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THE IMPACT OF DIGITAL TRANSFORMATION ON FIRM PERFORMANCE: THREE EMPIRICAL STUDIES BASED ON PANEL DATA

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PhD

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The Impact of Digital Transformation on Firm Performance: Three Empirical Studies Based on Panel Data

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A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

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Abstract

With the emergence of disruptive "ABCD" technologies represented by artificial intelligence, blockchain, cloud computing, and big data, the digital economy is reshaping the global economic landscape and emerging as a new driver of China's economic growth. As significant micro-entities within economic activities, firms have undergone profound changes in their organizational structures, management paradigms, as well as the nature and format of their business activities amid the ongoing digital transformation. In practice, despite the widespread interest and active engagement of numerous firms in digital transformation, only a minority have achieved noteworthy results. Theoretically, scholars have yielded inconsistent findings regarding the relationship between digital transformation and firm performance, suggesting that digital transformation appears to be a dilemma for many firms. Therefore, it is imperative to unlock the "black box" of digital transformation and elucidate its impact on firm performance, as this holds both theoretical and practical significance.

When confronted with decisions regarding digital transformation, firms often grapple with several key questions. First, should they allocate resources towards advancing digital transformation, and will it effectively enhance their performance? Second, which key areas should they prioritize in implementing digital transformation, and what core elements should be incorporated? Third, under what specific circumstances can digital transformation yield more pronounced performance improvements for firms? These inquiries are intimately linked to the motivation and commitment of firms towards digital transformation. A thorough exploration of these issues can not only deepen the theoretical understanding of the relationship between digital transformation and firm performance but also offer tailored managerial insights for firms.

Building upon extensive dialogue with relevant literature, this thesis aims to complement

existing research and address the challenges faced by firms in digital transformation. Drawing on theoretical frameworks such as the natural-resource-based view, upper echelons theory, attention-based view, and resource-based view, this thesis collects and synthesizes large-sample secondary data from multiple sources. Furthermore, it employs rigorous econometric empirical methods to conduct three studies that are logically interrelated.

Study 1, proceeding from the dimension of digital technology, investigates how the use of digital technology influences firms' environmental performance, and further examines the moderating effects of lean production and environmental leadership. Grounded in the natural-resource-based view, Study 1 utilizes panel data from 3308 A-share listed companies between 2007 and 2021. Employing fixed-effects regression models, the study conducts a comprehensive analysis of the data and performs a series of robustness checks to address potential endogeneity issues and ensure the consistency of research findings. The results of Study 1 unveil a significant positive impact of digital technology use on firms' environmental performance. Additionally, it is found that lean production and environmental leadership play significant roles in moderating the relationship between digital technology use and firms' environmental performance. Specifically, for firms that possess higher levels of lean production and environmental leadership, the positive impact of digital technology use on environmental performance is more pronounced.

Study 2, proceeding from the dimension of digital talent, delves into the impact of the appointment of chief digital officers (CDOs) on firms' financial performance, as well as the moderating effects of appointment mode (internal promotion versus external recruitment), scope of responsibilities (generalists overseeing overall digital transformation initiatives versus specialists focusing on specific domains), and board diversity. Drawing upon upper echelons theory and attention-based view, Study 2 utilizes panel data from 158 companies listed in the S&P 500 index spanning the period from 2002 to 2019. It employs a fixed-effects regression model to analyze the data and conducts robustness checks to mitigate potential endogeneity concerns and ensure the reliability of the research findings. The study reveals that appointing a CDO within the top management team significantly enhances a firm's financial performance. Furthermore, "outsider" CDOs, "generalist" CDOs, and board diversity are associated with more pronounced improvements in financial performance for firms.

Study 3, proceeding from the dimension of digital policy, explores the influence of intelligent manufacturing (IM) pilot policy on operational performance in manufacturing firms, while examining the moderating effects of internal operational resources (e.g., employee human capital quality and R&D intensity) and external operational environment (e.g., industry competition). Anchored in the resource-based view, Study 3 employs panel data from 1786 A-share listed manufacturing companies between 2010 and 2020. It adopts a staggered difference-in-differences method to analyze the data and conducts a series of robustness tests to ensure the consistency of research findings. Study 3 finds that the adoption of IM significantly enhances labor productivity in manufacturing firms. Moreover, firms with higher employee human capital quality, greater R&D intensity, and those operating in more competitive industries are inclined to achieve more substantial improvements in labor productivity through the adoption of IM.

The theoretical contributions and innovations of this thesis are mainly manifested in the following aspects. First, it expands the perspective of empirical research on firms' digital transformation and deepens the understanding of the role of non-technological factors (e.g., digital talents and digital policies) in the process of digital transformation. Second, it enhances the understanding of the relationship between different factors in digital transformation and multidimensional firm performance, providing new empirical evidence on the impact of these factors on firm performance and the moderating effects of contextual factors, thereby enriching the literature on the firm-level consequences of digital transformation in the field of operations management. Third, this thesis collects and synthesizes secondary data from multiple sources, employs various econometric methods to analyze the relevant data, and mitigates endogeneity issues as much as possible. Consequently, it enriches the methodological landscape of digital transformation studies to a certain extent.

Keywords: digital transformation; performance implications; digital technology; chief digital officer; intelligent manufacturing; contingency factors

Publications Arising from the Thesis

Published Journal Articles:

Zhu, M., Yeung, A. C. L., & Zhou, H. (2021). Diversify or concentrate: The impact of customer concentration on corporate social responsibility. *International Journal of Production Economics*, 240, 108214.

Zhu, M., Liang, C., Yeung, A. C. L., & Zhou, H. (2024). The impact of intelligent manufacturing on labor productivity: An empirical analysis of Chinese listed manufacturing companies. *International Journal of Production Economics*, 267, 109070.

Zhu, M., Miao, S., Lam, H. K. S., Liang, C., & Yeung, A. C. L. (2024). Navigating through geopolitical risk: The role of supply chain concentration. *International Journal of Operations & Production Management*, forthcoming.

Liang, C., Zhu, M., Lee, P. K. C., Cheng, T. C. E., & Yeung, A. C. L. (2024). Combating extreme weather through operations management: Evidence from a natural experiment in China. *International Journal of Production Economics*, 267, 109073.

Liang, C., Lee, P. K. C., Zhu, M., Yeung, A. C. L., Cheng, T. C. E., & Zhou, H. (2024). The bright side of being uncertain: The impact of economic policy uncertainty on corporate innovation. *International Journal of Operations & Production Management*, 44(11), 1918-1945.

Zhang, J., Zhu, M., & Liu, F. (2024). Find who is doing social good: Using machine learning to predict corporate social responsibility performance. *Operations Management Research*, 17(1), 253-266.

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Chapter 1 Introduction

1.1 Research Background

As the global economic landscape evolves and technological advancements progress, the digital economy is reshaping the global economic map and has become a critical pillar and driving force for China's economic development. Digital transformation, the prevailing trend in global economic development, has garnered widespread attention from major economies worldwide. These economies have prioritized digitalization in their development strategies to foster robust growth in the digital economy. Intensifying international competition surrounding digital technologies, talent reserves, standardization systems, international rulemaking, and data resources constitutes key drivers for future national development and serves as significant benchmarks for measuring a country's international competitiveness.

At the firm level, digital transformation is essential for achieving high-quality development. With increasingly fierce market competition and diversifying consumer demands, traditional enterprises face an urgent need for transformation and upgrading. According to data from the Ministry of Industry and Information Technology of China, digital transformation and intelligent upgrades are crucial pathways for firms to improve quality and efficiency and achieve transformation and upgrading. By deeply integrating digital technologies, firms can achieve intelligent, flexible, and customized production processes, significantly enhancing production efficiency and product quality while reducing production costs and resource consumption (Belhadi *et al*., 2024; Choi *et al*., 2018; Roscoe *et al*., 2019). This integration leads to higher quality and more sustainable development goals.

Leveraging digital transformation to acquire core resources for firm survival and growth while ensuring continuous improvement in customer satisfaction has become a key aspect of future firm competition. Despite the success and remarkable achievements of some leading companies in digital transformation, a significant number of firms are struggling with their transformation processes. According to the “2023 Digital Transformation Index of Chinese Enterprises” released by Accenture, only about 14% of Chinese firms have achieved significant results in digital transformation. Although many companies maintain a positive attitude towards digital transformation, skepticism remains regarding whether the transformation can yield tangible returns.

When making decisions related to digital transformation, firms and governments often face several critical issues. First, should firms invest resources in implementing digital transformation? This question addresses whether digital transformation can achieve expected goals such as improving performance, increasing efficiency, reducing risks, and promoting sustainable development. The answer to this question not only determines the motivation for firms to undertake digital transformation but also helps expand the understanding of its outcomes. Existing literature on the outcomes of digital transformation at the firm level predominantly focuses on financial and innovation performance. However, research on how digital transformation affects a firm’s environmental performance remains limited. Furthermore, as a data-driven emerging managerial practice, digital transformation theoretically conflicts with mature operations management practices such as lean management, which are human-centered, emphasize continuous improvement, and are less technology-focused. Although some theoretical articles suggest that digital transformation and lean management can be effectively integrated to achieve operational goals and gain competitive advantages, this perspective currently lacks empirical evidence to support it.

Second, from which aspects should firms initiate their digital transformation? While digital technology is generally considered the foundation of digital transformation, it involves comprehensive changes across technology, talent, processes, business models, organizational culture, and corporate strategy. Digital transformation is often viewed as a “top leadership” project, indicating that senior leaders must spearhead digital initiatives rather than delegating them to a specific department or implementing minor functional changes. Appointing suitable digital talent to lead the company's digital transformation efforts is crucial. Specifically, the role of the chief digital officer (CDO), an emerging strategic position responsible for overseeing a company's digital transformation, has been underexplored in prior studies (Firk *et al*., 2021). The effectiveness of appointing a CDO—whether a CDO can genuinely enhance firm performance and under what circumstances this performance improvement can be amplified—requires further empirical investigation.

Third, do government policies related to digital transformation help firms better achieve their digital transformation objectives? In China, the government significantly influences firm operations through policy guidance and intervention in various areas. The government formulates relevant industrial policies (such as industrial planning, technological innovation, and market access policies) to support and guide the development of specific industries and enterprises according to national development strategies and industrial layouts. A series of policies related to digital transformation have been introduced in recent years, and it remains to be evaluated whether these policies truly assist enterprises in achieving their digital transformation goals. Furthermore, it is worth studying which types of firms can derive better digital transformation performance from these policies. Answering this question will help the government understand the impacts of implementing digital transformation policies, providing an objective evaluation of the policies' effectiveness and feasibility. This, in turn, can assist the government in improving the scientific and accurate formulation of future policies while reducing the risks associated with policy implementation. As one of the key objectives of digital transformation in manufacturing firms, intelligent manufacturing has garnered widespread attention in recent years. The government has also introduced a series of policies related to intelligent manufacturing to enhance the level of smart operations within manufacturing firms.

Existing studies on intelligent manufacturing primarily focus on theoretically analyzing its technological characteristics and industrial applications, with relatively little attention paid to its commercial value, such as whether it can improve operational performance. Moreover, there is limited exploration of the contextual factors influencing intelligent manufacturing. It is necessary to employ large-sample panel data to conduct quantitative analyses on the operational outcomes of intelligent manufacturing adoption and the associated contingency factors.

1.2 Research Objectives and Design

In summary, the goal of this thesis is to consolidate current knowledge on digital transformation in the field of operations management, investigate whether, how, and why digital transformation affects firms' environmental, financial, and operational performance, and assist firms in better tailoring digital transformation solutions. Consequently, I organized three independent but logically interconnected studies as follows.

Study 1, grounded in the natural-resource-based view (NRBV), provides an in-depth analysis of the impact of digital technology deployment on firms' environmental performance. Hart (1995) posited that the rapid growth of industrial activities and resource consumption challenges the capacity of natural resources, suggesting that natural resources could limit a firm's potential to sustain its competitive advantage. The NRBV theory proposes three interrelated environmental strategies for firms: pollution prevention, product stewardship, and sustainable development. In empirical studies, these strategies are often categorized as resource utilization and green innovation (Ye *et al.*, 2023). Accordingly, Study 1 analyzes how digital technology deployment can effectively enhance resource utilization efficiency and promote green innovation, thereby improving environmental performance. Furthermore, Study 1 examines the moderating effect of lean management practices (e.g., lean production and environmental leadership) on the aforementioned relationships. On one hand, the data-driven nature of digital technology deployment conceptually conflicts with the human-centered, continuous improvement, and de-technologized nature of lean management practices (Margherita & Braccini, 2024). On the other hand, some conceptual papers suggest that digital technology and lean management can be effectively integrated to achieve operational goals (Cifone *et al*., 2021; Rosin *et al*., 2020). Study 1 explores how lean management practices moderate the impact of digital technology deployment on environmental performance from the "lean is green" perspective (King & Lenox, 2001). Based on data from publicly listed Chinese companies, this study employs multi-source secondary data and rigorous empirical methods to test the relevant hypotheses.

Study 2 focuses on examining the impact of digital talent in the process of digital transformation. The theoretical foundations for this study are the upper echelons theory (Hambrick & Mason, 1984; Hambrick, 2007) and the attention-based view (Ocasio, 1997). Specifically, this study investigates whether the appointment of a CDO, a new strategic position responsible for overseeing the company's digital agenda, can truly enhance a firm's financial performance. Furthermore, it examines the effects of different appointment methods (internal promotion versus external recruitment) and scopes of responsibility (generalist overseeing overall digital transformation versus specialist focusing on specific areas) on the relationship between CDO appointment and financial performance. Additionally, considering the decisive role of the board of directors in corporate decision-making, this study also investigates the moderating effect of board diversity. Given the rarity of CDOs in China and considering data availability, this study collected data on CDOs from U.S. publicly traded companies from multiple sources and employed rigorous empirical methods to test the relevant hypotheses.

Study 3 investigates the impact of government digital economy policies on firm operational outcomes. Focusing on the policy shock of intelligent manufacturing pilot demonstration projects, this study explores the relationship between the adoption of intelligent manufacturing and labor productivity in manufacturing firms. Using the resource-based view (Barney, 1991) as the theoretical lens, Study 3 analyzes how the adoption of intelligent manufacturing optimizes a firm's resource base and improves resource allocation, thereby enhancing labor productivity. Furthermore, existing research indicates that the effectiveness of adopting a new technology or manufacturing system is closely related to a firm's internal operational resources and external operating environment (Kunc & Morecroft, 2010; Lam *et al*., 2019). Accordingly, this study examines the moderating effects of R&D intensity, employee human capital quality, and industry competition on the intelligent manufacturing-labor productivity relationship. These analyses contribute to a deeper understanding of how intelligent manufacturing affects labor productivity in firms. The findings provide guidance for manufacturing firms in formulating strategies and optimizing resource allocation to improve production efficiency, as well as offer insights for policymakers to consider various influencing factors when developing relevant policies.

Overall, this thesis investigates the core question of "How does digital transformation affect firm performance?" By focusing on the three primary input elements of digital transformation (i.e., technology, talent, and policy), three closely related yet relatively independent studies are designed to comprehensively examine the impact of different elements on firms' operational, financial, and environmental performance during digital transformation. This thesis not only broadens the perspective of digital transformation studies and deepens the understanding of its outcomes but also provides valuable practical insights for firm managers and policymakers.

Figure 1.1 summarizes the research framework of this thesis.

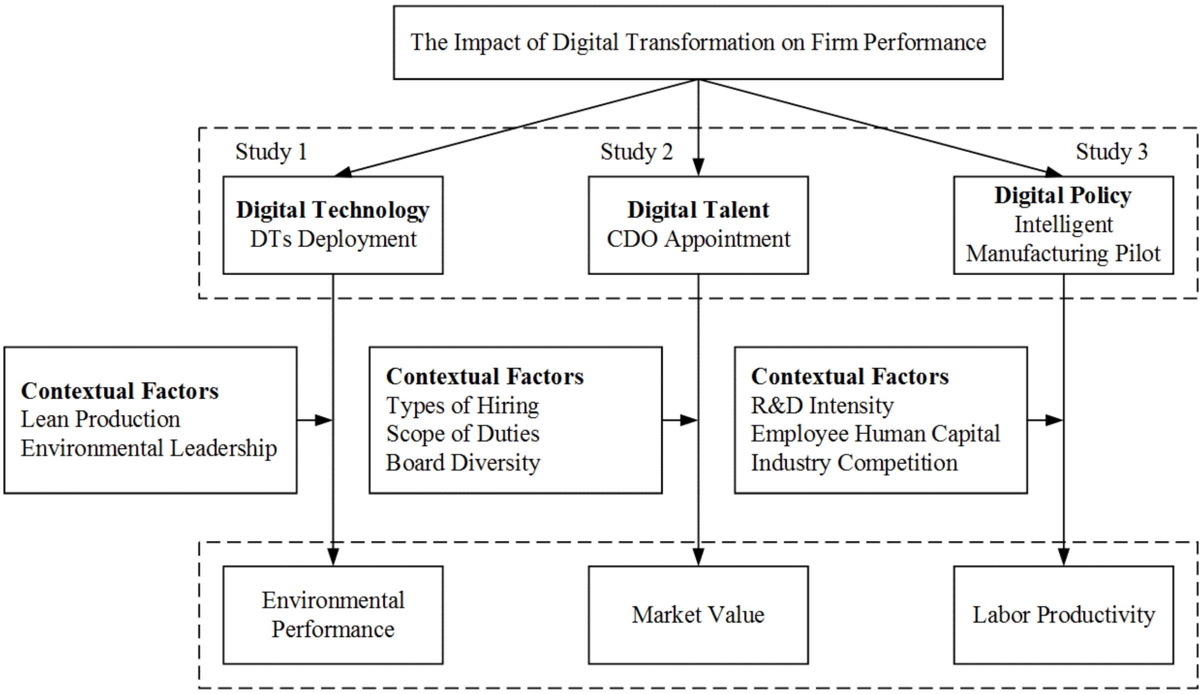

Figure 1.1 Research framework of the thesis

1.3 Research Importance

This thesis addresses the core question of “How does digital transformation affect firm performance?” through three studies that are logically interconnected from multiple perspectives. Overall, this thesis presents potential contributions in research perspectives, content, and methodologies. It expands the research perspective on firm-level digital transformation, deepens the understanding of the relationships between different elements of digital transformation and multidimensional firm performance metrics, enriches the literature on the outcomes of digital transformation in the field of operations management, and diversifies the research methods for studying digital transformation. Specifically, the main contributions of this thesis are reflected in the following aspects:

First, this thesis broadens the perspective of empirical research on firm digital transformation, enhancing the understanding of the role of non-technical elements in the process of digital transformation. Existing research on digital transformation often focuses on digital technologies from a technological determinism viewpoint. Regarding the impact of digital transformation on firm performance, prior studies primarily explore the relationship between specific digital technologies or overall digital technology deployment and firm financial or operational performance (e.g., Chen *et al*., 2022; Raguseo *et al*., 2020; Zhang *et al*., 2024). While digital technologies are fundamental and essential for digital transformation and thus warrant significant attention from researchers, equating digital transformation solely with digital technology usage is insufficient. Other elements such as talent and policy also play crucial roles. Focusing exclusively on technological elements without adequate attention to other factors may lead to a partial understanding of digital transformation, hindering the development of a comprehensive and in-depth theoretical framework, and limiting the ability to provide targeted practical insights. In light of this, the three studies in this thesis delve into key elements of digital transformation, namely digital technology, digital talent, and digital policy. This approach not only broadens the empirical research perspective on digital transformation but also deepens the recognition of the critical roles of digital talent and government policy in the process.

Second, this thesis deepens the understanding of the relationships between different elements of digital transformation and multidimensional firm performance metrics, enriching the literature on the outcomes of digital transformation in the field of operations management. Prior research in operations management field mainly focuses on the impact of digital technology usage on financial or operational performance, with insufficient consideration of other performance dimensions such as environmental performance (Li *et al*., 2022; Sousa-Zomer *et al*., 2020; Tian *et al*., 2023). As an essential aspect of sustainable operations management, environmental performance has not received adequate attention in current research on the outcomes of digital transformation. Although some studies have sporadically explored the impact of digital technology usage on firms' environmental performance, their findings are inconsistent (Li, 2022; Li *et al*., 2020; Saunila *et al*., 2019; Ye *et al*., 2023). This thesis provides new empirical evidence based on large-sample secondary data from China on the relationship between digital technology usage and firms' environmental performance. Furthermore, there are inconsistent views in the extant studies regarding the relationship between the technology-driven Industry 4.0 paradigm and the human-centered, continuous improvement-focused, de-technologized lean management production paradigm. Some studies argue that these two paradigms are divergent and conflicting, while others suggest that firms can effectively integrate them to achieve operational goals such as improved environmental performance (Cifone *et al*., 2021; Rosin *et al*., 2020). However, most discussions on these paradigms remain at the conceptual level, with few studies providing large-sample empirical evidence to substantiate their relationship. This thesis examines the moderating effect of lean management practices on the relationship between digital technology deployment and firms' environmental performance. The empirical results indicate that firms with better lean management practices can indeed achieve greater environmental performance improvements from digital technology usage, providing new insights into the relationship between digital transformation and lean management.

In addition, the role of the CDO as a key participant in the digital transformation process is relatively underexplored in existing literature. Only a few studies have investigated the antecedents of CDO appointments and their short-term stock price effects (Nishant *et al*., 2020; Zhan *et al*., 2022), with a lack of long-term assessments of the value brought by CDOs. This thesis uses panel data spanning approximately twenty years to examine the impact of CDOs on firm value, further exploring the effects of the scope of CDO responsibilities and board diversity on CDO effectiveness. This research provides empirical evidence on the value enhancement brought by CDOs and deepens the understanding of the critical role of talent in digital transformation. What's more, prior operations management literature has rarely addressed the impact of government digital economy policies on firm outcomes. Due to data availability issues, there is also a lack of research on the operational performance effects of intelligent manufacturing. Using the intelligent manufacturing pilot demonstration project as a digital transformation policy shock, this thesis provides direct evidence of the positive impact of intelligent manufacturing adoption on labor productivity in manufacturing firms. Furthermore, it explores the influence of internal operational resources and external operational environments on the effectiveness of intelligent manufacturing adoption. This research expands the scope of digital transformation outcomes from the perspective of government policies and enriches the literature on the operational performance impacts of intelligent manufacturing.

Third, this thesis contributes to the methodological advancement of firm-level digital transformation research by employing large-sample secondary data and rigorous econometric techniques. Many existing studies rely on conceptual frameworks (e.g., Baiyere *et al*., 2020; Hanelt *et al*., 2021; Verhoef *et al*., 2021; Vial, 2019), qualitative case analyses or cross-sectional survey data (e.g., Li *et al*., 2022; Nasiri *et al*., 2022; Stark *et al*., 2023), which, while insightful, are often constrained by limited generalizability, potential recall or self-reporting biases, and challenges in establishing causal inferences (Ketokivi, 2019). In contrast, the empirical operations management literature has increasingly emphasized causal inference and the mitigation of endogeneity concerns, areas where longitudinal panel data offer important advantages (Ketokivi & McIntosh, 2017; Lu *et al*., 2018; Mithas *et al*., 2022). This thesis adopts a quantitative approach grounded in panel data econometrics, drawing on large-scale secondary datasets from multiple sources that span extended time horizons and diverse firm contexts. The use of panel data enables the control of unobserved firm-level heterogeneity and allows for the examination of temporal dynamics, which enhances the validity of the findings. Moreover, this thesis applies rigorous empirical strategies, including fixed-effects models, instrumental variable approaches, and staggered difference-in-differences designs, to address potential endogeneity concerns and mitigate estimation biases. These methodological advancements not only improve the credibility and robustness of empirical evidence on digital transformation but also provide a replicable framework for future research seeking to explore the complex interplay between digital initiatives and firm performance in dynamic organizational environments.

However, the use of secondary data also entails inherent challenges, particularly in behavioral studies where underlying constructs, such as managerial attention or strategic intention, must be proxied using observable variables. The validity of these proxies may vary, and their interpretation requires caution to avoid overgeneralization. This thesis acknowledges these limitations and adopts several robustness checks and sensitivity analyses to assess the reliability of the proxies used. Therefore, while the secondary data approach offers breadth, replicability, and stronger identification strategies, its findings should be interpreted within the context of these constraints. Future research may consider complementing such data with qualitative insights to better capture behavioral dimensions of digital transformation.

In summary, this thesis offers novel empirical insights into how firms' digital transformation—across dimensions of technology, talent, and policy—affects multiple aspects of firm performance, including environmental, financial, and operational outcomes. The findings demonstrate that digital technology adoption improves environmental performance, particularly for firms with strong lean practices and environmental leadership; that appointing a CDO enhances financial performance, with heterogeneity driven by CDO characteristics and board diversity; and that intelligent manufacturing policies significantly boost labor productivity, especially in firms with strong internal capabilities and those operating in competitive environments. These findings collectively highlight the contingent value of digital transformation and underscore the critical role of contextual and organizational factors in realizing its performance benefits.

Chapter 2 Study One: Does Digital Technologies Deployment Promote Environmental Performance? Evidence from Chinese Listed Companies

2.1 Introduction

Over the past three decades, the astronomical growth of environment-related legislation, the increasing cost of waste disposal, the decreasing supply of raw materials, and the increasing consumer preference for green products have greatly attracted the interest in sustainable manufacturing and increased the pressure on firms to make a green transition (Adebanjo *et al*., 2016; Pil and Rothenberg, 2003). Management scholars have long viewed environmental performance as one of the core objectives of firms' operations (Angell and Klassen, 1999; Corbett and Klassen, 2006), and how to employ managerial tools or strategies to improve firms' environmental performance has naturally become an important and relevant issue for both management researchers and practitioners. In recent years, the rapid development of emerging digital technologies (DTs) such as artificial intelligence, machine learning, big data analytics, blockchain, cloud computing, 3D printing, Internet of Things and so on have put forward new solutions to this critical issue (Liu *et al*., 2020). Some anecdotal evidence suggests that the deployment of DTs can help firms confront environmental challenges. For example, Ant Group, the world's leading Internet financial services company, noted in its environment, social and governance (ESG) report that: "We have always believed that technology can and should be used to drive green and sustainable development". Specifically, Ant Group took the lead in launching Carbon Matrix, an enterprise carbon neutral SaaS management system, in September 2021[1]. Currently, Carbon Matrix has been used in Ant Group's carbon neutrality management. Based on the tamper-evident and traceable features of blockchain technology, it makes the

[1] https://antchain.antgroup.com/community/articles/1374?Source=sy_baidu_my_12344

processes of Ant Group's carbon emission, carbon reduction, settlement, regulation, and audit open and transparent, and the relevant records can be traced and verified at any time. Through the ability of blockchain security computing, it helps firms to disclose environment-related data transparently and completely under the premise of ensuring data security.

Nevertheless, while in practice, DTs deployment appears to be increasingly accepted as a key effort to enhance firms' environmental performance, little empirical evidence has been provided to support this relationship to date. In addition, findings in the extant literature about this issue are also inconclusive. While some studies document that DTs deployment has positive effects on firms' environmental performance (Li *et al*., 2020; Ye *et al*., 2023), others indicate a non-linear relationship (Li, 2022) or no direct impact (Saunila *et al*., 2019). These inconsistent results may be due in part to differences in samples (survey vs large-scale secondary dataset), variables of interest (individual DT initiative vs holistic DTs deployment), and potential estimation bias (e.g., sample selection bias) (Bendig *et al*., 2023). This prompts our research to investigate the following question:

*RQ*1. How does DTs deployment influence firms' environmental performance?

