\quad * Operational\ Complexity_{it} + \beta_3 AI\ Investments_{it} \\
&\quad * Industry\ Dynamism_{it} + \beta_4 AI\ Investments_{it} * R\&D\ Intensity_{it} \\
&\quad + \beta_5 AI\ Investments_{it} * Inventory\ Turnover\ Ratio_{it} + \sum \beta_6 x_{it} \\
&\quad + \mu_i + \lambda_i + \varepsilon_{it}
\end{aligned}
$$

where i and t are firm and year indices, respectively. x_{it} represents a series of other control variables, which are described in Section 2.3.2. μ_i is the unobservable individual effect. λ_i indicates the time effect of i. ε_{it} is the error term, which follows the normal distribution and is not correlated with μ_i and λ_i. An 1-year lag between the dependent variable and other variables is important to ensure unbiased estimations.

(2) Dynamic Panel Data (DPD) Model

Because firms' operational efficiency could be persistent over time depending on past performance (Lam et al., 2016), I constructed a DPD model to test my hypotheses as follows:

$$\begin{aligned} &Operational\ Efficiency_{i(t+1)} \\ &\quad = \beta_0 + \beta_1 Operational\ Efficiency_{it} + \beta_2 AI\ Investments_{it} \\ &\quad + \beta_3 AI\ Investments_{it} * Operational\ Complexity_{it} \\ &\quad + \beta_4 AI\ Investments_{it} * Industry\ Dynamism_{it} \\ &\quad + \beta_5 AI\ Investments_{it} * R\&D\ Intensity_{it} + \beta_6 AI\ Investments_{it} \\ &\quad * Inventory\ Turnover\ Ratio_{it} + \sum \beta_9 x_{it} + \mu_i + \lambda_i + \varepsilon_{it} \end{aligned}$$

where i and t are firm and year indices, respectively. x_{it} represents a series of other control variables, which are described in Section 2.3.2. μ_i is the unobservable individual effect. λ_i indicates the time effect of i. ε_{it} is the error term, which follows the normal distribution and is not correlated with μ_i and λ_i. The addition of lagged dependent variable makes my model "dynamic" across the years by taking the continuous impact of past efficiency patterns into consideration. An 1-year lag between the dependent variable and other variables is also set to ensure unbiased estimations.

(3) System Generalized Method of Moments (GMM) Estimation

Although I specified a 1-year lag between operational efficiency and AI investments in the DPD model, there is still potential concern about endogeneity issues (Wintoki et al., 2012). In particular, it is possible that operational efficiency and AI investments influence each other interactively. On the one hand, AI investments can bring a series of benefits for firms, such as improving the production process, reducing operating costs, and improving demand forecast accuracy, improving overall operational efficiency. On the other hand, firms with better operational efficiency and performance will have enough capital to invest in AI, making two-way causal influences possible.

Moreover, other unobserved firm factors, such as firm culture, may influence firms' AI investments decision and operational efficiency simultaneously, thus inflating the relationship between AI investments and operational efficiency.

There is an endogeneity concern in my DPD models. To address this issue, I followed recent studies (Guo et al., 2020; Pennetier et al., 2019; Ryoo et al., 2021) to adopt the system GMM estimator (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). The system GMM estimator is similar to conventional instrumental variables techniques in that it is based on the construction of instruments to tackle the endogeneity issue. However, the system GMM estimator does not require external measures of individual firms' characteristics outside my data set to develop instruments. Instead, it internally transforms the current measures to develop new instruments, thus solving the possible problem of weak exogeneity of external measures. Flannery and Hankins (2013) indicated that compared to other instrumental variable techniques, the system GMM estimator is one of the most robust methods for imbalanced panels with endogenous variables. As a result, GMM estimation addressed the endogeneity issue and enhanced my estimates' robustness.

2.4 Results and Analyses

2.4.1 Main Effects

Table 2.5 illustrates the summary and correlation data of variables. The results demonstrate that firms' operational efficiency is significantly related to AI investments' lagged value ($r = 0.107$, $p < 0.01$). Table 2.6 presents the main effect of the panel data models. Model 1 and Model 2 are basic models with a list of variables lagged for one year (except the dependent variable), including and excluding year fixed effects and industry fixed effects. The two models both show that AI investments have a significantly positive impact ($p < 0.01$) on operational efficiency. Table 2.7 presents the main effect of GMM models. Model 1 shows that AI investments have a significantly positive impact ($p < 0.01$) on operational efficiency. Therefore, Hypothesis 1 is supported.

The number of observations is 2,508 in models whose variables (except for the dependent variable) are lagged for one year and 2,203 in models whose variables (except the dependent variable) are lagged for two years, suggesting that there are sufficient sample firms in my data analysis. Over the years, the repeated measurement of the same firms enables us to obtain robust results by clustering the standard errors by firms.

Table 2.5 Variable Summary Statistics and Correlation Matrix

Variables	**Observed**	**Mean**	***SD***	**Min**	**Max**	Operational Efficiency	AI Investments	Operational Complexity	Industry Dynamism	R&D Intensity	Inventory Turnover Ratio	Size	Age	ROA	ppegt	bm
Operational Efficiency	2,508	0.650	0.159	0.018	0.956	1.000										
AI Investments	2,508	0.305	0.698	0.000	6.011	0.111***	1.000									
Operational Complexity	2,508	24.649	242.756	-2785.285	3601.879	0.012	0.093***	1.000								
Industry Dynamism	2,508	14522.088	16297.097	50.790	191265.625	0.023*	0.755***	0.000	1.000							
R&D Intensity	2,508	-3.252	8.319	-47.799	0.458	0.015	-0.016	-0.054***	0.000	1.000						
Inventory Turnover Ratio	2,508	7.343	38.585	0.240	1190.037	-0.016	-0.016*	-0.015	0.022**	0.038***	1.000					
Size	2,508	1.653	1.063	0.041	5.485	0.145***	0.489***	-0.010	-0.030***	-0.029***	-0.056***	1.000				
Age	2,508	25.992	8.330	5.000	55.000	0.110***	0.105***	0.014	-0.097***	-0.030**	-0.041***	0.358***	1.000			
ROA	2,508	0.144	0.092	-0.950	0.782	0.450***	0.129***	0.162***	-0.031***	-0.064***	-0.103***	0.416***	0.333***	1.000		
ppegt	2,508	1712.261	5374.865	0.000	112096.000	0.038***	0.223***	0.073***	0.328***	-0.005	-0.004	0.277***	0.125***	0.070***	1.000	
bm	2,508	0.441	0.310	0.003	3.809	-0.291***	-0.128***	-0.009	0.070***	0.003	0.027***	-0.051***	0.065***	0.038***	0.035***	1.000

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table 2.6 Main Model Regression Results with Independent Variable Lagged by 1 Year (Fixed Effects Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**
AI Investments	**.0176684*** **	**.0179971*** **
	(.0049118)	**(.0045702)**
Operational Complexity	.0001066***	.0000404**
	(.0000256)	(.0000195)
Industry Dynamism	3.800e-06***	1.300e-06**
	(9.000e-07)	(6.000e-07)
R&D Intensity	.000053	.0000786
	(.0005871)	(.0002868)
Inventory Turnover Ratio	.0000187	.0000197
	(.000038)	(.0000368)
Cons	Included	Included
Control	Yes	Yes
Year Fixed	Yes	No
Industry Fixed	Yes	No
Observations	2,508	2,508
R-squared	.2676415	.2292455

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table 2.7 Main Model Regression Results with Independent Variable Lagged by 1 Year (GMM Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Lagged Operational Efficiency	**.4071688*** **	**.4210957*** **	**.4284183*** **	**.4183393*** **	**.4318749*** **	**.4663583*** **
	(.0691692)	**(.0671403)**	**(.0645287)**	**(.0662445)**	**(.0663349)**	**(.0570417)**
AI Investments	.0094352	.0043307	.0123312**	.009709	.0056179	.0107129*

	(.0061174)	(.0066081)	(.0058882)	(.0061083)	(.0062626)	(.0060352)
Operational	.0000117	5.700e-06	8.000e-07	5.700e-06	.000011	1.300e-06
Complexity	(.0000246)	(.0000202)	(.0000218)	(.000024)	(.0000247)	(.0000172)
Industry Dynamism	3.000e-07	4.000e-07	5.000e-07**	3.000e-07	3.000e-07	5.000e-07**
	(3.000e-07)	(3.000e-07)	(2.000e-07)	(3.000e-07)	(3.000e-07)	(2.000e-07)
R&D Intensity	.0001694	.0002204	.0002448	.0001292	.0001805	.0000766
	(.0002137)	(.0002085)	(.0001987)	(.0002414)	(.0002149)	(.0002247)
Inventory Turnover Ratio	.0000765	.0000772	.0000764	.0000741	.0001163	.0002163***
	(.0000723)	(.0000706)	(.000072)	(.0000719)	(.0000786)	(.0000466)
AI Investments ×		**.0000436****				**.0000542*****
Operational Complexity		**(.0000196)**				**(.0000181)**
AI Investments ×			**8.000e-07*****			**1.100e-06*****
Industry Dynamism			**(3.000e-07)**			**(3.000e-07)**
AI Investments ×				**.0001337*****		**.00038****
R&D Intensity				**(.0001520)**		**(.0001732)**
AI Investments ×					**.0009013****	**.0006093*****
Inventory Turnover Ratio					**.0003989**	**(.0001996)**
Year Dummies	Included	Included	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included	Included	Included
Cons	Included	Included	Included	Included	Included	Included
Number of Instruments	332	332	332	332	332	392
Arellano-Bond Test for AR (2)	0.413	0.497	0.440	0.441	0.418	0.487
Instrument Validity Test	0.419	0.449	0.366	0.345	0.361	0.975
Observations	2,392	2,392	2,392	2,392	2,392	2,392

Robust standard errors are in parentheses.

**** $p < .01$, ** $p < .05$, * $p < .1$*

2.4.2 Interaction Effects

Model 1 – Model 4 in Table 2.8 illustrate the moderating role of operational complexity, industry dynamism, R&D intensity, and inventory turnover ratio, respectively.

Evidence shows that Operational Complexity strengthens the positive effect of AI Investments on Operational Efficiency (p<0.01). Figure 2.2 and Figure 2.3 illustrate that this positive impact is also strengthened by R&D Intensity (p<0.01), and Inventory Turnover Ratio (p<0.01). These findings support Hypotheses 2 - Hypotheses 5. Hypothesis 3 is also supported by Figure 2.2 which illustrates that Industry Dynamism plays a positive moderating role in this model.

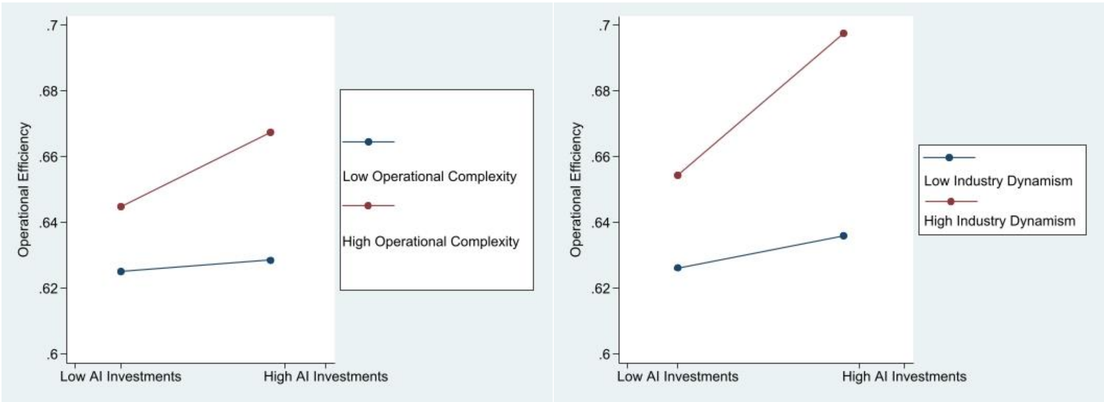


Figure 2.2 Moderating Roles of Operational Complexity and Industry Dynamism

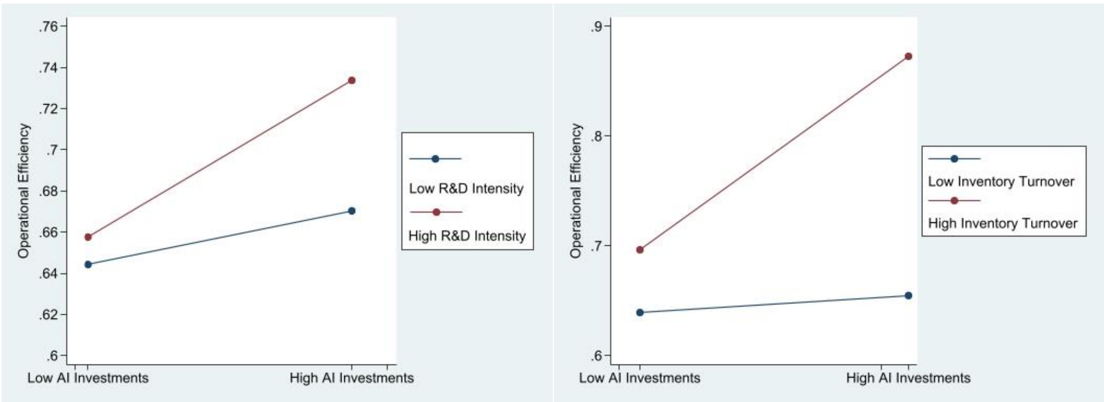


Figure 2.3 Moderating Roles of R&D Intensity and Inventory Turnover Ratio

Table 2.8 Main Model Regression Results with Independent Variable Lagged by 1 Year (Fixed Effects Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
AI Investments	.0060963	.020463***	.0158639***	.006661	.0099366	.0131364**
	(.0058473)	(.005754)	(.0050382)	(.0055359)	(.00664)	(.006261)
Operational Complexity	.0000928***	.0001039***	.0001129***	.0001099***	.0001008***	.0000679***
	(.0000265)	(.0000261)	(.0000266)	(.0000263)	(.000027)	(.0000181)
Industry Dynamism	2.900e-06***	2.800e-06***	3.800e-06***	3.000e-06***	4.000e-07	1.200e-06***
	(1.000e-06)	(9.000e-07)	(9.000e-07)	(1.000e-06)	(6.000e-07)	(3.000e-07)
R&D Intensity	.0004403	.0004995	.0008128	.000508	.0008146	.0001382
	(.0005747)	(.0005757)	(.0005859)	(.0005711)	(.0005778)	(.0003275)
Inventory Turnover Ratio	.0000336	.0000339	.0000334	5.100e-06	8.500e-06	6.600e-06
	(.0000317)	(.0000319)	(.0000317)	(.000037)	(.0000338)	(.0000354)
AI Investments ✕ Operational Complexity	**.0000783***				**.0000911***	**.0000904***
	(.0000258)				**(.0000274)**	**(.0000261)**
AI Investments ✕ Industry Dynamism		**2.200e-06****			**2.500e-06****	**2.400e-06****
		(1.100e-06)			**(1.20e-06)**	**(1.10e-06)**

AI Investments ×			**.0019911*****		**.0026618*****	**.002227*****
R&D Intensity			**(.0005629)**		**(.0006159)**	**(.0005817)**
AI Investments ×				**.0018782*****	**.0010286***	**.0009082***
Inventory Turnover Ratio				**(.0006244)**	**(.0005394)**	**(.0004834)**
Cons	Included	Included	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	No
Industry fixed	Yes	Yes	Yes	Yes	Yes	No
Observations	2,508	2,508	2,508	2,508	2,508	2,508
R-squared	.27585	.274775	.2671742	.2691379	.2745609	.2202725

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

2.4.3 Robustness Check

By using different evaluation strategies and alternative measurement methods, I conducted many tests to evaluate the robustness of my results. Tables 2.9–2.11 present the robustness check results, and I discuss the procedures below. In general, the robustness check offers further support and rules out some alternative explanations of my research findings.