Also, prior studies have suggested that DTs-enabled Industry 4.0 may create conflicts with human-centered production paradigm, i.e., lean management, which has been one of the dominant management paradigms in the industry nowadays (Cagliano *et al*., 2019). Contrary to technology-driven production paradigm, lean emphasizes continuous improvement stemmed from employees, learning, and leadership, and requires minimal reliance on information technology (Hopp and Spearman, 2021). For example, the extant research has suggested that lean production, comprised by a set of lean principles, has several advantages over computerized approaches such as reducing the cost of information transfer, improving the accuracy of recording and communicating information in a dynamic environment, synchronizing all items demand, delegating control decisions to foremen and workers, and making it easier for employees to have a clear understanding of production status and requirements without navigating complex software (Riezebos *et al*., 2009; Yang and Yee, 2022). In addition, effective leadership is believed to be essential for the successful implementation and sustainability of lean principles within an organization. It creates challenging goals for firms to survive and leads with passion to reach those goals while simultaneously developing people (Bortolotti *et al*., 2015). Although in reality, there is no universally accepted definition of what lean leadership is or what makes a lean leader (Netland *et al*., 2020), there is a recognition that when talking about environment-related issues, more and more firms realize that they need to develop environmental leadership to face tomorrow's climatic and environmental realities. Also, environmental leadership is closely associated with lean management in terms of waste reduction, resource efficiency, continuous improvement, engagement and culture, among others. Some recent conceptual articles suggest that the DTs and lean can be effectively integrated to enhance organizational performance and achieve sustainable competitive advantage (Buer *et al*., 2018; Cifone *et al*., 2021), but empirical evidence is still lacking. In addition, although previous research shows that lean production has a direct positive impact on firms' environmental performance (King and Lenox, 2001), it remains unclear whether lean production and environmental leadership could moderate the DTs deployment-environmental performance link. In other words, can firms couple DTs with lean production and environmental leadership to yield more environmental benefits? Thus, this study attempts to further address the following question:

*RQ*2. How do lean production and environmental leadership moderate the relationship between DTs deployment and firms' environmental performance?

We examine these research questions by leveraging the natural-resource-based view (NRBV) as the theoretical lens and collecting and combining secondary longitudinal data from multiple sources. The results show that DTs deployment significantly positively impacts firms' environmental performance, and this positive effect is greater for firms with higher levels of lean production as well as environmental leadership. Our findings still hold after a series of robustness checks such as alternative measures, instrumental variable approach, difference-in-differences analysis, and propensity score matching approach. These findings help managers better understand the environmental performance implications of DTs deployment and its boundary conditions.

This study makes several important contributions. First, it advances literature about the outcomes of DTs deployment by directly linking DTs deployment and firms' environmental performance and providing empirical evidence with large-scale sample to support the view that firms can achieve environmental benefits from the implementation of DTs. Moreover, our research enriches the NRBV literature by opening the black box of mechanisms of DTs deployment-environmental performance relationship and examining the effectiveness of the solutions proposed by the NRBV. Finally, this study responses to the recent calls (e.g., Komkowski *et al*., 2023) and enhances the understanding of the integration between Industry 4.0 and lean by examining the moderating impacts of lean production and environmental leadership on the environmental performance effect of DTs deployment. Thus, the findings provide firms with new solutions to enhancing environmental performance and achieving sustainable development goals based on the combination of DTs and lean production and environmental leadership.

2.2 Literature Review and Hypothesis Development

2.2.1 DTs Deployment and Firm Outcomes

In the era of Industry 4.0, DTs as key company assets have become one of the most frequently discussed topics both in academia and industry (Li *et al*., 2020). DTs deployment refers to the adoption of diverse DTs by companies within and across organizations to achieve computation, connectivity, communication, and automation (Li *et al*., 2022). Many of these DTs such as additive manufacturing, blockchain, and big data analytics have been extensively and successfully applied in a range of sectors, including manufacturing, service, maritime, and banking (Cohen, 2018; Frank *et al*., 2019). Among the rich literature related to DTs, a significant number of studies have examined whether the deployment of DTs improves multiple dimensions of organizational outcomes such as innovativeness, financial performance, firm growth, reputation, competitive advantage and the corresponding mechanisms and boundary conditions (Vial, 2019). We also position our study into this research stream.

On the one hand, a large number of conceptual and empirical studies have shown that DTs deployment has positive impacts on organizational performance, such as the enhancement of operational efficiency, financial performance, customer satisfaction, innovativeness, corporate reputation, and firm resilience (Li *et al*., 2022; Svahn *et al*., 2017). The positive impacts of DTs deployment on the above-mentioned firm outcomes are mainly achieved through mechanisms such as improving enterprise resource allocations, optimizing operating processes, enhancing governance levels, and innovating business models. For example, the connectivity and openness of DTs can help firms obtain massive user data from various channels, grasp more comprehensive market information and consumer preferences, and thus conduct digital portraits and personalized marketing for users. The digital business model also enables users to become potential resource providers and brand value co-creators (Ramaswamy and Ozcan, 2016). In addition, DTs make it possible to break down information and knowledge silos and achieve real-time information sharing and communication, which facilitates better synergy in different parts of value creation such as design, R&D, production, operations, sales, and logistics, thus improving firms' resource utilization efficiency as well as intra- and inter-organizational communication and collaboration and finally gaining sustainable competitive advantages (Sousa-Zomer *et al*., 2020; Zhan and Tan, 2020).

On the other hand, some recent studies have also indicated that DTs deployment may lead to unintended adverse consequences on intellectual property rights, data security and privacy issues, employee capabilities, internationalization as well as organizational performance (Choi *et al*., 2022; Zhou and Li, 2023). For example, it was reported that almost half of the US firms employing IoT had faced cybersecurity breaches in 2017 (Choi *et al*., 2022). If a single company's security protocol proves to be vulnerable, that vulnerability is likely to spill over to other members of the supply chain because a weak link in an integrated system allows hackers to access to the data of all other firms (Creazza *et al*., 2022). Also, DTs deployment requires high fixed cost expenditure and may have a time lag in its effect, thus resulting in an insignificant or even negative impact on firms' short-term financial performance (Kohtamäki *et al*., 2020).

2.2.2 Environmental Performance

Firms' environmental performance has become the center of a growing number of academic studies and professional reports in recent decades, and this research stream has evolved through several distinct periods (Duanmu *et al*., 2018). Scholars' research interest in environmental performance has shifted from creating environmental awareness, exploring moral responsibility, and establishing a business case for sustainability in the early years (Shrivastava, 1995) to clearly asking whether environmentally responsible business practices really make sense for firms, especially if they lead to financial returns (e.g., Flammer, 2013; Jacobs *et al*., 2010).

The operations management literature has long introduced the concept of environmental management into firms' production and operations processes and regarded environmental performance as one of the important operations objectives (Angell and Klassen, 1999; Corbett and Klassen, 2006; de Burgos-Jiménez and Céspedes Lorente, 2001), because manufacturing activities such as the production of goods inevitably generates waste that may discharge harmful substances (e.g., chemicals, gases, liquids, and metals) into the environment (Muthulingam *et al*., 2022). While stakeholders have consistently demanded that firms improve their environmental performance, many practical factors such as the lack of universal standards for reporting environmental initiatives, potential conflicts between environmental investments and financial returns as well as principal-agent issues deriving from inconsistencies between the management team's goals and vision for environmental management and employees' day-to-day operational decisions often prevent firms from achieving this objective (Modi and Cantor, 2021; Wichmann *et al*., 2016). In line with this logic, much effort has been devoted to assessing how various internal and external operational resources might affect a firm's environmental performance (Modi and Cantor, 2021). Some researchers have suggested that internal resources such as the adoption of lean practices (Garza-Reyes *et al*., 2018; King and Lenox, 2001), the deployment of environmental management systems (Jeong and Lee, 2022; Melnyk *et al*., 2003), and employees' involvement in environmental behaviors (Alt *et al*., 2015; Hanna *et al*., 2000) could positively influence firms' environmental performance. Other studies demonstrate that external resources in a firm's supply chain or network may impact its environmental performance. For instance, buyer-supplier relationship is often viewed as a key source of both buyer and supplier's environmental behaviors and outcomes (e.g., Kumar *et al*., 2020; Lee and Klassen, 2008; Zhu *et al*., 2021). In addition to intra- and inter-organizational resources, scholars have also provided solid empirical evidence that other operational policies, procedures, tools, and strategies such as incentives and penalties (Porteous *et al*., 2015; Roehrich *et al*., 2017), punitive and supportive strategies (Dhanorkar *et al*., 2018), relative aspirational financial performance (Wiengarten *et al*., 2019), and inspection activities (Mani and Muthulingam, 2019) significantly affect corporate environmental performance.

2.2.3 Industry 4.0 and Lean Management

The most recent wave of DTs is often described as Industry 4.0 (Cifone *et al*., 2021), which introduces high-tech approaches through diverse innovations in soft- and hardware (Komkowski *et al*., 2023). In contrast, as a low-tech approach, lean concentrates on continuous improvement driven by workers, learning, and leadership to eliminate wasteful activities and improve productivity and quality from customers' perspective (Hopp and Spearman, 2021; Tortorella *et al*., 2019). How do they interact and support each other and how to integrate both production paradigms to become smart and lean rather than managing singular transformation is increasingly in the spotlight of researchers and manufacturers (Buer *et al*., 2018). Among the many discussions on this topic, two perspectives dominate the extant literature. One is that lean exerts facilitating impacts on Industry 4.0 implementations (i.e., lean supports Industry 4.0), and the other is that Industry 4.0 can support and further develop lean practices (i.e., Industry 4.0 supports lean) (Buer *et al*., 2018; Ding *et al*., 2023).

The first perspective argues that lean is a basis for successful implementations of Industry 4.0, with firms that have previously adopted lean having a better chance of embracing Industry 4.0 and grasping its potentials (Cifone *et al*., 2021). Since the core idea of lean is to achieve operational excellence by removing muda (waste), mura (variability) and muri (overburden) from the operational processes (Hopp and Spearman, 2021), this ensures that unproductive operations are not digitalized or automated according to previously agreed automation norms (Buer *et al*., 2021). Also, mature lean management brings a number of success factors such as a learning culture, senior management leadership, inter-functional team development, change governance framework, and training activities. As the maturity of lean increases, so does the likelihood of effective Industry 4.0 integration (Komkowski *et al*., 2023). The second research stream describes Industry 4.0 as being a significant complement to lean. Short series manufacturing typically increases unit costs and is not cost competitive due to lack of economies of scale. Lean manufacturing thus streamlines a manufacturer's production process, creating finished goods at the speed required by the customer with little or no waste (Ding *et al*., 2023). In addition to product quality and cost competitiveness, diverse customer demands are also one of the challenges faced by manufacturers, which may make traditional lean practices less effective. Industry 4.0 therefore could be employed for lean to achieve mass production of highly customized products (Cifone *et al*., 2021; Tortorella *et al*., 2019).

2.2.4 Hypothesis Development

We employ the NRBV of the firm as our theoretical lens to illustrate how DTs deployment will affect firms' environmental performance. As the extension of the resource-based view (RBV), the NRBV developed by Hart (1995) more highlights the interaction between an organization and its natural environment. Hart (1995) points out that it is unavoidable that businesses will be constrained by and dependent upon nature. In other words, it is likely that strategy and sustainable competitive advantage in the future will be rooted in capabilities that facilitate environmentally sustainable economic activity. For this end, the NRBV contends that there are three key interrelated strategic capabilities that a firm needs to address: pollution prevention, product stewardship, and sustainable development. Each of these dimensions is associated with an environmental driving force that in one way or another could bring up sustainable competitive advantage. Pollution prevention means that firms should prevent or minimize emissions, effluents, and waste rather than cleaning them up "at the end of the pipe", which is related to cost reductions in areas such as operations or waste disposal. Product stewardship expands the scope of pollution prevention to incorporate the perspectives of external stakeholders throughout the entire value chain or life cycle of a firm's product systems to minimize the environmental impacts, which helps firms effectively integrate "voice of the environment" into the product development and planning processes (e.g., reduce waste, use green raw materials, avoid toxic substances) and creates the potential for competitive advantage via reputation or legitimacy. Finally, sustainable development argues that firms should embrace continuous innovation and change to achieve a sustainable production paradigm that can be maintained indefinitely into the future rather than merely seeking to do less environmental damage. Theoretically and empirically, these dimensions are closely linked to resource utilization and green innovation (Ye *et al*., 2023), we therefore argue that DTs deployment could enhance firms' environmental performance through better resources utilization and more efficient and effective green innovation activities.

Our first hypothesis considers the direct impact of DTs deployment on firms' environmental performance. A number of studies have suggested that DTs deployment allows firms to enhance the flexibility of production, facilitate energy-efficient operations, and improve efficiency in resource allocation (Koh *et al*., 2019). For example, DTs deployment enables firms to produce products additively and intensively by removing redundant steps from the manufacturing processes such as tooling, line-changeovers, and subassemblies and using fewer raw materials and generating significantly less waste compared to traditional production processes (Ford and Despeisse, 2016). Also, the sensors and microchips embedded in products can also store relevant data about their life cycles and track the status of products' components for better reuse, recycling, and remanufacturing in the future (Li, 2022). Furthermore, DTs have dramatically increased the information processing capabilities of firms (Li *et al*., 2020), which allows them to collect, store, extract, compute, and analyze a huge amount of data, thus achieving production flexibility, modularity, mass customization as well as full utilization of resources (Koh *et al*., 2019).

Moreover, prior literature shows that green innovation is an information-intensive and complex knowledge activity that covers information in various fields such as energy conservation, alternative energy production, waste treatment, and pollution prevention (Takalo and Tooranloo, 2021). Studies have well demonstrated that DTs deployment can accelerate information flow, enhance information availability, and improve firms' information integration capability (Li *et al.*, 2021). On the one hand, DTs deployment largely breaks down the information silos within the organization, improves the information exchange among various departments, promotes knowledge interaction among multiple teams of different skill sets, and realizes the integration and sharing of green, low-carbon, environmental protection, and other related information (Zhan and Tan, 2020). This will help firms grasp the information needed for green innovation and lower green innovation risks. On the other hand, DTs deployment can also help firms reduce the cost of external knowledge search as well as expand the breadth and depth of this activity (Trantopoulos *et al.*, 2017), which enhances knowledge transfer effectiveness and enables firms to search and employ up-to-date green technologies and knowledge that are outside the firms' core domain in a more agile and efficient way (Iyengar *et al.*, 2015). Benitez *et al.* (2020) and Marion and Fixson (2021) also suggest that DTs deployment allows firms to achieve green value co-creation with their stakeholders via collaborative innovation. The above discussion indicates that DTs deployment helps firms improve resource utilization and makes it easier for firms to embrace green innovation, leading to the following hypothesis.

H1: DTs deployment has a positive impact on firms' environmental performance.

Our second hypothesis considers the moderating effect of lean production. As a strategy or philosophy consisting of a set of practices (e.g., Kaizen, JIT, TQM), lean production aims to minimize waste and improve operational outcomes (e.g., inventory) and thus finally enhance firm performance (Eroglu and Hofer, 2011). Prior studies have well demonstrated that there exists a positive relationship between lean production adoption and firms' financial performance (e.g., Fullerton and Wempe, 2009; Hofer *et al.*, 2012). Improved financial performance allows firms to alleviate financial restrictions and have more sufficient funds to invest in DTs, thus leading to a better environmental performance. In addition, lean production emphasizes continuous improvement, which could drive firms to take higher risks and attempt high-risk projects (Netland and Ferdows, 2016). This also means that lean firms may be more risk-prone and seek novel attempts, thus providing suitable environment and experience for firms to deploy DTs (Yang and Yee, 2022), which in turn improves corporate environmental performance. Moreover, lean production results in a continuous identification and elimination of waste from firms' production and operations processes, which makes value-added activities remain in a firm's value stream (Komkowski *et al*., 2023). This guarantees that non-productive operations are not digitalized or automated (Buer *et al*., 2021), enabling DTs to focus more on processing information that related to value-added activities, improve resource utilization efficiency, and reduce the energy consumption required to implement DTs.

In addition, as a human-centered approach, lean production creates a better and clearer communication between people and departments. For example, value stream mapping (VSM) can identify the flow of communication, information as well as materials (Yilmaz *et al*., 2022). The extant literature also indicates that firms that adopt lean production normally have a parallel-meso organizational structure, which involves lean and technical expertise at multi-functional levels (Yiu *et al*., 2020). In this case, lean production is conducive to facilitating the role of DTs deployment in information exchange and sharing, thus laying the foundation for green innovation and improved environmental performance. We thus expect that lean production could magnify the positive effect of DTs deployment on firms' environmental performance and propose the following hypothesis:

H2: The impact of DTs deployment on environmental performance is more positive for firms with higher lean production level.

Our third hypothesis considers the moderating effect of environmental leadership. Prior studies have pointed out that lean not only encompasses specific production and analytics tools, but also requires leadership to realize the goals of respecting people and leading employees to continuously improve the organization (Martens, 2022). Leadership is both a process and property. The former refers to the use of noncoercive influence to direct and coordinate the activities of the members of a firm to the accomplishment of the firm's vision, objectives, and processes, while the latter is the set of qualities or features attributed to those who are perceived to effectively leverage such influence (Yukl, 1989). Moyano-Fuentes and Sacristán-Díaz (2012) suggests that effective strategy and alignment can only be delivered through strong leadership. We thus speculate that leadership plays an important role in the relationship between DTs deployment and environmental performance. Specifically, we focus on environmental leadership in this paper, which is relevant to both DTs deployment and environmental performance and is provoking a powerful paradigm shift in how operations norms and cultures have advanced from the top levels of firms (Bendoly *et al*., 2021).

Egri and Herman (2000) broadly define environmental leadership as the ability to influence individuals and mobilize organizations to realize a vision of long-term ecological sustainability. Managers with environmental leadership are believed to have better understanding of the value of environmental protection, pay more attention to diverse stakeholders' environmental expectations, and are more willing to find solutions to firms' environmental concerns such as new technologies adoption, green process/product design, environmentally-focused stakeholder partnerships, and internal and external education initiatives (Dechant and Altman, 1994; Zhang and Ma, 2021). For instance, environmental leadership creates a culture that encourages employees to feel free to innovate and explore opportunities to improve product and reduce waste, which helps employees increase their green organizational identity and better use DTs to conduct green innovations and thus finally amplify the positive impact of DTs deployment on environmental performance (Chen, 2011). Furthermore, environmental managers provide timely and adequate training to employees (especially new hires), which could help employees develop environmental awareness and keep up to date on new environmental technologies, regulations, and community concerns. Well-trained employees are more receptive to new production routines enabled by DTs and could in turn be the source of innovative ideas in emerging pollution prevention technologies and processes (Dechant and Altman, 1994; Gabler *et al*., 2023). In short, environmental leadership helps employees better embrace DTs-transformed production activities and encourages employees to proactively engage into green innovation. Hence, we propose that environmental leadership positively moderates the impact of DTs deployment on environmental performance.

H3: The impact of DTs deployment on environmental performance is more positive for firms with higher environmental leadership.

The conceptual model shown in Figure 2.1 summarizes our three proposed hypotheses.

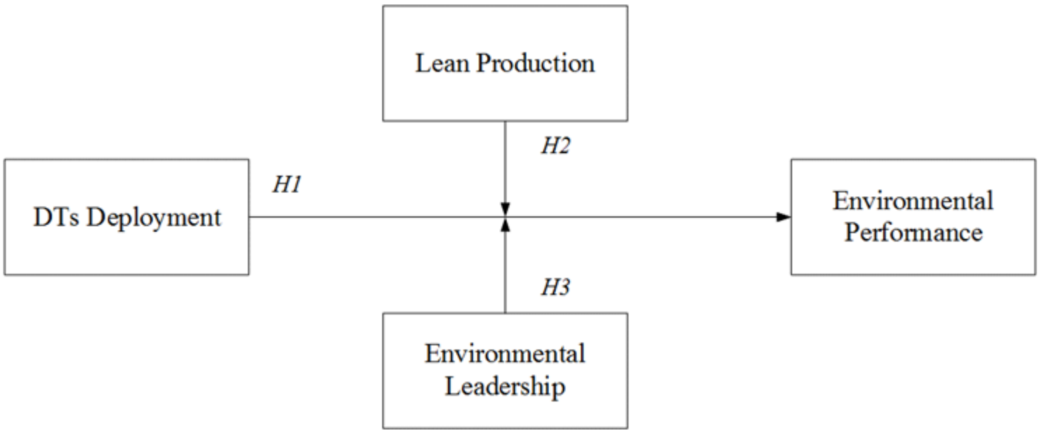

Figure 2.1 Conceptual model of Study 1

2.3 Methodology

2.3.1 Data and Sample

Our initial sample consists of all A-share firms listed on both the Shanghai and Shenzhen stock exchanges between 2007 and 2022. The year 2007 is selected as the initial year for the sample because it is the year in which China implements the new accounting standards. We collect data from multiple sources to measure the variables used in our estimation. The financial and environmental data of the sample firms is obtained from China Stock Market & Accounting Research (CSMAR) database, which has been widely used in prior China-related empirical studies. Additionally, we extract textual terms from the annual reports of all listed companies to construct an index that measures the extent of a firm's DTs deployment. We first remove the observations in the financial sector, given their distinct accounting standards and regulatory requirements (Zhu *et al*., 2021). Then, we exclude less polluting and lean service industries (i.e., industry codes from H to S, such as Information transmission, software and information technology services, leasing and business services, scientific research and technical services, public facilities management, and culture, sports and entertainment). Furthermore, we drop observations that have missing values for variables used in the subsequent regression analyses. As a result, our final sample is an unbalanced panel dataset consisting of 28,417 firm-year observations with 3,308 unique firms between 2007 and 2021, with all explanatory and control variables lagging one year behind to alleviate potential endogeneity concerns derived from reverse causality. Panels A and B of Table 2.1 present the sample distribution by industry and year, respectively.

Table 2.1 Distribution of sample firms

Panel A: Distribution of sample firms across industries

CSRC industry code	Industry	Frequency	Percentage (%)
A	Agriculture, forestry, animal husbandry and fishery	525	1.85
B	Mining	830	2.92
C	Manufacturing	22,113	77.82
D	Electricity, heat, gas and water production and supply	1,168	4.11
E	Construction	861	3.03
F	Wholesale and Retail	1,771	6.23
G	Transportation, warehousing and postal services	1,149	4.04
Total sample size		28,417	100

Panel B: Distribution of sample firms across years

Year	Frequency	Percentage (%)
2007	1,073	3.78
2008	1,158	4.08
2009	1,182	4.16
2010	1,291	4.54
2011	1,575	5.54
2012	1,824	6.42
2013	1,926	6.78
2014	1,951	6.87
2015	2,015	7.09
2016	2,135	7.51
2017	2,346	8.26
2018	2,634	9.27
2019	2,691	9.47
2020	2,841	10.00
2021	1,775	6.25
Total sample size	28,417	100.00

2.3.2 Measures

Environmental Performance. Consistent with previous studies, we measure a firm's environmental performance based on a composite index of several dimensions of environmental strengths and concerns (Modi and Cantor, 2021; Walls *et al*., 2012). Specifically, we derive data on environmental strengths and concerns from the CSMAR database, where environmental strengths include environment protection-related concepts (e.g., disclosure of a firm's environmental protection concept, policy, and circular economy development model, etc.), goals (e.g., completion of environmental protection goals), management systems (e.g., superior commitment to environmental management systems), education and training, special activities (e.g., participation in environmental protection activities), emergency event mechanism (e.g., establishment of emergency response mechanisms for major environmental emergencies), honor and reward, "Three Simultaneity" system, pollutant emission compliance, and ISO14001 implementation. Each of these indicators is represented by a binary variable which takes a value of 1 if a company performs these practices in year *t* and 0 otherwise. In contrast, a firm's environmental concerns consist of sudden environmental accidents, environmental violations, environmental petition cases, and being identified as a key pollution monitoring unit. Similar to environmental strengths, a binary variable is created to indicate the presence or absence of each concern dimension in year *t*. We calculate the composite rating for environmental strengths and concerns separately and then use the difference between them to derive a measure of corporate environmental performance, whereby a higher score denotes superior environmental performance. The composite environmental score reflects a company's endeavors to minimize irresponsible environmental practices and to promote sustainable operations (Liu, 2020). However, prior research also raises concerns about whether the composite index could accurately reflect pollution levels (Walls *et al*., 2012). To address this concern, in our robustness check section, we use the opposite value of environmental violations (i.e., environmental concerns only) as an alternative proxy for corporate environmental performance.

DTs Deployment. Drawing on prior research, we develop a firm-level measure of DTs deployment through textual analysis (e.g., Mishra *et al*., 2022; Niu *et al*., 2023; Zhou and Li, 2023). Specifically, we first use Python to extract the annual reports of all A-share listed companies on the Shanghai and Shenzhen stock exchanges (excluding financial companies) from 2007 to 2020. The text content is obtained using the Java PDFbox library and served as a data pool for subsequent check tags filtering. Next, we locate the terminologies that describe a firm's DTs deployment (i.e., artificial intelligence, big data, cloud computing, blockchain, and the applications of DTs, see Figure 2.2) and then compute their frequency to reflect a firm's DTs deployment level. We take the logarithm of one plus a firm's DTs deployment word frequency in year *t* as the proxy for a firm's DTs deployment.

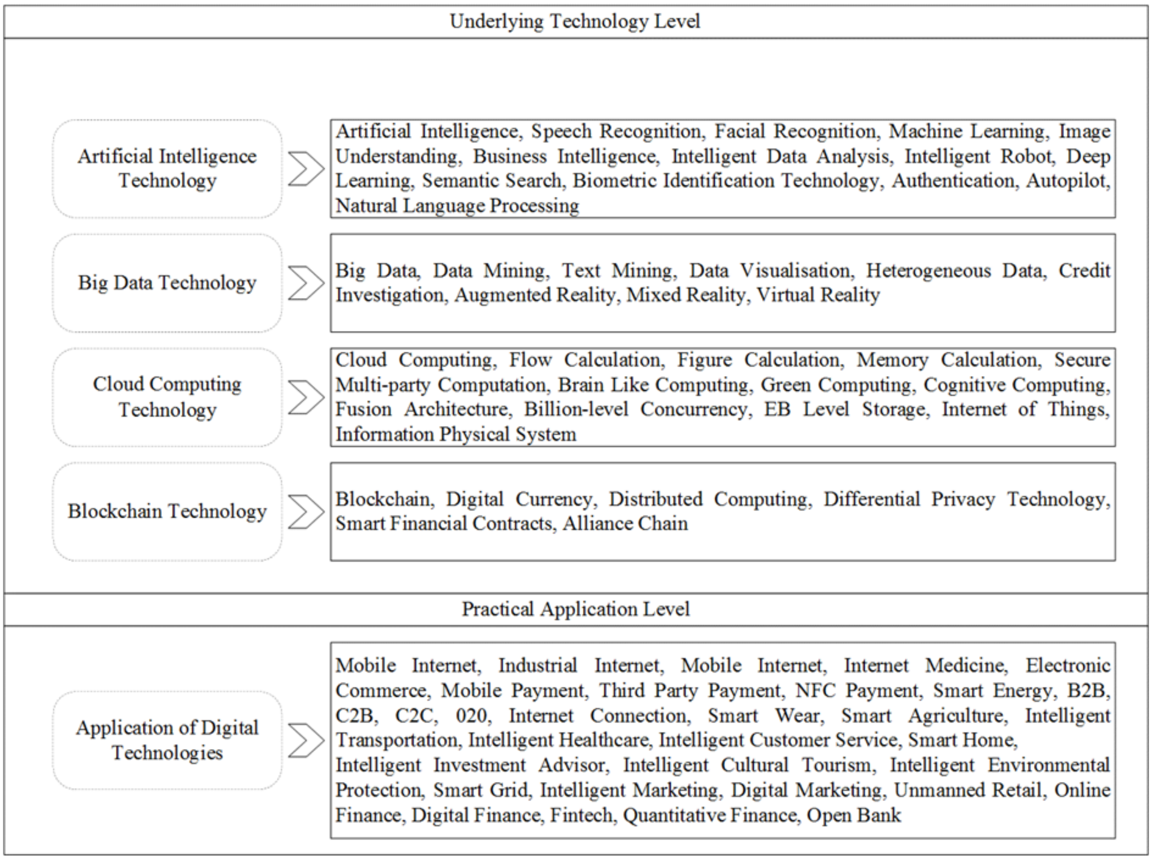

Figure 2.2 DTs deployment feature word atlas

Lean Production. Considering that the level of inventory control is the basis of lean production, the extant studies suggest that the elimination of excess inventory is a major indicator to measure a firm's lean level (Yang and Yee, 2022). We therefore follow Eroglu and Hofer (2011) and Barker *et al*. (2022) and use Empirical Leanness Indicator (ELI) to assess a firm's inventory leanness relative to similar-sized firms operating in the same industry, which accounts for economies of scale and corrects for bias in parameter estimation. Specifically, for each industry (*j*) and year (*t*), we regress firms' natural logarithm of inventory on their natural logarithm of sales.

$$\ln(Inventory_{ijt}) = \propto_{ijt} + \beta \ln(Sales_{ijt}) + \varepsilon_{ijt}$$

where $\ln(Inventory_{ijt})$ represents the natural logarithm of the firm's ending inventory in year *t*, and $\ln(Sales_{ijt})$ is the natural logarithm of annual total sales. The opposite value of residuals in the regression is used to measure a firm's inventory leanness within its one-digit industry. Most of the values of *Lean Production* fall within the range of -3 to 3 (-2.547 for 1st percentile and 2.888 for 99th percentile, respectively), which is consistent with previous research results (Eroglu and Hofer, 2011). In the robustness test, we also employ inventory turnover, defined as the ratio of a firm's cost of goods sold to its inventory level, as an alternative measure of inventory leanness.