First, I set the lagged year for all variables except dependent variables (operational efficiency) as two years. As shown in Table 2.10, the main effect in Model 1 and Model 2, and the moderating effects in Models 3–8 all remain consistent with results in the previous analysis. I also checked the moderating effect of all moderators with or without year and industry fixed effects in Model 9 and Model 10, and the results remain consistent with the previous analysis.

Second, I winsorized the dependent variable (operational efficiency) at the 1% level (Liu et al., 2023), as shown in Table 2.11. Model 1 and Model 2 show that the main effects and moderating effects remained consistent with the previous analysis. Model 3 and Model 4 show the results after I winsorized continuous explanatory variables at the 1% level; they remain consistent and significant when all variables (except the dependent variable) are lagged for 1 year and 2 years.

Next, I added the squared item of AI investments to my model to check the potential nonlinear relationship between AI investments and operational efficiency (Yiu et al., 2020). Model 5 and Model 6 show that the squared item of AI investments is not statistically significant ($p > 0.1$). AI investments are still significantly positive ($p < 0.01$) after putting the squared item in the model, supporting the linear relationship between AI investments and operational efficiency when all variables (except the dependent variable) are lagged for 1 year and 2 years.

Then, following previous studies (Cheng & Bang, 2021; Park et al., 2023), I tested the sensitivity of my results to the modeling choices in the system GMM model in Table 2.9. I did not use all available lagged values beginning with t – 2, i.e. (t – 2, t – maximum), as instruments for the difference equation, but instead constrained the maximum number of lags to t – 6 by choosing a smaller set of instruments, i.e. (t – 2, t - 3), (t - 2, t – 4), (t – 2, t – 5), and (t – 2, t – 6). The Hansen and AR2 test results in all models are insignificant ($p > 0.1$), demonstrating the validity of these alternative instruments employed in my system GMM estimation. All estimation results from the alternative models agree with my earlier system GMM model findings.

Moreover, I followed previous literature (Babina et al., 2021; Babina et al., 2023) to consider alternative cutoffs of 0.05 and 0.15 for defining AI-related job postings $\omega_j^{Narrow\ AI}$ in Table A4. AI job postings are defined as job postings with continuous job-level measure $\omega_j^{Narrow\ AI}$ above 0.05 in Panel 1, and job postings with continuous job-level measure $\omega_j^{Narrow\ AI}$ above 0.15 in Panel 2. Model 1-2 show the main effects with all continuous explanatory variables lagged for 1 year and 2 years, respectively. Model 3-4 show all moderating effects with all continuous explanatory variables lagged for 1 year and 2 years, respectively. All these measures yield a positive and significant effect of AI investments, confirming that job-postings-based measures are highly robust.

Finally, I consider alternative independent variables general AI investments, general R&D investments and R&D intensity to confirm whether this impact is specially led by narrow AI investments in Table A5. All these results are insignificant which confirm that this Impact is only led by narrow AI investments and my findings are robust.

Table 2.9 Robustness Check for GMM Models

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Lagged Operational	**.4663583*** **	**.4886865*** **	**.5008442*** **	**.4941245*** **	**.4971789*** **

Efficiency	**(.0570417)**	**(.0516412)**	**(.0493089)**	**(.0477303)**	**(.0468228)**
AI Investments	.0107129*	.010306**	.0114709**	.0117443**	.0115856**
	(.0060352)	(.0051979)	(.0050984)	(.0051425)	(.0051002)
Operational	1.300e-06	1.200e-06	3.200e-06	5.200e-06	5.100e-06
Complexity	(.0000172)	(.0000156)	(.000016)	(.0000163)	(.0000162)
Industry Dynamism	5.000e-07**	5.000e-07***	6.000e-07***	6.000e-07***	6.000e-07***
	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)
R&D Intensity	.0000766	.0000936	.000164	.0001688	.0001929
	(.0002247)	(.0002206)	(.0002151)	(.0002212)	(.0002198)
Inventory Turnover Ratio	.0002163***	.0002113***	.0002148***	.0002099***	.0002117***
	(.0000466)	(.0000517)	(.0000494)	(.0000508)	(.0000534)
AI Investments ✕	**.0000542***	**.0000476***	**.0000464***	**.0000409***	**.0000424***
Operational Complexity	**(.0000181)**	**(.0000167)**	**(.0000159)**	**(.0000159)**	**(.000016)**
AI Investments ✕	**1.100e-06***	**1.100e-06***	**1.100e-06***	**1.100e-06***	**1.100e-06***
Industry Dynamism	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**
AI Investments ✕	**.00038**	**.0003704**	**.0002755**	**.0002542**	**.0002663**
R&D Intensity	**(.0001732)**	**(.0001688)**	**(.0001435)**	**(.000144)**	**(.0001423)**
AI Investments ✕	**.0006093***	**.0005802***	**.0005171***	**.0004963***	**.0004644**
Inventory Turnover Ratio	**(.0001996)**	**(.0001856)**	**(.0001856)**	**(.0001922)**	**(.0001876)**
Year Dummies	Included	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included	Included
Cons	Included	Included	Included	Included	Included
Number of Instruments	293	428	548	653	743
Arellano-Bond test for AR (2)	0.474	0.497	0.522	0.521	0.523
Instrument Validity Test	0.448	0.999	1.000	1.000	1.000
Observations	2,292	2,292	2,292	2,292	2,292

Robust standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table 2.10 Robustness Check for Panel Data Models with Fixed Effects

Dependent Variable: Operational Efficiency	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
AI Investments	.0188058***	.0193526***	.0079859	.0307739***	.0228277***	.0080477	.0335153***	.0430538***
	(.0056201)	(.005182)	(.0069803)	(.0062673)	(.0056903)	(.0062064)	(.0128392)	(.0124245)
Operational Complexity	.0000778***	.0000227	.000072***	.0000591***	.0000817***	.000085***	.0000755***	.0000156
	(.000024)	(.0000158)	(.0000227)	(.0000179)	(.0000252)	(.0000248)	(.0000236)	(.0000158)
Industry Dynamism	2.600e-06***	7.000e-07	2.400e-06***	1.000e-07	2.600e-06***	2.000e-06**	2.000e-07	1.300e-06***
	(8.000e-07)	(7.000e-07)	(9.000e-07)	(7.000e-07)	(8.000e-07)	(9.000e-07)	(6.000e-07)	(3.000e-07)
R&D Intensity	.0001269	.0000259	.0000746	.0003102	.0004897	.0001964	.0006422	.0002058
	(.000559)	(.0003131)	(.0005581)	(.000558)	(.0005748)	(.0005613)	(.0005769)	(.0003501)
Inventory Turnover Ratio	.000033	.0000328	.0000333	.0000341	.000032	5.100e-06	2.500e-06	2.000e-06
	(.0000333)	(.0000341)	(.0000333)	(.0000332)	(.0000332)	(.0000114)	(.000014)	(.0000146)
AI Investments × Operational Complexity			**.0001149*** (.0000397)**				**.0000847*** (.0000302)**	**.0005650*** (.0000293)**
AI Investments × Industry Dynamism				**9.000e-07*** (3.000e-07)**			**2.000e-06*** (6.000e-07)**	**2.300e-06*** (6.000e-07)**
AI Investments × R&D Intensity					**.0018429*** (.0005755)**		**.0023544*** (.0005662)**	**.0020169*** (.0005806)**
AI Investments × Inventory Turnover Ratio						**.0019366*** (.0005626)**	**.0015287*** (.000491)**	**.0014641*** (.0004182)**
Cons	Included	Included	Included	Included	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Industry Fixed	Yes	No	Yes	Yes	Yes	Yes	Yes	No
N	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203
R-squared	.2469231	.1970686	.2506848	.2438558	.2481695	.2530802	.2588637	.2083664

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table 2.11 Robustness Check for Panel Data Models with Fixed Effects

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
AI Investments	**.0234232***	**.0364241*****	**.030667****	**.0364241*****	**.0193301*****	**.0273201*****
	(.0127123)	**(.0139449)**	**(.0140948)**	**(.0139449)**	**(.0145299)**	**(.0146873)**
Operational Complexity	.000101***	.0000754***	.0000934***	.0000661***	.0000957***	.0000677***
	(.0000273)	(.0000236)	(.0000275)	(.0000221)	(.0000281)	(.0000229)
Industry Dynamism	1.100e-06	2.000e-07	1.400e-06	3.000e-07	1.300e-06	2.000e-07
	(1.100e-06)	(6.000e-07)	(1.000e-06)	(1.200e-06)	(1.000e-06)	(1.200e-06)
R&D Intensity	.0008594	.0006487	.0008485	.0006322	.0008415	.0006354
	(.0005863)	(.0005718)	(.0005891)	(.0005749)	(.0005886)	(.000574)
Inventory Turnover Ratio	9.400e-06	1.800e-06	.0000117	3.100e-06	.0000112	2.700e-06
	(.0000316)	(.0000138)	(.0000314)	(.000014)	(.0000315)	(.0000139)
AI Investments ✕	**.0000906*****	**.0001275*****	**.0001049*****	**.0001607*****	**.0000972*****	**.0001534*****
Operational Complexity	**(.0000272)**	**(.0000333)**	**(.0000331)**	**(.0000411)**	**(.0000356)**	**(.0000451)**
AI Investments ✕	**2.400e-06****	**1.900e-06*****	**2.800e-06****	**2.200e-06*****	**2.700e-06****	**2.200e-06*****
Industry Dynamism	**(1.200e-06)**	**(6.000e-07)**	**(1.200e-06)**	**(7.000e-07)**	**(1.200e-06)**	**(7.000e-07)**
AI Investments ✕	**.0026792*****	**.0023235*****	**.0028387*****	**.0025809*****	**.0027532*****	**.0025279*****
R&D Intensity	**(.000607)**	**(.0005599)**	**(.0006349)**	**(.0005852)**	**(.000647)**	**(.0005894)**
AI Investments ✕	**.0010322****	**.0015017*****	**.0008969***	**.0013926*****	**.0009222***	**.0014146*****
Inventory Turnover Ratio	**(.0005071)**	**(.0004864)**	**(.0004682)**	**(.0004248)**	**(.0004863)**	**(.0004444)**
Squared AI					**6.000e-07**	**7.000e-07**
Investments					**(7.000e-07)**	**(9.000e-07)**
Cons	Included	Included	Included	Included	Included	Included

Control	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	2,508	2,203	2,508	2,203	2,508	2,203
R-squared	.2829825	.2583293	.2812599	.2571412	.281424	.2572692

Standard errors are in parentheses.

**** $p < .01$, ** $p < .05$, * $p < .1$*

2.5 Conclusions and Discussions

2.5.1 Conclusions

Using secondary data from U.S.-listed manufacturing firms, I investigated the impact of AI investments on operational efficiency and the moderating effects of operational complexity, industry dynamism, and inventory turnover ratio. Table 2.12 summarized the research findings in Study 1.

For the main effects, I found that AI investments are positively related to operational efficiency (H1 is supported). Moreover, this effect was robust and consistent in my tests. Regarding the moderating effects, operational complexity, industry dynamism, R&D intensity, industry dynamism, and inventory turnover ratio enhance the impact of AI investments on operational efficiency (H2–H5 are supported).

Table 2.12 Results of Hypotheses

Hypothesis (Hypothesized Sign)	**Result (Actual Sign)**
HYPOTHESIS 1 (H1). AI investments have a positive impact on operational efficiency.	Supported (+)
HYPOTHESIS 2 (H2). Higher operational complexity will strengthen the positive impact of AI investments on operational efficiency.	Supported (+)
HYPOTHESIS 3 (H3). Higher industry dynamism will strengthen the positive impact of AI investments on operational efficiency.	Supported (+)
HYPOTHESIS 4 (H4). Higher R&D intensity will strengthen the positive impact of AI investments on operational efficiency.	Supported (+)
HYPOTHESIS 5 (H5). Higher inventory turnover ratios will strengthen the positive impact of AI investments on operational efficiency.	Supported (+)

2.5.2 Discussions

For the main effects, based on rigorous analysis, my research findings strongly support that firms' AI investments can significantly improve their operational efficiency. Moreover, this effect was even more significant two years after the firms' operational efficiency. These are inspiring findings. For large firms, who have the strength to invest in AI to maintain competitiveness in the market continuously. Small firms can invest their limited fundings in urgent issues based on the comprehensive assessment of their development to improve operational efficiency more effectively. At the same time, due to the time-delay effect of AI investments, firms need to be determined to carry out process optimization and maximize the benefits of AI investments while patiently waiting for the returns.

From the perspective of environmental factors, the current global economy is under great uncertainty, and it will take time for weak market demand and depressed market confidence to recover in the post-pandemic era. The Russia-Ukraine war has brought great challenges to the global supply chain. My research results show that AI investments can help firms respond to operational risks, improve their ability to withstand crises, and enhance operational efficiency more effectively. These are inspiring findings for those firms in crisis. Ai investments help them achieve better operational performance in complex environments.

From the perspective of operation factors, R&D intensity is a representative indicator that displays the intensity of firms' R&D. As the saying goes, drops of water outwear the stone. Firms that can operate in complex market environments without collapsing not only value short-term interests, but also invest more fundings in long-term planning. Making appropriate R&D investments based on a firm's scale is a good example. This inspires more firms to not place too much emphasis on short-term benefits in the development process, but to establish R&D capabilities that match their own strength to maintain their core competitiveness in the long term. On the other hand, inventory turnover is a commonly used indicator in operational management and plays an important positive moderating role in the impact of AI investments. Among firms with high inventory turnover, they are more likely to benefit from AI investments due to their fast inventory turnover, rapid demand changes, and high inventory volatility. This provides us with an interesting perspective. When conducting AI investments and making more targeted investments based on the characteristics of our industry, it will significantly benefit the development of firms.

Chapter 3 Study 2: Spillover Effect of the Impact of Focal Firms' AI Investments on Suppliers' Operational Efficiency

3.1 Introduction

3.1.1 Research Background

In Study 1, I confirmed that AI Investments can improve operational efficiency in the scope of focal firms, due to the close buyer-supplier relationship, I further investigate the spillover effect of AI Investments in the Buyer-supplier Relationship in Study 2. In recent years, increasing numbers of listed firms not only focus on their operational performance improvement, but also hope to achieve win–win situations in the supply chain network. Therefore, the spillover effect of R&D expenditures has always been one of the most important topics in OM.

Executives in the industry are uncertain about the actual effect of AI investments in the supply chain network to improve operations. There are widespread concerns that optimism about the potential value of AI is misplaced and unfounded and that the overall impact of AI on operations might be hyped up in the years ahead. From the perspective of social network theory, AI investments may benefit the supply chain network by fostering strong ties and deep embeddedness (Liang et al., 2023). Therefore, there is an urgent need to explore the actual economic impact of focal firms 'AI on the operational performance of suppliers. However, so far, little research has examined the impact of focal firms' AI on suppliers' operational performance in the supply chain network.

The lack of empirical evidence from a large sample of individual firms is mainly due to the difficulty in obtaining AI usage data in the supply chain network (Furman & Seamans, 2019). In this research, I overcome this problem using FactSet Revere - a data set covering a wealth of microdata of firms' information in the supply chain network (Babina et al., 2020; Hershbein & Kahn, 2018). Driven by AI technologies' reliance on human capital rather than physical assets (Babina et al., 2020), I use a unique measure of AI investments based on detailed firms' AI talent recruitment data. I implement the social network theory perspective on focal firms' AI investments to understand the more important conditions for AI investments.

3.1.2 Research Objectives

To narrow existing research gaps, Study 2 investigates two research questions.

Research Question 1: What is the spillover effect of focal firms' AII on suppliers' OE in the U.S. manufacturing industry?

I address this question by matching Burning Glass Technologies' AI job postings with Compustat's financial data and FactSet Revere Supply Chain Relationship data and using FEM and DPD models.

Research Question 2: How could different contextual factors potentially strengthen or weaken this spillover effect?

I address this question from perspectives of complexity and connectedness factors and apply generalized method of moments (GMM) techniques.

3.2 Literature Review and Hypotheses Development

3.2.1 Spillover Effect of the impact of AI Investments on Operational Efficiency

In Study 1, I demonstrated that the AI investments of focal firms have a significant positive effect on their own operational efficiency. This positive effect is even more significant in complex operating environments. On this basis, I extend my research to buyer–supplier relationships in supply chain networks and further explore the impact of focal firms' AI investments on suppliers' operational efficiency.

The spillover effect refers to the fact that an organization's activities will not only have the desired effect of the activity but also impact people or society outside the organization (Welbourne & Cable, 1995). Spillover effects are mainly divided into knowledge spillovers, technology spillovers, and economic spillovers. Typically, knowledge and technology diffuse spatially between innovative organizations in terms of trade (formal) and non-trade (informal) (Arrow, 1962). Knowledge spillover is the optimal path to promote innovation efficiency (Capello, 1999).

The basic idea of social network theory is that organizations in social situations think and act similarly because of their relationships, explaining social behavior as a whole (Mitchell, 1969; Tichy et al., 1979). Furthermore, in the supply chain network, focal firms, core suppliers, and customers establish relationships through long-term cooperation; understand each other's needs; and form strong ties which are characterized by a high level of interaction, communication, emotional engagement, and trust, which can reduce opportunity risks and facilitate the transfer of complex knowledge (Lowik et al., 2012; Pfeffer & Parra, 2009).

Strong ties facilitate trust and reduce uncertainty, especially when firms face complex problems, strong ties can increase reciprocity to solve problems. Strong ties generally develop among individuals with similar socioeconomic characteristics, and the information and resources conveyed are mostly overlapping (Granovetter, 1973). Strong ties lead to organizational commitment (Prasad & Harrison, 2006). Members with strong ties help each other, trust each other, are prone to attachment, and feel belonging to the community. In this context, relational social capital allows knowledge transfer from buyers to suppliers. We can easily understand the spillover effect of operational efficiency from the perspective of social network theory.

In Study 1, I confirmed that firms with more AI investments achieve higher operational efficiency than the market average. Network density denotes how closely connected firms are to other firms in the network. With the growth of AI Investments, information interaction between focal firms and their core partners become more effective, the higher network density is, the faster information transformation is, the better their absorption of knowledge, and the higher the performance of this externally dependent resource acquisition (Blumenberg et al., 2009; McEvily & Marcus, 2005).

Businesses with greater network density have faster access to the latest information and a higher degree of heterogeneity of information and resources, resulting in a clearer view of their environment that can help improve their decision-making accuracy. Increasing firms' network scale and density promotes a wealth of knowledge and information inflow, which is conducive to firm decision-making. The network also has a certain degree of exclusivity; with greater network density comes closer cooperation between node organizations and therefore more exclusivity and closure (Srivastava & Gnyawali, 2011). This phenomenon is highly beneficial for firms with more AI investments. Because of this exclusivity and closure, the communication between network subjects is closer, unifying standard behavior between members and improving their network efficiency. Another advantage of this closure is that it can form strategic isolation to prevent competitor imitation, which is conducive to maintaining a long-term competitive advantage and improving performance levels. A firm's competitive strategy is inseparable from its internal knowledge base and core capabilities, which can be improved through R&D investment and are ultimately reflected in operational efficiency. External resources and knowledge can enrich and diversify the firm's original knowledge base, and multiparty verification of technology can reduce R&D risks and help it effectively obtain strategic assets from the market. Therefore, having a certain number of high-quality network relationships can stimulate the conversion of AI investments in focal firms, thereby improving operational efficiency. Therefore, I propose Hypothesis 1 as follows:

HYPOTHESIS 1 (H1). Focal firms' AI investments have a positive impact on suppliers' operational efficiency.

3.2.2 Moderating Role of Horizontal Complexity

Next, I focus on the complexity issue in supply chain relationships. Horizontal complexity is the breadth level (width) of the supply base, usually explained by the number of Tier 1 suppliers. The higher the number of Tier 1 suppliers, the higher the level of complexity (Dong et al., 2020). First, AI investments raise focal firms' network density, which can promote firms' integration with the upstream and downstream partners to strengthen connections. In this process, firms with higher horizontal complexity due to their larger number of Tier 1 suppliers can more effectively strengthen relationships with partners (Chand et al., 2022). As AI investments increase in the process of focal firm cooperation, the absorption capacity of firms in the network increases, and the cost of regulating cooperations decreases. That is, AI investments can not only enhance information transformation but also improve firms' goal congruence and responsiveness (Correani et al., 2014), significantly improving their operational efficiency. On the other hand, when the number of suppliers is less, core firms tend to rely on traditional ways of cooperation, which lacks innovation impetus, and the effect of AI investments is insignificant. Hence, I propose the following hypothesis:

HYPOTHESIS 2 (H2). Higher horizontal complexity will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.

3.2.3 Moderating Role of Spatial Complexity

With the deepening of economic globalization, fierce competition in the market environment, and rapid changes in science and technology, it is difficult for firms to master all the required knowledge and skills, forcing them to obtain the required resources through the global market. As a result, firms are increasingly embracing strategies that access resources through partnerships with external partners (Radhakrishnan et al., 2014). Spatial complexity represents the level of the supply base's geographical distribution. When focal firms' Tier 1 suppliers are located in more countries, the spatial complexity increases and the firms' range of supplier partners widens. This may bring about different management methods, institutional environments, and different production styles of firms, and increasing the difficulty of cooperation.

To better handle these challenges, AI investments facilitate multiple and frequent interactions between firms and stakeholders, such as suppliers, increasing the density of their networks. AI investments rely on the benefits of network density to further improve operational efficiency. For firms with higher spatial complexity, the more AI investments, the more significantly they can improve their connection with globally distributed suppliers, adopt new technologies for collaborative R&D, update products, achieve economies of scale and scope, ensure operational efficiency, promote the transformation process of R&D results, and continue to carry out new product R&D. Frequent communication and collaboration can enhance the cooperation of supply chain partners and cooperative firms in the process of resource sharing, resource transfer, and resource divestment in multiple departments such as R&D, production, and marketing, which can reduce resource waste through complementary advantages. Hence, I propose a further hypothesis as follows:

HYPOTHESIS 3 (H3). Higher spatial complexity will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.

3.2.4 Moderating Role of Supply Concentration

Supply concentration refers to the continuous measurement of the ratio of purchases from the five largest suppliers to total purchases. This indicator reflects the degree of embeddedness of focal firms and their supply chain partners. *Embeddedness* refers to the tendency to remain in a social network and create, renew, and expand network relationships over time (Ding et al., 2023).

Focal firms' AI investments have a direct impact on suppliers' operational efficiency. First, AI investments increase firm network density. AI promotion requires significant human, material, and financial resources. For example, Huawei maintains a level of

R&D investment of more than 14% year-round to ensure the vitality of R&D innovation. As a firm's AI strength and the number and proportion of R&D personnel increase, the richness and speed of information flow within the firm will also increase with the complexity of the relationship network of R&D personnel. As AI investments increase, the network connections formed within the network gradually increase, and the frequency of contact between the firm and other members of the supply chain network also increases.

Firms with higher supply concentration have higher network density, more frequent interaction between supply chain network members, more connections, more efficient information transmission, and higher network operation efficiency. More frequent communication and interaction between focal firms and suppliers leads to a greater understanding of business laws and firms' situations, allowing the firm to promote a trusting relationship between network members and improve organizational learning ability and problem-solving ability (Zaheer et al., 1998). The improvement of trust between organizations leads to the reduction of management costs in the later stage, which increases the possibility of cooperation success. Network members in this highly sticky interaction process are affected by normative pressure, and R&D employees across firms will be affected by such pressure in high-frequency interactions, prompting them to adopt similar standards in operational management (Dittfeld et al., 2018). Organizations have memory and cognitive systems that can form and maintain specific behavior patterns, thinking principles, cultures, and values, which can actively influence the learning of their members and improve operational efficiency. Therefore, I propose a further hypothesis as follows:

HYPOTHESIS 4 (H4). Higher supply concentration will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.

3.2.5 Moderating Role of Supply Interconnectedness

Supply interconnectedness refers to the number of sales agreements between suppliers in a supply base (Dong et al., 2020; Lu & Shang, 2017).

The larger the supply interconnectedness, the stronger the connections formed between focal firms' suppliers. A strong tie is a social relationship between two actors through long-term cooperation, which means cooperating in multiple social contexts; understanding and supporting the needs of partners; providing some sense of emotional support, belonging, and personal identity; and investing resources in mutual relationships (Leonard & Onyx, 2003; Wellman & Gelman, 1992). Firms can benefit from strong ties because they are essential sources of information that can drive social integration (Pfeffer & Parra, 2009). Strong ties are characterized by high levels of interaction, communication, emotional engagement, and trust, which can reduce opportunity and risk and facilitate the transfer of complex knowledge (Lowik et al., 2012).

Strong ties lead to organizational commitment (Prasad & Harrison, 2006). Supply chain members with strong ties help each other, trust each other, are prone to attachment, and feel a sense of belonging to the community. Especially in the face of complex problems, strong ties can increase reciprocity, accelerate effective communication, improve the efficiency of information transmission, tap undiscovered market opportunities, win competitive market advantages for firms, and help firms grow and make innovative breakthroughs. At the same time, the strength of the connection determines the quality of the heterogeneous and effective resources that firms possess in the network, and firms with strong ties can better obtain advantages, improve operational efficiency, and promote operational benefits. Finally, I propose the last hypothesis as follows:

HYPOTHESIS 5 (H5). Higher supply interconnectedness will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.

The full theoretical framework is shown in Figure 3.1.