Environmental Leadership. Due to data availability, we have no access to public secondary data that directly measure firms' environmental leadership. Agency theory suggests that the board of directors can serve as an information system, and that shareholders can use this system to supervise the firms' operations to meet their needs (Fama and Jensen, 1983). Given that environmental issues are increasingly becoming an important factor for companies to gain competitive advantages or even survive, shareholders thus have strong incentives to demand that firms behave in a sustainable way and engage in production and operations activities in a green manner (Walls *et al*., 2012). Prior studies have well-demonstrated that female on boards could be viewed as a critical resource improving firms' environmental management capability as female incline to be more sensitive to environmental issues than their male counterparts and are more active in making strategic changes and setting the green agenda of a firm (Kumar and Paraskevas, 2018; Wiengarten *et al*., 2017). We therefore draw on Liu (2018) and Zhang and Ma (2021) to use the proportion of female on the board of directors as the proxy for firm-level environmental leadership, which is then standardized within its one-digit industry to ensure comparability across industries (Lam and Zhan, 2021; Modi and Cantor, 2021).

We select a series of control variables that have been identified to potentially affect corporate environmental performance in previous studies, including firm size, firm age, ROA, sales growth, leverage, capital intensity, labor productivity, and R&D intensity (Modi and Cantor, 2021; Walls *et al*., 2012). We measure firm size as a firm's total assets, firm age as the natural logarithm of the number of years since a firm was founded, ROA as the ratio of a firm's earnings before interest and tax (EBIT) to total assets, sales growth as a firm's sales for the current year divided by last year's sales then minus one, leverage as the ratio of total debt to total assets, capital intensity as capital expenditure divided by total assets. We also control for labor productivity because it could potentially influence a firm's competitive actions (Modi and Cantor, 2021). Labor productivity is measured as the natural logarithm of the ratio of operating income to number of employees (Lo *et al*., 2014).

2.3.3 Identification Strategy

We introduce the following panel data model to empirically examine the impact of DTs deployment on corporate environmental performance.

$$Environmental\ Performance_{i,t+1} = \beta_0 + \beta_1 DTs\ Deployment_{i,t} + \beta_2 Lean\ Production_{i,t} + \beta_3 Environmental\ Leadership_{i,t} + \beta_4 DTs\ Deployment_{i,t} \times Lean\ Production_{i,t} + \beta_5 DTs\ Deployment_{i,t} \times Environmental\ Leadership_{i,t} + \beta_6 Controls_{i,t} + YearFEs + FirmFEs + \varepsilon_{i,t}$$

where the subscripts i and t denote firm and year, respectively. $Controls_{i,t}$ are our firm-level control variables. $YearFEs$ and $FirmFEs$ are year and firm fixed effect, respectively. $\varepsilon_{i,t}$ is the error term. We rely on β_1 to determine the direct effects of DTs deployment on environmental performance while β_4 and β_5 to capture the moderating role of lean production and environmental leadership. We lag the independent and control variables by one year to alleviate the potential endogeneity issues due to reverse causality. The inclusion of firm fixed effect can absorb the time-invariant characteristics that potentially affect a firm's environmental performance. Moreover, all continuous variables are winsorized at the 1st and 99th percentiles to reduce the potential impact of outliers.

2.4 Empirical Results

2.4.1 Descriptive Statistics and Baseline Results

The descriptive statistics and correlation matrix of our research variables are presented in Table 2.2. The dependent variable (i.e., environmental performance) ranges from -2 to 9, with an average of 1.64. In particular, the minimum value for DTs deployment is 0, indicating a lack of DTs deployment in certain companies. The maximum variance inflation factor (VIF) score is 1.39, which is far below the threshold of 10. This suggests that multicollinearity is not a major concern in this study.

Table 2.2 Correlation matrix and descriptive statistics

Variables		1	2	3	4	5	6	7	8	9	10	11
1	*Environmental Performance*	1.000										
2	*DTs Deployment*	0.057***	1.000									
3	*Firm Size*	0.325***	0.074***	1.000								
4	*Firm Age*	0.098***	0.175***	0.044***	1.000							
5	*ROA*	0.077***	0.023***	0.006	-0.062***	1.000						
6	*Sales Growth*	-0.013**	0.017***	0.011*	-0.059***	0.233***	1.000					
7	*Leverage*	0.079***	-0.055***	0.256***	0.089***	-0.395***	0.025***	1.000				
8	*Capital Intensity*	0.039***	-0.112***	0.005	-0.206***	0.154***	0.084***	-0.062***	1.000			
9	*Labor Productivity*	0.166***	0.088***	0.301***	0.172***	0.118***	0.127***	0.201***	-0.116***	1.000		
10	*Lean Production*	-0.020***	-0.023***	-0.064***	0.001	0.121***	0.048***	-0.100***	0.100***	0.121***	1.000	
11	*Environmental leadership*	-0.077***	0.033***	-0.093***	0.004	0.028***	0.006	-0.113***	-0.002	-0.059***	0.019***	1.000
Mean		1.64	0.97	12.03	2.83	0.04	0.18	0.44	0.05	13.77	-0.02	-0.02
Standard deviation		1.96	1.18	28.96	0.36	0.07	0.43	0.21	0.05	0.86	0.96	0.99
Minimum		-2.00	0.00	0.28	0.69	-0.28	-0.58	0.05	0.00	11.83	-5.35	-1.35
Maximum		9.00	4.49	207.6	4.16	0.22	2.89	0.98	0.24	16.43	10.9	5.76

Notes: *p < 0.1, **p < 0.05, ***p < 0.01.

Table 2.3 documents the test results based on the fixed-effect regression analysis. Model 1 only includes the explanatory variable (i.e., DTs deployment), year and firm fixed effects. Model 2 further incorporates the control variables into our estimation. Models 3 and 4 introduce the moderating effects of lean production and environmental leadership, respectively. Model 5 is the full model. The coefficient of DTs deployment is positive and significant across Models 1 to 5, indicating a positive relationship between DTs deployment and environmental performance ($p < 0.05$). Thus, H1 is supported. Regarding the moderating effect of lean production, the result in Model 3 shows that the coefficient for the interaction term between DTs deployment and environmental performance is positive and statistically significant ($p < 0.01$). This suggests that the positive impact of DTs deployment on environmental performance will be accentuated for companies with higher inventory leanness. Similarly, the interaction term of DTs deployment and environmental leadership has a significant positive coefficient ($p < 0.05$), indicating that the positive effects of DTs deployment will be magnified when a company has superior environmental leadership. Therefore, our H2 and H3 are both supported as well.

Table 2.3 Baseline results-DTs deployment and environmental performance

	Environmental Performance				
	Model 1	Model 2	Model 3	Model 4	Model 5
DTs Deployment	0.040***	0.029**	0.028**	0.030**	0.029**
	(3.30)	(2.40)	(2.33)	(2.43)	(2.36)
Firm Size		0.007***	0.007***	0.007***	0.007***
		(9.46)	(9.56)	(9.51)	(9.60)
Firm Age		0.508***	0.508***	0.508***	0.508***
		(4.58)	(4.58)	(4.58)	(4.58)
ROA		0.885***	0.882***	0.886***	0.883***
		(5.26)	(5.24)	(5.26)	(5.25)
Sales Growth		-0.036*	-0.037*	-0.036*	-0.038*
		(-1.78)	(-1.85)	(-1.80)	(-1.87)
Leverage		-0.042	-0.043	-0.042	-0.044
		(-0.53)	(-0.56)	(-0.54)	(-0.56)
Capital Intensity		0.141	0.134	0.146	0.138
		(0.66)	(0.63)	(0.68)	(0.65)
Labor Productivity		0.044**	0.045**	0.045**	0.046**
		(2.18)	(2.19)	(2.22)	(2.23)
Lean Production		-0.009	-0.037**	-0.009	-0.037**
		(-0.61)	(-2.20)	(-0.60)	(-2.17)
Environmental Leadership		-0.025*	-0.025*	-0.044***	-0.043***
		(-1.95)	(-1.93)	(-2.85)	(-2.80)
DTs Deployment × Lean Production			0.033***		0.033***
			(3.54)		(3.51)
DTs Deployment × Environmental Leadership				0.020**	0.019**
				(2.24)	(2.19)
Constant	0.581***	-1.216***	-1.217***	-1.231***	-1.230***
	(14.63)	(-3.29)	(-3.30)	(-3.33)	(-3.33)
Year F.E.	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES
N	28,417	28,417	28,417	28,417	28,417
Within R-squared	0.1327	0.1383	0.1387	0.1385	0.1389

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

2.4.2 Robustness Checks

We conduct several supplementary analyses to confirm the robustness of our research findings, as reported in Table 2.4. First, instead of using the difference between environmental strengths and environmental concerns, we use the opposite value of environmental violations as a substitute for corporate environmental performance, which could capture a firm's compliance with environmental regulations more accurately (Walls *et al*., 2012). The result reconfirms that firms with higher levels of DTs deployment are more likely to reduce environmental violations and achieve superior environmental performance (Model 1). Second, we conduct a sub-sample analysis that restricts our sample to the manufacturing industry and the result in Model 2 demonstrates the robustness of our findings. Regarding the moderating variable, we also employ an alternative measure of lean production based on inventory turnover. Specifically, we compute the ratio of a firm's cost of goods sold to its inventory level, standardized by its industry (Gaur *et al*., 2005). The interaction term of DTs deployment and lean production remains positive and significant after taking the alternative measure (Model 3). Regarding environmental leadership, we leverage employee human capital quality as an alternative measure, which is calculated as the proportion of rank-and-file employees whose education level is beyond the threshold of bachelor's degree out of the total number of rank-and-file employees (Si and Xia, 2023). Firms that boast employees with higher human capital quality are often better equipped to understand and address complex environmental challenges. This expertise aligns with the need for comprehensive knowledge to develop and implement effective environmental initiatives. Also, employees with advanced educational backgrounds tend to possess enhanced problem-solving skills, critical thinking abilities, and continuous learning capacities. These skills are invaluable for staying informed about emerging environmental trends and evolving best practices and identifying innovative solutions to environmental issues, contributing to a firm's environmental leadership. Employees with higher education levels tend to possess better communication skills, facilitating the dissemination of environmental goals and strategies both internally and externally. The result in Model 4 once again demonstrates that there exists a positive moderating effect of environmental leadership on the DTs deployment- environmental performance link. Model 5 is the complete model with both alternative moderating variables.

Table 2.4 Robustness checks

	Environmental Performance				
	Model 1	Model 2	Model 3	Model 4	Model 5
DTs Deployment	0.018***	0.019***	0.028**	0.029**	0.029**
	(5.94)	(5.40)	(2.30)	(2.21)	(2.18)
DTs Deployment × Lean Production			0.019**		0.016*
			(2.36)		(1.71)
DTs Deployment × Environmental Leadership				0.021**	0.021**
				(2.19)	(2.21)
Control variables	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES
N	28,417	22,113	28,415	23,717	23,716
Within R-squared	0.3099	0.3397	0.1387	0.1336	0.1336

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

2.4.3 Endogeneity Issues

Instrumental variable (IV) approach

Although we have controlled for the time-invariant influential factors, it is plausible that a firm's disposition towards DTs and its environmental performance might be simultaneously affected by certain time-variant unobservable omitted variables, leading to biased coefficient estimates. Consequently, we estimate a two-stage least squares (2SLS) model with IVs to mitigate this concern. Similar to Zhou and Li (2023), we utilize the total telecommunications business revenue (IT_VOL) and total employees in Information transmission, software and information technology industries (IT_EMPLOY) within each province as IVs for a firm's DTs deployment. The scale of regional telecommunications business reflects the maturity of communication infrastructure. The proliferation of telecommunications services within a given area signifies a more robust network infrastructure and enhanced Internet connectivity, thereby furnishing firms with the dependable network foundation requisite for digital transformation. Furthermore, firms located in regions endowed with a wealth of IT talents are inclined to realize successful progress in their digital transformation initiatives. However, these two IVs does not exert a direct impact on a firm's environmental performance. The first-stage regression result shows that two IVs (IT_VOL and IT_EMPLOY) are both significantly and positively correlated with firms' DTs deployment. The Kleibergen-Paap underidentification test statistic indicates that our IVs can be fully identified. In addition, both the Cragg-Donald Wald F and Kleibergen-Paap Wald F values exceed the 10% threshold of the Stock-Yogo weak identification critical values, confirming the high relevance and validity of our selected instruments. Overall, the result remains consistent with the baseline result after adopting the IV approach.

Heckman two-step model

As companies voluntarily disclose their DTs deployment progress in their annual reports, we employ a Heckman two-step model to alleviate the potential sample selection bias problem. In the first step, we use a probit model to estimate the probability of undertaking digital transformation, where the dependent variable equals one if firm i conducts digital transformation (DTs deployment > 0) in year t and equals zero otherwise. The control variables in the probit model are consistent with those in the baseline model. We then calculate the inverse Mills ratio (IMR) and include it as an extra control variable in the second step regression to correct the potential sample selection. The coefficient of IMR is not significant, indicating that the self-selection issue is not a major concern in this study. Moreover, the consistently significant and positive coefficient of DTs deployment reaffirms the robustness of our findings.

Evidence from a quasi-natural experiment

To further mitigate the endogeneity concern, we leverage an exogenous shock and treat it as a quasi-natural experiment that fosters corporate digitalization. Specifically, in August 2015, the Chinese government unveiled the "Big Data Development Action Plan", which incentivizes companies to engage in research and development related to big data underlying technologies. The introduction of the action plan not only improves the disclosure of digital information but also significantly promotes the digital transformation process of certain firms (Zhou and Li, 2023). We assign a sample firm to the treatment group if its average annual DTs deployment value is greater than the industry average during our sample period, and to the control group otherwise. Treat is a binary variable that takes the value of one for treatment group and zero for control group. *POST* is also a binary variable that equals zero before 2015 and one after 2015. The model is as follows:

$$Environmental\ Performance_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_2 Controls_{i,t} + YearFEs + FirmFEs + \varepsilon_{it}$$

Before performing the difference-in-differences (DID) analysis, we employ the propensity score matching (PSM) approach to ensure that the treatment and control groups are as similar as possible across each dimension. We use nearest-neighbor matching (one-to-one matching, without replacement, with a caliper of 0.01) to match each treatment firm to the control firm with the closest propensity score. The result of DID analysis based on the PSM-matched firms is presented in Table 2.5, where the dependent variables are the composite environmental performance score and the opposite value of environmental violations, respectively (Columns 5 and 6). The corresponding results suggest that the significant positive impact of DTs deployment on environmental performance still holds after the employment of PSM-DID analysis. Overall, the above endogeneity tests further reinforce the validity of our research findings.

Table 2.5 Endogeneity tests

	IV		Heckman		PSM+DID	
	(1) First Stage	(2) Second Stage	(3) First Stage	(4) Second Stage	(5) EnvPerf	(6) EnvPerf_concern
DTs Deployment		0.572*	0.028**	0.030*		
		(1.90)	(2.33)	(1.88)		
Treat× Post					0.069*	0.068***
					(1.84)	(7.22)
IT_VOL	0.003***					
	(3.31)					
IT_EMPLOY	0.001***					
	(3.27)					
IMR				-0.001		
				(-0.09)		
Firm Size	0.004***	0.005***	0.003***	0.007***	0.009***	-0.002***
	(8.74)	(3.29)	(4.16)	(9.45)	(11.43)	(-7.87)
Firm Age	0.155**	0.406***	-0.169**	0.508***	0.549***	-0.000
	(2.37)	(2.91)	(-2.29)	(4.58)	(4.41)	(-0.00)
ROA	0.044	0.877***	0.314	0.885***	0.592***	-0.089*
	(0.48)	(5.22)	(1.52)	(5.26)	(3.17)	(-1.89)
Sales Growth	0.022*	-0.047**	0.053**	-0.036*	-0.056**	-0.002
	(1.85)	(-2.12)	(2.14)	(-1.79)	(-2.52)	(-0.33)
Leverage	0.184***	-0.151	0.161*	-0.042	-0.091	0.071***
	(4.31)	(-1.47)	(1.83)	(-0.54)	(-1.06)	(3.32)
Capital Intensity	0.158	0.058	-0.698***	0.142	0.353	0.056
	(1.44)	(0.25)	(-2.64)	(0.66)	(1.45)	(0.92)
Labor Productivity	0.078***	0.002	0.001	0.044**	0.041*	0.003
	(6.56)	(0.05)	(0.03)	(2.18)	(1.77)	(0.55)
Lean Production	-0.007	-0.003	-0.025	-0.009	-0.013	0.002
	(-0.79)	(-0.18)	(-1.52)	(-0.61)	(-0.79)	(0.42)
Environmental Leadership	-0.009	-0.021	0.018	-0.025*	-0.017	-0.002
	(-1.29)	(-1.54)	(1.24)	(-1.95)	(-1.23)	(-0.51)
Constant	-0.079	0.464	-1.420***	-1.215***	-1.342***	-0.004
	(-0.17)	(0.99)	(-4.15)	(-3.29)	(-3.21)	(-0.04)
Year F.E.	YES	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES	YES
N	27,985	27,985	33,875	28,417	25,310	25,310
Kleibergen-Paap rk LM statistic	44.89***					

Kleibergen-Paap rk Wald F statistic	21.87
Cragg-Donald Wald F statistic	29.77
Stock-Yogo 10% critical value	8.68

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the *p*-values are two-tailed. *t* statistics in parentheses.

2.5 Summary, Discussion, and Future Research

2.5.1 Summary and Principal Findings

The relationship between the firm and the environment has garnered increasing attention in both academic and professional literature in the past three decades, especially for firms operating in emerging markets such as China. Management scholars have long identified environmental performance as one of the important operations objectives and the driver of other types of manufacturing improvements (e.g., superior quality, better financial performance) (de Burgos-Jiménez *et al*., 2013; Liu, 2020; Pil and Rothenberg, 2003). In recent years, DTs-enabled Industry 4.0 has greatly transformed firms' production and operations activities, and some studies suggest that this transformation provides firms with technical support to achieve environmental sustainability (Bendig *et al*., 2023; Li *et al*., 2020; Ye *et al*., 2023). Other researchers, however, argue that DTs deployment may not necessarily lead to superior environmental performance, given the high energy consumption and generation of electronic waste (Li, 2022). We thus are motivated by these inconsistent findings and investigate if DTs deployment could help firms improve environmental performance. In addition, different from technology-driven management paradigm, the wide-adopted lean paradigm focuses on continuous improvement derived from low-tech factors (Hopp and Spearman, 2021). Whether DTs and lean can go hand in hand and how to integrate DTs and lean in the organization to achieve desired benefits (e.g., environmental performance) have been an important issue. We therefore join this research stream and examine the moderating effect of lean management on the relationship between DTs deployment and firms' environmental performance.

Employing the NRBV as our theoretical lens and analyzing a large-scale panel dataset of Chinese publicly traded firms, we provide direct empirical evidence that there is a significant positive relationship between DTs deployment and firms' environmental performance. In addition, we find that lean production and environmental leadership positively moderate DTs deployment-environmental performance link, which indicates that environmental benefits from DTs deployment could be strengthened by lean management practices in terms of lean production and environmental leadership. Our results still hold after a set of robustness checks. These findings have several implications for literature and practices which are discussed below.

2.5.2 Implications for Research

This study contributes to the literature in several ways. First, our research expands the NRBV literature by empirically uncovering the environmental performance effect of DTs deployment and investigating critical contingency factors that influence this effect. While the extant literature has applied various theories (e.g., dynamic capability theory, information processing theory, stakeholder theory) to the field of DTs deployment (e.g., Li *et al*., 2020; Li, 2022), the application of the NRBV in this field is still scarce. The NRBV holds that the rapid growth of industrial activities and resource use challenge the extent to which natural resources can be loaded and natural resources may limit the potential of companies to maintain their advantages. Consequently, a firm's strategic positioning and competitive advantage are likely to stem from its proficient utilization of finite natural resources and its capability to facilitate environmentally sustainable economic activity. Hart (1995) therefore proposed three environmental countermeasures for firms to refer to: pollution prevention, product stewardship, and sustainable development. Pollution prevention is the most basic stage, and the common approach is to minimize or prevent emissions, waste, and effluents, which to a great extent helps firms save cost in areas such as operations or waste disposal and creates a cost advantage over their rivals. Product stewardship focuses on the entire product supply chain, aiming to reduce pollution during the whole product life cycle. Sustainable development refers to the continuous promotion of innovation and change to minimize the negative impacts of firms' growth and development on the environment, so as to create a long-run competitive advantage in harmony with the natural environment. Theoretically and empirically, these three solutions are closely related with resource utilization and green innovation (Ye *et al*., 2023). Our analysis shows that DTs deployment provides powerful technical support for firms to improve manufacturing processes, optimize resource allocation and utilization, and have easier access to green innovation knowledge, thereby laying a solid foundation for firms to enhance environmental performance. Also, the environmental performance effect of DTs deployment is contingent on firms' lean production and environmental leadership, which further supports the argument of the NRBV that resource utilization and green innovation are two main pathways for firms to achieve environmental superiority. Our study thus confirms the value of the NRBV in explaining the influence of DTs deployment on firms' environmental performance and examines the effectiveness of the solutions to improving environmental performance proposed by the NRBV, which further enhances our understanding of the NRBV.

Moreover, prior firm-level empirical research about DTs deployment consequences mainly concentrates on financial and operational variables such as market value, firm resilience, delivery, product quality, and innovation performance, among others (e.g., Sousa-Zomer *et al*., 2020; Yang and Yee, 2022). While some recent studies have investigated environmental implications of DTs deployment, their findings are not consistent. For example, Li *et al*. (2020) use survey data with 188 useful responses from Chinese manufacturing companies to examine the impact of DTs on economic and environmental performance. The results indicate that DTs have significant positive effects on both economic and environmental performance and the relationship is mediated by digital supply chain platforms. Similarly, Ye *et al*. (2023) use a sample of 273 Chinese pollution-intensive firms with 1,009 observations from 2016 to 2020 to explore how digital investment may affect environmental performance. Their findings are consistent with Li *et al*. (2020) that digital investment has a positive impact on firms' environmental performance. However, Li (2022) employs survey data with 223 effective responses from Chinese companies that had participated in digital transformation and demonstrates that there exists an inverted-U relationship between digital transformation and environmental performance. Lange *et al*. (2020) also suggest that digitalization increases energy consumption overall. These inconsistent findings may result from different methods and samples. As Eroglu and Hofer (2011) suggested, survey-based studies rely on subjective assessments of firm performance in addition to subjective evaluations of practice adoption. This approach may introduce systematic measurement error leading to biased estimation results. Also, these studies may not consider endogeneity in their data sets, which means that the respondents who deploy and benefit from DTs may be more likely to respond to the surveys, thus introducing potential self-selection bias (Ketokivi, 2019). Although Ye *et al*. (2023)'s analyses are based on an objective secondary data set, their data were collected from 11 pollution-intensive industries which may ignore some industry-specific factors, and the authors did not deal with potential endogeneity issues in the paper as well. We join this debate by employing a large-scale panel data set and tackling the endogeneity issues appropriately. Our results indicate that DTs deployment positively impacts environmental performance for Chinese publicly listed companies, which offers more empirical evidence about this issue and enhances our understanding of the influence of DTs deployment on firms' environmental performance.

Finally, our study contributes to the emerging literature about the integration of Industry 4.0 and lean. The growing proliferation of DTs worldwide has significantly changed firms' operations activities, increasing firms' productivity, flexibility, financial performance, and innovation output (Gillani *et al*., 2020). This transformation, however, may also create tensions with another wide-adopted management paradigm, i.e., lean management, which is a human-centered production paradigm that emphasizes continuous improvement stemmed from workers, learning, and leadership and argues that management principles that can, and often should, be operationalized with very few or even without information technologies (Hopp and Spearman, 2021). Although prior literature on Industry 4.0 and lean has been predominantly optimistic about their integration (e.g., Cifone *et al*., 2021; Rosin *et al*., 2020), these studies are usually conceptual or qualitative method-based articles which lack ample empirical evidence about whether the two different production paradigms can be effectively combined to enhance organizational outcomes. As Buer *et al*. (2018) conclude, it remains unclear how an introduction of Industry 4.0 will affect already established management practices like lean and how already established lean practices will impact the implementation of Industry 4.0. We position our study in the latter stream and go one step further by investigating the moderating effects of lean production and environmental leadership on the relationship between DTs deployment and environmental performance. Our results suggest that there exists a synergistic effect between lean production and environmental leadership and DTs deployment in enhancing firms' environmental performance. This study thus responds to the recent calls that more efforts should be devoted to conducting longitudinal studies with more objective data and providing solid empirical evidence on the effective integration between Industry 4.0 and lean (Tortorella *et al*., 2019), which further enhances our understanding of how to leverage DTs and lean together to improve corporate environmental performance and reach sustainable development goals.

2.5.3 Implications for Practices

The issues addressed in this study also provide some practical implications for managers and policymakers. First, the most straightforward implication from our results is that firms can achieve environmental performance benefits from the adoption of DTs, which to some extent removes managers' doubt about if DTs-enabled transformation could improve environmental performance and allows managers to better decide whether to invest resources in DTs projects.

Environmental protection and sustainability issues nowadays have attracted tremendous attention from entrepreneurs, investors, and governments (Xiao and Shen, 2022). Our study thus provides firms with one promising solution to this important issue by suggesting firms apply DTs to their production and operations activities to alleviate environmental pressures.

Second, this study finds that lean production and environmental leadership significantly strengthen the positive DTs deployment-environmental performance relationship, which encourages firms to integrate DTs and lean to better enhance environmental performance. Specifically, as one of the hard lean practices, lean production more highlights that firms should improve resource utilization and reduce waste in the operational processes. On the other hand, environmental leadership requires managers to well understand the importance of environmental protection and the value of employees, and guide and encourage employees to find novel solutions to environmental issues such as green innovation. Thus, firms should pay attention to both hard and soft practices (e.g., the adoption of inventory control system, develop and recruit managers with environmental leadership) and combine them with DTs to better achieve firms' environmental objectives.

Third, policymakers may benefit from our findings as well. How to strike a balance between economic development and environmental protection is an eternal proposition for government decision-making. In particular, the Chinese government has proposed a "dual carbon" target (i.e., carbon peak by 2030 and carbon neutrality by 2060) in 2020. Policymakers thus could introduce a set of policies to encourage firms to deploy DTs and enhance firms' digital transformation level to better improve environmental performance. For example, "Smart City Pilot" has been studied as one of the effective ways to improve digital transformation, save energy, and reduce carbon emissions (Wang *et al*., 2019).

2.5.4 Limitations and Future Research Directions

As with any research, this study suffers from some limitations, which also provides opportunities for future research. First, similar to other empirical studies using secondary data (e.g., Yiu *et al*., 2020), the measurements of constructs are one of the biggest challenges of our study. In this research, we aim to investigate whether the environmental performance of DTs deployment is improved or hindered as a result of lean management adoption (i.e., inventory leanness and environmental leadership). While the environmental advantages and concerns as well as ELI are widely used in prior studies, the measurements of DTs deployment and environmental leadership are less straightforward due to data availability. In this paper, we follow prior literature and quantify the level of firms' DTs deployment based on publicly available information through text analysis rather than conducting a direct investigation into the firm. Likewise, we use female board member proportion as the proxy for environmental leadership. Although we have a large-scale sample, it is likely that we have missed some firms who have DTs deployment but have not clearly mentioned in their annual reports. Alternatively, they may mention terms not on our keywords list. Future research may develop a more comprehensive construct of DTs deployment and environmental leadership or use survey instruments as supplements to operationalize these variables.