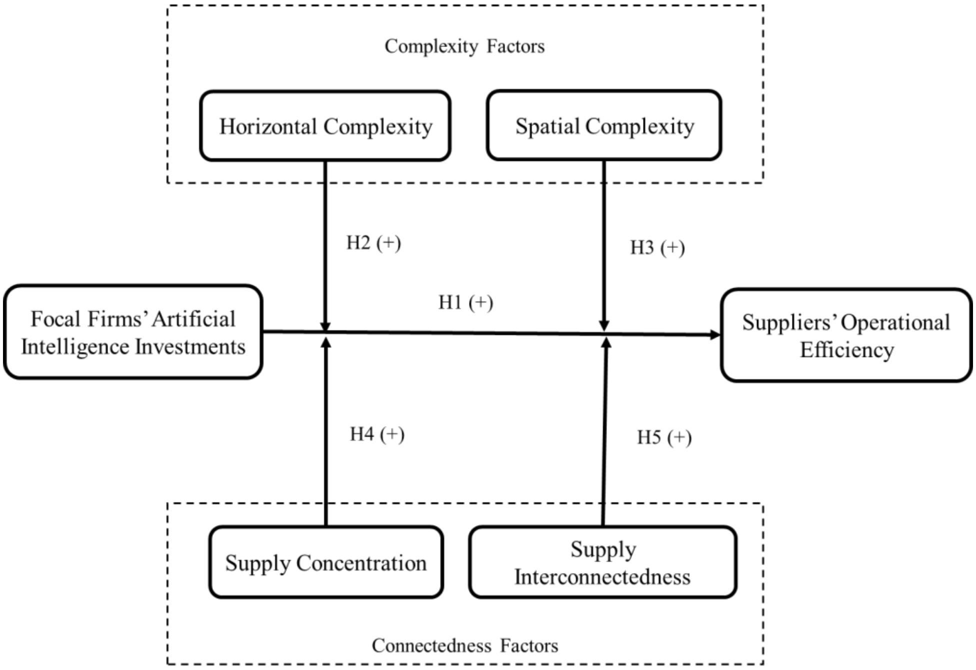


Figure 3.1 Theoretical Framework of Study 2

3.3 Research Methodology

3.3.1 Data Collection

Similar to Study 1, I used a unique proprietary data set developed by Burning Glass Technologies (BGT) that contains over 180 million firm-level recruitment data in the United States from 2010 to 2022. Using machine-generated keywords to identify AI specialist jobs, I examined specific recruitment information on the AI talent of individual firms from the massive BGT database.

Table 3.1 illustrates the data-cleaning process. Similar to Section 2,3,1, I focused on U.S.-listed manufacturing firms (SIC codes: 2000-3999) and recruitment information from 2010 to 2021. I also obtained extra firm-level information (e.g., top five major customers, top five major suppliers) from the FactSet Revere Supply Chain Relationship database. Compared with the other two popular supply network data sets, Compustat Segment and Bloomberg SPLC, FactSet has substantially broader coverage than Compustat Segment (25,000 versus 1,000 relationships per year) and a longer history than Bloomberg SPLC (going back to 2003 versus 2010) (Ding et al., 2023)[1].

Table 3.1 Data Cleaning Process

Panel A: Data Development for Selection Model				
No.	**Data Screening Steps**	**Number of Firms Reduction**	**Number of Firms**	**Database Used**
1	Start with firms with available data between 2010 and 2021	N/A	12,100	Compustat
2	Remove firms in service industries with few or no physical products	3,000	9,210	Compustat
3	Remove firms without inventory and employee data	3,000	6,210	Compustat
4	Remove firms not headquartered in the United States	10	6,200	Compustat
5	Remove firms with no job posting data sources in BGT database	3,692	2,508	BGT
6	Remove firms	594	1,914	FactSet Revere

	with no supply chain relationship data in the FactSet database			Supply Chain Relationship

3.3.2 Sample and Variables

(1) Measurement of Focal Firms' AI Investments

See Section 2.3.2 in Study 1.

(2) Measurement of Suppliers' Operational Efficiency

Following prior studies on operational efficiency (Chen et al., 2015; Chuang et al., 2019; Dutta et al., 2005; Lam et al., 2016; Li et al., 2010), I applied SFE methodology to compute **suppliers' operational efficiency**. Similar to Section 2.3.2, I first developed a production function to model the relationships between a supplier's operational inputs and its operational outcome as follows:

$$\begin{aligned}\ln\,(Operating\ Income)_{ijt} &= \alpha_0 + \alpha_1 \ln\,(Number\ of\ Employees)_{ijt} \\ &+ \alpha_2 \ln\,(Cost\ of\ Goods\ Sod)_{ijt} + \alpha_3 \ln\,(Capital\ Expenditure)_{ijt} \\ &+ \varepsilon_{ijt} - \eta_{ijt}\end{aligned}$$

where ε_{ijt} is the stochastic random error term, and η_{ijt} denotes the operational inefficiency of firm i in industry j in year t. η_{ijt} ranges from 0 to 1, with 0 as the zero-level of inefficiency (i.e., the full efficiency frontier). Accordingly, the operational efficiency of supplier i in industry j in year t can be calculated as follows:

$$Supplier's\ Operational\ Efficiency_{ijt} = 1 - \widehat{\eta_{ijt}}$$

To ensure meaningful comparisons within a narrowly defined industry, I adopted a four-digit SIC code, which is important because the relative performance of operational efficiency is likely to deviate significantly across different sectors.

(3) Measurement of Horizontal Complexity

Horizontal complexity is described as the number of Tier 1 suppliers (Dong et al., 2020; Lu & Shang, 2017). To consider product portfolio heterogeneity across focal firms, I calculated horizontal complexity by dividing the number of Tier 1 suppliers in a focal firm by a weighted sum of its product groups, where the weighting mechanism captures the varying sizes of product groups.

(4) Measurement of Spatial Complexity

Spatial complexity reflects the varying degree of supplier presence in the country where the headquarters are located. It is the sum of the number of unique headquarters countries in a supply base based on supplier headquarter country data from Compustat (Dong et al., 2020; Lu & Shang, 2017; von Corswant & Fredriksson, 2002).

(5) Measurement of Supply Concentration

Following the form in Bharadwaj et al. (1999) and Dong et al. (2020), supply concentration is computed as follows:

$$Concentration\_s_{it} = \sum_{j=1}^{J} \left[\left(\frac{ssale_{ijt}}{ssale_{it}} \right)^2 \times r_{ijt} \right]$$

where J is the total number of focal firm i's suppliers, $ssale_{ijt}$ refers to the total sales of supplier j of firm i in year t, and r_{ijt} is the revenue proportion of supplier j from focal firm i in year t. Therefore, $\frac{ssale_{ijt}}{ssale_{it}}$ represents supplier j's proportion of total sales in the total sales of firm's supply base in year t, whose square terms are weighted by r_{ijt}. Then, Supply concentration is measured by the sum of the weighted squared share of top 5 largest suppliers in the firm's supply base.

(6) Measurement of Supply Interconnectedness

Supply interconnectedness indicates the amount of sales agreements between suppliers in a supply base (Bellamy et al., 2014; Lu & Shang, 2017) and is shown as follows:

$$Intercon\_s_{it} = \sum_{j=1}^{J} \sum_{k=j+1}^{J} link_{jkt}$$

where i represents focal firm i, t presents year t, and j and k present two different suppliers in the supply base of focal firm i with a total number of suppliers J. $link_{jkt}$ represents the relationship between supplier j and supplier k in year t, which is marked as 6 if there are 6 sales agreements between these two suppliers, if there is no sales agreement between them, this value is 0. For example, if a firm has a supply base with two suppliers, A and B, where A also has a sales relationship with B, the commercial interconnectedness of the supply base is 1.

(7) Measurement of Reasonable Control Variables

Consistent with prior studies, I included a set of variables in my analysis to control for various factors that may influence suppliers' operational efficiency.

Following Section 2.3.2 (7), I included five control variables in my study that are likely to be associated with operational efficiency, namely firm size (*Size*), firm age (*Age*), firm profitability (*ROA*), property, plant and equipment (*ppegt*), book to market ratio (*bm*) (Kortmann et al., 2014; Lam et al., 2016; Wu et al., 2010). I also included year and industry dummies in my research for any unobserved trends, industrial characteristics, and geographic variations to eliminate persistent time-specific and industry-specific effects. Table 3.2 summarizes the definition of key variables.

Table 3.2 Definition of Key Variable Measurements

Variables	**Source**	**Definition**	**Source**
Horizontal Complexity	FactSet Revere (Supply Chain Relationship)	Number of Tier 1 suppliers	(Dong et al., 2020); Lu and Shang (2017)
Spatial Complexity	FactSet Revere (Supply Chain Relationship)	Number of supplier countries	(Dong et al., 2020); Lu and Shang (2017)
Supply Concentration	FactSet Revere (Supply Chain Relationship)	Continuous measure for the ratio of purchases from the five largest suppliers to the total purchases	(Jiang et al. (2023)

Supply Interconnectedness	FactSet Revere (Supply Chain Relationship)	Number of sales agreements between suppliers in a supply base	(Dong et al., 2020); Lu and Shang (2017)
Vertical Complexity	FactSet Revere (Supply Chain Relationship)	The average number of Tier 2 suppliers per Tier 1 supplier	(Dong et al., 2020); Lu and Shang (2017)
Customer Concentration	FactSet Revere (Supply Chain Relationship)	Continuous measure for the ratio of sales from the five largest customers to the total sales	Jiang et al. (2023)

3.3.3 Model Specifications

(1) Static Panel Data Model with Fixed Effects

To investigate the impact of focal firms' AI investments on suppliers' operational efficiency, the following econometric model must first be established:

$$
\begin{aligned}
&Suppliers'\ Operational\ Efficiency_{i(t+1)} \\
&\quad = \beta_0 + \beta_1 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad + \beta_2 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Horizontal\ Supply\ Base\ Complexity_{it} \\
&\quad + \beta_3 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Spatial\ Supply\ Base\ Complexity_{it} \\
&\quad + \beta_4 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Supply\ Base\ Concentration_{it} \\
&\quad + \beta_5 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Supply\ Base\ Commercial\ Interconnectedness_{it} + \sum \beta_6 x_{it} + \mu_i \\
&\quad + \lambda_i + \varepsilon_{it}
\end{aligned}
$$

where i and t are firm and year indices, respectively. x_{it} represents a series of other control variables, which are described in Section 3.3.2. μ_i is the unobservable individual effect. λ_i indicates the time effect of i. ε_{it} is the error term, which follows the normal distribution and is not correlated with μ_i and λ_i. An one-year lag between the dependent and independent variables is important to ensure unbiased estimations.

(2) Dynamic Panel Data (DPD) Model

Because firms' operational efficiency could be continuous over time depending on previous performance (Lam et al., 2016), I constructed a DPD model to test my hypotheses as follows:

$$
\begin{aligned}
&Suppliers'\ Operational\ Efficiency_{i(t+1)} \\
&\quad = \beta_0 + \beta_1 Suppliers'\ Operational\ Efficiency_{it} \\
&\quad + \beta_2 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad + \beta_3 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Horizontal\ Supply\ Base\ Complexity_{it} \\
&\quad + \beta_4 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Spatial\ Supply\ Base\ Complexity_{it} \\
&\quad + \beta_5 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Supply\ Base\ Concentration_{it} \\
&\quad + \beta_6 Focal\ Firms'\ AI\ Investments_{it} \\
&\quad * Supply\ Base\ Commercial\ Interconnectedness_{it} + \sum \beta_7 x_{it} + \mu_i \\
&\quad + \lambda_i + \varepsilon_{it}
\end{aligned}
$$

where i and t are firm and year indices, respectively. x_{it} represents a series of other control variables, which are described in Section 3.3.2. μ_i is the unobservable individual effect. λ_i indicates the time effect of i. ε_{it} is the error term, which follows the normal distribution and is not correlated with μ_i and λ_i. The addition of lagged dependent variables makes my model "dynamic" across the years by taking the continuous impact of past efficiency patterns into consideration. An 1-year lag between the dependent variable and other variables is also set to ensure unbiased estimations.

(3) System Generalized Method of Moments (GMM) Estimation

Although I specified a 1-year lag between suppliers' operational efficiency and focal firms' AI investments in the DPD model, there is still potential concern about endogeneity issues (Wintoki et al., 2012). Particularly, it is possible that operational efficiency and AI investments influence each other interactively. On the one hand, AI investments can confer a series of benefits on firms, such as improving the production process, reducing operating costs, and improving demand forecast accuracy, so as to improve overall operational efficiency. On the other hand, firms with better operational efficiency and performance will have enough capital to invest in AI, making two-way causal influences possible. Moreover, unobserved firm factors may influence focal firms' AI investments decision and suppliers' operational efficiency simultaneously, thus inflating the relationship between AI investments and operational efficiency.

Endogeneity is a concern in my DPD models. To address this issue, I followed recent studies (Guo et al., 2020; Pennetier et al., 2019; Ryoo et al., 2021) by adopting the system generalized method of moments (GMM) estimator (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). The system GMM estimator is similar to conventional instrumental variables techniques in that it is based on the construction of instruments to tackle the endogeneity issue. However, the system GMM estimator does not require external measures of individual firms' characteristics outside my data set to develop instruments. Instead, it internally transforms the current measures to develop new instruments, thus solving the possible problem of weak exogeneity of external measures. As a result, the system GMM estimator addresses endogeneity concerns and enhances the robustness of my estimates.

3.4 Results and Analyses

3.4.1 Main Effects

Table 3.3 illustrates the descriptive and correlated data of my research variables. The results show that suppliers' operational efficiency is highly correlated with focal firms'

AI investments' lagged value ($r = 0.107$, $p < 0.01$). Table 3.4 presents the main effect of the panel data models. Model 1 and Model 2 are basic models that include a list of variables lagged for one year (except the dependent variable), including and excluding adding year fixed effects and industry fixed effects. The two models both show that AI investments have a significantly positive impact ($p < 0.01$) on operational efficiency. Table 3.5 presents the main effect of the GMM models. Model 1 shows that AI investments have a significantly positive impact ($p < 0.01$) on operational efficiency. Therefore, Hypothesis 1 is supported.

The number of observations is 1,914 in models whose variables (except the dependent variable) are lagged for one year and 1,820 in models whose variables (except the dependent variable) are lagged for two years, suggesting that there are sufficient sample firms in my data analysis. Repeatedly measuring the same firms over the course of years enables us to obtain robust results by clustering the standard errors by firms.

Table 3.3 Variable Summary Statistics and Correlation Matrix

Variable	N	Mean	SD	Min	Max
Operational Efficiency	1,914	0.660	0.183	0.001	0.998
AI Investments	1,914	0.974	1.772	0.000	8.145
Horizontal Complexity	1,914	0.433	0.045	0.000	1.468
Spatial Complexity	1,914	14097.697	14548.019	50.790	191265.625
Supply Concentration	1,914	0.135	1.760	0.000	421.253
Supply Interconnectedness	1,914	1.653	1.063	0.041	5.485
firm_size	1,914	25.992	9.581	5.000	59.602
firm_age	1,914	0.144	0.092	-0.950	0.782
roa	1,914	6869.970	24031.589	0.673	294882.000
ppegt	1,914	0.013	0.045	-0.547	0.679
bm	1,914	0.421	0.330	0.013	3.899

Variables	Operational Efficiency	AI Investments	Horizontal Complexity	Spatial Complexity	Supply Concentration	Supply Interconnectedness	Size	Age	ROA	ppegt	bm
Operational Efficiency	1.000										

AI Investments	0.66***	1.000									
Horizontal Complexity	0.595***	0.264***	1.000								
Spatial Complexity	0.182***	0.530***	-0.015*	1.000							
Supply Concentration	0.005	0.799***	0.516***	0.018**	1.000						
Supply Interconnectedness	0.429***	0.3924***	0.7987***	-0.002	0.146	1.000					
Size	0.013	-0.026***	-0.146***	0.000	0.017	0.009	1.000				
Age	0.004	0.227***	0.061***	0.262***	-0.006	-0.002	-0.226***	1.000			
ROA	0.008	0.284***	0.068***	0.226***	-0.006	-0.002	-0.203***	0.877***	1.000		
ppegt	0.038***	0.903***	0.024***	-0.038***	-0.008	-0.002	-0.036***	0.220***	0.315***	1.000	
bm	-0.253***	-0.228***	-0.019	0.051***	0.011	0.023***	-0.049***	0.062***	0.036***	0.031***	1.000

**** p < 0.01, ** p < 0.05, * p < 0.1*

Table 3.4 Main Model Regression Results with Independent Variable Lagged by 1 Year (Fixed Effects Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**
AI Investments	**.0255174*****	**.0539866*****
	(.0002687)	**(.0002439)**

Horizontal Complexity	.0000797	.0000886
	(.000135)	(.0001512)
Spatial Complexity	.0020098	.0044574
	(.0033535)	(.0035264)
Supply Concentration	1.88e-08**	2.19e-08***
	(8.68e-09)	(6.82e-09)
Supply Interconnectedness	.6283559***	.645247***
	(.0134959)	(.0149682)
Cons	Included	Included
Control	Yes	Yes
Year Fixed	Yes	No
Industry Fixed	Yes	No
Observations	1,914	1,914
R-squared	.4938078	.1162804

Standard errors are in parentheses.

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 3.5 Main Model Regression Results with Independent Variable Lagged by 1 Year (GMM Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Lagged Operational	**.4673061*** **	**.4682125*** **	**.4838506*** **	**.4596588*** **	**.4740687*** **	**.4845186*** **
Efficiency	**(.0420398)**	**(.0423249)**	**(.0404913)**	**(.0409223)**	**(.041332)**	**(.0392347)**
AI Investments	.0106764**	.0653443**	.0157006***	.0020476	.0087584*	.050636**
	(.0045517)	(.0288063)	(.0054864)	(.0067932)	(.0045119)	(.0248729)
Horizontal Complexity	.0043646*	.0039763**	.0057794**	.0047616**	.0043604*	.0255386***
	(.0022381)	(.0017641)	(.0022828)	(.0022346)	(.0022377)	(.0040171)
Spatial Complexity	2.000e-07	2.000e-07	2.000e-07	2.000e-07	2.000e-07	1.000e-07
	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)
Supply Concentration	.0519700*	.0742900**	.0552900*	.0488100	.0499600	.0767900**
	(.0311300)	(.0346400)	(.0306200)	(.0301300)	(.0309300)	(.0322400)
Supply Interconnectedness	1.27e-06	1.16e-06	1.30e-06	3.47e-07	5.83e-06	6.09e-06
	(7.31e-06)	(7.24e-06)	(7.28e-06)	(6.90e-06)	(7.92e-06)	(.0000123)
AI Investments ✕		**.0039763** **				**.0002113** **
Horizontal Complexity		**(.0017641)**				**(.0000958)**
AI Investments ✕			**.0000579** **			**.0089415** **
Spatial Complexity			**(.0000244)**			**(.0036725)**
AI Investments ✕				**.0000607*** **		**.0000247** **
Supply Concentration				**(.0000169)**		**(.0000115)**
AI Investments ✕					**.0000281*** **	**.0000358** **
Supply Interconnectedness					**(8.35e-06)**	**(.0000153)**
Year Dummies	Included	Included	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included	Included	Included
Cons	Included	Included	Included	Included	Included	Included
Number of Instruments	582	641	641	641	641	818
Arellano-Bond Test for AR	0.255	0.260	0.276	0.251	0.257	0.280

(2)						
Instrument Validity Test	0.974	1.000	1.000	1.000	1.000	1.000
Observations	1,914	1,914	1,914	1,914	1,914	1,914

Robust standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

3.4.2 Interaction Effects

Model 1 – Model 4 in Table 3.6 illustrate the moderating role of horizontal complexity, spatial complexity, Supply Concentration, and supply interconnectedness, respectively.

Evidence shows that horizontal complexity strengthens the positive effect of focal firms' AI investments on suppliers' operational efficiency ($p < 0.01$). Figure 3.2 and Figure 3.3 illustrate that this positive impact is also strengthened by spatial complexity ($p < 0.01$), supply concentration ($p < 0.01$), and supply interconnectedness ($p < 0.01$). These findings support Hypotheses 2–5. Model 5 and Model 6 respectively show the full model, including all moderating effects with and without year and industry fixed effects, respectively. The results are consistent with the previous analysis.

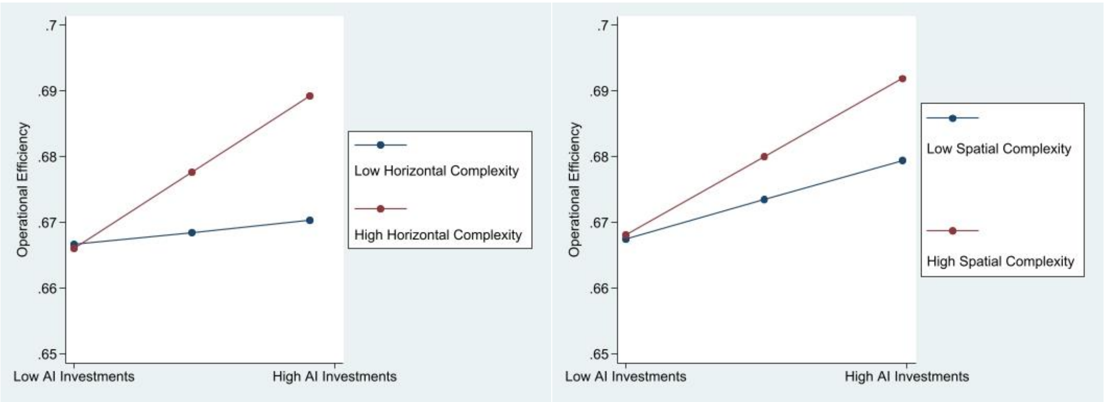


Figure 3.2 Moderating Roles of Horizontal Complexity and Spatial Complexity

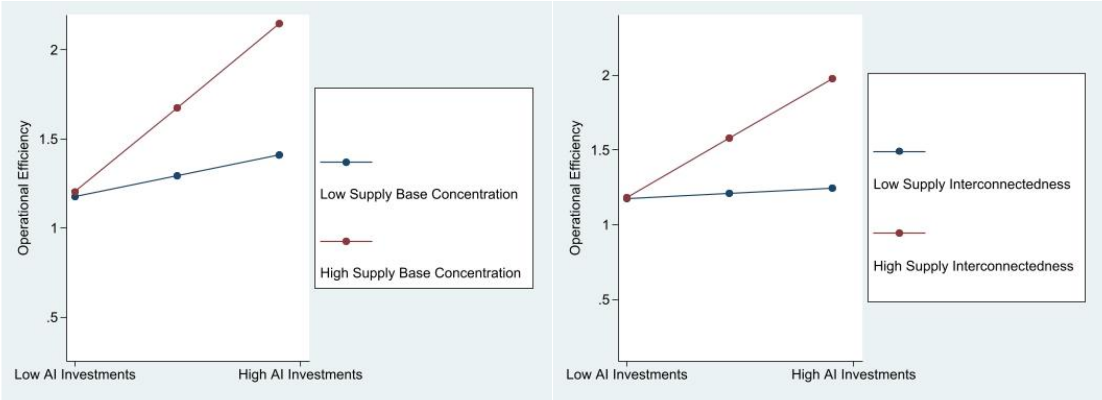


Figure 3.3 Moderating Roles of Supply Concentration and Supply Interconnectedness

Table 3.6 Main Model Regression Results with Independent Variable Lagged by 1 Year (Fixed Effects Model)

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
AI Investments	**.0159953***** **(.0010449)**	**.0239097***** **(.0006283)**	**.0176486***** **(.0010191)**	**.0246005***** **(.0004822)**	**.0133676***** **(.0050508)**	**.0879863***** **(.0048599)**
Horizontal Complexity	.0122115 (.0161684)	.0541252*** (.0153895)	.048403*** (.0153802)	.0555108*** (.0153743)	.0087536 (.0161424)	.1632989*** (.0157969)
Spatial Complexity	1.900e-06*** (1.000e-07)	1.900e-06*** (1.000e-07)	2.000e-06*** (1.000e-07)	2.000e-06*** (1.000e-07)	1.900e-06*** (1.000e-07)	7.000e-07*** (1.000e-07)
Supply Concentration	5.31e-08*** (1.64e-08)	5.33e-08*** (1.64e-08)	2.57e-08 (2.53e-08)	5.33e-08*** (1.64e-08)	2.70e-09 (1.94e-08)	1.33e-08 (2.79e-08)
Supply Interconnectedness	.0005173** (.0002551)	.0005389** (.0002556)	.0005451** (.0002547)	.0004185 (.0002735)	.000348** (.0001491)	.0006059*** (.0002329)
AI Investments × Horizontal Complexity	**.0739224***** **(.0108349)**				**.067332***** **(.0108289)**	**.1820011***** **(.0106739)**
AI Investments × Spatial Complexity		**1.000e-07**** **(.003319)**			**1.000e-07**** **(.003459)**	**6.000e-07***** **(.003433)**
AI Investments × Supply Concentration			**.0000146**** **(7.23e-06)**		**.0000113**** **(5.53e-06)**	**.0000127***** **(3.08e-06)**
AI Investments ×				**.0000281*****	**.0000358****	**.0000477*****

Supply Interconnectedness						
				(8.35e-06)	**(.0000153)**	**(.0000151)**
Cons	Included	Included	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	No
Industry Fixed	Yes	Yes	Yes	Yes	Yes	No
Observations	1,914	1,914	1,914	1,914	1,914	1,914
R-squared	.4941979	.4938254	.4941062	.4939579	.4944536	.4237065

Standard errors are in parentheses.

**** $p < .01$, ** $p < .05$, * $p < .1$*

3.4.3 Robustness Check

By using different evaluation strategies and alternative measurement methods, I conducted many tests to evaluate the robustness of my results. Tables 3.7–3.9 present the robustness check results, and I discuss the procedures below. In general, the robustness check offers further support and rules out some alternative explanations of my research findings.

First, I set the lagged year for all variables except dependent variables (operational efficiency) as two years. As shown in Table 3.8, the main effect in Model 1 and Model 2 and moderating effects in Models 3–6 all remain consistent with results in the previous analysis. I also checked the moderating effect of all moderators with and without year and industry fixed effects in Model 7 and Model 8, and the results remain consistent with the previous analysis.

Second, I winsorized the dependent variable (operational efficiency) at the 1% level (Liu et al., 2023), as shown in Table 3.9. Model 1 and Model 2 show that the main effects and moderating effects remain consistent with the previous analysis. Model 3 and Model 4 show the results after I winsorized the continuous explanatory variable at the 1% level, they remain consistent and significant when all variables (except the dependent variable) are lagged for 1 year and 2 years.

Next, I measured operational efficiency by introducing another measurement containing inventory turnover as illustrated in Section 2.4.3 (Sakakibara et al., 1997; Wu et al., 2019; Yiu et al., 2020). Model 5 and Model 6 show the corresponding results that the moderating effects remain consistent and significant ($p < 0.01$) when all variables (except the dependent variable) are lagged for 1 year and 2 years.

Moreover, I added the squared item of AI investments to my model to check the potential nonlinear relationship between AI investments and operational efficiency. Model 7 and Model 8 show that the squared item of AI investments is not statistically significant ($p > 0.1$). AI investments are still significantly positive ($p < 0.01$) after putting the squared item in the model, supporting the linear relationship between AI investments and operational efficiency when all variables (except the dependent variable) are lagged for 1 year and 2 years.

Finally, following previous studies (Cheng & Bang, 2021; Park et al., 2023), I tested the sensitivity of my results to the modeling choices in the system GMM model in Table 3.7. I did not use all available lagged values beginning with t – 2, i.e. (t – 2, t – maximum), as instruments for the difference equation, but instead constrained the maximum period of lags to t – 6 by choosing a smaller set of instruments, i.e. (t – 2, t - 3), (t - 2, t – 4), (t – 2, t – 5), and (t – 2, t – 6). The Hansen and AR2 test results in all models are insignificant ($p > 0.1$), demonstrating the validity of these instruments employed in my system GMM estimation. All estimation results from the alternative models agree with my earlier system GMM model findings.