Second, our sample is from Chinese publicly traded companies, which limits the generalizability of our findings to Chinese listed firms only. Our findings may not be applicable to smaller firms or firms operating in other economies whose characteristics, capabilities, and institutional environments may be quite different from those in our sample. We therefore encourage future research to extend this study by investigating environmental implications of DTs deployment in other private and smaller firms and firms in other markets to verify the conclusions drawn in our research.

Third, due to data availability, this paper only considers the moderating effects of lean production and environmental leadership. In fact, lean is a practice-based umbrella concept which contains a diverse set of practices such as quality management, supplier and customer relationship, the level of employee involvement, among others (Åhlström *et al*., 2021). Future studies may consider exploring the moderating effects of other lean variables or conducting multi-methods research to further enrich the literature of the interaction and integration between lean and Industry 4.0 to enhance organizational performance.

Chapter 3 Study Two: Protagonists in Digital Transformation: The Impact of Chief Digital Officers on Firms' Financial Performance

3.1 Introduction

Digital transformation is the integration of digital technology across all the areas of an organization, fundamentally transforming its operations and value creation processes. Although digital transformation is considered both critical and essential nowadays, the process is highly challenging and uncertain. A recent survey by Dell Corporations found that although 75 percent of decision makers worldwide agreed that digital transformation had become an imperative for all the organizations and digital transition should be extensive throughout the firm, only 33 percent were committed to implementing the critical digital business attributes across their business (Dell, 2018). That is, even though decision makers are well aware of the importance, potential, and urgency of establishing a digital strategy, many have not been doing it. It seems that plenty of firms are stuck in the digital transformation paradox (Bacros, 2018).

Even in firms that have implemented the digital transformation strategy, tensions, frictions, and conflicts often emerge, such as tensions between the IT department and the broader business units, frictions between various business units and the organization as a whole, and conflicts between individual interests and the common good (Folkestad, 2019). For instance, digital changes are perceived as a threat and something that really touches the nerve and may lead to redundancy of some employees. On the contrary, to the whole organization, such changes represent a critical strategy for the long-term survival and success of the firm. Also, digital practices break the relatively closed state of data, information, knowledge, resources, and technical solutions among different departments, which might cause frictions between units and the organization as a whole. Such frictions may come from the silo mentality, i.e., over-emphasizing the interests of small groups and ignoring the firm's overall goals and interests.

How to reconcile the paradox of digital transformation, how to alleviate the tensions and problems associated with digital changes, and how to face a future defined by advanced digital technologies have become urgent and strategic issues for many firms around the world. Some industry pioneers have made the bold move of appointing the chief digital officer (CDO) in their top management teams (TMTs) to respond to the above challenges. Research of PwC indicates that about 21 percent of large public firms have now appointed the CDO (Péladeau and Acker, 2019). In addition, a report jointly published by Oxford's Saïd Business School and digital learning company General Assembly suggests that firms with CDOs are more inclined to really implement digital strategies, and the primary responsibility of the CDO is to facilitate digital changes in organizations by managing organizational tensions and frictions, especially by setting common goals and advocating collaboration, and facilitating understanding and clarifying ownership across decision processes, domains, and interest groups (Brooks *et al.*, 2018). There is prima facie evidence that the appointment of the CDO to lead the digital agenda has brought considerable benefit to the firm concerned. Taking Starbucks as example, the world's professional coffee giant, Starbucks appointed Adam Brotman as the CDO in March 2012. During his tenure, Brotman was committed to optimizing the payment-related issues (e.g., mobile order and pay, loyalty programmes etc.) as well as strengthening in-store Wi-Fi to enhance consumers' experience. The outcomes show that such measures have been effective. At the end of 2017, mobile orders accounted for 11 percent of Starbucks' store transactions in the US, and loyalty card users accounted for 37 percent of the net revenue.

With the emergence and rise of the CDO, some questions have aroused the interest of researchers: What role does the CDO play in the process of digital transformation? Why does the appointment of the CDO make firms more motivated for digital transformation? What impact does the presence of the CDO have on organizational consequences? What contextual factors will affect the CDO presence-firm outcomes link? The existing studies have made some preliminary explorations on some of the above questions (e.g., definitions, responsibilities, types, antecedents etc.) (e.g., Firk *et al*., 2021; Kunisch *et al*., 2022). Yet, to the best of our knowledge, very little research has been conducted to investigate the impact of the CDO's presence on firm outcomes based on secondary data in the longitudinal setting. Seeking to address this underexplored question, our study first employs upper echelons theory (UET) and the attention-based view (ABV) to explain why the existence of the CDO enables firms to truly implement digital strategies. We argue that the CDO actually serves as an attention carrier. The appointment of the CDO in the TMT facilitates the firm to devote more managerial attention and resources to the digital issues, prompting the firm to truly undertake strategic digital actions, so improving firm performance. We use the data of S&P 500 companies for around 20 years to test our speculation. The results show that the presence of the CDO is significantly and positively related to firms' financial performance in terms of Tobin's q. The positive relationship remains after a series of robustness tests, confirming that the appointment of the CDO in the TMT indeed adds value to the firm. Moreover, we find that the positive CDO presence-financial performance link is stronger when the CDO is an outsider hired from the external market, when the CDO is a generalist who has responsibilities over a wide range of cross-functional digitalization issues within the firm, and when the firm has a more diversity in its board (in terms of board members' nationality and tenure).

This study makes several contributions both in theory and practice. First, our study advances understanding of UET and the ABV, and provides a fresh view on the appointment of executives with specific functional roles. Second, this study also enhances understanding of the boundary conditions of the CDO's effectiveness. Third, we contribute to the board diversity literature by decomposing board diversity into four dimensions and examining their moderating effects. Fourth, we extend the unit of analysis of TMT studies to executive dyad, which has been advocated by prior studies (e.g., Menz, 2012; Simsek *et al*., 2018). Last but not the least, we answer Roels and Staats' (2021) call that more attention be paid to people-centric operations and more efforts be devoted to exploring "how people affect the performance of operational processes". Our study also offers rich practical implications for firms to better realize digital transformation.

3.2 Literature Review and Hypothesis Development

3.2.1 Literature on Digital Transformation

In the age of digital economy, digital transformation is critical to the industry and academia, and more and more firms regard digital transformation as the core of their operational strategies. Yet, to date, there is still no unified definition for the concept of digital transformation in extant literature. A strand of literature, based on the perspective of technology, describes digital transformation as the adoption and integration of emerging digital technologies (e.g., artificial intelligence, big data analytics, blockchains, cloud computing, Internet of Things, robotics, and virtual reality) to achieve major business improvements so as to enhance consumer experience, streamline operations, create new business models, and finally obtain sustained competitive advantages and appropriate higher firm value (Verhoef *et al*., 2021; Warner and Wäger, 2019). Another school of scholars argue that organizational change is the essence of digital transformation, and they define it as "organizational change that is triggered and shaped by the widespread diffusion of digital technologies" (Hanelt *et al*., 2021; Vial, 2019).

Obviously, both definitions emphasize that digital technologies play a pivotal role in the process of digital revolution. In fact, existing studies on digital transformation has also principally been conducted around new digital technologies. In particular, the linkage between digital transformation and organizational outcomes has been the major focus in this domain. This research stream attempts to answer the question if digital transformation (especially the employment of digital technologies) can really bring a set of true benefits to firms, such as reducing transactional costs, increasing operational efficiency, and enhancing firm performance. This has been seen as an influential way to make the "business case" for digital transformation. For instance, using information processing theory lens, Li *et al*. (2020) investigate influences of digital technologies adoption on economic and environmental performance. Their findings reveal that digital technologies indeed have significantly positive impacts on both economic and environmental performance, and digital supply chain platforms serve as the mediator in the above linkages. Sousa-Zomer *et al*. (2020) conceptualize and explore the relevant drivers of digital transformation capability and the impact of this capability on firm performance. They find that digital-savvy skills (individual dimension), digital intensity (processual dimension), and context for action and interaction (structural dimension) are three main micro-foundations that build digital transformation capability, and this capability has significantly positive influence on firms' operational and market performance. Likewise, Wielgos *et al*. (2021) use a mixed-method approach to operationalize the digital business capability (DBC) construct. Their results show that DBC contributes to firms' financial and customer relationship performance, and this capability is of more value for business-to-consumer than for business-to-business firms.

Although digital technologies have garnered increasing attention in studies of digital transformation, the existing research on the role of "people" in this revolutionary process is still pretty scarce, especially in the IS and OM disciplines. A simple point of view is that no matter what kind of technologies, assets, resources, or skills, they all need to be organically deployed by people to realize and maximize their value. Otherwise, the "resource curse" may occur even though a firm possesses advanced technologies or substantial resources. Roels and Staats (2021) call for future research to concentrate more on people-centric operations and to conduct more studies about "how people affect the performance of operational processes". Our research echoes this call and is an initial attempt to investigate the role of people, particularly top managers, in digital transformation at the firm level.

3.2.2 Upper Echelons Theory and Attention-Based View

Scholars have a long-term debate on the issue of what drives strategic action and organizational outcomes (Nadkarni and Barr, 2008). Some traditional views (e.g., institutional theory, contingency theory) contend that industrial structure is the primary driver of strategic action. They follow the "structure-conduct-performance (SCP)" paradigm and just simply treat the strategic decision-makers in a highly abstract way, like any other firm assets, and incorporate them into the strategic analysis framework as a purely economic factor with complete rationality (Caves *et al*., 1984; Porter, 1985). On the contrary, the managerial cognition studies argue that top managers are unable to fully perceive and understand the complex internal and external environment due to bounded rationality. Instead, top executives' cognitions, values, and perceptions determine their interpretation of relevant information, influence their decision making, and then affect firms' strategic action and organizational outcomes. That is, "the organization is a reflection of its top managers" (Carpenter *et al*., 2004; Hambrick, 2007; Hambrick and Mason, 1984; Ocasio, 1997; Ocasio, 2011). Our study joins this debate and seeks to explore the important role of a new TMT position (CDO in our setting) in digital transformation by using the managerial cognition theoretical lens.

UET emphasizes that in the process of complex decision making, individual executive is limited by his or her own knowledge and abilities, so the best way to break through this limitation is to adopt team decision making (Hambrick and Mason, 1984). The various characteristics of the TMT members provide assurance for mutual collaboration and correct decision making. Since the cognitions, values, and perceptions of top managers are difficult to measure, and their meanings are neither specific nor clear (Pfeffer, 1983), the UET invokes previous demographic studies to suggest that managerial characteristics (e.g., gender, age, education, nationality, tenure, functional expertise, and social ties) are reasonable proxies for potential differences in cognitions, values, and perceptions. Further, attention-based view (ABV) (Ocasio, 1997) supplements the significant influence of the specific context or situation in which decision-makers are embedded on strategic decision making. The theory holds that a firm is a problem-solving entity with limited attention, and its essence is the attention allocation system of decision-makers. To explain firms' action and outcomes is to explain how firms distribute and allocate their decision-makers' managerial attention.

Prior studies have provided a wealth of empirical evidence for the diverse impacts of observable characteristics heterogeneity on organizational outcomes at the individual or team level along the logic of UET and ABV. For instance, Tang *et al*. (2015) establish a link between CEO hubris and corporate social responsibility. Similarly, at the individual level, many studies have shown that top executives' personal characteristics or prior experience (e.g., overconfidence, narcissism, charisma, humility, ability, marriage, political ideology, social capital, military experience, poverty experience, bankruptcy experience, country-specific experience, and early-life disasters) have a series of significant impacts on firm behaviors (Benmelech and Frydman, 2015; Bernile *et al*., 2017; Chang *et al*., 2010; Chatterjee and Hambrick, 2007; Chin *et al*., 2013; Ding *et al*., 2021; Fogel *et al*., 2018; Galasso and Simcoe, 2011; Gopalan *et al*., 2021; Hegde and Mishra, 2019; Ou *et al*., 2018; Wowak *et al*., 2016). Another set of studies focus on the influences of TMTs or boards' characteristics on organizational outcomes. For example, Chang and Wu (2021) study if board connectedness affects firm innovation. The results reveal that well-connected boards have a significantly positive impact on both firms' innovation activities and quality. Nielsen and Nielsen (2013) find that nationality diversity of the TMT is positively associated with firm performance, and this influence is more salient when teams have longer tenure, when firms are highly internationalized, and when firms operating in munificent environments.

In addition to the aforementioned research on the linkage between individual- or team level-heterogeneity and firm outcomes, a substantial research stream also addresses the influences of inclusion or exclusion of particular functional positions in TMT or C-suite (e.g., Arora *et al*., 2020; Boyd *et al*., 2010; Fu *et al*., 2020; Germann *et al*., 2015; Hendricks *et al*., 2015; Homburg *et al*., 2014; Koo and Lee, 2018; Kumar *et al*., 2021; Roh *et al*., 2016). We position our study in this research stream as well. One of the core propositions of the UET is that firms' senior executives in general have significant impacts on firms' strategies and outcomes. In particular, different small teams of the TMT affect the organization's understanding and significance of specific issues. In other words, the structure of a TMT influences the interaction of TMT members and then affects decision making and organizational performance (Menz, 2012). Naturally, we hope to know how executives with specific positions and expertise (e.g., chief financial officer, chief marketing officer, chief supply chain officer, chief sustainability officer, chief legal officer, and chief digital officer) shape decisions and consequences in specific domains.

Apart from examining potential consequences of a single functional role of the organization, the extant literature also explores how the interaction of two or more executives may influence firms' strategic action (e.g., Florackis and Sainani, 2021; Nath and Bharadwaj, 2020; Nath and Mahajan, 2011). These studies have suggested that there are differences in the power and status of various executives. Scholars aim to answer the questions of how these differences lead executives to adopt certain strategies to expand the voice of their departments and strive for more managerial resources, and how relationships of cooperation, competition, or coopetition among executives have impacts on the organization.

In short, UET and ABV help understand the salience of strategic issues in the managerial decision-making process. In addition to objective economic factors, people's (especially top managers) cognitions, values, and perceptions have a great influence on firm strategic action and outcomes.

3.2.3 CDO Appointment and Digital Transformation

Traditionally, IT department and the chief information officer (CIO) are responsible for IT-driven business change. Prior IS literature has provided substantial evidence about the value of IT department and CIO in long-term sustainable business activities (Armstrong and Sambamurthy, 1999; Chatterjee *et al*., 2001; Santhanam and Hartono, 2003). Despite the skills and achievements obtained by CIOs, recent studies suggest that CIOs seem to have lost strategic leadership roles in their firms, because their positions are regarded as more technology instead of business-oriented (Gonzalez *et al*., 2019). Weill and Woerner (2013) study CIOs' time management and find that most CIOs' main priority is to ensure the delivery of infrastructure, applications, and projects, which makes it difficult for them to spare sufficient time to engage in more strategic and cross-functional activities. This could to some degree explain why CDOs are now leading company-wide digital agenda.

Anecdotal evidence suggests that the position of CDO symbolizes a firm's determination to embrace digital transformation. As the head of a firm's digital transformation business, CDO emerges as a response to the challenges of digital revolution and its number continues to grow during the past decade (Riccio, 2017). More and more firms are beginning to appoint this position in their TMTs to help them achieve digital transition faster and better. Notable examples include Brian Tilzer at Best Buy, David Godsman at Coca-Cola, Jennifer Felch at Dell, Ragu Gurumurthy at Deloitte, Noam Paransky at Gap, Lucy Brady at McDonald's, and Adam Brotman at Starbucks.

Although CDOs appear to be strategically important to the industry, the academic research on this new position is still in its infancy. Horlacher and Hess (2016) are among the first to discuss the phenomena of the establishment of CDOs in TMTs, suggesting that CDOs primarily pay attention to the strategic and communicational issues of the digital transformation and closely cooperate with their CIOs if both positions exist in a firm. This view is supported by Singh *et al*. (2020). By conducting a multiple-case study, they find that CDOs' tasks mainly lie in combining diverse formal and informal activities to bring together employees who engaged in digital transformation activities in various departments and at various levels. Further, Tumbas *et al*. (2017) interview 35 CDOs from various sectors, and they identify the domains in which successful CDOs construct digital capabilities as well as three different kinds of CDO (digital accelerators, digital marketers, and digital harmonizers). In their subsequent research, they find that CDOs incline to deliberately use the term "digital" to highlight the difference between them and existing executive roles and to obtain legitimacy and reinforce their sense of identity in the firm. In general, CDOs play a critical role in at least two aspects: (1) elucidating and advancing the emerging "digital" logic of actions and (2) establishing this digital logic via tactics such as bridging, grafting, and decoupling to deal with conflicts between current and emerging access to innovation by the use of digital technologies (Tumbas *et al*., 2018).

Despite the above qualitative studies' valuable insights, just few articles have taken a quantitative approach to investigating the emergence, nature, determinants, and consequences of the CDO position. Both Firk *et al*. (2021) and Kunisch *et al*. (2022) use large-scale panel data to explore what factors drive firms to appoint CDOs (i.e., the antecedents of CDO presence). Their findings reveal that several factors related to firms' transformation urgency, coordination needs, strategic leadership, and mimicry behavior that have impacts on the probability of CDO existence. Moreover, the analysis of CDOs' titles and role descriptions indicate that there are two conceptually different types of CDOs: generalists and domain specialists. Nishant *et al*. (2020) and Zhan *et al*. (2022) employ event study method to examine how stock market reacts towards the appointments of CDOs. They find that while the stock market has a neutral reaction to newly created CDO positions announcements, it does have a positive reaction when appointing firms with high growth prospects and without existing CIOs.

3.2.4 The Impact of CDO Presence on Firms' Financial Performance

We argue that the appointment of a CDO to a firm's TMT will have a positive impact on a firm's value. For this hypothesis, we primarily reason from two aspects. First, we argue that the addition of the CDO position to a firm's TMT represents an overt commitment to the incorporation of digital transformation expertise within the TMT, versus just instilling digital transformation responsibilities into another role (e.g., CIO). That is, the appointment of a CDO by a firm is a clear indication for the firm's commitments to digital transformation initiatives; second, digital transformation has a positive influence on firms' financial performance in terms of Tobin's q. We first analyze the former by integrating UET and ABV.

UET implies that a firm's strategic decision mainly reflects its top managers' perception and understanding of the environment and the amount of attention these chief executives pay to it (Hambrick and Mason, 1984). Further, Hambrick (2007) points out that a TMT's "subteam" has a significant impact on the knowledge and prominence of specific issues within the firm. In other words, the structural design of a TMT influences how its members interact with each other and how the managerial attention is allocated across different departments (Menz, 2012). Likewise, ABV emphasizes that the attention of top executives is a scarce and critical resource. Senior managers' choices of which organizational units or issues to focus on therefore has a profound impact on the firm's strategic direction. Thus, the central argument of ABV is that "firm behavior is the result of how firms channel and distribute the attention of their decision-makers" (Ocasio, 1997). A natural corollary is that the more attention a certain strategic issue receives, the more resources and managerial support the firm will allocate to it, making it easier to solve the corresponding problems and achieve the desired results. In fact, prior studies suggest that managerial attention has critical impacts on firm strategic behavior and organizational outcomes, such as innovation performance, entry into a radical new technological market, responses to environmental changes, firm growth, and strategic change, among others (Eggers and Kaplan, 2009; Joseph and Wilson, 2018; Li *et al*., 2013; Nadkarni and Barr, 2008; Ocasio *et al*., 2018; Yadav *et al*., 2007).

We believe that the CDO as a functional and professional top manager indeed serves as an attention carrier for all issues concerning digital transformation. Extant research shows that the presence of specific attention carriers and their strategic behaviors largely affect the allocation and diffusion of limited managerial attention in the firm. For instance, Bouquet and Birkinshaw (2008) find that multinational enterprises' foreign subsidiaries as attention carriers can gain attention from their headquarters by strategically using some tactics. Female directors as attention carriers can deliver stakeholders' demands of gender equality to firms and attract firms' attention to make some changes (Abdullah *et al*., 2016; Gul *et al*., 2011). Also, sexual minority (e.g., LGBT) as attention carriers can convey the voice of society against discrimination and pursuit of sexual equality to firms and raise the latter's attention to create a workplace with more diversity (Hossain *et al*., 2020; Shan *et al*., 2017). Implementing digital transformation requires a large amount of resources and support and is associated with complexity and uncertainty (Li, 2020), to say nothing of that there are many important and urgent issues in other departments that are also competing for scarce managerial attention within the organization at the same time. Thus, the successful implementation of digital transformation heavily relies on if a firm has an attention carrier that can effectively gain organizational attention to the related issues. We posit that a CDO can perform his or her duty as an attention carrier by leveraging his or her capabilities and expertise in digital transformation and paying constant attention to the associated issues. Through CDO acting as an attention carrier, the importance of digital transformation activities is likely to be significantly increased, strengthening the relevant decision-making and execution. We therefore argue that the appointment of a CDO is an important milestone to move firms through the digital transformation stages.

Next, we will elucidate why digital transformation might improve firms' financial performance. Via digital transformation (i.e., the appointment of CDO and employment of digital technologies), firms can gain at least a few benefits. First, digital transformation has changed and even reshaped firms' internal management process, breaking the data closure between different links, modules, and departments within the organization (Porter and Heppelmann, 2014). More efficient operations management based on accurate data collection, analysis and decision-making can greatly lower a set of transaction costs such as search cost, information cost, negotiation cost, execution cost, and time cost. For example, the application of digital technologies enables producers to directly face consumers and realize fast communication, which eliminates the conventional and multi-level distribution system, thus significantly reducing the negotiation cost and contract cost in the transaction process (Verhoef *et al.*, 2021).

Second, through the implementation of digital transformation, firms could apply digital technology products into internal production management and embed them in all aspects of production and operations activities. In this way, digital transformation enables intelligent production and sales process reengineering for firms' production activities, as well as digital technical support for raw materials and intermediate product procurement (Jeffers *et al.*, 2008). This transition also helps to reduce inefficient and redundant internal and external links, and optimize business processes. By enhancing the coordination among production factors, the efficiency of resource allocation can be improved, thus strengthening the firm's capability in value creation.

Third, digital transformation can effectively deal with the problem of asset specificity of firms' fixed assets or human capital, as well as the dilemma of excessively high labor costs faced by firms, thereby enhancing their firm value. Finally, one of the tasks of the cross-functional position of CDO is to strengthen collaboration and communication between different departments (Kunisch *et al*., 2022). Some key capabilities of CDO, such as digital competence, change management, and inspirational skills can bring sufficient transformational leadership to the firm, which also ensures that the firm can constantly renew and execute digital strategies, thereby contributing to performance improvement (Sousa-Zomer *et al*., 2020).

Supported by the discussions above, the CDO's presence is likely to bring value to firms and have a positive impact on financial performance. Therefore, we propose the following hypothesis:

H1: CDO presence is positively associated with firms' financial performance.

3.2.5 Moderating Effects

If CDO presence does have a positive influence on firms' financial performance, we wonder under what circumstances the appointment of a CDO can be more effective. The answer to this question can not only enhance our understanding of UET and ABV, but also provide certain managerial implications for firms hiring CDOs.

One of the premises of ABV is that managerial attention is embedded to certain contexts. That is, "what issues and answers decision-makers focus on, and what they do, depends on the particular context or situation they find themselves in" (Ocasio, 1997). Contextual factors that affect decision-makers' managerial attention distribution process will in turn have impacts on the effectiveness of CDOs as attention carriers (Fu *et al*., 2020). In this paper, we investigate the moderating effects of individual and board-level heterogeneity: type of hiring, scope of duties, and board diversity.

Type of hiring (insider versus outsider)

The choice of "insider" or "outsider" has always been one of the important considerations when firms appoint senior managers (Stamper and Masterson, 2002). In general, the advantages of insiders over outsiders lie in two aspects. First, insiders usually have better knowledge about a firm's specific operating status (e.g., products, competitors, markets, customers, and employees). Second, insiders have established social networks (e.g., superiors, subordinates, peers, and others) through which they obtain the specific internal information and support needed to perform duties (Chung *et al*., 1987; Wiengarten *et al*., 2017). However, organizational equilibrium theory suggests that the longer an employee stays in a company, the fewer novel ideas and the worse work performance when coping with new environments and challenges (Helmich, 1977). Conversely, the appointment of an outsider is regarded as an attempt to break the past (Boyd *et al*., 2010). Outsiders are not enmeshed in organizational politics and are more likely to make objective and dramatic changes with less considerations about past decisions made in that firm. Experiences in different firms or industries make outsiders have broader perspectives. Their awareness and grasp of new things are usually more acute and profound than insiders, and they have more willingness to challenge existing practices and make decisive strategic changes (Friedman and Singh, 1989; Peteraf and Shanley, 1997).

Firms pursuing digital transformation not only need to adopt advanced digital technologies, but also need change managerial thoughts. This also means that the CDO, as the head of firms' digital transformation activities, should have more fresh ideas, awareness of change, and courage to challenge existing practices. In the process of rapid digital transformation, outsiders are usually more able to objectively observe the company's difficulty and urgency, that is, lookers-on see most of the game, and their accumulated experience and skills from other companies or sectors can bring better practices and new insights to the organization (Boeker, 1997; Guthrie and Datta, 1997). UET indicates that top managers' cognitions, values, and perceptions have significant impacts on their decision-making. The attributes possessed by outsiders are obviously different from those of insiders. We therefore argue that, in general, when a CDO is hired from outside by a firm, this firm's digital transformation can be better implemented, which will lead to superior financial performance.

H2: Firms appointing outsiders as CDOs achieve higher financial performance compared with firms appointing insiders.

Scope of duties (domain specialist versus generalist)

Kunisch *et al*. (2022) analyze CDOs' titles and role descriptions and point out that there are two conceptually different kinds of CDOs: domain specialist and generalists. The former means that CDOs assume roles and responsibilities that focus on specific functional areas (e.g., digital experience, digital marketing, digital innovation, and digital product), while the latter means that CDOs take on roles and responsibilities associated with a wide range of cross-functional digitalization issues in their firms. We agree that domain specialist CDOs can indeed build specific capabilities and make certain contributions to firms in their professional fields. For example, CDOs that play the role of digital marketers concentrate on building data analytics capabilities to build close relationships with customers as well as achieve a consistent customer experience across different channels. However, the cross-functional position of CDO is always about people, processes, technology, and how digital enables that (Zetlin, 2017). A domain specialist CDO's attention is usually focused on his/her own professional field, but rarely pays attention to issues outside specific domain. As a result, he/she may ignore the demands of other departments and fail to apply digital technologies with different features and functions to various processes. Unlike domain specialist CDO, a generalist CDO is globally responsible for a firm's digital transformation affairs, which can better achieve cross-departmental communication and collaboration. This is also one of the vital guarantees for the success of a firm's digital strategies.

In addition, prior studies suggest that managerial discretion influences the extent to which top managers matter to firm decision-making and outcomes (Hambrick, 2007; Wangrow *et al.*, 2015). When a chief executive has more discretion, his/her impacts on the firm are more salient (Crossland and Hambrick, 2007; Kumar *et al.*, 2021; Li and Tang, 2010). As a generalist CDO is responsible for the company-wide digital transformation activities, in general, it has more managerial discretion than a domain specialist CDO, enabling the former to have more say in the digital transformation issues. This also helps to be allocated more managerial attention and resource support and thus firms' digital transition can be better achieved, which will lead to better performance. Therefore, we hypothesize that:

H3: Firms with CDOs as generalists achieve higher financial performance comparing with firms with CDOs as domain specialists.

Board diversity

A board of directors occupies a core position in organizational operations and corporate governance by providing strategic focus and influencing firm performance (Baker *et al.*, 2020). The 2008 global financial crisis led to a significant drop in stakeholders' trust in the effectiveness of the board, forcing regulators and policymakers to reform the existing board systems to better respond to environmental changes (Terjesen *et al.*, 2009). In fact, many countries and regions have legislated to change board composition during the past decade. For instance, Norway mandates that companies have at least 40 percent representation of both genders on their boards. Diversity including gender, nationality, race, age, tenure, education, among others is the central source of the effectiveness of board. In essence, board diversity is a combination of human and social capital, and the board of directors uses these capitals to perform its governance and monitor function (Van der Walt and Ingley, 2003). Naturally, we are curious about how a diverse board would affect the CDO presence-financial performance link.