Table 3.7 Robustness Check for GMM Models

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**

Lagged Operational	**.4931688*****	**.4779713*****	**.4752042*****	**.4697979*****	**.4845186*****
Efficiency	**(.0082885)**	**(.0089662)**	**(.0087711)**	**(.0087404)**	**(.0092347)**
AI Investments	.0106722**	.0653498**	.0157012***	.01204761***	.0087584***
	(.0045521)	(.0288011)	(.0054821)	(.0067932)	(.0023221)
Horizontal Complexity	.0473092*	.050149**	.0521465**	.0524281**	.050636**
	(.0248039)	(.0245399)	(.0245221)	(.0246338)	(.0248729)
Spatial Complexity	1.000e-07	1.000e-07	1.000e-07	1.000e-07	1.000e-07
	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)	(2.000e-07)
Supply Concentration	.2206836***	.2200569***	.2252378***	.2249209***	.2273773***
	(.0694009)	(.0696364)	(.0698274)	(.0702347)	(.0696902)
Supply Interconnectedness	.0007398**	.0007357**	.0007479**	.0007461**	.0007679**
	(.0003234)	(.0003225)	(.0003227)	(.0003245)	(.0003224)
AI Investments ×	**.1143192****	**.1186178****	**.1232755****	**.124271****	**.1190576****
Horizontal Complexity	**(.0550893)**	**(.0541788)**	**(.0542659)**	**(.0546146)**	**(.05485)**
AI Investments ×	**5.000e-07***	**5.000e-07***	**5.000e-07***	**5.000e-07***	**5.000e-07***
Spatial Complexity	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**	**(3.000e-07)**
AI Investments ×	**.063223****	**.0597808***	**.0613779***	**.0627668****	**.0611997***
Supply Concentration	**(.0319271)**	**(.0314298)**	**(.0314304)**	**(.0316076)**	**(.0318226)**
AI Investments × Supply	**.7786255*****	**.6402455*****	**.4778374*****	**.4040296****	**.6983122***
Interconnectedness	**(.0754586)**	**(.0726423)**	**(.0708823)**	**(.1708151)**	**(.3447142)**
Year Dummies	Included	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included	Included
Cons	Included	Included	Included	Included	Included
Number of Instruments	762	860	888	902	818
Arellano-Bond Test for AR (2)	0.289	0.271	0.269	0.263	0.280
Instrument Validity Test	1.000	1.000	1.000	1.000	1.000
Observations	1,820	1,820	1,820	1,820	1,820

Robust standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table 3.8 Robustness Check for Panel Data Models with Fixed Effects

Dependent Variable: Operational Efficiency	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
AI Investments	**.0131566*** **	**.0114453*** **	**.0342046*** **	**.0161909*** **	**.0058373*** **	**.0238461*** **	**.0145699*** **	**.0146179*** **
	(.0004102)	**(.0004998)**	**(.0029302)**	**(.0004407)**	**(.0005915)**	**(.0004768)**	**(.0026971)**	**(.0051423)**
Horizontal Complexity	.1022014***	.0159269	.0277996*	.1097617***	.028053**	.0623107***	.0183042	.0826256***
	(.013242)	(.0135744)	(.0145559)	(.0132743)	(.0132756)	(.0153692)	(.014447)	(.0159502)
Spatial Complexity	1.500e-06***	6.000e-07***	1.500e-06***	1.700e-06***	1.600e-06***	1.900e-06***	1.700e-06***	1.900e-06***
	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)
Supply Concentration	.0350660*	.0534880**	.0363700*	.0345950*	.0329150*	.0142700	.0329240*	.0034910*
	(.0194090)	(.0260320)	(.0190800)	(.0195650)	(.0169270)	(.0353900)	(.0170650)	(.0018920)
Supply Interconnectedness	.6233236***	.6426145***	.6229115***	.6324036***	.6234436***	0.4152388***	.6324036***	.5896101***
	(.0134403)	(.0149701)	(.0134137)	(.0131978)	(.0132203)	(0.0435989)	(.0131978)	(.0113069)
AI Investments ✕ Horizontal Complexity			**.1058159*** **				**.0267981*** **	**.058062*** **
			(.0065025)				**(.0062476)**	**(.0109778)**
AI Investments ✕ Spatial Complexity				**3.000e-07*** **			**3.000e-07*** **	**2.000e-07*** **
				(.0108349)			**(.0106349)**	**(.0123316)**

AI Investments ✕					**.1285277*****		**.1238949*****	**.0229055*****
Supply Concentration					**(.0026578)**		**(.0027346)**	**(.0046652)**
AI Investments ✕ Supply						**.7341723*****	**.5341693*****	**.5466208*****
Interconnectedness						**(.1243796)**	**(.1113279)**	**(.1260699)**
Cons	Included	Included	Included	Included	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	No	No	Yes	Yes	Yes	Yes	No
Industry Fixed	Yes	No	No	Yes	Yes	Yes	Yes	No
Observations	1,820	1,820	1,820	1,820	1,820	1,820	1,820	1,820
R-squared	.5443299	.1161553	.5453736	.5451597	.5532959	.4937035	.5539418	.4614469

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table 3.9 Robustness Check for Panel Data Models with Fixed Effects

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
AI Investments	**.000617**	**.0056541**	**.003616**	**.0007728**	**.0134594*****	**.0264503*****	**.0056541**	**.0007728**

	(.0051423)	**(.0050971)**	**(.0052343)**	**(.0050303)**	**(.0037616)**	**(.0034473)**	**(.0050971)**	**(.0050303)**
Horizontal Complexity	.0826253***	.0784521***	.0783271***	.0632448***	.1381582***	.1393358***	.0784521***	.0632448***
	(.0159502)	(.0159891)	(.01598)	(.0160943)	(.015117)	(.0121106)	(.0159891)	(.0160943)
Spatial Complexity	1.900e-06***	1.900e-06***	1.900e-06***	1.900e-06***	1.600e-06***	1.000e-07***	1.900e-06***	1.900e-06***
	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-07)	(1.000e-08)	(1.000e-07)	(1.000e-07)
Supply Concentration	.0349100*	.0352400*	.0346100*	.0315500*	.0030900	.0698700***	.0352400*	.0315500*
	(.0189200)	(.0187300)	(.0188200)	(.0187000)	(.0454800)	(.0186900)	(.0187300)	(.018700)
Supply Interconnectedness	.5896101***	.5896403***	.5897084***	.5823642***	.5537223***	.5009103***	.5896403***	.5823642***
	(.0113069)	(.0112907)	(.0112979)	(.011259)	(.0089626)	(.0089867)	(.0112907)	(.011259)
AI Investments ✕	**.0580622*** **	**.0667569*** **	**.0644687*** **	**.0630394*** **	**.095013*** **	**.1556593*** **	**.0667569*** **	**.0630394*** **
Horizontal Complexity	**(.0109778)**	**(.0111549)**	**(.0112436)**	**(.0110111)**	**(.00821)**	**(.0079214)**	**(.0111549)**	**(.0110111)**
AI Investments ✕	**2.000e-07*** **	**2.000e-07*** **	**2.000e-07*** **	**1.000e-07*** **	**2.000e-07*** **	**3.000e-07** **	**2.000e-07*** **	**1.000e-07** **
Spatial Complexity	**(1.000e-08)**	**(1.000e-08)**	**(1.000e-08)**	**(1.000e-08)**	**(1.000e-08)**	**(1.500e-08)**	**(1.000e-08)**	**(5.000e-08)**
AI Investments ✕	**.0229054*** **	**.028289*** **	**.0238341*** **	**.0156498*** **	**.0462955*** **	**.0364826*** **	**.028289*** **	**.0156498*** **
Supply Concentration	**(.0046652)**	**(.0043206)**	**(.0046517)**	**(.0042084)**	**(.0051219)**	**(.0046122)**	**(.0043206)**	**(.0042084)**
AI Investments ✕ Supply	**.5466197*** **	**.5887454*** **	**.5552628*** **	**.5580545*** **	**.9764087*** **	**.2614741** **	**.5887454*** **	**.5580545*** **
Interconnectedness	**(.1260699)**	**(.124977)**	**(.1259387)**	**(.1260012)**	**(.1251639)**	**(.1124431)**	**(.124977)**	**(.1260012)**

Squared AI							**-.0064792**	**-.0064964**
Investments							**(.0219500)**	**(.0219700)**
Cons	Included	Included	Included	Included	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Observations	1,914	1,820	1,914	1,820	1,914	1,820	1,914	1,820
R-squared	.461447	.4604292	.4614688	.5451597	.4374905	.108734	.4982951	.4650337

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

3.5 Conclusions and Discussions

3.5.1 Conclusions

Expanding upon the findings of Study 1, in Study 2, I further explored the impact of focal firms' AI investments on operational efficiency and the moderating effects of horizontal complexity, spatial complexity, supply concentration, and supply interconnectedness. Table 3.10 summarized the research findings in Study 2.

In terms of the main effects, I found that focal firms' AI investments are positively related to suppliers' operational efficiency (H1 is supported). Moreover, this effect was robust and consistent in my tests. In terms of the moderating effects, horizontal complexity, spatial complexity, supply concentration, and supply interconnectedness all enhance the impact of focal firms' AI investments on suppliers' operational efficiency (H2–H5 are supported).

Table 3.10 Results of Hypotheses

Hypothesis (Hypothesized Sign)	**Result (Actual Sign)**
HYPOTHESIS 1 (H1). Focal firms' AI investments have a positive impact on suppliers' operational efficiency.	Supported (+)
HYPOTHESIS 2 (H2). Higher horizontal complexity will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.	Supported (+)
HYPOTHESIS 3 (H3). Higher spatial complexity will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.	Supported (+)
HYPOTHESIS 4 (H4). Higher supply concentration will strengthen the positive impact of focal firms' AI investments on suppliers' operational efficiency.	Supported (+)

HYPOTHESIS 5 (H5). Higher supply interconnectedness will strengthen the positive impact of focal firms’ AI investments on suppliers’ operational efficiency.	Supported (+)

3.5.2 Discussions

By introducing FactSet Revere Supply Chain Relationships data, I further investigated the spillover effect of AI investments in the supply chain network. For the main effects, my research findings strongly support that focal firms’ AI investments can significantly improve suppliers’ operational efficiency. These robust findings confirm the spillover effect of AI investments in the buyer-supplier relationship. This is exciting news for firms actively building supply chain network partnerships. Based on the social network theory, firms can establish strong ties and form strong embeddedness with partners in the network. This will be beneficial for information sharing, knowledge dissemination, and the conversion of focal firms' AI investments into operational efficiencies in buyer-supplier relationships.

From the perspective of complexity factors, the issue of complexity has been raised extensively in previous studies, with many studies highlighting its negative effects (Dong et al., 2020). This study focuses on the effects of horizontal complexity and spatial complexity on the spillover effect. When the level of complexity is high, firms can increase the frequency of communication and information sharing to absorb domain-specific knowledge, improve target consistency and responsiveness, and improve operational efficiency. When the number of suppliers is low, the connection relationship formed between focal firms and suppliers is relatively simple, and it is not suitable to carry out large-scale AI investments. When the spatial complexity is high, the suppliers of the focal firms are widely distributed in many countries, which may result in more difficult cooperation and coordination. In addition, due to the changing international situation and strong uncertainty, firms should fully use the advantages of AI investments to improve operational coordination and problem-solving capabilities.

From the perspective of connectedness factors, supply concentration reflects the concentration of focal firms' suppliers. Drawing on the social network perspective, the higher the supply concentration, the stronger the ties between focal firms and their suppliers. It can effectively promote the flow and sharing of information and help firms effectively obtain resources to solve complex problems. With AI investments, focal forms with higher supply concentration can improve supplier target alignment and responsiveness, thereby jointly improving operational efficiency. Higher supply interconnectedness brings stronger ties between suppliers of focal firms in the supply chain network, which can foster information sharing and organization learning. When focal firms implement AI investments, suppliers can also improve organizational learning activities, obtain resources, jointly solve problems, and improve operational efficiency.Chapter 4 Conclusions and Suggestions for Future Research

4.1 Summary of Research Findings

In this thesis, I conducted two interrelated studies to investigate the impact of AI investments on operational efficiency and examined their spillover effect in the supply chain network. The major findings of these two studies are presented as follows.

Study 1 mainly focuses on the impact of AI investments on operational efficiency and the moderating effects of operational complexity, industry dynamism, and inventory turnover ratio. For the main effects, AI investments are positively related to operational efficiency (H1 is supported). Regarding the moderating effects, operational complexity, industry dynamism, R&D intensity, industry dynamism, and inventory turnover ratio enhance the impact of AI investments on operational efficiency (H2–H5 are supported).

Based on the findings of Study 1, in Study 2, I further explored the impact of focal firms' AI investments on operational efficiency and the moderating effects of horizontal complexity, spatial complexity, supply concentration, and supply interconnectedness. Regarding the main effects, I found that focal firms' AI investments are positively related to suppliers' operational efficiency (H1 is supported). Moreover, this effect was robust and consistent in my tests. Regarding the moderating effects, horizontal complexity, spatial complexity, supply concentration, and supply interconnectedness all enhance the impact of focal firms' AI investments on suppliers' operational efficiency (H2–H5 are supported).

4.2 Theoretical Implications

(1) **This thesis enriches the understanding of AI investments and operational efficiency and provides a wealth of evidence that AI investments are effective in the U.S. context.** Previous studies have mainly focused on the relationship between general R&D investments and operational performance, and the effectiveness of AI investments remains controversial (Donelson & Resutek, 2012; Pennetier et al., 2019; Ugur et al., 2016; Yiu et al., 2020; Zhang et al., 2022). In this thesis, I adopted a novel angle to consider operational efficiency, namely operational capacity, and focused on the influence of AI investments on firms.

(2) **This thesis provides new insights into the spillover effect of AI investment.** Previous studies mainly discussed spillover effects in fields of information systems and accounting studies, but researchers have not yet examined how focal firms' AI investments influence suppliers' operational efficiency (Pennetier et al., 2019; Zhang et al., 2022). Specifically, buyer-supplier relationships are crucial in influencing operational efficiency under the context of complex environments and different levels of connectedness. Accordingly, my research further demonstrates the importance of investigating AI investments in supply chain network relationships in OM studies.

(3) **This thesis extends the research on the factors that moderate the impact of AI investments on operational efficiency and provides new findings on where it is more worthwhile to adopt AI investments.** Existing studies have paid little attention to how to make AI investments more worthwhile in different market environments, such as those with high operational complexity and industry dynamism. The findings of this

thesis indicate that AI investments not only improve operational efficiency but also have a more positive impact in complex market environments. Future research may examine other potential moderators of environmental, operational, complexity, and concentration factors from different perspectives.

(4) **This thesis employs multiple data sources and methodologies to explore the effectiveness of AI investments and generates comprehensive and solid conclusions on the impact of AI investments.** Existing research on U.S. firms has seldom adopted job posting data. This thesis used secondary data from multiple sources and adopted a panel data model with fixed effects and a DPD model to examine the impact of AI investments on operational efficiency. In addition, based on secondary data from the FactSet Revere Supply Chain Relationships database, this study explored the spillover effect of AI investments from the supply chain perspective. Using multiple data sources and data analytics extends the technology management research in the context of U.S. firms.