The existing literature on board diversity offers two general conflicting perspectives regarding the impact of board diversity on organizational outcomes. On the one hand, some scholars from the social psychological perspective find that a diverse board can potentially be a disadvantage. The primary reason is that board diversity increases the conflict among board members, which leads to more disagreement and the lag of the firm's responses and decision-makings (Adams and Ferreira, 2009). The rise of diversity may also lead to the formation of small groups (i.e., in-groups and out-groups) within the board, resulting in less communication, complicated decision-making, and impaired team cohesion (Baker *et al*., 2020). Also, a diverse board tends to allocate more effort to monitoring. The greater intervention by directors in decision-making could cause a breakdown in communication between managers and directors, thus impeding decision-making and hindering the ability of firms to make strategic change (Adams and Ferreira, 2009; Triana *et al*., 2014). From this perspective, when the diversity of board increases, board members' perception and understanding difference of digital transformation issues will also increase, which makes it not easy to achieve consensus on some important decisions involving digital strategies. Given the urgency and complexity of digital transformation, a board's slow decision-making could hamper the functioning of a CDO, thereby reducing the effectiveness of this role.

On the other hand, previous research from organizational theory also suggests that heterogeneous boards tend to have a greater knowledge base, innovation, creativity, and flexibility than homogeneous boards, which makes the former more likely to discuss tougher issues and have more rational discussions and therefore becomes a competitive advantage

(Miller and Triana, 2009; Srinidhi *et al*., 2011; Watson *et al*., 1993). In addition, board diversity makes it possible for directors to participate more in decision-making, monitor top managers more strictly, and better protect the interests of stakeholders (Adams and Ferreira, 2007; Adams and Ferreira, 2009; Delis *et al*., 2017; Hillman and Dalziel, 2003; Nielsen and Nielsen, 2013). These actions can in turn improve corporate governance (Beji *et al*., 2021; Bernile *et al*., 2018; Isidro and Sobral, 2015). Since a board is viewed as the key to overcoming the agency problem between managers and shareholders, it is generally believed that better corporate governance can bring greater decision-making, lower firm risks, and higher firm value (Bhagat and Bolton, 2008; Hermalin and Weisbach, 2003). Also, such heterogeneity can provide rich perspectives due to diverse human and social capital in terms of expertise, experience, power, status, and networking (Baker *et al*., 2020). From this point of view, a diverse board is more inclined to accept new things (e.g., digital technologies), embrace new ideas (e.g., digital strategies), and be more capable of supporting CDOs to cope with challenges when faced with environmental changes (e.g., digital revolution). Good corporate governance brought by board diversity also provides a certain guarantee for CDO to achieve effective cross-departmental communication and collaboration. From the above discussion, we argue that the moderating effect of board diversity on CDO presence-financial performance relationship is *ex ante* unclear. Thus, we propose the following pair of competing hypotheses:

H4a: The positive association between CDO presence and financial performance is less pronounced when a firm's board is more diverse.

H4b: The positive association between CDO presence and financial performance is more pronounced when a firm's board is more diverse.

The conceptual model of Study 2 is summarized in Figure 3.1.

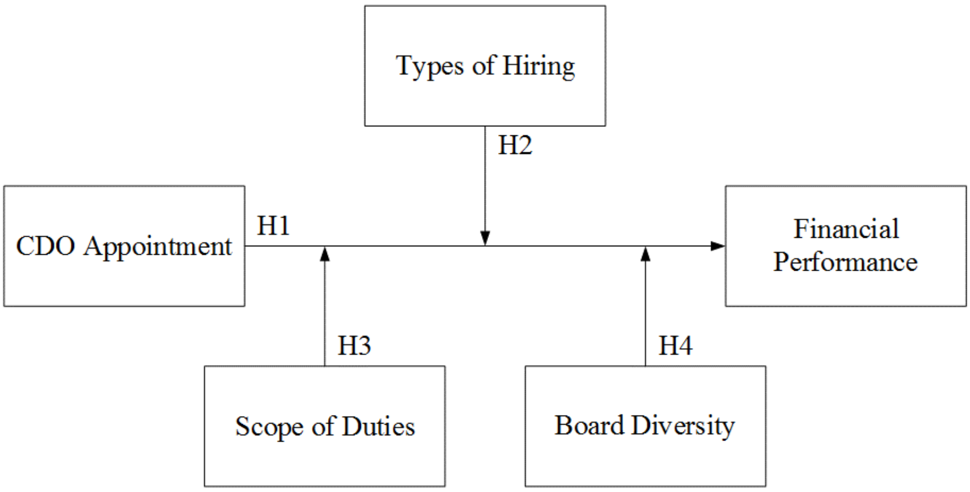

Figure 3.1 Conceptual model of Study 2

3.3 Methodology

3.3.1 Data and Sample

Our data are collected from several sources to measure the research variables explored in this study. First, consistent with prior research on executive appointments (e.g., Fu *et al*., 2020; Hoitash *et al*., 2016), we identify firms' CDO appointments via BoardEx, a comprehensive database covering the detailed profiles of over one million of top management team (TMT) members and board directors of publicly listed firms and large private companies. We prefer identifying CDO appointments via the subscription-based BoardEx rather than publicly available sources (e.g., news announcements) because BoardEx provides detailed information about individual CDOs such as their employment histories and role descriptions that enable us to measure CDO-related moderating variables (Firk *et al*., 2021; Kunisch *et al*., 2022). Moreover, different from prior research that has to rely on news announcements to identify the announcement dates (i.e., event dates) of CDO appointments for conducting short-term event studies (Drechsler *et al*., 2019; Zhan *et al*., 2022), our analysis is based on annual data and focuses on the years of CDO appointments which can be obtained from BoardEx.

To identify individuals holding the CDO positions, we follow prior research (e.g., Firk *et* *al*., 2021; Kunisch *et al*., 2022) by downloading all individual records from BoardEx with the term "digital" in their titles. This is to ensure that those individuals included in our analysis are actually CDOs and avoid any role ambiguity. We acknowledge that this approach may ignore some individuals whose roles are related to digital transformation but without "digital" in their titles, but this should not be a major concern in our research. This is because our data analysis is based on firms with CDO appointments rather than on firms with and without CDO appointments, avoiding the bias arising from misclassifying firms with CDOs as firms without CDOs. Therefore, this identification approach may result in a reduced sample for our analysis but should not lead to biased results due to misclassification.

We then follow prior research (Fu *et al*., 2020; Firk *et al*., 2021) by focusing on those CDO appointments made by firms included in the S&P 500 index, for several reasons. First, firms included in the S&P 500 index are publicly listed firms, enabling us to obtain their accounting and financial data for measuring our dependent variable and other control variables. Moreover, the S&P 500 index mainly covers large, well-established firms whose accounting and financial data are more likely to be available over our whole investigation period, reducing possible survivorship bias. This also suggests that the CDOs of these firms are more visible, with more detailed individual records from BoardEx for us to measure CDO-related moderating variables. Finally, S&P 500 is a composite index including firms from various manufacturing and services industries, ensuring the generalizability of our findings. Considering that the earliest CDO appointment that can be retrieved in the BoardEx database occurred in 2002, we first obtain a list of firms included in S&P 500 companies index between 2002 and 2019. For each of these S&P 500 firms, we search the downloaded BoardEx data to check whether the firm made any CDO appointment between 2002 and 2019. For firms that have appointed CDOs multiple times during this period, we only retain the CDOs they first appointed, because compared with other subsequent appointments of the same firm, these new appointments for the first time should better capture the firms' attention paid to digital transformation. This approach also allows us to employ a firm-level fixed-effect estimation strategy to examine the influence of firms' appointments of CDOs on the performance over time. It should also be noted that we have to limit our sample to firms with CDO appointments only because some of our moderating variables are concerned with CDO characteristics, which are unavailable for firms without CDO appointments. Overall, we are able to identify 158 S&P 500 firms that appointed their CDOs for the first time between 2002 and 2019.

Table 3.1 Panel A presents the year distribution of these firms' first CDO appointments. More than 50% of the firms made their first CDO appointments within the last three years (2017-2019), demonstrating the increasing popularity of CDO appointments in recent years. Panel B of the same table further suggests that CDO appointments have been made by firms across different industries that range from manufacturing to services. Finally, some descriptive statistics about firms' characteristics in terms of number of employees, market value, sales, total assets, total debt, total dividends, and cash and short-term investments are presented in Panel C.

Table 3.1 Descriptive statistics

Panel A: Distribution of Sample Firms' CDO Appointments Across Years

Year	Frequency	Percentage
2003	2	1.3
2005	3	1.9
2007	2	1.3
2008	2	1.3
2009	2	1.3
2010	3	1.9
2011	8	5.1
2012	6	3.8
2013	10	6.3
2014	11	7.0
2015	10	6.3
2016	16	10.1
2017	25	15.8
2018	30	19.0
2019	28	17.7
All Years	158	100

Panel B: Distribution of Sample Firms Across Industries

Two-digit SIC Code	Industry	Frequency	Percentage
10 – 14	Mining	2	1.3
15 – 17	Construction	1	0.6
20 – 39	Manufacturing	48	30.4
40 – 49	Transportation & Public Utilities	19	12
50 – 51	Wholesale Trade	4	2.5
52 – 59	Retail Trade	25	15.8
60 – 67	Finance, Insurance, & Real Estate	40	25.3
70 – 89	Services	18	11.4
99	Nonclassifiable Establishments	1	0.6
All SIC Codes	All Industries	158	100

Panel C: Characteristics of Sample Firms

Firm Characteristics	Unit	Mean	Std. Deviation	Minimum	Maximum
Number of Employees	Thousand	70.0	91.1	0.9	440.0
Market Value	Million US$	43413.6	65544.2	391.2	531312.4
Sales	Million US$	24459.5	31903.4	728.7	201159.0
Total Assets	Million US$	105551.0	321926.5	970.5	2359141.0
Total Debt	Million US$	24263.2	78412.0	0.0	571130.0
Total Dividends	Million US$	972.1	1841.6	0.0	12040.0
Cash and Short-Term Investments	Million US$	15381.2	60991.4	22.0	471833.0

We then collect data on these 158 firms from other sources such as Compustat and the Center for Research in Security Prices (CRSP) for measuring different research variables. In particular, we rely on accounting and financial data from Compustat and CRSP to compute our dependent variable and other control variables concerned with firm and industry characteristics. For moderating variables, we obtain individual-level data from BoardEx to measure CDO characteristics (e.g., whether a CDO is externally recruited or internally promoted, and whether a CDO is assigned a generalist or specialist role) and board-level data from the same database to measure different dimensions of board diversity. The detailed variable measures are shown below and summarized in Table 3.2.

Table 3.2 Variable measurements

Variables	Measurements	Data Sources	References
Tobin's *q*	A firm's market value of assets divided by book value of assets; mathematically, (Common Shares Outstanding × Share Price + Total Assets − Book Value of Common Equity) / Total Assets	Compustat, CRSP	Kahle and Stulz (2017); Yiu *et al.* (2020)
CDO Appointment	Code 1 from the year of CDO appointment and after, and 0 for all years before the appointment	BoardEx	Kunisch *et al.* (2022); Firk *et al.*

	year		(2021)
External CDO	Code 1 if a CDO is recruited externally and 0 if a CDO is promoted internally	BoardEx	Hendricks *et al*. (2015); Zhan *et al*. (2022)
Generalist CDO	Code 1 if a CDO's role indicates a general responsibility for digital transformation across the firm and 0 if a CDO's role is focused on a specific function (e.g., marketing, customer engagement) or business unit	BoardEx	Drechsler *et al*. (2019); Kunisch *et al*. (2022)
Board Gender Diversity	Proportion of female directors on a firm's board	BoardEx	Beji *et al*. (2021); Katmon *et al*. (2019)
Board Nationality Diversity	Proportion of directors from different countries on a firm's board	BoardEx	Beji *et al*. (2021); Katmon *et al*. (2019)
Board Age Diversity	Standard deviation of the ages of a firm's board directors	BoardEx	Beji *et al*. (2021); Katmon *et al*. (2019)
Board Tenure Diversity	Standard deviation of directors' number of years on a firm's board	BoardEx	Beji *et al*. (2021); Katmon *et al*. (2019)
Firm Size	Natural logarithm of a firm's total assets	Compustat	Yiu *et al*. (2020); Zhan *et al*. (2022)
Firm Age	Natural logarithm of a firm's number of years since being covered by CRSP	CRSP	Kahle and Stulz (2017); Sabherwal *et al*. (2019)
Firm Leverage	A firm's total debt divided by total assets	Compustat	Firk *et al*. (2021); Yiu *et al*. (2020)
Cash Holdings	A firm's cash and short-term investments divided by total assets	Compustat	Bao *et al*. (2012); Firk *et al*. (2021)
Dividend Payout	A firm's total dividends divided by the market value of equity	Compustat, CRSP	Kahle and Stulz (2017); Lam (2018)
Industry Competition	One minus the Herfindahl index, where the Herfindahl index is calculated as the sum of the squares of each firm's market share in an industry (four-digit SIC code)	Compustat	Jacobs *et al*. (2015); Wiengarten *et al*. (2017)
Industry Dynamism	Standard error of the slope coefficient obtained by regressing the sales of an industry (four-digit SIC code) over the past five years divided by the average industry sales over the same period	Compustat	Jacobs *et al*. (2015); Wiengarten *et al*. (2017)
Industry Munificence	Slope coefficient obtained by regressing the sales of an industry (four-digit SIC code) over the past five years divided by the average industry sales over the same period	Compustat	Jacobs *et al*. (2015); Wiengarten *et al*. (2017)

3.3.2 Measures

Tobin's q. Consistent with prior research on executive appointments (e.g., Germann *et al*., 2015), we measure the performance impact of a CDO appointment in terms of Tobin's q, which represents a firm's market value of assets divided by its book value of assets. This suggests that

Tobin's q is a forward-looking, market-based measure that takes account of the market's evaluation of a firm's future prospects (Yiu *et al*., 2020). This measure thus suits our research context because a CDO appointment and the consequent digital transformation may affect a firm's current but also future performance, which is more likely to be captured by market-based rather than accounting-based measures. Mathematically, we compute a firm's Tobin's q as (Common Shares Outstanding × Share Price + Total Assets − Book Value of Common Equity) / Total Assets (Kahle and Stulz, 2017).

CDO Appointment. After identifying the year when a sample firm first appoints its CDO, we code CDO presence for this firm as 1 for all years starting from the year of appointment and 0 for all years before the appointment year. For instance, if a firm appoints a CDO for the first time in 2011, for this firm, we then code 1 from 2011 to 2019 and code 0 from 2002 to 2010. This coding approach allows us to do a firm-level fixed-effect estimation as introduced below to investigate the influence of CDO presence on firms' Tobin's q over time.

External CDO. For all appointed CDOs included in our analysis, we download their complete employment records from the BoardEx database. We then search these records and identify their serving firms before being appointed as the CDOs of the sample firms. If the names of the two firms are the same, we view the appointments as internal promotions and code this variable as 0. By contrast, if the two firms are different, we view the appointments as external recruitments and code this variable as 1 (Hendricks *et al*., 2015; Zhan *et al*., 2022). For example, based on the BoardEx records, Tamara Faber-Doty held an information technology role in CMS Energy (our sample firm) before being appointed as the CDO of the same company in 2019, so we code this appointment as 0. By contrast, as Derek Kramer served at Service King Collision Repair Centers (a private company) before being appointed as the CDO of American Electric Power (our sample firm) in 2018, we code this appointment as 1.

Generalist CDO. We determine whether a CDO is a generalist or specialist based on the

CDO's role as recorded in the BoardEx database. Specifically, we code this variable as 1 if a CDO's role indicates a general responsibility for digital transformation across the firm and 0 if a CDO's role is focused on a specific function (e.g., marketing, customer engagement) or business unit (Drechsler *et al*., 2019; Kunisch *et al*., 2022). Some examples of generalist CDO are "Chief Digital Officer" and "Senior VP - Digital", while specialist CDO includes such examples as "Chief Digital Marketing Officer" and "Digital Platform Officer".

Board Diversity. Board diversity is a multi-dimensional concept that may indicate the diversity of a board's members in terms of gender, nationality, age, tenure as well as other individual differences (Beji *et al*., 2021; Katmon *et al*., 2019). This suggests that it is less appropriate to view board diversity as an overall, composite measure because different dimensions of board diversity may influence the performance impact of a CDO appointment in different ways. We also have developed competing hypotheses for the moderating role of board diversity, indicating the need to reveal how different dimensions of board diversity may play different moderating roles. In this research, we focus on gender, nationality, age, and tenure, four dimensions of board diversity that have been widely investigated in prior research (Beji *et al*., 2021; Katmon *et al*., 2019). Specifically, we measure a firm's board gender diversity as the proportion of female directors on the board, board nationality diversity as the proportion of directors from different countries on the board, board age diversity as the standard deviation of board directors' ages, and board tenure diversity as the standard deviation of board directors' number of years on the board.

Control Variables. We include a list of control variables at the firm and industry levels that may be related to a firm's Tobin's q. Specifically, at the firm level, we control for size, leverage, dividend payout, age, and cash holdings because large firms, firms relying on debt financing, and firms paying generous dividends to shareholders may find it more difficult to maintain high Tobin's q, but well-established firms and firms having more cashes on-hand may have more resources to enhance their Tobin's q (Bharadwaj *et al*., 1999; Kahle and Stulz, 2017; Modi and Mishra, 2011; Yiu *et al*., 2020). For industry-level controls, we include industry competition, dynamism, and munificence because firms operating in a competitive and dynamic environment may face more uncertainties in improving performance, but a munificent environment can provide more opportunities for performance improvement (Jacobs *et al*., 2015; Sabherwal *et al*., 2019; Wiengarten *et al*., 2017). The data sources and measurements of these control variables can be found in Table 3.2.

3.3.3 Identification Strategy

A fixed-effect estimation at firm level is employed (Bockstedt *et al*., 2015; Shan and Zhu, 2013) to examine the influence of a firm's CDO presence on its Tobin's q for several reasons. First, although we have included a comprehensive list of control variables at the firm and industry levels, it is still possible that some unobservable firm characteristics such as corporate culture may be associated with a firm's decision to appoint CDO and its Tobin's q at the same time, which may lead to a potential endogeneity problem (Lu *et al*., 2018). The firm-level fixed-effect estimation that is based on a panel dataset with repeated firm measures across years helps address this concern because it removes any unobservable time-invariant effects due to firm characteristics. Another potential endogeneity concern is reverse causality, which suggests that while we have hypothesized a firm's CDO appointment has influence on its Tobin's q, the firm's Tobin's q may also affect its decision to appoint CDO, implying possible co-determination between CDO appointment and Tobin's q (Wooldridge, 2010). We utilize the panel structure of our data to maintain a one-year lag between Tobin's q (in year $t+1$) and CDO appointment and other controls (in year t) to make sure that our causality direction is on the track.

Besides addressing the endogeneity concerns, the fixed-effect estimation also fits our research context because our sample is focused on firms with CDO appointments and we aim to investigate the impact of firms' CDO presence on their own Tobin's q (i.e., within-firm effects) rather than to compare the difference in Tobin's q between firms with and without CDO appointments (i.e., between-firm effects). Empirically, we also conduct the Hausman specification test to check whether the fixed-effect or random-effect estimation is more suitable for our research model (Wooldridge, 2010). The Hausman specification test is statistically significant ($\chi^2 = 89.11$, $p < 0.01$), showing a preference for the consistent fixed-effect estimator over the efficient random-effect estimator. Mathematically, the firm-level fixed-effect regression model is shown below.

$$
\begin{aligned}
&Tobin's\ q_{i(t+1)} \\
&= \alpha_0 + \alpha_1 Firm\ Size_{it} + \alpha_2 Firm\ Age_{it} + \alpha_3 Firm\ Leverage_{it} + \alpha_4 Cash\ Holdings_{it} \\
&+ \alpha_5 Dividend\ Payout_{it} + \alpha_6 Industry\ Competition_{it} + \alpha_7 Industry\ Dynamism_{it} \\
&+ \alpha_8 Industry\ Munificence_{it} + \alpha_9 External\ CDO_{it} + \alpha_{10} Generalist\ CDO_{it} \\
&+ \alpha_{11} Board\ Gender\ Diversity_{it} + \alpha_{12} Board\ Nationality\ Diversity_{it} \\
&+ \alpha_{13} Board\ Age\ Diversity_{it} + \alpha_{14} Board\ Tenure\ Diversity_{it} + \alpha_{15} CDO\ Appointment_{it} \\
&+ \alpha_{16} CDO\ Appointment_{it} \times External\ CDO_{it} + \alpha_{17} CDO\ Appointment_{it} \times Generalist\ CDO_{it} \\
&+ \alpha_{18} CDO\ Appointment_{it} \times Board\ Gender\ Diversity_{it} \\
&+ \alpha_{19} CDO\ Appointment_{it} \times Board\ Nationality\ Diversity_{it} \\
&+ \alpha_{20} CDO\ Appointment_{it} \times Board\ Age\ Diversity_{it} \\
&+ \alpha_{21} CDO\ Appointment_{it} \times Board\ Tenure\ Diversity_{it} + \delta_i + \varepsilon_{it}
\end{aligned}
$$

where i and t are firm and year indices, respectively, δ_i represents fixed effects at firm level, and ε_{it} is the error term. We use α_{15} to estimate the influence of a firm's CDO presence on Tobin's q (H1). α_{16} and α_{17} indicate the moderating roles of external CDO (H2) and generalist CDO (H3), respectively, while α_{18} to α_{21} show how different dimensions of board diversity moderate the impact of CDO presence on Tobin's q (H4).

3.4 Empirical Results

Correlation matrix is presented in Table 3.3. All dependent and independent variables' correlations, means, and standard deviations can be found in this table. Table 3.4 documents the fixed-effect regression results. Five regression models are included in Table 3.4. Model 1 the baseline model including firm-level fixed effects and all control variables, Model 2 adds the main effect of CDO presence, and Models 3 to 5 add the moderating effects of external CDO, generalist CDO, and board diversity, respectively. We see that there are 2516 firm-year observations across these five models, suggesting that there are on average 16 years of observations for each sample firm (unbalanced). This relatively long observation period further supports our decision to perform the fixed-effect estimation to reveal how a firm's CDO appointment affects its Tobin's *q* over time. All the five models are significant at 1% level based on the *F*-tests, and *R*-squared (within) values range from 9.77% to 11.20%.

We see that the four controls, including firm size, firm age, cash holdings, and dividend payout are significant at 1% level within the five models. Particularly, although firm size and dividend payout have negative association with Tobin's *q*, firm age and cash holdings are positively related to Tobin's *q*. This suggests that firms that are more established, hold more cashes, have smaller sizes, and pay less dividends to shareholders tend to have higher Tobin's *q*. There are also some significant, direct relationships between board diversity and Tobin's *q*. In particular, while board gender diversity is positively related to Tobin's *q* ($p < 0.1$; Models 1-4), board age diversity has a negative relationship with Tobin's *q* ($p < 0.05$; Models 1-5). Therefore, a firm has a higher Tobin's *q* if it has more female directors on the board and its board directors have similar ages.

We see that across Models 2 to 5, CDO appointment remains positive and significant, suggesting that a firm's CDO existence does improve its Tobin's *q*. Thus, our H1 is supported. In respect of the moderating effects, we find that the interaction between CDO appointment and external CDO is significantly positive ($p < 0.05$), as presented across Models 3 to 5. It means that a firm's CDO presence improves its Tobin's q more significantly if the CDO is recruited externally rather than promoted internally, supporting H2. Similarly, there is a positive and significant ($p < 0.01$) interaction between CDO appointment and generalist CDO as shown in Models 4 and 5, demonstrating that the improvement in Tobin's q due to the CDO appointment is more pronounced if the CDO is assigned a generalist rather than domain specialist role. H3 is supported. Finally, Model 5 shows positive and significant ($p < 0.05$) interactions between CDO appointment and the nationality and tenure dimensions of board diversity, but the gender and age dimensions of board diversity do not moderate the relationship between CDO appointment and Tobin's q ($p > 0.1$). This suggests that a firm's CDO appointment has a more positive impact on Tobin's q if its board has more foreign directors and the tenures of these board directors are more diversified, but the impact due to the CDO presence is independent of whether the board has more female directors or whether the board directors have more dissimilar ages. Therefore, H4a is rejected and H4b is partially supported as only some dimensions of board diversity (i.e., nationality and tenure) show positive and significant moderating effects. This finding also highlights that not all dimensions of board diversity are created equal, supporting our decision to measure and examine their diverse roles in our research context.

Table 3.3 Correlation matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. Tobin's *q*	1.000															
2. Firm Size	-0.416	1.000														
3. Firm Age	-0.264	0.203	1.000													
4. Firm Leverage	-0.153	0.211	0.078	1.000												
5. Cash Holdings	0.451	-0.178	-0.194	-0.122	1.000											
6. Dividend Payout	-0.215	0.241	0.211	0.145	-0.198	1.000										
7. Industry Competition	-0.074	0.164	-0.049	0.019	0.031	0.091	1.000									
8. Industry Dynamism	-0.080	-0.030	-0.160	0.043	0.003	0.046	-0.041	1.000								
9. Industry Munificence	0.097	-0.074	-0.190	-0.051	0.069	-0.144	0.003	-0.060	1.000							
10. External CDO	-0.015	0.027	0.024	0.058	-0.068	0.037	0.025	-0.076	0.078	1.000						
11. Generalist CDO	0.105	-0.083	-0.007	-0.072	0.015	-0.052	0.088	-0.048	0.037	-0.155	1.000					
12. Board Gender Diversity	-0.064	0.175	0.154	0.031	-0.124	0.132	-0.096	-0.111	-0.130	0.028	-0.049	1.000				
13. Board Nationality Diversity	0.133	0.069	-0.029	0.052	0.076	0.018	-0.036	-0.047	0.015	0.048	0.011	0.032	1.000			
14. Board Age Diversity	0.170	-0.211	-0.254	-0.048	0.152	-0.148	-0.021	0.031	0.043	-0.015	0.075	-0.159	0.024	1.000		
15. Board Tenure Diversity	0.042	-0.144	0.340	-0.104	0.101	0.041	-0.075	0.013	-0.031	-0.132	0.024	-0.018	-0.052	0.128	1.000	
16. CDO Appointment	0.044	0.135	0.084	0.010	-0.040	0.045	0.002	-0.079	-0.069	-0.012	0.025	0.293	0.072	0.040	-0.027	1.000
Mean	2.096	9.876	3.341	1.076	0.132	0.019	0.755	0.021	0.040	0.627	0.816	0.190	0.143	7.026	5.544	0.249
Standard Deviation	1.402	1.653	0.761	2.332	0.132	0.022	0.219	0.020	0.070	0.484	0.388	0.098	0.176	2.023	2.898	0.432

Notes: Correlations with absolute values higher than 0.039 are significant at 0.05 level.

Table 3.4 Empirical results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	5.353*** (0.427)	5.613*** (0.431)	5.597*** (0.431)	5.702*** (0.431)	5.710*** (0.435)
Firm Size	-0.457*** (0.040)	-0.459*** (0.040)	-0.459*** (0.040)	-0.468*** (0.040)	-0.471*** (0.041)
Firm Age	0.310*** (0.071)	0.226*** (0.074)	0.233*** (0.074)	0.237*** (0.074)	0.260*** (0.075)
Firm Leverage	-0.005 (0.008)	-0.004 (0.008)	-0.002 (0.008)	-0.003 (0.008)	-0.003 (0.008)
Cash Holdings	1.240*** (0.262)	1.248*** (0.261)	1.198*** (0.262)	1.166*** (0.261)	1.166*** (0.261)
Dividend Payout	-3.424*** (0.845)	-3.407*** (0.843)	-3.440*** (0.842)	-3.382*** (0.841)	-3.550*** (0.842)
Industry Competition	0.321 (0.264)	0.375 (0.264)	0.391 (0.264)	0.350 (0.264)	0.338 (0.264)
Industry Dynamism	0.016 (0.947)	-0.075 (0.945)	-0.175 (0.945)	-0.138 (0.943)	-0.323 (0.945)
Industry Munificence	0.081 (0.258)	0.101 (0.258)	0.125 (0.258)	0.161 (0.257)	0.093 (0.259)
Board Gender Diversity	0.747*** (0.241)	0.463* (0.252)	0.453* (0.252)	0.470* (0.251)	0.348 (0.271)
Board Nationality Diversity	-0.129 (0.155)	-0.164 (0.155)	-0.175 (0.155)	-0.174 (0.154)	-0.291* (0.163)
Board Age Diversity	-0.032*** (0.012)	-0.033*** (0.012)	-0.033*** (0.012)	-0.033*** (0.012)	-0.030** (0.013)
Board Tenure Diversity	-0.002 (0.009)	-0.001 (0.009)	-0.002 (0.009)	-0.002 (0.009)	-0.005 (0.010)
CDO Appointment		0.183*** (0.048)	0.189*** (0.048)	0.196*** (0.048)	0.159*** (0.056)
CDO Appointment × External CDO			0.192** (0.082)	0.238*** (0.083)	0.244*** (0.083)
CDO Appointment × Generalist CDO				0.300*** (0.102)	0.302*** (0.102)
CDO Appointment × Board Gender Diversity					0.255 (0.424)
CDO Appointment × Board Nationality Diversity					0.437** (0.212)
CDO Appointment × Board Age Diversity					-0.010 (0.019)
CDO Appointment × Board Tenure Diversity					0.033** (0.016)
Firm-level fixed-effects	YES	YES	YES	YES	YES
Number of firms	158	158	158	158	158
Number of observations	2,516	2,516	2,516	2,516	2,516
F-test	21.16***	20.78***	19.73***	19.05***	15.52***
R-squared (within)	9.77%	10.33%	10.54%	10.87%	11.20%

Notes: *p<0.1, **p<0.05, and ***p<0.01 (two-tailed tests). Standard errors are in parentheses. One-year lag between the dependent variable (Tobin's q) and all the independent variables. The direct effects of External CDO and Generalist CDO are omitted as they are time-invariant variables.