4.3 Managerial Implications

This thesis has some managerial implications. Because AI investments can promote the persistent improvement of operations and operational efficiency, firms should actively invest in AI technology to reduce operation interruption and minimize adverse impacts on personnel. In particular, my findings show that firms investing in AI technology can achieve more significant improvement in operational efficiency after two years than one year. This illustrates that firms should actively invest in AI technology and wait patiently for its benefits in the sustainable development of firms.

For Study 1, from the perspective of environmental factors, firms in complex market environments with high operational complexity should increase AI investments to improve operational efficiency. In such complex environments, firms should pay attention to their labor intensity and geographic diversity when conducting AI investments. For firms with higher labor intensity, AI implementation training should be increased in human resource management to promote human–machine collaboration and improve the value of AI investments. In addition, for firms with higher geographic diversity and a high degree of operation globalization, AI investments should be effectively used to identify operational problems and avoid the negative impacts caused by higher geographic diversity. Therefore, when conducting AI investments, firms should comprehensively consider the constituent factors of operational complexity. From the perspective of operational factors, as a crucial resource base, R&D intensity provides a solid guarantee for firms' operations. In a turbulent environment, R&D intensity helps firms focus on core operational processes, conduct innovative activities, and gain competitive advantages. Because investors want to benefit from AI investments, firms should adhere to a reasonable R&D expenditure plan every year to improve their resource capacity reserves.

The inventory turnover ratio is an essential operating indicator of firms. In the manufacturing industry, this ratio of diverse types of firms varies greatly. The formulation of AI operation strategy requires firms to consider their operational characteristics. Given the higher inventory turnover ratio and faster product upgrading speed in the FMCG industry, firms require more effort to the application of AI in operation. Firms should continually reassess their AI strategies and imitate other firms who are implementing AI successfully to gain competitiveness. Although firms in heavy machinery and other large-scale industries are less affected by the fluctuations of the market environment, in view of the increasing emphasis on AI technology, they also need to pay attention to demand in daily operations. Firms should recognize the importance of managing inventory turnover in formulating AI investment strategies.

For Study 2, from the perspective of complexity factors, the issue of complexity has been raised extensively in previous studies, with many studies highlighting its negative effects (Dong et al., 2020). When the level of complexity is high, firms can make full use of AI investments to improve the frequency of communication and information sharing to absorb domain-specific knowledge, improve target consistency and responsiveness, and improve operational efficiency. When the number of suppliers is low, the connection formed between focal firms and suppliers is relatively simple, and it is not suitable to carry out large-scale AI investments. Due to the changing international situation and strong uncertainty, firms should fully use the advantages of AI investments to improve operational coordination and problem-solving capabilities.

From the perspective of connectedness factors, drawing on the social network perspective, the higher the supply concentration leads to the stronger the ties between focal firms and their suppliers. It can effectively promote the flow and sharing of information and help firms effectively obtain resources to solve complex problems. With AI investments, focal forms with higher supply concentration can improve supplier target alignment and responsiveness, thereby jointly improving operational efficiency. Higher supply interconnectedness brings stronger ties between suppliers of focal firms in the supply chain network, which can foster information sharing and organization learning. Focal firms and suppliers should take advantages of AI investments to improve organizational learning activities, obtain resources, jointly solve problems, and improve operational efficiency.

For example, in the production process of new energy vehicle's power battery, whether the particles produced by metal welding fall on the surface, whether there is missing coating, and whether the welding process is consistent are the details that must be tested after each process. The quality of power batteries is extremely critical. Once defects occur, without the assistance of other system design in the end market, it can lead to significant property safety issues. In the highly complex supply chain network, BYD closely cooperates with its core supplier CATL, adopts the model based on YOLO and ResNet backbone, and uses computer vision technology to upgrade the monitoring method. Compared with the traditional detection algorithm, the overall product detection has reduced the kill rate by 66.7%, and the defect missing rate is lower than 1DPPB, which also greatly reduces the production line research and development costs.

4.4 Limitations and Future Directions

Although this thesis introduces multiple data sources, adopts some methods to investigate the effectiveness of AI Investments, and provides valuable theoretical and practical contributions, it still exists limitations and provides directions for future research.

First, in examining the relationship between AI investments and operational efficiency, I adopted job posting data from BGT as the data source. Other possible data sources may include Cognism, a service provider of employment data for lead generation and customer relationship management. Cognism obtains resumes from a variety of sources, including publicly available online profiles, collaborations with recruiting agencies, third-party resume aggregators, human resources databases of partner organizations, and direct user-contributed data (Fedyk et al., 2022). Therefore, the robustness will be improved if operational efficiency is measured based on different databases.

Second, Study 1 includes moderators from the perspective of environmental factors and operational factors. Future research may further discover the range of moderating factors from corresponding theoretical perspectives, such as market environment and operation uncertainty. Also, because this thesis is based on U.S.-listed firms, other market environments that contain unique features should be further studied, such as political connections and the lack of legal protection in the Chinese market.

Third, Study 2 includes moderators from the perspective of complex factors and concentration factors. Future research may further investigate the range of moderating factors from corresponding theoretical perspectives, such as market uncertainty and political environment. Also, because this thesis is based on U.S.-listed firms, other market environments that contain unique features should be studied.

Appendices

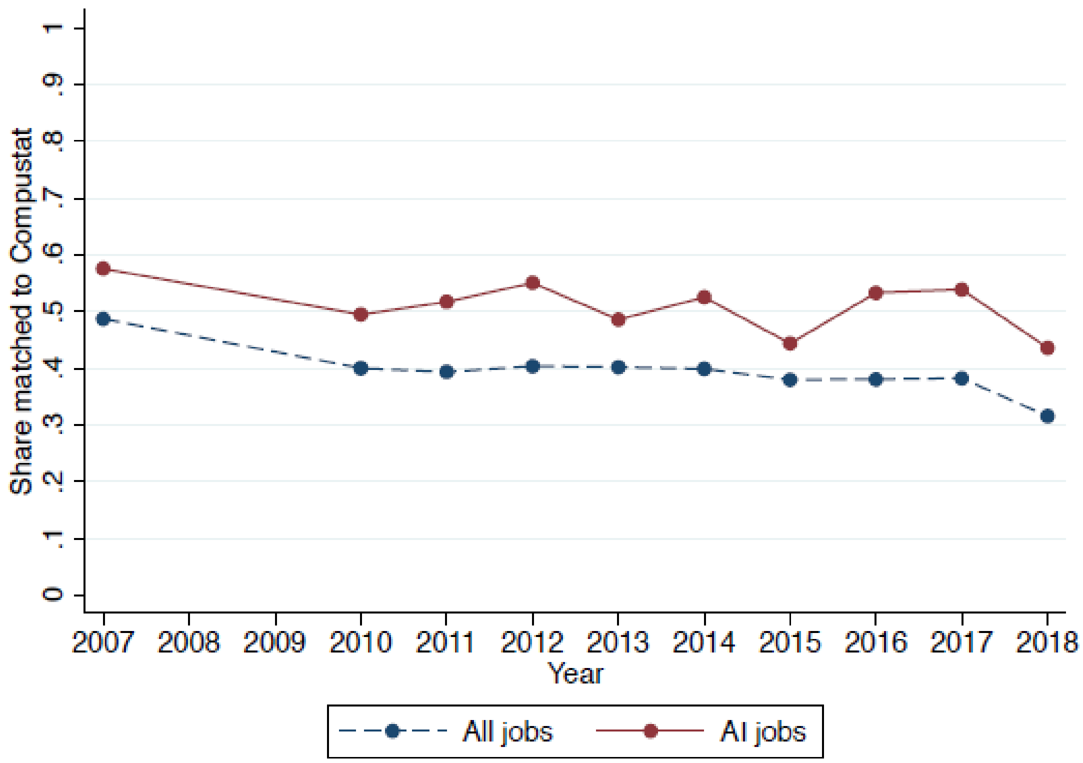
The data are available as requested.

Table A1. Top-30 Skills with High AI-Relatedness Measures in BGT Job Postings

Table A1 lists the top-30 skills in BGT data ranked by the skill-level AI measure ω_s^{AI}. For each skill, I report the percentage of jobs requiring that skill that also require one of the five core AI skills: artificial intelligence (AI), machine learning (ML), natural language processing (NLP), deep learning (DL), and computer vision (CV). For example, of the jobs that required "Recurrent Neural Network (RNN)," 96.5% also required one of the five core AI skills. Only skills that appear in at least 50 job postings are included.

#	Skills	AI-Relatedness Score
1	Artificial Intelligence	1.000
2	Computer Vision	1.000
3	Machine Learning	1.000
4	Natural Language Processing	1.000
5	Deep Learning	1.000
6	ND4J (Software)	0.980
7	Kernel Methods	0.979
8	Microsoft Cognitive Toolkit	0.975
9	Xgboost	0.972
10	Sentiment Classification	0.971
11	Long Short-Term Memory (LSTM)	0.971
12	Libsvm	0.968
13	Semi-Supervised Learning	0.968
14	Recurrent Neural Network (RNN)	0.965
15	Word2Vec	0.956
16	MXNet	0.953
17	Caffe Deep Learning Framework	0.950

18	Autoencoders	0.949
19	MLPACK (C++ library)	0.942
20	Keras	0.941
21	Theano	0.938
22	Torch (Machine Learning)	0.932
23	Wabbit	0.929
24	Boosting (Machine Learning)	0.905
25	TensorFlow	0.904
26	Vowpal	0.903
27	Convolutional Neural Network (CNN)	0.897
28	Jung Framework	0.894
29	OpenNLP	0.894
30	Natural Language Toolkit (NLTK)	0.892



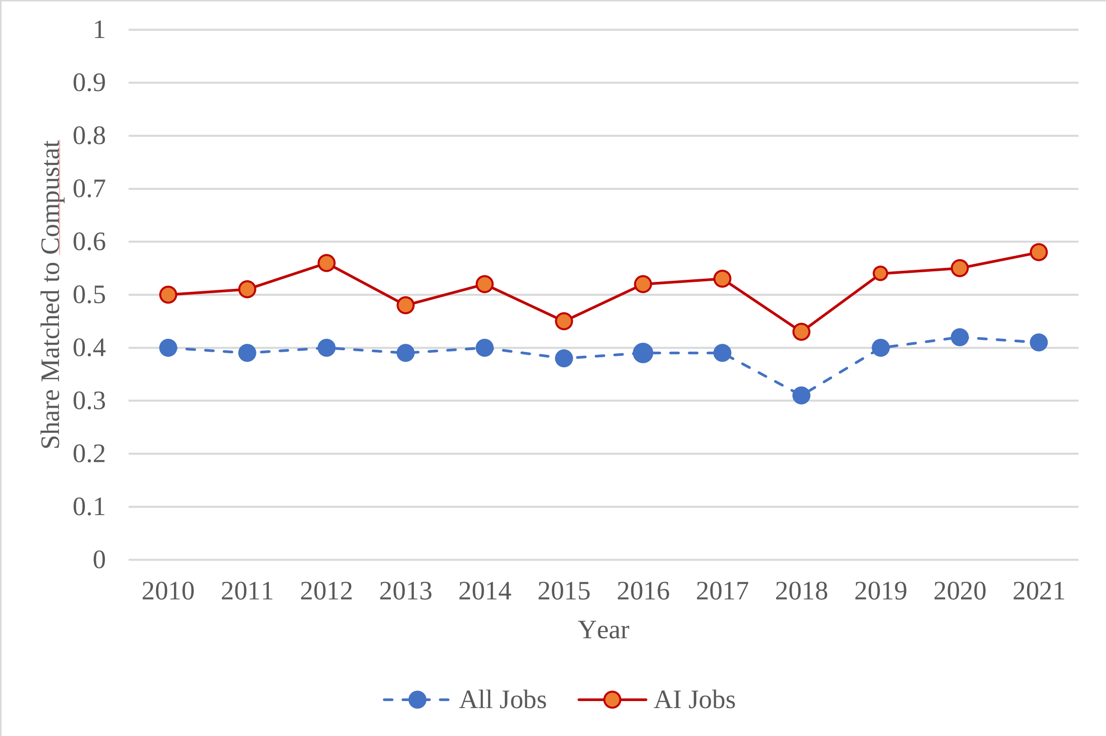


Figure A1. Matching Rate to Compustat in Job Postings Data

Note: This figure shows the time series of the share of all job postings and the share of AI job postings (job postings with continuous measure ω_j^{AI} above 0.1) that are matched to Compustat firms in the BGT data in each year from 2010 to 2021.

Table A2. Examples of AI and Non-AI Job Postings in BGT

This table displays examples of job postings and their continuous AI measure ω_j^{AI}. Jobs 1–10 are examples of AI-skilled jobs, with the first five being non-data-specific and the last five being data-specific. Jobs 11–20 are examples of non-AI-skilled jobs, with the first five being data-specific and the last five being non-data-specific. The AI relatedness score of each skill is listed in parentheses.