3.4.1 Robustness Tests

We conduct several additional tests to check the robustness of our findings and to account for alternative explanations. For brevity, Table 3.5 only shows the test results for the hypothesized variables, but control variables are also included in all regression models. First, we check the consistency of the test results when a different time lag between the dependent and independent variables is used. Model 1 suggests that the test results remain consistent when a two-year (rather than one-year) lag is used, although the coefficient of CDO presence is less significant ($p < 0.1$) than that shown in Table 3.4 (one-year lag; $p < 0.01$). Model 2 further shows that when the time lag is increased to three years, the interaction terms are still consistent, but the coefficient of CDO appointment becomes insignificant ($p > 0.1$). These test results suggest that CDO appointments have the most significant impact on Tobin's q in one year after the appointments, supporting our decision to maintain a one-year lag between the dependent and independent variables in the main analysis.

We also check the robustness of our test results to alternative sample and investigation periods. Specifically, we first exclude CDO appointments made in 2019 from the sample to account for COVID-19's impact on firms' Tobin's q in 2020 and the COVID-19-induced digital transformation that may confound the performance impact due to the CDO appointments in 2019 (LaBerge *et al*., 2020). The test results based on this reduced sample remain consistent, as shown in Model 3. Moreover, by limiting our investigation to a period ranging from three years before to three years after CDO appointments, we obtain qualitatively similar test results despite a smaller number of observations, as shown in Model 4.

We then employ alternative approaches to estimate our regression model. First, although the Hausman specification test does suggest that it is more appropriate to perform fixed-effect rather than random-effect estimation for our regression model, we also present test results based on the random-effect estimation in Model 5 to enable a direct comparison. The test results are generally consistent between the two estimation approaches, although the interaction between CDO presence and board tenure diversity is less significant ($p = 0.12$) based on the random-effect estimation.

Another alternative estimation approach employed is based on instrumental variables (IV). Although the fixed-effect estimation helps remove time-invariant firm-level effects and we have also included a comprehensive list of control variables at the firm and industry levels, we still cannot completely rule out the possibility that some unobservable, time-variant factors may affect firms' decision to appoint CDOs and their performance in terms of Tobin's *q*, inflating the relationship between CDO appointments and Tobin's *q* and leading to possible endogeneity concern. Mathematically, endogeneity occurs when the independent variable (e.g., CDO appointment) is correlated with the error term. The IV approach helps address this concern by instrumenting the endogenous independent variable with other variables that are highly correlated with the endogenous variable (the relevance condition) but orthogonal to the error term (the exclusion condition). In line with previous research (e.g., Fu *et al*., 2020; Ho *et al*., 2017), we instrument CDO appointment with two variables: one is the percentage of firms with CDOs in an industry (four-digit SIC code) and the other is the three-year lag of a firm's CDO appointment. This is because a firm should be more likely to appoint CDO if a higher percentage of its industry peers have CDOs and there should be a high correlation between a firm's current and previous CDO appointment (the relevance condition). By contrast, it is less likely that a firm's Tobin's *q* is affected by the percentage of CDO appointments at the industry level. Also, Model 2 (Table 3.5) suggests that there is no significant relationship between the three-year lagged CDO appointment and Tobin's *q* (the exclusion condition). Empirically, the Cragg-Donald statistic based on these two instruments is significant ($p < 0.01$) and higher than the Stock-Yogo critical value, rejecting the weak instruments assumption and satisfying the relevance condition. Moreover, the Sargan-Hansen statistic is not significant ($p > 0.1$), failing to reject the null hypothesis that the instruments are uncorrelated with the error term and thus satisfy the exclusion condition. Taken together, the two instruments used in our research are valid. The IV estimation results based on these instruments remain consistent as shown in Model 6, suggesting that our research findings are not driven by the endogeneity concern.

Finally, we explore how CDO's impact on Tobin's *q* may be influenced by other TMT members such as chief information officer (CIO) and chief executive officer (CEO). Specifically, we first investigate whether CDO's performance impact depends on the presence of CIO in the TMT. Empirically, we code CIO presence as 1 for firms with CIOs (and 0 otherwise) based on data from BoardEx (Kunisch *et al*., 2022) and compute the interaction between this variable and CDO appointment. The test results in Model 7 show a non-significant interaction ($p > 0.1$), suggesting that CDO's performance impact is independent of whether CIO is present in the TMT. This finding helps address the concern that CDO may be less effective in the presence of CIO due to the possible role overlap between the two positions (Kunisch *et al*., 2022).

We are interested in how CEO duality, an indication of CEO power, may influence CDO's effectiveness. We code CEO duality as 1 if a CEO also holds the board chair or president position (and 0 otherwise) based on data from BoardEx (Fu *et al*., 2020) and compute the interaction between this variable and CDO appointment. We find a significant negative interaction ($p < 0.1$) as shown in Model 8, indicating that a firm's CDO appointment has a less positive impact on Tobin's *q* if the firm has a powerful CEO. This finding is consistent with our argument that CDO needs autonomy and power to make successful digital transformation.

Table 3.5 Robustness checks

Variables	Model 1 Maintain two-year lag between dependent and independent variables	Model 2 Maintain three-year lag between dependent and independent variables	Model 3 Exclude CDOs appointed in 2019	Model 4 Focus on three years before and after CDO appointments	Model 5 Perform random-effect estimation	Model 6 Perform instrumental variables estimation	Model 7 Add the influence of CIO presence	Model 8 Add the influence of CEO duality
CDO Appointment	0.105* (0.060)	-0.014 (0.065)	0.140** (0.058)	0.108* (0.062)	0.205*** (0.055)	0.167** (0.082)	0.124* (0.075)	0.147*** (0.056)
CDO Appointment × External CDO	0.253*** (0.094)	0.264** (0.110)	0.321*** (0.086)	0.156* (0.087)	0.203** (0.083)	0.206** (0.082)	0.250*** (0.084)	0.247*** (0.083)
CDO Appointment × Generalist CDO	0.342*** (0.119)	0.350** (0.146)	0.363*** (0.107)	0.239** (0.106)	0.290*** (0.103)	0.331*** (0.101)	0.307*** (0.103)	0.320*** (0.103)
CDO Appointment × Board Gender Diversity	0.656 (0.479)	1.455** (0.563)	0.546 (0.448)	-0.012 (0.478)	0.351 (0.426)	0.270 (0.475)	0.251 (0.424)	0.191 (0.426)
CDO Appointment × Board Nationality Diversity	0.790*** (0.241)	1.214*** (0.278)	0.553** (0.226)	0.527** (0.224)	0.458** (0.214)	0.349* (0.211)	0.437** (0.212)	0.405* (0.213)
CDO Appointment × Board Age Diversity	0.006 (0.020)	0.024 (0.022)	-0.019 (0.020)	-0.007 (0.021)	-0.005 (0.019)	-0.001 (0.019)	-0.010 (0.019)	-0.014 (0.019)
CDO Appointment × Board Tenure Diversity	0.046** (0.018)	0.062*** (0.020)	0.034** (0.017)	0.030* (0.017)	0.024 (0.016)	0.032** (0.016)	0.033** (0.016)	0.034** (0.016)
CDO Appointment × CIO Presence							0.104 (0.149)	
CDO Appointment × CEO Duality								-0.125* (0.073)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-level fixed-effects	YES	YES	YES	YES	NO	YES	YES	YES
Number of firms	158	157	130	156	158	158	158	158
Number of observations	2,362	2,207	2,066	868	2,516	2,379	2,516	2,516
F-test	12.19***	9.96***	10.14***	3.31***		13.37***	14.76***	14.90***
R-squared (within)	9.58%	8.52%	9.13%	8.31%		10.57%	11.21%	11.31%
Wald test					382.63***			
R-squared (overall)					30.09%			

Notes: *p<0.1, **p<0.05, and ***p<0.01 (two-tailed tests). Standard errors are in parentheses.

3.5 Summary, Discussion, and Future Research

3.5.1 Discussion of Test Results

In the era of digital economy, digital transformation has become a strategic issue that firms must pay attention to. Increasingly, organizations are trying to implement digital strategies to establish dynamic capabilities, obtain sustainable competitive advantages, and gain a number of opportunities (Sousa-Zomer *et al*., 2020; Wessel *et al*., 2021). However, the existing research on digital transformation mainly focuses on digital technologies, and less consideration has been given to the role of people in this profound revolution. We approach this issue from a different perspective. Also, there has been an ongoing debate over what drives strategic action and organizational outcomes. We follow the logic of managerial cognition literature and argue that CDOs occupy a pivotal position and are protagonists in digital transformation. As a positive response to the challenges of digital transition, CDOs have emerged over the past decade and are increasingly being appointed to firms' TMTs to lead the digital agenda. Although some scholars have turned their attention to this emerging functional role, studies on CDOs are so far still sparse. Extant literature primarily uses qualitative methods to discuss the CDOs' emergence, responsibilities, types, and determinants (e.g., Firk *et al*., 2021; Kunisch *et al*., 2022; Singh *et al*., 2020; Tumbas *et al*., 2017; Tumbas *et al*., 2018). However, there is still almost a blank as to what impact the CDO presence will bring to the firm. As an initial attempt, we use UET and ABV lens and employ secondary data in a longitudinal setting to investigate the impact of CDO on firms' financial performance. Our study shows that CDO presence is positively associated with firms' financial performance and this relationship still holds after a series of robustness tests (e.g., lagged variables, alternative sample and investigation periods, estimation method change, instrumental variable approach, and addition of control variables), which indicates that CDOs could be a positive force for change and do bring value to firms.

We further show that this positive relationship is more significant when appointing an outsider as CDO (H2), CDO as a generalist (H3), and a firm has a diverse board (partially supporting H4b). The positive interaction results indicate that the effectiveness of CDO could be influenced by individual- and board-level contingencies. Specifically, the CDO could play a better role when he/she is appointed externally, when he/she is generally responsible for the company-wide digital transformation tasks, and when the CDO is in a firm with more board diversity. Yet, interestingly, the moderating effects of two dimensions of board diversity (i.e., gender diversity and age diversity) are not significant in our context. This finding shows that board diversity is a complex concept composed of multiple dimensions, and different diversity dimensions may have dissimilar impacts on firms, which also inspires us to think about diversity in the boardroom from a more broader perspective (Baker *et al*., 2020).

As for board gender diversity, although many governments have legislated to increase the proportion of female directors on the board in order to enhance gender equality, findings about the relationship between board gender diversity and organizational outcomes are mixed and often context dependent, with some results positive (Bear *et al*., 2010; Carter *et al*., 2003; Gul *et al*., 2011), some negative (Abdullah *et al*., 2016; Shrader *et al*., 1997), and some nonsignificant (Dwyer *et al*., 2003; Miller and Triana, 2009). Adams and Ferreira (2009) suggest that gender-diverse boards usually have tougher monitoring, but excessive monitoring could also lead to organizational inertia and slow strategic actions, so gender diversity in the boardroom does not necessarily add value in our context. In addition, Triana *et al*. (2014) reveal that there exists a small negative relationship between board gender diversity and the amount of strategic change, and board gender diversity in fact plays the role of double-edge sword. In our context, while we agree that gender-diverse boards theoretically could provide a wider range of knowledge, information, and views and generate more innovative and creative solutions compared with homogeneous boards, prior studies also indicated that female directors are generally more conservative and risk-averse than their male counterparts (Croson and

Gneezy, 2009; Faccio *et al*., 2016; Owen and Temesvary, 2018; Palvia *et al*., 2015). Also, female directors incline to demand more information before making a decision and are more prudent in comprehending all details, while male directors are apt to rely on just few important informational cues that are critical to their decision-making (Graham *et al*., 2002). In view of the urgency, complexity, and high risks of digital transformation, a gender-diverse board usually requires more information and longer time to discuss issues related to digital strategies, and it is often difficult to reach consensus. This could be a possible reason for the nonsignificant moderating factor of gender diversity.

Similarly, the growth of age brings rich experience to directors, but it might also lead to more conservative decisions (Okun, 1976). It is well accepted that decision-making involves emotional and cognitive processing. In general, age diversity might reduce the communication among people with different age group, and there are more likely to have differences regarding the decisions towards digital transformation (Talavera *et al*., 2018). Collectively, in general, board diversity has a positive influence on CDO effectiveness, albeit that the impacts of some dimensions in our study are not significant due to these benefits may be offset by some potential weaknesses (Menz and Scheef, 2014).

3.5.2 Implications for Research

Our work makes several theoretical contributions to the literature. First, this study advances our understanding of UET and ABV by examining the impact of the emerging functional role (CDO in our setting) on organizational outcomes in terms of financial performance. One of the core propositions of UET is that a firm's top managers largely shape this firm's strategic choices and outcomes (Hambrick and Mason, 1984). ABV further emphasizes that what decision-makers do depend on what issues and answers they pay their attention to (Ocasio, 1997). Although the existing literature has done a wealth of explorations along the logic of these two theories, prior studies mainly focus on CEO or the whole TMT, and there are relatively few studies on other TMT roles with specific expertise except CEO (e.g., Davidson *et al*., 2019; Faleye *et al*., 2014; Galasso and Simcoe, 2011; Haleblian and Finkelstein, 1993; Jenter and Lewellen, 2015). Our study represents early attempt to establish the link between CDO appointments and financial performance based on longitudinal setting in digital transformation domain. By integrating UET and ABV, our research provides a new perspective to understand the appointment of specialized top managers. We argue that as a functional position in TMT, CDO indeed serves as an attention carrier. Thus, the appointment of a CDO represents a firm's commitment to comprehensively implement digital strategies and recognition of their roles, resources, and orientations within the firm's strategic decision-making, and more managerial attention and support will accordingly be allocated to digital business, thereby adding firm value. To sum up, this study indicates that managerial attention allocated and distributed to various domains, as enabled by specific functional roles in TMT, has critical impacts on firm behavior and outcomes in these areas (Cho and Hambrick, 2006; Fu *et al*., 2020; Yadav *et al*., 2007).

Second, this study also advances our understanding of the boundary conditions of the effectiveness of CDOs, that is, under what conditions can CDOs be more beneficial. We explore the moderating effects of individual- and board-level heterogeneity (i.e., type of hiring, scope of duties, and diversity of board). These moderators help us further understand the underlying mechanism of CDO presence-financial performance linkage, and they can also to some extent explain why CDOs do not achieve the expected goals in some companies. Some articles express concerns about the value of CDOs and hold that CDOs may lead firms to fall into chaos. They even jokingly call CDO the chief dazzling officer or chief departed officer (Overby, 2019; Wade, 2020). In contrast, our research suggests that CDOs can indeed add firm value. It is not the CDO itself that has problems, but more consideration should be given to questions such as whether to hire CDO in an appropriate way (external or internal), whether CDO takes full responsibility for the company-wide digital issues (generalist or domain specialist), and whether the board is diverse enough to better assist CDO to successfully lead digital strategy (board diversity).

Third, our study contributes to the literature with respect to board diversity. In Baker *et al.*'s (2020) systematic review article, the authors point out that extant research on board diversity concentrates on gender diversity, with relatively less focus on age, nationality, ethnicity, professional background, and cognition. In this article, we decompose board diversity into four dimensions (i.e., gender, nationality, age, and tenure) to comprehensively examine the impact of diversity in the boardroom, and our empirical results partially support the hypothesis 4b that diverse boards could strengthen the positive relationship between CDO existence and financial performance. We also make some potential explanations for why the moderating effects of some diversity dimensions (i.e., gender and age) are nonsignificant.

Fourth, we extend the analysis unit of TMT research to executive dyad (e.g., CDO-CIO/CEO dyads). Menz (2012) and Simsek *et al*. (2018) call that TMT studies should not be limited to the entire TMT or a single functional executive. Roh *et al*. (2016) also point out that future research should consider structural features of the TMT as the existing positions in the TMT may not only influence which roles will be added into the team, but may also moderate the relationship between the presence of new roles and firm performance. We echo their calls by examining if CDOs' effectiveness will be affected by other chief officers such as CIO or CEO. Some hold that it is unnecessary for firms to appoint CDOs to lead digital business, and firms just need to delegate these tasks and responsibilities to CIOs. Yet, our research shows that the existence of CIO does not affect the effectiveness of CDO. In other words, CDO is not a copy of CIO, but an independent, professional, and promising position. In addition, our results indicate that the power of the CEO negatively affects the positive relation between CDO presence and financial performance, which implies that CDOs need to be given sufficient autonomy and discretion so as to function better.

Finally, we also echo Roels and Staats's (2021) call that more attention should be paid to people-centric operations and more studies should be conducted to investigate "how people affect the performance of operational processes". Previous digital transformation research primarily focuses on digital technologies while ignores the importance of people (especially CDOs) in the digital revolution. We approach digital transformation issue from a novel perspective by exploring and confirming the value of firms' head of digital agenda (i.e., CDO) in this transition. Our study contends that firms should not only focus on advanced digital technologies when considering digital change, but also need to recruit an appropriate CDO to lead the digital agenda.

3.5.3 Implications for Practices

The empirical findings of this study offer multiple interesting and relevant managerial implications. First, our research shows that it is important and necessary for companies that want to undergo digital transformation to hire a CDO to lead the digital revolution. CDO is a "booster" rather than a "stumbling block" for the company to achieve the goal of sound and rapid digital transformation. Moreover, we do not find that the existence of CIO has a significant impact on CDO presence-financial performance relationship. To put it another way, these two roles are actually relatively independent. Although some people think that the responsibilities of digital transformation can be instilled to CIO or other executive positions, our research advocates that professional work should be handled by dedicated and specialized professionals. Adding the role of CDO in TMT not only allows the digital transformation business to obtain the limited managerial attention and resources within the organization, but also allows TMT to gain expertise, skills, ideas, and leadership on digital issues.

Second, this study reveals that there is a more significant positive relationship between externally recruited CDOs and financial performance. This inspires managers to think more about hiring CDOs from external job markets. In general, external CDOs are less enmeshed in organizational politics and past decisions, making them less susceptible to the unproductive impacts of superiors, peers, and subordinates. In addition, with experience in other companies or industries, outsider may bring a broader vision, more fresh ideas and stronger ability to change to the organization. In particular, new ideas and awareness of change are essential when talking about digital transformation. Also, for external hiring, the pool of potential candidates is larger compared with internal promotion, especially if companies are willing to invest heavily in complementary hiring and screening strategies. Digital transformation is usually accompanied by risks, uncertainties and complexity. With a relatively unknown quality but from a larger pool, external recruitments have strong upside potential, so external hires may sometimes be a "superstar", making external recruitments worth the risk. Finally, external hiring fills one vacancy without creating another, while internal promotion creates a series of new vacancies within the job hierarchy.

Third, we find that the positive CDO presence-financial performance link is more salient when appointing a generalist CDO, which indicates that the CDO needs to be given more autonomy to be responsible for the whole company's digital issues. In fact, the CDO plays a cross-border horizontal role, which is constantly moving and switching throughout the organization. As David Godsman, the CDO of Coca Cola, said, "for CDOs, during the day, you might discuss marketing, operations, or supply chain product development with different heads, and you might even need to build a digital brand". A generalist is easier to control the overall situation and better realize the digitization of functional areas from different stakeholders, such as the firm's internal departments, employees, consumers, suppliers, distributors, and retailers. Conversely, a domain specialist CDO may focus on one specialized area but ignore other important aspects.

Finally, this study indicates that diverse boards have a positive impact on the effectiveness of CDOs. Regulators and policy-makers may consider introducing relevant policies to gradually create a more diverse board composition based on the actual situation. In fact, this is also the hot topic and future trend of global board reforms. Also, understanding the influence of various dimensions of board diversity on the performance and decision-making of different sub-teams or groups could help firm boards and managers better allocate attention and resources to deal with particular challenges and conflicts that caused by diversity.

3.5.4 Limitations and Future Research Directions

Despite the above implications, this study has certain limitations that provide scholars with avenues for future research. First, our study is based on large US publicly traded firms. In fact, there exist many differences between publicly traded firms and private firms, between large firms and small and medium enterprises, and between firms operating in different regions and cultures (Gupta and Gupta, 2019; Ndubisi *et al*., 2021). Some industry reports suggest that large firms in developed countries are more likely to appoint CDOs. Future studies could investigate if our findings are generalizable to firms that are private, smaller, or in other geographical or cultural contexts (e.g., emerging economies).

Second, out study linked CDO presence to firms' financial performance. In addition to financial performance, there are several other valuable outcomes waiting to be explored by future research. For example, future studies could investigate the impact of CDO presence on function-specific consequences that are more closely related to digital transformation issues, such as digital innovation, digital capability, and organizational reconfiguration (Firk *et al*., 2021).

Third, although we have made some preliminary explorations of the interfaces between

CDO and other chief executives (e.g., CIO, CEO), more other top managers, such as CFO, CMO, COO, and CSCO, can be considered in future research as well. As mentioned above, CDO plays a cross-border horizontal role, which means that this position has to frequently interact with the heads of various departments inside and outside the organization. Therefore, studies on the interfaces between CDO and other top managers and how CDO presence-firm outcomes link will be affected by other executives are promising directions (Nath and Bharadwaj, 2020).

Fourth, we only used simple binary variable (i.e., presence or not) to describe CDO in this article. Actually, the impact of CDO on firm outcomes largely depends on its power. Thus, it is interesting to explore the source, size and influence of CDO power in the following studies. For instance, Florackis and Sainani (2021) construct an index (CFO index) that allows us to differentiate between "strong" and "weak" CFOs based on their ability to affect organizational consequences. Future research may also consider constructing a CDO index to comprehensively measure CDO power.

Finally, this study examines some individual- and board-level contextual factors that affecting CDO effectiveness. Future research could explore more interesting contextual factors that may influence CDO behavior and organizational outcomes. For example, prior studies have confirmed that a number of individual attributes can affect executives' strategic action, such as hubris, charisma, overconfidence, humility, and materialism. We are curious if these characteristics also have influences on CDOs' decision-making, if so, how do they make impacts? The answer to these questions will help us further understand the micro-foundations of CDO behavior.

Chapter 4 Study Three: The Impact of Intelligent Manufacturing on Labor Productivity: An Empirical Analysis of Chinese Listed Manufacturing Companies

4.1 Introduction

It is critical for firms to invest in appropriate manufacturing technology, not only because it often requires a significant involvement of resources, but also due to its potential to navigate dynamic business environment, create competitive advantage, and improve firm performance (Lam *et al*., 2019; Sharma *et al*., 2023). In the current highly competitive business environment, firms are trying their best to continuously identify novel technologies that support their strategic goals and match internal and external resources and environments (Choi *et al*., 2022; Hitt *et al*., 2016). As a new manufacturing mode integrating a variety of disruptive information technologies and advanced manufacturing technologies such as artificial intelligence (AI), big data analytics, cloud computing, Internet of Things (IoT), augmented reality (AR), 3D printing, and among others, intelligent manufacturing (IM) has rapidly gained traction among the business community in recent years (Peres *et al*., 2020; Stornelli *et al*., 2021). According to the U.S. National Institute of Standards and Technology (NIST), IM can be defined as "fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs" (NIST, 2014). As the world's largest market research store, Research and Markets (2023) recently released a comprehensive report which provides in-depth analysis of the global IM market. It suggests that as the demand for intelligent automation increases, the global IM market is expected to grow rapidly. Specifically, the report shows that the global IM market was estimated to be valued at $186.68 million in 2022, and the compound annual growth rate is 6.1%, with an estimated value of $301.5 million by 2030. Also, by end-use industry, the top three industries in terms of IM adoption are automotive, semiconductors, and mining.

While the market has witnessed great progress of IM within the past few years, little empirical evidence has been provided about its impact on firm performance (Lu *et al*., 2023). For example, Zhou *et al*. (2022) take a systematic literature review approach to analyze 208 IM-related production and operations management (POM) studies between 2005 and 2020. The findings show that IM-related POM research is still in its infancy, and the majority of these studies are either conceptual articles which in general discuss the intentions, benefits, limitations, and social-economic influences of IM (Shen and Su, 2008; Osterrieder *et al*., 2020) or analytical model-based papers dealing with specific IM-related issues such as production planning, scheduling, logistics, and optimization (Ke *et al*., 2022; Su *et al*., 2022). In recent years, quantitative empirical investigations of IM adoption start to emerge. While some scholars have examined the determinants of IM implementation using surveys (Ghobakhloo and Ching, 2019; Jo, 2023) or explored the business models enabled by IM leveraging computer-aided modelling and simulation (Geng and Du, 2022), very few empirical studies have been conducted that use objective secondary data to investigate the operational performance implications of IM adoption at the firm-level (Lu *et al*., 2023, Ying *et al*., 2022). This motivates our research to investigate the following question:

*RQ*1. Does IM adoption improve Chinese listed manufacturing companies' operational performance in terms of labor productivity?

In addition, prior technology management studies suggest that it is less likely that companies with different resources and operating in different environments will gain the same benefits from their innovative technology adoption (Chen *et al*., 2022; Lam *et al*., 2019). For instance, although the adoption of IM may enable listed companies to partially replace human intelligence due to its utilization of disruptive technologies which reduce human involvement and intervention into manufacturing activities and systems (Wang *et al*., 2021), the human factor, especially human capital quality, still plays a key role in IM systems because an increased share of employees with good educational background and skills training is believed as one of the necessary conditions for a smaller number of workers to operate advanced IM systems (Li *et al*., 2023). In addition to human capital, previous literature shows that firms' knowledge capital (i.e., investment in R&D) is another critical internal factor affecting IM adoption and productivity growth (Aw *et al*., 2011; Lu *et al*., 2023). While anecdotal evidence suggests that listed companies could access the insights they need to improve results across their operations through IM, the benefits may rely upon a company's R&D capability to effectively and efficiently scan, assimilate, and integrate these insights and knowledge into its operations (Cohen and Tripsas, 2018; Foss *et al*., 2013). Besides, a number of extant studies demonstrate that industry structure (e.g., industry competition) significantly impacts firm behavior (e.g., novel technology adoption) and finally affects organizational performance (Karuna, 2007; Kunc and Morecroft, 2010). While operating in less competitive environments may support public firms with sufficient resources to implement IM (Lam *et al*., 2019), companies operating in more competitive environments may have more IM adoption needs and application scenarios (Jansen *et al*., 2006). Therefore, this study further considers how the labor productivity due to IM adoption varies across companies with different human and knowledge capital and operating in different environments. We thus are motivated to further investigate the following question:

*RQ*2. How do internal resources (i.e., human capital and R&D intensity) and external operating environment (i.e., industry competition) affect the relationship between IM adoption and labor productivity of Chinese listed manufacturing companies?

We attempt to address the above research questions by leveraging the resourced-based view (RBV) (Barney, 1991) as the theoretical lens and using a large-scale panel dataset of Chinese publicly traded manufacturing firms (1,786 unique firms with 16,441 firm-year observations) to examine the relationship between IM adoption and labor productivity and the moderating effects of firm-level and environmental contingencies. The results show that the adoption of IM has significantly positive impact on Chinese listed manufacturing companies' labor productivity. Moreover, companies with higher level of employee human capital quality and R&D intensity as well as operating in more competitive industry environments could experience more productivity improvement from IM implementation. These findings help managers and policy makers better understand the operational performance implications of IM adoption and its boundary conditions.

Our study contributes to the OM literature in multiple ways. First, this study represents one of the early research efforts that empirically examine the operational performance implications of IM adoption through secondary data (e.g., Lu *et al*., 2023; Ying *et al*., 2022). The positive IM implementation-labor productivity link documented in this study thus provides empirical support for Chinese listed manufacturers to adopt IM. Second, this paper extends the emerging IM literature by providing insights into the moderating effects of firm-level and environmental contingencies on the linkage between IM adoption and labor productivity, which supports the view that successful adoption derives from a proper fit between novel technology and firms' internal resources and external operating environments (Maghazei *et al*., 2022; Sharma *et al*., 2023). Third, from the research methodology perspective, previous technology management studies usually employ the event study method to examine the impacts of novel technology initiatives on listed companies' short-term stock returns (e.g., Klöckner *et al*., 2022; Lam *et al*., 2019; Liu *et al*., 2022). Our study demonstrates the possibility and advantages of using secondary data to conduct causal inference research to investigate the effects of innovative technology adoption on listed firms' long-run operational performance indicators.

The rest of this article is organized as follows. In Section 2 we briefly review related research on IM and propose our hypotheses. Section 3 describes the data source, sample, measures, and estimation strategy. Section 4 presents the test results and several robustness checks. Finally, in Section 5, we discuss in detail about the results and implications, and point out some limitations as well as possible future research directions.

4.2 Literature Review and Hypothesis Development

4.2.1 Related Research on IM

In the past two decades, the concept of IM and Industry 4.0 has continuously evolved, and the practices have been constantly improved and diffused as well (Arcidiacono *et al*., 2023; Ivanov *et al*., 2021; Olsen and Tomlin, 2020). Experts and practitioners in disciplines such as robotics, electronics, computer science, and production engineering have made great contributions to this field (Hassan *et al*., 2022; Koh *et al*., 2019). As a novel manufacturing mode, there is still no uniform definition of IM in academia (Radziwon *et al*., 2014; Zhou *et al*., 2022). Wang *et al*. (2021) summarize the definitions of IM from different views during past decades. For example, from a system integration view, Oztemel (2010) suggests that IM combines manufacturing processes and systems with various degrees of machine intelligence. Wang (2019) takes an intelligence science view and contends that the purpose of IM is to establish adaptive manufacturing operations and systems locally or globally by integrating advanced information and manufacturing technologies. Other researchers describe IM as a composite system optimally integrating human-, physical-, and cyber-systems that cooperate to achieve diverse manufacturing goals from a human-cyber-physical system (HCPS) perspective (e.g., Pacaux-Lemoine *et al*., 2017; Zhou *et al*., 2019). Although scholars have different focuses on the definition of IM, some common features such as connectivity, optimization, transparency, prediction, and agility have been widely discussed and accepted (Koh *et al*., 2019; Zhou *et al*., 2022). These characteristics enable IM to accurately predict requirements, identify errors, and make innovation and the manufacturing process more manageable (Qi and Tao, 2018; Tao *et al*., 2018).

Mittal *et al*. (2019) indicate that IM and other related concepts such as smart manufacturing, digital manufacturing, cloud manufacturing, advanced manufacturing, and industry 4.0 are indeed being used synonymously on occasion by some researchers. These concepts share the commonalities such as the purpose of smart decision-making in manufacturing systems and the optimization of varied manufacturing resources (Zheng *et al*., 2018). In addition, some advanced technologies such as AI, cloud computing, big data analytics, 5G, IoT etc., are often used within these diverse concepts (Dolgui and Ivanov, 2022; Rai *et al*., 2021; Zhong *et al*., 2017). There are also some differences between these manufacturing paradigms including research efforts, application scenarios, and supporting technologies (Thoben *et al*., 2017). For example, IM highlights the important role of AI, focuses on the human-machine and machine-to-machine interactions, and consolidates human-centricity as one of the key components of the value-creation systems supported by advanced technologies (Ivanov, 2023; Zhong *et al*., 2017). Cloud manufacturing concentrates more on the configuration and modeling of manufacturing services (e.g., Manufacturing-as-a-Service, Supply Chain-as-a-Service) (Ivanov *et al*., 2022; Zhang *et al*., 2022). Digital manufacturing pays attention to the significance of digital technologies application throughout the product life cycle (Ardolino *et al*., 2024). At a more macro level, digital supply chain is advocated by OM scholars as it is “a cyber-network of end-to-end visibility representing a physical supply chain with associated operational data and performance assessments” and it represents the future of the current supply chain (MacCarthy and Ivanov, 2022). Dolgui *et al*. (2020) suggest that the digital supply chain framework and other supply chain characteristics such as resilience, leanness, and sustainability can be integrated within the Reconfigurable Supply Chain framework.

The literature in this evolving field can be generally divided into two main streams according to the research objectives and methodologies applied. The first research stream of literature primarily focuses on technological characteristics and industrial applications of IM by applying systematic literature review or analytical models to conceptually investigate the implementation path and specific application scenarios for IM in various settings (Zhou *et al*., 2022). On the one hand, scholars are interested in which technologies are necessary to support the successful implementation of IM (Egger and Masood, 2020; He and Bai, 2021; Yang *et al*., 2019). A number of technologies have been discussed in prior studies to be particularly important when adopting an IM approach, including AR, IoT, AI/machine learning-based analytics, robotics, digital twins, and data lakehouse solutions. For example, Egger and Masood (2020) conduct a systematic literature review concerning AR and demonstrate that AR is a core technology that facilitates human integration into IM systems, providing an interface for people to interact with the digital world of smart factories. Yang *et al*. (2019) present a review about IoT technologies. The findings show that realizing the full potential of IM relies on the IoT for data-enabled engineering innovations, indicating that IoT technologies and systems are the drivers and foundations of data-driven innovations in IM. Harby and Zulkernine (2022) compare the strengths and weaknesses of existing data warehouse and data lake technology and argue that the need to generate actionable knowledge quickly from unstructured data ingested from distributed sources requires a combination of data warehouses and data lakes to create a data lakehouse. A data lakehouse is a modern, open architecture that offers the advantages of both data warehouse (i.e., finding new insights quickly from processed merged data) and data lake (i.e., ingesting and storing high-speed unstructured data with post-storage transformation and analysis capabilities), which enables manufacturers to store, understand, and analyze almost all types of data (Armbrust *et al*., 2021). On the other hand, previous studies have also explored some specific areas in IM adoption such as agent-based systems (Guo and Zhang, 2009; Shen *et al*., 2006), sustainable issues and energy efficiency (Ma *et al*., 2020;

Meng *et al*., 2018), and performance measurement towards IM systems (Kamble *et al*., 2020).

The second stream of literature seeking to understand the implications of IM adoption has started to emerge in recent years. Studies in this research stream leverage multiple empirical methods to provide preliminary discussions about the potential business value of IM adoption from both strategic and operational perspectives (Lu *et al*., 2023; Ying *et al*., 2022). For example, using a knowledge-based theoretical perspective, Roscoe *et al*. (2019) develops an empirical framework that illustrates how individuals, processes, and structures interact to establish a microfoundation of the operational capabilities of digital manufacturing, which helps to open the black box of capabilities generation in the digital manufacturing implementation process. As for the consequences of IM implementation, due to data availability, most of the empirical studies in this stream of literature are conducted at the macro level (i.e., industry-, state-, or country-level) (Seamans and Raj, 2018). For instance, based on province-level panel data for 30 provinces in mainland China from 2005 to 2008, Yang *et al*. (2022) examine the impact of manufacturing intelligence on green innovation via a dynamic spatial lag model. The findings suggest that manufacturing intelligence has a significantly positive impact on green innovation performance at the national level. Acemoglu and Restrepo (2020) theoretically hypothesize and empirically examine the influence of industrial robots on the U.S. labor market. Using industrial- and national-level data on industrial robots, the authors show that there are robust negative effects of industrial robots on employment and wages.

In this study, we leverage the RBV to help explain the relationship between IM adoption and labor productivity. The RBV has emerged as a prominent theoretical framework across several disciplines (Chahal *et al*., 2020; Hitt *et al*., 2016). Originating in the 1980s, the RBV posits that a firm’s competitive advantage is driven by the uniqueness, value, rarity, and inimitability of its internal resources and capabilities. Scholars such as Wernerfelt (1984) and Barney (1991) have highlighted the significance of firm-specific resources, such as technological expertise, organizational knowledge, skilled human capital, and brand and reputation in shaping a firm's sustained performance and competitive advantage. However, it is worth noting that studies in this period merely attributed firms' competitive advantages to their possession of heterogeneous resources from a static perspective, overlooking the dynamic acquisition of such resources, which led to the disconnection between the RBV and practice in an increasingly turbulent external environment. Some studies published later have criticisms of the RBV in terms of oversight of dynamism, environmental contingences, and managers' role (e.g., Bromiley and Rau, 2016; Kunc and Morecroft, 2010; Sirmon *et al*., 2007). For example, Priem and Butler (2001) suggest that merely possessing strategic resources does not guarantee the development of competitive advantages or the creation of value. Firms need to accumulate, combine, and exploit resources to realize value creation (Sirmon and Hitt, 2003). Also, the RBV does not describe the decision-making process that managers follow to develop their resources, which ignores the role of managers in developing and using such resources (Kunc and Morecroft, 2010; Miller, 2003). Additionally, the processes involved in managing resources are affected by firms' operating environment (Lichtenstein and Brush, 2001), and it is quite difficult for firms to sustain a competitive advantage over time due to varying degrees of environmental munificence (Morrow *et al*., 2007).To address the above challenges, following studies introduced the concept of dynamic capability to mitigate the limitations of RBV and integrated theories such as managerial cognition and organizational behavior, focusing on the influencing factors, process mechanisms and performance effects of firm resource action in a specific context (e.g., Baker and Nelson, 2005; Sirmon *et al*., 2011; Teece *et al*., 1997). We argue that the adoption of IM presents a compelling context to apply the lens of RBV. IM entails the integration of advanced technologies, data analytics, and automation, all of which introduce new dimensions to a firm's resource configuration. Our study's focus on investigating the impact of IM on labor productivity aligns with the RBV's core tenets. By scrutinizing the specific resources and capabilities that are harnessed during the adoption of IM, we could discern how firms create value through the exploitation of technology-driven competencies. Additionally, the RBV's emphasis on sustained competitive advantage resonates with the need to understand how the adoption of IM may lead to enduring improvements in labor productivity due to the development of distinctive, difficult-to-replicate resources. Therefore, the RBV provides a conceptual framework to explore the relationship between IM adoption and firms' labor productivity, offering insights into the mechanisms through which technology-related resources contribute to enhanced performance outcomes. Our study therefore aims to complement the literature by providing empirical evidence of the operational performance implications of IM adoption and the boundary conditions.

4.2.2 Hypothesis Development

Our first hypothesis considers the direct impact of IM adoption on manufacturers' operational performance. The RBV contends that a firm is a distinct collection of tangible (e.g., equipment, land, raw material) and intangible (e.g., brand, reputation, patent, human capital) resources that are possessed or controlled by this firm (Barney, 1991). In addition, the RBV argues that the valuable, rare, inimitable, and nonsubstitutable resources and capabilities possessed by a firm are the cornerstones of competitive advantage and superior performance (Amit and Schoemaker, 1993; Barney, 1991). On the one hand, the use of multiple advanced technologies in IM has greatly changed the shape and structure of firms' resources (Dąbrowska *et al*., 2022). Previous studies demonstrate that IM could integrate multiple value-creating stages such as product processing, service provision, and platform construction (Tao and Qi, 2019), making them form data resources with standardized and structured characteristics corresponding to physical resources (Li *et al*., 2022; Zhou *et al*., 2022). These data resources could be utilized, diffused, absorbed, and adjusted efficiently and flexibly in various production and operations scenes (Salam, 2021), thus making firms' resources valuable and rare. Besides, IM could also change the value characteristics of resources. A firm's resources can be connected and reorganized in diverse ways after being digitized by the IM system, making it possible for firms to form heterogenous resources (Marques *et al*., 2017). In other words, IM allows firms to better reorganize and reallocate their resources, which could optimize firms' resource base and generate new resources that are difficult to imitate and substitute by their competitors.

In addition, prior IS literature has well documented that the fit between a firm's information processing capability and information processing needs has important impacts on organizational outcomes (Wang, 2003). The higher the fit between the two, the better a firm's performance will be (Premkumar *et al*., 2005). The information processing needs of firms come from addressing the uncertainty and ambiguity of the internal and external environment (Tushman and Nadler, 1978). It is well acknowledged that contemporary business operations have entered the era of VUCA (i.e., volatility, uncertainty, complexity, and ambiguity) (Bennett and Lemoine, 2014). The environmental characteristics of VUCA make firms' information processing needs continuously increase (Xie *et al*., 2022). One of the key benefits of IM is that it could enhance firms' information processing capability to match the increasing information processing needs (Chen, 2017). Specifically, IM could improve firms' information processing capability in three aspects: information collection, information transmission, and information utilization (Tao *et al*., 2018). First, IM enables firms to obtain real-time data about product manufacturing and consumer feedback, thus helping firms to achieve near-universe and diversified information (Zhou *et al*., 2022). Second, IM may remove both intra- and inter-organizational information barriers to facilitate information transmission (Tiwari, 2021). For example, IoT could realize the connection and communication between physical devices and networks, and cloud computing services could remotely store real-time operating data (Chen *et al*., 2022; Xu *et al*., 2014), so that the information required for manufacturing can be fully shared (Son *et al*., 2014). Third, IM could help firms make full use of information and conduct intelligent decision-making (Zhong *et al*., 2017). For instance, big data analytics techniques allow firms to fully process massive information, helping firms realize visualization and interconnection of manufacturing processes, which contributes to more rational planning of production and operations processes (Choi *et al*., 2018).

Moreover, in the traditional manufacturing mode, companies usually need to make a trade-off between mass production and personalization (Clark and Huckman, 2012). Traditionally, providing a diverse product portfolio leads to more operating costs (Kovach *et al*., 2015). IM follows a new business logic where downstream customer demand determines upstream production supply (Li *et al*., 2012). Employing big data analytics, AI and other technologies, IM could accurately depict customer portraits and meet the individualized needs of customers in product design, production, sales, and other activities, so as to improve customer satisfaction (Shan *et al*., 2020). Also, one of the typical features of IM is connectivity (Zhou *et al*., 2022). IM creates an intelligent ecosystem which organically connects manufacturers, suppliers, and customers through cloud platforms and IoT to achieve collaborations across the firms' value chain (Zhou *et al*., 2022). This helps firms to respond to consumer needs quickly and flexibly, enhance manufacturing and value co-creation capabilities, and finally improve firm performance (Zhang *et al*., 2022).

Taken together, IM makes it possible for firms to reallocate and reorganize resources effectively and efficiently, which is beneficial for firms to achieve heterogenous strategic resources. Also, IM helps firms establish powerful information processing and manufacturing capabilities, allowing firms to successfully handle operational complexity, lower operating costs, increase customer satisfaction, and enhance collaboration with supply chain partners, and finally lead to productivity improvement. Accordingly, the first hypothesis is:

H1: IM adoption has a positive impact on Chinese listed manufacturing companies' labor productivity.

Our second hypothesis considers the moderating effect of employee human capital quality. The human capital embodied in employees, no matter at the individual, team, or organizational level, is rare, intangible, inimitable, nonsubstitutable, and often tacit in nature (Riley *et al*., 2017). These characteristics are precisely the same attributes of resources that could bring competitive advantage and superior performance to firms emphasized by the RBV (Barney, 1991; Ray *et al*., 2023). As one of the key characteristics of human capital, human capital quality (i.e., education level) has an important impact on organizational outcomes. In particular, it has been well documented that a higher education level of employees plays an important role in improving firms' information environment (Si and Xia, 2023). For instance, Pham *et al*. (2023) find that compared with the firms whose CEOs without legal expertise, firms that led by CEOs with law degrees (i.e., lawyer CEOs) have better credit ratings and around 10 percent lower cost of debt. The mechanism analysis shows that CEO with law degree is closely related with a reduction in information risk and a lower future volatility of stock returns. In the OM field, both practices and literature suggest that the appointment of well-educated chief supply chain and operations management executives could better predict product demand, integrate supply chains, control supply chain risk, determine the extent of outsourcing, select major customers and establish relationships with them, and reduce the incidence of product recalls, among others (e.g., Hendricks *et al*., 2015; Kroes *et al*., 2022; Roh *et al*., 2016).

While IM could greatly enhance firms' information processing and manufacturing capabilities, a realistic problem is that almost every process, whether it is machine operation, maintenance, related data collection and record, or even final decision making, cannot be separated from human (Li *et al*., 2023). Neglecting the factor of human may lead to a series of consequences such as injury, system failure, inaccurate data collection, and decision-making error (Vijayakumar *et al*., 2022). Take operations manager for example, a well-educated operations manager may be able to know product demands more accurately in their interaction with customers and more likely to spot and report potential errors in sales data in a timely manner compared with his/her less-educated counterpart. This could enable firms to obtain more timely and accurate data in the process of implementing IM, improve firms' internal information environment, and enhance the information processing ability of IM, thereby ultimately enhancing firms' productivity. In addition, it is generally believed that education level of workforce is positively correlated with knowledge accumulation and learning ability (Vega-Jurado *et al*., 2008). The implementation of IM requires employees to adjust existing operations routines and learn new skills (Benešová and Tupa, 2017). Well-educated employees could better adapt to the changes brought about by IM and integrate their knowledge and skills with the IM system to enhance productivity. We thus hypothesize that:

H2: The positive impact of IM adoption on Chinese listed manufacturing companies' labor productivity is more pronounced for companies with higher employee human capital quality.

Our third hypothesis considers the moderating effect of firms' R&D intensity. Extant studies show that R&D investment plays an important role in the adoption and utilization of novel technologies (Lin *et al*., 2020; Liu *et al*., 2022). Firms generally engage in R&D activities in two ways, either in-house by employing researchers and investing the capital needed for R&D, or by establishing partnerships with universities, research institutions, etc. to carry out R&D activities or even outsourcing them (Spithoven *et al*., 2011). Prior studies suggest that one of the greatest benefits of R&D activities is to help companies build proprietary and original know-how and accumulate knowledge and intellectual property (Lee *et al*., 2022). In particular, from the perspective of absorptive capacity, the accumulation of internal knowledge is critical for firms to scan, screen, and absorb external knowledge effectively and efficiently (Cohen and Levinthal, 1989).

In our context, firms with higher R&D intensity have at least two ways to strengthen the positive relationship between IM implementation and operational performance. First, although IM-related issues are theoretically mature, in practice, the development of IM systems and how to successfully embed them into a firm's various operational processes are still in its nascent stage, especially in emerging economies such as China (Enholm *et al*., 2022; Sundarakani *et al*., 2021). In this case, firms may face the challenge of integrating existing internal resources, capabilities, and structures with the external resources and knowledge that IM systems bring to the table. Having higher R&D intensity means that a company has more internal knowledge accumulation and stronger absorption capacity (Tsai, 2001), so that it could absorb the knowledge and capabilities from IM adoption more fully and efficiently. Also, it is more likely that the knowledge and capabilities generated by IM will have a complementary effect with the company's distinct resources and capabilities (Caloghirou *et al*., 2004; Karimi *et al*., 2007), thus enhancing the operational performance improvement effect caused by the implementation of IM. Second, previous research suggests that higher R&D intensity indicates that firms tend to engage in more exploratory innovation, which also implies that firms face a more technologically dynamic environment (Benner and Tushman, 2002; Lo *et al*., 2013). Conversely, if a firm's R&D intensity is low, it indicates that this firm's products and processes are more likely to be standardized and that the firm is better suited to operate in a technologically stable environment (Lo *et al*., 2013). The important purposes of adopting IM include meeting customers' diverse and personalized product requirements, flexibly adjusting production and process control processes, and conducting strict and continuous monitoring of product quality (Zhou *et al*., 2022). This indicates that high R&D intensity provides appropriate application scenarios in which IM systems can be applied to improve operational performance to a greater extent, leading to the hypothesis below:

H3: The positive impact of IM adoption on Chinese listed manufacturing companies' labor *productivity is more pronounced for companies with higher R&D intensity.*

Our fourth hypothesis considers the moderating effect of industry competition. As one of the important features of industry structure, industry competition is believed to have significant impacts on firm behavior and performance (Cusumano *et al*., 2015). Industry competition reflects the number of competitors in an industry and the concentration of market shares (Jansen *et al*., 2006). A low industry concentration means that there are a large number of competitors in the industry, and conversely, when an industry is monopolized by a few oligopolies, it is more concentrated (Lam *et al*., 2019). When there are plenty of competitors in an industry, firms have incentives to break the race to the bottom competition of low prices to differentiate themselves from competitors who offer homogeneous products or services through approaches such as differentiated product development, new market exploration, and improved after-sales service (Chen *et al*., 2014). In addition, the fierce competition in the industry compels firms to control costs more carefully. The adoption of IM could help firms achieve the above goals of differentiation and cost control (Salam, 2021). By processing a complex set of information, IM can accurately forecast demand information and flexibly adjust production lines to meet individual customer needs and lower operational and innovation costs (Zhong *et al*., 2017). Besides, in a highly competitive industry, IM adoption may also send positive signals to the market that a company is capable of providing high-quality products and services, which helps customers build dependence on firms and brands, thereby stimulating new demand (Thoben *et al*., 2017). Therefore, IM implementation may be of greater value when the industry is more competitive. Thus, we hypothesize that:

H4: The positive impact of IM adoption on Chinese listed manufacturing companies' labor productivity is more pronounced for companies operating in more competitive industries.

The conceptual model shown in Figure 4.1 summarizes our four proposed hypotheses.

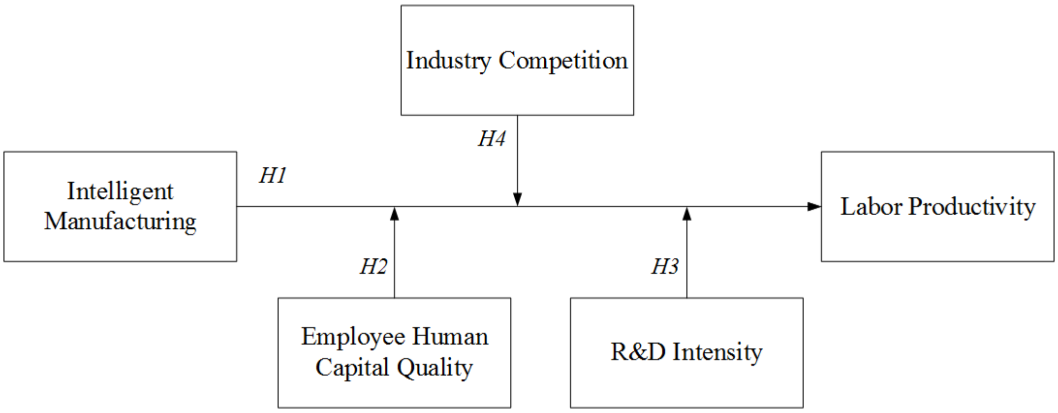

Figure 4.1 Conceptual model of Study 3

4.3 Methodology

4.3.1 Data and Sample

We collect and combine secondary longitudinal data from multiple sources to measure the research variables investigated in this study. First, we rely on the IM pilot demonstration project as an exogenous shock to identify the IM adoption of publicly traded firms in China. Specifically, the Ministry of Industry and Information Technology (MIIT) of China (www.miit.gov.cn) annually released a list of IM pilot demonstration projects from 2015 to 2018, with a total of 306 projects in four years, of which 46 were in 2015, 64 were in 2016, 97 were in 2017, and 99 were in 2018. The IM pilot demonstration project is a policy launched by MIIT based on the requirements of "China Intelligent Manufacturing 2025" and "China Intelligent Manufacturing Development Plan (2016-2020)". It aims to screen out firms at the forefront of IM and help these companies better develop IM capabilities in the future. Other firms can refer to the successful experience of these industry pioneers to gradually develop their own IM capabilities, ultimately enhancing the overall intelligence level of China's manufacturing industry. For instance, Fuyao Glass Industry Group (Fuyao Group, ticker symbol: 600660), a well-known multinational company specializing in the manufacture of automobile safety glass and industrial technical glass, was selected as the pilot firm for automobile glass smart factory in 2016. We first compile a list of pilot IM firms, and then we search the online database Qichacha (www.qcc.com) for their full names to determine whether they are publicly listed firms, and if so, we record their stock codes. Qichacha is officially designated as one of the largest enterprise credit information inquiry platforms in China, which provides users with rapid inquiry services for firm information (e.g., business information, risk status, intellectual property rights, and firm relations) (Li *et al*., 2021b; Zhang *et al*., 2019).

Next, we obtain firm- and industry-level financial and governance data from the China Stock Market & Accounting Research (CSMAR) database. CSMAR is one of the largest listed company databases in China (similar to COMPUSTAT in the US), which provides researchers with abundant and reliable firms' background, financial, governance, and other information. This database has been extensively used in the extant China-related empirical OM studies (e.g., Lu *et al*., 2021; Shen *et al*., 2023).

Our initial sample includes all manufacturing listed companies on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) between 2010 and 2020. The sample firms were divided into a treatment group and a control group according to whether a firm is on the IM pilot list or not. Consistent with prior literature, we require the sample firms to have at least five observations to mitigate the potential estimation bias caused by the relatively short sample period (Fu *et al*., 2020). We also drop the special treatment (ST) and particular transfer (PT) firms as these firms are in financial distress and face severe regulation (Chen *et al*., 2020; Xu *et al*., 2021). After eliminating the observations with missing data, our final sample comprises 1,786 unique firms and 16,441 firm-year observations, of which the treatment group is of 1,298 firm-years (for 124 firms) and the control group is of 15,143 firm-years (for 1,662 firms). Panels A, B, C, and D in Table 4.1 present the distribution of our sample firms by industry, year, region, and treatment, respectively. We note that the observations from the eastern coastal areas and developed provinces account for a large proportion (e.g., Guangdong, Jiangsu, Shanghai, and Zhejiang). In addition, observations of the treatment group account for only 7.89% of the full sample, indicating that the proportion of Chinese-listed manufacturing firms implementing IM is relatively low in our sample.

4.3.2 Measures

Dependent Variable. The dependent variable of this study is labor productivity. It is a widely adopted proxy for manufacturing operational performance in the previous empirical OM literature (e.g., Heim and Peng, 2010; Sartal *et al*., 2020). At a general level, labor productivity, defined as total output divided by labor input, indicates the degree to which a firm's labor force effectively creates output. We draw on prior literature to measure labor productivity as the natural logarithm of the ratio of firm sales to the number of employees (Datta *et al*., 2005; Sartal *et al*., 2020).

Independent Variable. Our variable of interest, IM, is a binary variable. After identifying the year in which a treatment firm is in the IM pilot list, we follow Jiang *et al*. (2019) and code IM as one for all years starting from the policy intervention year and 0 for all years before the policy intervention year. For the control firms, IM is always zero. For instance, when a firm is in the IM pilot list in 2016, we code 2016-2020 as 1 for this firm and 2010-2015 as 0 for the same firm. If a firm was not on the pilot list between 2015 and 2018, we code 0 for this firm during the whole sample period.

Moderating Variables. We examine three moderators in this study. Our first moderator is employee human capital quality. We follow Si and Xia (2023) and download data from the RESSET database. The RESSET database is a provider of Chinese financial research data and has been widely used in prior empirical studies (e.g., Cao *et al*., 2020; Li *et al*., 2021a). We then measure firm-level employee human capital quality by calculating the proportion of rank-and-file employees whose education level is beyond the threshold of bachelor's degree out of the total number of rank-and-file employees. Our second moderator is R&D intensity. Prior studies suggest that R&D intensity reflects the extent to which a firm invests in innovation for process improvement and new product development (Shou *et al*., 2021), thus serving as an appropriate indicator of innovation capability. We follow prior literature to calculate a firm's R&D intensity as the ratio of this firm's R&D expenses to its sales (Shou *et al*., 2021; Yiu *et al*., 2020). Our third moderator is industry competition. We follow extant OM studies to use one minus Herfindahl-Hirschman index (i.e., one minus the sum of squared market shares of the firms in an industry) as the proxy of industry competition (Lam *et al*., 2019; Xia *et al*., 2016).