	Job Title	Employer	Skills	Score
	AI Jobs			
1	Research Engineer—Natural Language Processing	InterActive Corp	Machine Learning (1), Natural Language Processing (1), Natural Language Toolkit (0.895), Computational Linguistics (0.777), WEKA (0.760), Information Extraction (0.709), Mahout (0.593), Information Retrieval (0.360), Apache Hadoop (0.204), Lucene (0.188), SOLR (0.142), C++ (0.067), Software Engineering (0.043), Python (0.116), Lexical Semantics	0.31

			(0.625), Ontologies (0.326), Java (0.040), PERL Scripting Language (0.034), Relational Databases (0.024), SQL (0.023), Search Analytics (0.022), Shell Scripting (0.020), Web Analytics (0.012), Research (0.011), Online Research (0.010), Extensible Markup Language (0.010)	
2	Computer Vision & Image Processing Researcher	Rambus Incorporated	Computer Vision (1), Object Recognition (0.725), OpenCV (0.689), Pattern Recognition (0.442), CUDA (0.362), Image Processing (0.179), Troubleshooting Technical Issues (0.006), C++ (0.067), Communication Skills (0.003), MATLAB (0.113), Self-Motivation (0.002), Optical System Design and Analysis (0.019), Research (0.011), Writing (0.004), OpenGL (0.117), Prototyping (0.042), Very Large Scale Integration (0.037), Creativity (0.007)	0.21
3	Algorithm Developer	IBM	Natural Language Processing (1), Machine Learning (1), IBM Watson (0.125), Java (0.040), Software Development (0.027), Candidate Generation (0.013), Creativity (0.007), Troubleshooting (0.003), English (0.002)	0.25
4	Senior Autonomous Vehicle Localization Software Engineer	Nvidia Corporation	Computer Vision (1), Deep Learning (0.859), Linear Algebra (0.187), OpenGL (0.117), C++ (0.067), Software Engineering (0.043), Geometry (0.009), Motor Vehicle Operation (0.006), Teamwork/Collaboration (0.005), Calibration (0.004)	0.230
5	Speech Recognition Scientist	Vocera Communications	Computational Linguistics (0.780), Automatic Speech Recognition (0.457), Speech Recognition (0.215), Experiments (0.045), Performance tuning (0.011), Research (0.011), Written Communication (0.003)	0.217
6	Data Scientist	Zappos	Machine Learning (1), Natural Language Processing (1), Boosting (Machine Learning) (0.902), Support Vector Machines (0.816), Naive Bayes (0.759), Matrix Factorization (0.738), Classification Algorithms (0.718), Data Science (0.379), Data Mining (0.159), NoSQL (0.119), Clustering (0.103), Data Structures (0.069), Relational Database Management System (0.028), SQL (0.023), Attribution Modeling (0.072), Detail-Oriented (0.002), Revenue Projections (0.003), Traffic Maintenance (0.002)	0.384

7	Data Mining Engineer	Apple Inc.	Artificial Intelligence (1), Natural Language Processing (1), Machine Learning (1), Unsupervised Learning (0.891), Supervised Learning (0.696), Mahout (0.593), Pattern Recognition (0.442), Apache Hadoop (0.204), Image Processing (0.179), Data Mining (0.159), NoSQL (0.119), Data Collection (0.008), Communication Skills (0.003), Java (0.040), Detail-Oriented (0.002), MATLAB (0.113), SQL (0.023), Network Engineering (0.007), Research (0.011), Python (0.116), Meeting Deadlines (0.002), R (0.248), Predictive Models (0.243)	0..309
8	Big Data Engineer	Socialwire	Machine Learning (1), Recommender Systems (0.843), MapReduce (0.285), Apache Hadoop (0.204), Big Data (0.196), Facebook (0.006), R (0.248), Pinterest (0.003), Writing (0.004), MATLAB (0.113)	0.290
9	Big Data Senior Data Scientist	AT&T	Machine Learning (1), WEKA (0.760), Clustering Algorithms (0.738), Mahout (0.593), Data Science (0.379), Big Data (0.196), Data Mining (0.159), Clustering (0.103), Simulation (0.028), Experimental Testing (0.039), R (0.248), SPSS (0.067), Creativity (0.007), SAS (0.053), Information Systems (0.007), Experiments (0.045), Presentation Skills (0.006), Research (0.011), Data Quality (0.025)	0.235
10	Data Scientist	Warby Parker	Natural Language Processing (1), Natural Language Toolkit (0.895), Random Forests (0.839), Pandas (0.498), Data Science (0.379), PIG (0.290), Apache Hadoop (0.204), Data Mining (0.159), Data Visualization (0.136), Tableau (0.074), Pentaho (0.058), NumPy (0.552), SQL (0.023), Python (0.116), Java (0.040), DevOps (0.039), Agile Development (0.030), Creativity (0.007), Django (0.039), Apache Webserver (0.034), Predictive Models (0.243), Relational Databases (0.024), Data Modeling (0.037)	0.249
	Non-AI Jobs			
11	Director of Business Intelligence	Odesus Incorporated	Data Science (0.379), Data Transformation (0.060), SQL (0.023), Communication Skills (0.003), SQL Server Reporting Services (0.009), SQL Server (0.009), SQL Server Analysis Services (0.034), Budgeting (0.001), Microsoft Sharepoint (0.002), Data Warehousing (0.025), MySQL (0.028),	0.037

			Key Performance Indicators (0.006), Problem-Solving (0.005), Web Analytics (0.012), Market Research (0.006), Data Modeling (0.037), Business Intelligence (0.026), Creativity (0.007)	
12	Director, Data & Analytics	Decision Resources	Big Data (0.196), Business Intelligence (0.026), Business Intelligence Industry Knowledge (0.020), Teamwork/Collaboration (0.005), Biopharmaceutical Industry Knowledge (0.004), Communication Skills (0.003)	0.042
13	Senior Healthcare Economics Data Analyst	UnitedHealth Group	Tableau (0.076), Advanced Statistics (0.149), SAS (0.053), Data Analysis (0.026), SQL (0.023), Economics (0.016), Database Design (0.014), Clinical Data Analysis (0.012), Clinical Data Review (0.010), Business Process (0.006)	0.039
14	Data Analyst	United Technologies Corporation	Data Analysis (0.026), Data Quality (0.025), Data Management (0.018), Database Design (0.014), Proposal Writing (0.007), Product Improvement (0.007), Business Planning (0.002)	0.014
15	SAS Database Administrator	Pitney Bowes	SAS (0.053), SQL (0.023), Business Strategy (0.009), Teradata DBA (0.005), Self-Starter (0.004), Database Administration (0.004), Pivot Tables (0.004), Market Analysis (0.004), Technical Support (0.002), Microsoft Excel (0.002)	0.011
16	Delivery Driver & Technician	Rotech Healthcare	Physical Abilities (0.000), Lifting Ability (0.000), Caregiving (0.000), Patient Contact (0.000), Patient Transportation and Transfer (0.000), HAZMAT (0.000), Hazardous Materials Endorsement (0.000)	0
17	Vice President Underwriting	Morgan Stanley	Workflow Management (0.005), Written Communication (0.003), Detail-Oriented (0.002), Financial Analysis (0.001), Mortgage Underwriting (0.001), Staff Management (0.001)	0.002
18	Quality Assurance Engineer	Amazon	Computer Engineering (0.034), Software Development (0.027), User Interface Design (0.016), Software Quality Assurance (0.010), Black-Box Testing (0.009), Quality Assurance and Control (0.003), Consumer Electronics (0.002)	0.014

19	Sales Associate	GNC	Sales (0.001), Retail Industry Knowledge (0.000), Retail Sales (0.000), Basic Mathematics (0.000)	0
20	Dog & Cat Department Manager	Petco	Creativity (0.007), Leadership (0.003), Budgeting (0.001), Sales Goals (0.001), Retail Industry Knowledge (0.000), Physical Abilities (0.000), Inventory Management (0.000)	0.002

Table A3. Top-50 Job Titles with High Average AI-relatedness Measures

This table reports Top-50 job titles in BGT with high average job-level AI measure ω_j^{AI}. I only included job titles with at least 50 job postings matched to Compustat firms.

	Job Title	Avg. Continuous AI Measure
1	Artificial Intelligence Engineer	0.497
2	Senior Data Scientist—Machine Learning Engineer	0.394
3	Lead Machine Learning Scientist—Enterprise Products	0.369
4	AI Consultant	0.369
5	AI Senior Analyst	0.358
6	Machine Learning Engineer	0.315
7	Technician Architecture Delivery Senior Analyst AI	0.311
8	Artificial Intelligence Analyst	0.308
9	Software Engineer—Machine Learning	0.307
10	Artificial Intelligence Architect	0.303
11	Machine Learning Researcher	0.300
12	Computer Vision Engineer	0.293
13	Senior Machine Learning Engineer	0.286
14	Senior Machine Learning Scientist	0.281
15	Senior Software Engineer—Machine Learning	0.278
16	Senior Engineer II—Data Scientist	0.265
17	Senior Machine Learning Researcher	0.264
18	Artificial Intelligence Consultant	0.263

19	Computer Vision Scientist	0.256
20	Lead Machine Learning Researcher	0.255
21	Senior AI Engineer	0.248
22	Senior Applied Scientist	0.245
23	Senior Engineer—Machine Learning	0.243
24	Senior Risk Modeler	0.241
25	Data Scientist—Engineer	0.238
26	Artificial Intelligence Manager	0.237
27	Machine Learning Scientist	0.230
28	Applied Scientist	0.230
29	Software Engineer—Data Mining/Data Analysis/Machine Learning	0.229
30	Senior Associate—Data Scientist	0.223
31	Director—Data Scientist	0.222
32	Big Data Hadoop Consultant	0.214
33	Vice President—Data Analytics	0.211
34	Data Scientist Specialist	0.210
35	Applied Researcher	0.209
36	Junior Data Scientist	0.205
37	Senior Staff Data Scientist	0.204
38	Principal Data Scientist	0.204
39	Director—Data Science	0.203
40	Research And Development Engineer—Data Mining/Data Analysis/Machine Learning	0.195
41	Manager—Data Scientist	0.192
42	Big Data Scientist	0.191
43	Architect—Relevance Infrastructure	0.191
44	Director—Data Science	0.189
45	Senior Manager—Data Science	0.189

46	Data Science Specialist	0.188
47	Data Scientist II	0.188
48	Senior Data Science Engineer	0.187
49	Staff Data Scientist	0.186
50	Lead Data Scientist	0.186

Table A4. AI Investments and Operational Efficiency: Using Alternative Cutoffs of the Job-postings-based AI Measure

This table reports the coefficients from regressions of operational efficiency from 2010 to 2021 on the contemporaneous changes in the share of AI job postings of U.S. listed firm. AI job postings are defined as job postings with continuous job-level measure $\omega_j^{Narrow\ AI}$ above 0.05 in Panel 1, and job postings with continuous job-level measure $\omega_j^{Narrow\ AI}$ above 0.15 in Panel 2. All regressions control for year and industry sector fixed effects. Standard errors are clustered at the 4-digit SIC industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: Cutoff = 0.05

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**
AI Investments	.0132386***	.0177261***	.0093432	.0057084
	(.0045102)	(.0050964)	(.0065136)	(.006594)
Operational Complexity	.0001074***	.0000773***	.0001014***	.000075***
	(.0000218)	(.0000218)	(.0000262)	(.000023)
Industry Dynamism	3.700e-06***	2.500e-06***	1.200e-06	1.120e-06
	(7.000e-07)	(7.000e-07)	(1.000e-06)	(1.100e-06)
R&D Intensity	.0001096	.0002156	.0007891	.0006674
	(.0004871)	(.000484)	(.0005633)	(.0005553)
Inventory Turnover Ratio	.0000249	.0000184	9.500e-06	5.000e-07
	(.0000227)	(.0000267)	(.0000276)	(.0000129)
AI Investments ✕ Operational			.0000911***	.0001271***
Complexity			(.0000265)	(.000032)
AI Investments ✕ Industry			2.300e-06**	1.900e-06***
Dynamism			(1.100e-06)	(6.000e-07)
AI Investments ✕			.0026218***	.0022506***
R&D Intensity			(.0005938)	(.0005447)

AI Investments ✕ Inventory Turnover Ratio			.0010048**	.001457***
			(.0004968)	(.0004755)
Cons	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	2508	2203	2508	2203
R-squared	.2813317	.251668	.2852999	.2591851

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Panel 2: Cutoff = 0.15

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**	**Model 4**
AI Investments	.0132386***	.0177261***	.0084395	.0055197
	(.0045102)	(.0050964)	(.0062622)	(.0060303)
Operational Complexity	.0001074***	.0000773***	.0001011***	.0000738***
	(.0000218)	(.0000218)	(.0000226)	(.000021)
Industry Dynamism	3.700e-06***	2.500e-06***	1.300e-06	1.000e-07
	(7.000e-07)	(7.000e-07)	(8.000e-07)	(1.000e-06)
R&D Intensity	.0001096	.0002156	.0006143	.0006486
	(.0004871)	(.000484)	(.0004997)	(.0004996)
Inventory Turnover Ratio	.0000249	.0000184	4.900e-06	8.100e-06
	(.0000227)	(.0000267)	(.0000198)	(.0000109)
AI Investments ✕ Operational Complexity			.0000894***	.0001246***
			(.0000243)	(.0000284)
AI Investments ✕ Industry Dynamism			2.200e-06**	1.900e-06***
			(1.000e-06)	(5.000e-07)
AI Investments ✕ R&D Intensity			.0023174***	.0019761***
			(.0005364)	(.0004983)
AI Investments ✕ Inventory Turnover Ratio			.000929**	.0013316***
			(.0004638)	(.000436)
Cons	Included	Included	Included	Included
Control	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	2508	2203	2508	2203
R-squared	.2813317	.251668	.2917927	.2652636

Standard errors are in parentheses.

**** p < .01, ** p < .05, * p < .1*

Table A5. AI Investments and Operational Efficiency: Using Alternative Independent Variables to Confirm this Impact is only Led by Narrow AI Investments

Dependent Variable: Operational Efficiency	**Model 1**	**Model 2**	**Model 3**
General AI Investments	.0002196		
	(.0003247)		
General R&D Investments		-.0000304	
		(.0000648)	
R&D Intensity			.0011753
			(.0009721)
Operational Complexity	.0001433***	-.1452579*	.0001071***
	(.000031)	(.0861158)	(.0000345)
Alternative IV ✕	5.84e-08	.0000708	2.270e-06
Operational Complexity	(7.29e-07)	(.0000754)	(1.420e-06)
Industry Dynamism	1.360e-06	-3.410e-07	1.900e-06
	(1.420e-06)	(1.260e-06)	(1.400e-06)
Alternative IV ✕	-2.06e-08	9.300e-11	1.59e-07
Industry Dynamism	(8.82e-08)	(1.260e-09)	(1.33e-07)
R&D Intensity	.0002139	.0005649	/
	(.0006551)	(.0006571)	/
Alternative IV ✕	.0000608	4.780e-07**	/
R&D Intensity	(.0000564)	(2.330e-07)	/
Inventory Turnover Ratio	.0000441	.0001218	-.0042009
	(.0001309)	(.0001553)	(.010236)
Alternative IV ✕	-7.700e-06	-2.710e-07	-.0009526
Inventory Turnover Ratio	(8.400e-06)	(1.810e-07)	(.0006091)
Cons	Included	Included	Included
Control	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes
N	2627	2627	2508
R-squared	.4117045	.4074869	.382983

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

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