Control Variables. Following prior studies (Datta *et al*., 2005; Sartal *et al*., 2020), we include a battery of control variables into the empirical model to control for multiple factors that are suggested to have impacts on firms' labor productivity. Specifically, we control firm age (the natural logarithm of the number of years since a firm was established), firm size (the natural logarithm of a firm's number of employees), financial slack (current assets divided by current liabilities), leverage (total debts divided by total assets.), sales growth (a firm's sales this year divided by last year's sales then minus one), cash holding (sum of cash and cash equivalents divided by total assets), and capital intensity (total assets divided by sales). We also include year, industry, and province dummies into the model to control for unobserved trends, industry features, and geographic differences (Han *et al*., 2024; Zhu *et al*., 2021).

4.3.3 Identification Strategy

The observational nature of our data leads to some challenges for identification of the treatment effects. For instance, in our dataset, each firm is either treated or untreated in each time period, and it is impossible for us to observe the counterfactual consequences in the unobserved condition. Also, the policy intervention of the IM pilot occurred at different points in time, which requires cautious computation of the treatment effects (Berman and Israeli, 2022). To deal with these challenges, we employ a staggered difference-in-differences (DID) approach as the identification strategy to estimate if the adoption of IM could really improve firms' operational performance in terms of labor productivity.

Compared to traditional DID method, which requires policy shock to occur at the same time, staggered DID is suitable for gradual implementation of the same policy in affected groups. For instance, Beck *et al*. (2010)'s highly impactful article leverages this approach to assess the influence of bank deregulation on the distribution of income in the United States based on the background that most states gradually removed restrictions on intrastate branching from the 1970s through the 1990s. This identification strategy is also consistent with extant research focusing on settings with staggered treatment events such as opening of high-speed railways, promotion of officials, deregulation of bank branches, and reform of corporate boards, among others (e.g., Beck *et al*., 2010; Flammer and Kacperczyk, 2016; Jiang, *et al*., 2019). Specifically, we estimate the following baseline regression set-up:

$$Labor\ Productivity_{i,t} = \alpha_1 + \beta_1 IM_{i,t} + \gamma_1 Controls_{i,t} + Year_t + Industry_j + Province_s + \varepsilon_{i,t}$$

where i, t, j, and s represent firm, year, industry, and province indices, respectively, and all the variables have all been defined in Section 3.2. The variable of interest is $IM_{i,t}$, and the coefficient on $IM_{i,t}$ (i.e., β_1) captures the difference in the adoption of IM between the treatment and control firms, which also indicates the impact of IM adoption on labor productivity (Beck *et al*., 2010). The panel regression is estimated by ordinary least squares (OLS) (Flammer and Kacperczyk, 2016). A positive and significant β_1 suggests that IM adoption exerts a positive effect on operational performance in terms of labor productivity. Before running regressions, all continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of possible spurious outliers in the sample (Bellamy *et al*., 2020; Shan *et al*., 2014).

Table 4.1 Descriptive statistics of sample firms

Panel A: The distribution of sample firms across industries

CSRC industry code	Industries	Frequency	Percentage (%)
C13	Farm products processing	351	2.13
C14	Food manufacturing	342	2.08
C15	Wine, drinks, and refined tea manufacturing	361	2.20
C17	Textile	289	1.76
C18	Textiles, garments and apparel industry	251	1.53
C19	Leather, fur, feathers, and related products and shoemaking	70	0.43
C20	Wood processing, and wood, bamboo, rattan, palm and grass products	62	0.38
C21	Furniture manufacturing	79	0.48
C22	Papermaking and paper products	234	1.42
C23	Printing and reproduction of recorded media	96	0.58
C24	Culture and education, arts and crafts, sports and entertainment products manufacturing	62	0.38
C25	Petroleum processing, coking and nuclear fuel processing	147	0.89
C26	Raw chemical materials and chemical products	1,690	10.28
C27	Pharmaceutical manufacturing	1,693	10.30
C28	Chemical fiber manufacturing	196	1.19
C29	Rubber and plastic product industry	493	3.00
C30	Non-metallic mineral products	697	4.24
C31	Smelting and pressing of ferrous metals	313	1.90
C32	Smelting and pressing of nonferrous metals	624	3.80
C33	Metal products	418	2.54
C34	General equipment manufacturing	922	5.61
C35	Special equipment manufacturing	1,437	8.74
C36	Automobile manufacturing	886	5.39
C37	Railway, shipbuilding, aerospace and other transportation equipment manufacturing	397	2.41
C38	Electric machines and apparatuses manufacturing	1,637	9.96
C39	Computer, communication and other electronical device manufacturing	2,283	13.89
C40	Instrument and meter manufacturing	253	1.54
C41	Other manufacturing	116	0.71
C42	Utilization of waste resources	42	0.26
Total sample size		16,441	100.00

Panel B: The distribution of sample firms across years

Year	Frequency	Percentage (%)
2010	949	5.77

2011	1,187	7.22
2012	1,318	8.02
2013	1,340	8.15
2014	1,376	8.37
2015	1,559	9.48
2016	1,624	9.88
2017	1,781	10.83
2018	1,775	10.80
2019	1,771	10.77
2020	1,761	10.71
Total sample size	16,441	100.00

Panel C: The distribution of sample firms across locations

Province	Frequency	Percentage (%)
Anhui (AH)	610	3.71
Beijing (BJ)	967	5.88
Chongqing (CQ)	205	1.25
Fujian (FJ)	567	3.45
Gansu (GS)	186	1.13
Guangdong (GD)	2,479	15.08
Guangxi (GX)	147	0.89
Guizhou (GZ)	158	0.96
Hainan (HI)	95	0.58
Hebei (HE)	351	2.13
Henan (HA)	523	3.18
Heilongjiang (HL)	185	1.13
Hubei (HB)	506	3.08
Hunan (HN)	488	2.97
Inner Mongolia (IM)	150	0.91
Jilin (JL)	232	1.41
Jiangsu (JS)	1,875	11.40
Jiangxi (JX)	273	1.66
Liaoning (LN)	333	2.03
Ningxia (NX)	87	0.53
Qinghai (QH)	97	0.59
Shandong (SD)	1,200	7.30
Shanxi (SX)	196	1.19
Shaanxi (SN)	275	1.67

Shanghai (SH)	951	5.78
Sichuan (SC)	620	3.77
Tianjin (TJ)	229	1.39
Tibet (XZ)	67	0.41
Xinjiang (XJ)	214	1.30
Yunnan (YN)	198	1.20
Zhejiang (ZJ)	1,977	12.02
Total sample size	16,441	100.00

Panel D: The distribution of sample firms by treatment

	Unique values	Frequency
Treatment group	124	1,298
Control group	1,662	15,143
Total sample size	1,786	16,441

4.4 Empirical Results

4.4.1 Descriptive Statistics and Correlation

The summary statistics and correlation matrix of all dependent and independent variables are reported in Table 4.2. We see that the mean and maximal values for *Leverage* are 0.4053 and 0.9423, respectively, suggesting that the sample manufacturing firms have relatively high levels of debt. In addition, the mean of *Sales Growth* is 0.2448, which indicates that the sample firms have strong growth. The results of the above descriptive statistics match the actual operating conditions of Chinese manufacturing firms, and the values of each variable have a great degree of variation, which is suitable for our subsequent data analysis. It shows that the hypothesized variable (i.e., *IM*) strongly correlates (p-values < 0.01) with the dependent variable (i.e., *Labor Productivity*), which provides us with a prediction that IM could improve firms' labor productivity. Most of the variables are highly correlated and the coefficients are less than 0.6 (Li *et al.*, 2021a). Before doing analysis, we test the variance inflation factor (VIF) and find that its largest and mean values are only 2.16 and 1.42, respectively, which is well below the threshold of 10 (Steinker *et al.*, 2017). This suggests that multicollinearity does not appear to be a major concern in our study.

Table 4.2 Correlation matrix and summary statistics

	1	2	3	4	5	6	7	8	9
1 *Labor Productivity*	1.000								
2 *IM*	0.099***	1.000							
3 *Size*	0.023***	0.223***	1.000						
4 *Age*	0.143***	0.086***	0.120***	1.000					
5 *Financial Slack*	-0.136***	-0.059***	-0.375***	-0.176***	1.000				
6 *Leverage*	0.206***	0.085***	0.411***	0.172***	-0.653***	1.000			
7 *Sales Growth*	-0.039***	-0.012	-0.097***	-0.008	0.002	0.016**	1.000		
8 *Cash Holding*	-0.071***	-0.037***	-0.198***	-0.192***	0.540***	-0.438***	0.034***	1.000	
9 *Capital Intensity*	-0.347***	-0.043***	-0.340***	-0.009	0.227***	-0.106***	0.170***	0.040***	1.000
Mean	13.6788	0.0328	7.7540	2.7526	2.6206	0.4053	0.2448	0.1586	2.1427
SD	0.7149	0.1782	1.1530	0.3884	2.7556	0.2027	0.5887	0.1271	1.4074
Min	12.1317	0	5.1180	1.3863	0.3829	0.0501	-0.6593	0.0095	0.4422
Max	15.8214	1	10.9086	3.4340	18.1407	0.9423	3.7110	0.6525	9.4681

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4.4.2 The Impact of IM on Labor Productivity

Table 4.3 documents the benchmark results for the relationship between IM adoption and labor productivity. There are four regression models in Table 4.3, and the dependent variable is *Labor Productivity* across four models. Model 1 only includes the explanatory variable (*IM*); In Model 2, we add year-, industry-, and province-level fixed effects into the regression model; Model 3 includes independent variable (*IM*) as well as all control variables but without year, industry, and province dummies; Model 4 is the full regression model which includes all variables. The full model shown in Column 4 suggests that firms with higher levels of financial slack, sales growth, and cash holding have higher labor productivity, which is consistent with the view that these companies have better access to slack resources and have more incentives to invest in productivity-enhancement technologies (Azadegan *et al*., 2013; Patel and Conklin, 2012). Also, we notice that firm age is significantly positively related to labor productivity, in line with the argument that learning curves have a positive effect on productivity (Saldanha *et al*., 2013). In contrast, we find that larger firms have lower productivity in our sample. Prior literature about firm size and productivity has inconsistent findings. While some believe that large firms have the advantage of economies of scale and are associated with the use of high-involvement work practices and with higher labor productivity (Sartal *et al*., 2020), others suggest that small firms facing market uncertainties, financial constraints, and other challenges may undertake actions that make them have more flexible management and lower response time to market changes than large firms, leading to higher productivity (De and Nagaraj, 2014; Dhawan, 2001).

We see that the coefficients of *IM* are positive and significant across various models from Columns 1 to 4, suggesting that the treated firms' labor productivity improves significantly from the pre-treatment period to the post-treatment period, after controlling for the labor productivity change of the control firms over the same period. Therefore, it shows that there exists a positive impact of IM adoption on the labor productivity of Chinese listed firms, supporting our H1.

Table 4.3 Baseline results - Intelligent manufacturing and labor productivity

	Dependent Variable = *Labor Productivity*			
	(1)	(2)	(3)	(4)
IM	0.3987***	0.2674***	0.4232***	0.3112***
	(12.81)	(9.52)	(14.82)	(11.96)
Size			-0.1502***	-0.1402***
			(-29.27)	(-28.96)
Age			0.2305***	0.0318**
			(17.59)	(2.33)
Financial Slack			0.0198***	0.0151***
			(7.49)	(6.26)
Leverage			1.0047***	0.9688***
			(29.73)	(30.34)
Sales Growth			0.0053	0.0325***
			(0.62)	(4.16)
Cash Holding			0.0489	0.4648***
			(1.04)	(10.54)
Capital Intensity			-0.2091***	-0.1887***
			(-54.17)	(-51.81)
Constant	13.6657***	14.4480***	14.1748***	15.2318***
	(2422.33)	(142.91)	(252.60)	(141.86)
Year	NO	YES	NO	YES
Industry	NO	YES	NO	YES
Province	NO	YES	NO	YES
N	16,441	16,441	16,441	16,441
F statistics	164.08	73.31	555.69	129.85
Adjusted R^2	0.0098	0.2328	0.2125	0.3733

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All p-values are two-tailed. t statistics are in parentheses.

4.4.3 Robustness Checks

We perform several additional tests to ensure the consistency of our findings. The corresponding results are presented across Tables 4.4 to 4.6. Below are the details of the procedures for conducting these tests.

First, to draw a causal inference from a DID research design, a key assumption is the pre-treatment parallel trend that requires the average variation in response variable has always been the same for the treatment and control groups prior to the treatment (Jiang *et al*., 2019). Specifically, we introduce ten indicator dummy variables representing different periods before and after the treatment event to capture the temporal trend in labor productivity (i.e., *Before 5 and earlier*, *Before 4*, *Before 3*, *Before 2*, *Before 1*, *Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5* *and beyond*). For example, *Before 2* indicates that it is two years before the IM policy intervention, while *Year 5 and beyond* implies that it is five or more years after the policy shock. The policy shock year is not included to avoid multicollinearity. This approach allows us to examine the dynamic effects of IM adoption on firms' labor productivity and has been commonly used in prior studies (Beck *et al*., 2010; Dang *et al*., 2022; Lam *et al*., 2022). We then replace the IM indicators in the previous baseline model with these ten dummy variables and re-estimate the coefficients of the dummy indicators in the new model that includes all control variables. The estimated coefficients of the ten dummy indicators are plotted in Figure 4.2 with 90 per cent confidence intervals. The result shows that the coefficients of IM dummy variables are not significantly different from zero across all years before treatment, with no pre-treatment trends in firm labor productivity. In contrast, firms in the treatment group have increased their labor productivity significantly in the years following the introduction of IM pilot policy, implying a long-term effect of IM adoption on firm labor productivity. Overall, the result shows that the improvement of labor productivity does not precede the announcement of IM and thus is more likely to be attributed to its implementation.

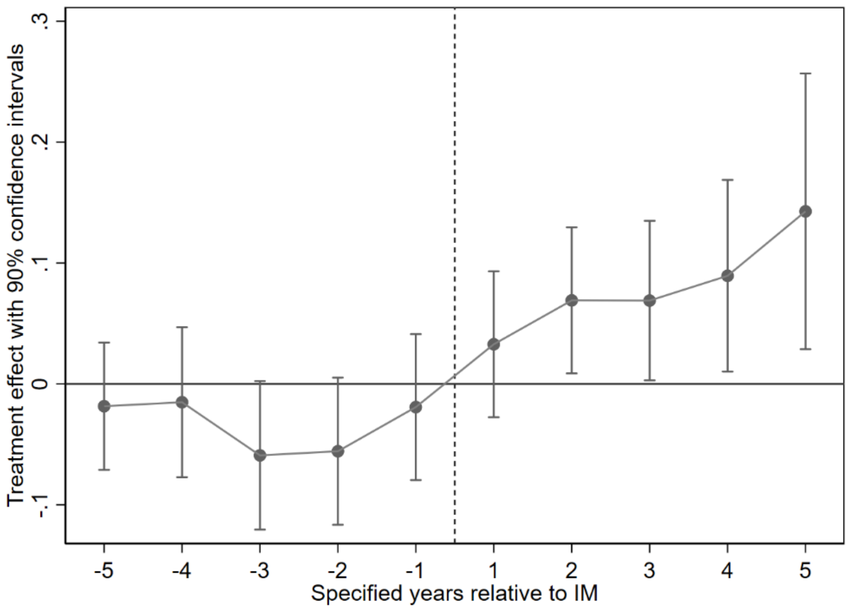

Figure 4.2 Parallel trend test plot

Second, although the IM pilot demonstration project, as a quasi-natural experiment, could largely avoid the problem of endogeneity, there is still the possibility of self-selection bias. We employ propensity score matching (PSM) approach to mitigate the potential endogeneity concern caused by sample bias. The basic idea of PSM here is to use a specific matching method to find a firm in the control group for each firm in the treatment group, so that the main characteristics of the firms in two groups remain the same as much as possible before being affected by the policy. In other words, the matched firms in the two groups only differ in whether they adopt IM or not. Specifically, we first employ some covariates to run a Logit regression to calculate propensity scores for the full sample. Next, we take the nearest neighbor, no-replacement, one-to-one matching standard within a caliper of 0.05 to pick one observation from the control group for each observation from the treatment group on the basis of their propensity scores (Ren *et al*., 2023; Ye *et al*., 2020).

Table 4.4 Panel A presents the first stage Logit regression results for estimating propensity scores. The results indicate that younger firms and firms with larger size are more likely to adopt IM. Table 4.4 Panel B reports the covariate balance check of the matched sample. We see that, after matching, the means of all covariates are statistically the same between two groups (p-values > 0.1), suggesting no significant differences between the treatment group and control group. Then, we re-estimate the Model 4 in Table 4.3 with the matched samples. Regression results can be found in Table 4.4 Panel C Column 1. Consistent with results reported in Table 4.3, the coefficient of *IM* remains significantly positive after the employment of PSM approach, and the adjusted R-squared values become even larger (from 0.3733 to 0.5001). In addition, we further conduct robustness check to see if the above findings are sensitive to the caliper value selected when performing the PSM. As Ren *et al*. (2023) suggested, there is a trade-off between a narrow caliper versus a wide caliper. A narrow caliper ensures that the treatment and control groups have a higher level of similarity, it however may also result in an excessively high removal of observations from the sample. We therefore follow Ren *et al*. (2023) and consider two additional caliper values (i.e., 0.3 and 0.5) to verify if our findings are sensitive to the narrow caliper (i.e., 0.05) we selected. The results can be found in Table 4.4 Panel C Columns 2 and 3. It shows that the coefficients of *IM* still keep positive and significant, and we see that the number of observations as well as the adjusted *R*-squared values increase gradually with the increase of caliper values. These test results demonstrate consistency of our findings.

Table 4.4 Robustness check - Propensity score matching (PSM) approach

Panel A: First stage Logit regression results

	Dependent Variable = *Treatment*	
	coefficients	*z statistics*
Size	1.1384***	29.55
Age	-0.5378***	-5.39
Financial Slack	0.0203	0.82
Leverage	-0.2121	-0.84
Sales Growth	-0.0399	-0.62
Cash Holding	-0.4153	-1.13
Capital Intensity	0.0345	1.06
Constant	-9.9325***	-18.88
Year	YES	
Industry	YES	
Province	YES	
N	15,331	
Pseudo R^2	0.2232	

Panel B: Covariate balance check of the matching

	Mean			
	Treated group (*N*= 1,196)	Control group (*N*= 1,196)	bias (%)	*p* values
Size	8.7809	8.7525	2.5	0.519
Age	2.7304	2.7161	3.6	0.382
Financial Slack	1.9096	1.9458	-1.5	0.647
Leverage	0.4791	0.4814	-1.2	0.764
Sales Growth	0.2109	0.2068	0.8	0.840
Cash Holding	0.1441	0.1400	3.5	0.347
Capital Intensity	1.7842	1.7752	0.7	0.835

Panel C: Regression results of matched samples

	Dependent Variable = *Labor Productivity*		
	(1)	(2)	(3)
	caliper 0.05	caliper 0.3	caliper 0.5
IM	0.2215***	0.2285***	0.2222***
	(7.09)	(7.46)	(7.43)
Size	-0.0703***	-0.0537***	-0.0514***
	(-5.11)	(-4.07)	(-4.07)
Age	-0.0121	-0.0159	-0.0107
	(-0.35)	(-0.47)	(-0.33)
Financial Slack	0.0304***	0.0336***	0.0342***
	(3.68)	(4.10)	(4.22)
Leverage	1.1812***	1.1889***	1.2026***

	(13.61)	(14.01)	(14.41)
Sales Growth	0.0339	0.0291	0.0249
	(1.46)	(1.26)	(1.10)
Cash Holding	0.7982***	0.7902***	0.8086***
	(6.35)	(6.39)	(6.76)
Capital Intensity	-0.1909***	-0.1895***	-0.1881***
	(-16.31)	(-16.45)	(-16.55)
Constant	14.3781***	14.2626***	14.2152***
	(77.77)	(78.92)	(81.03)
Year	YES	YES	YES
Industry	YES	YES	YES
Province	YES	YES	YES
N	2,392	2,502	2,596
F statistics	37.80	39.93	41.65
Adjusted R^2	0.5001	0.5029	0.5045

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All p-values are two-tailed. t statistics are in parentheses.

We then examine whether our results are consistent when using alternative measures for the independent variable. We follow the emerging literature which employs textual analysis to investigate the impacts of new technology adoption on firm performance (e.g., Mishra *et al*., 2022; Ye *et al*., 2023) and apply this method to analyze the unstructured texts from the annual reports of firms, and to capture the degree of IM adoption (i.e., *IM Focus*) based on the textual analysis results. The logic of constructing the *IM Focus* variable is that if firms are innovative and concentrating on IM, this should be reflected in their official written documents (i.e., annual reports) to impress the investors, the market, and other stakeholders. Therefore, textual analysis provides us with a structural approach to uncover the strategic and operational intent in a company's annual report. We follow Lu *et al*. (2023) and Mishra *et al*. (2022) and construct the *IM Focus* variable by searching for the frequency of 57 IM-related terms (e.g., robotic, sensor, artificial intelligence, numerical control system) in all the annual reports for the entire sample period and scale it by the total number of words in the annual report. Moreover, we follow Niu *et al*. (2023) and take the natural logarithm of firm *i*'s frequency of IM-related keywords plus one in year *t* as an alternative measure for robustness check. The re-estimation results are presented in Table 4.5. It can be found that the coefficients of *IM Focus* in both Columns 1 and 2 are positive and statistically significant, indicating the consistency with the main results.

Table 4.5 Robustness check - Alternative measures of independent variable

	Dependent Variable = *Labor Productivity*	
	(1)	(2)
IM Focus	0.0970***	0.0291***
	(3.35)	(6.09)
Constant	14.9917***	14.9295***
	(110.46)	(109.70)
Controls	YES	YES
Year	YES	YES
Industry	YES	YES
Province	YES	YES
N	15,594	15,594
F statistics	128.32	128.88
Adjusted R^2	0.3829	0.3840

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All *p*-values are two-tailed. *t* statistics are in parentheses.

In addition, we follow Shou *et al*. (2020) and Zhu *et al*. (2021) to use one-year lag of independent and control variables instead of their present values and rerun the regression to alleviate the potential endogeneity problem induced by reverse causality. Table 4.6 Column 1 reports the results. It can be seen that the coefficient of *L.IM* is still positive and significant. In addition, considering that firm performance could be path dependent and persistent over time (Lam *et al*., 2016; Mukherji *et al*., 2011), we also add lagged dependent variables as regressors into the model. In Table 4.6 Column 2 we see that when including one-year lag dependent variable into the model, the coefficient of *L.IM* is still significantly positive, suggesting that our findings remain consistent after dealing with potential reverse causality issue.

Table 4.6 Robustness check - Lagged variables

	Dependent Variable = *Labor Productivity*	
	(1)	(2)
L.IM	0.2364***	0.0490***
	(6.80)	(2.91)
L.Labor Productivity		0.8685***
		(83.25)
Constant	14.1109***	1.4810***
	(72.94)	(8.33)
L.Controls	YES	YES
Year	YES	YES
Industry	YES	YES
Province	YES	YES
N	2,132	2,132
F statistics	33.85	251.71
Adjusted R^2	0.4966	0.8844

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All *p*-values are two-tailed. *t* statistics are in parentheses.

Finally, to make sure that our results are not driven by chance, we conduct a placebo test to rule out the impact of confounding factors other than IM adoption on our previous findings. If the increase in labor productivity is indeed due to IM adoption rather than other unobservable factors, there is a high probability that a randomly selected pseudo-treatment group from the entire sample will lead to insignificant estimated parameters. Following Amiram *et al*. (2019), we first randomly choose 124 pseudo-treatment manufacturing firms (the same number of firms as the truly treated firms) from the full sample and assign each pseudo-treated firm a spurious IM adoption year between 2010 and 2020. We re-estimate our baseline model with this placebo trial and iterate this random simulation process 500 times. Figure 4.3 plots the distributions of β_1 generated in the simulation process, with most of the coefficients gathered around zero. For comparison purposes, we also include a vertical and a horizontal line that represents the actual estimated coefficient and p value of IM adoption in our baseline model (β_1=0.3112, p < 0.001). The result suggests that the treatment effects are no longer significant when using pseudo treatment sample and treatment years. Therefore, it is unlikely that our finding is driven by confounding events and unobserved shocks.

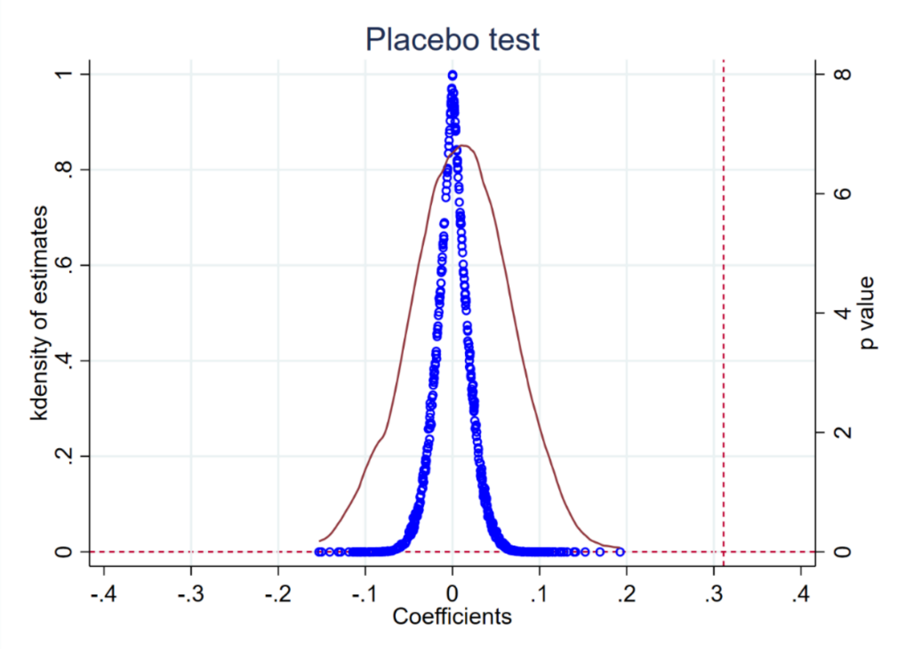

Figure 4.3 Placebo test

4.4.4 The Moderating Effect Results

The regression result of moderating effect of human capital quality are summarized in Table 4.7 Column 1. We see that the coefficient of the interaction term, i.e., *IM×Human Capital* is positive and statistically significant (p-values < 0.05). The result suggests that the positive IM adoption-labor productivity linkage is stronger for firms with higher human capital quality, thus supporting our H2. Table 4.7 Column 2 reports the moderating effect of firms' R&D intensity. It shows that the coefficient of the interaction term (*IM×R&D Intensity*) is significantly positive (p-values < 0.01), which suggests that firms with higher level of R&D intensity could reap more productivity benefits from IM implementation and supports H3. Finally, we see that in Table 4.7 Column 3, the coefficient of the variable of interest (i.e., *IM×Industry Competition*) is significantly positive as well (p-values < 0.1). The results indicate that a high level of industry competition will make the positive effect of IM implementation on labor productivity more pronounced, thus supporting our H4.

Table 4.7 Moderating effect analysis

	Dependent Variable = *Labor Productivity*		
	(1)	(2)	(3)
IM×Human Capital	0.3493**		
	(2.28)		
IM×R&D Intensity		3.5918***	
		(2.75)	
IM×Industry Competition			0.5475*
			(1.75)
Human Capital	1.1938***		
	(36.22)		
R&D Intensity		-2.8796***	
		(-8.37)	
Industry Competition			-0.3156*
			(-1.95)
IM	0.1865***	0.2904***	0.3092***
	(6.88)	(11.08)	(11.88)
Size	-0.1401***	-0.1359***	-0.1402***
	(-27.66)	(-26.89)	(-28.97)
Age	-0.0064	0.0088	0.0315**
	(-0.47)	(0.63)	(2.31)
Financial Slack	0.0121***	0.0194***	0.0152***
	(5.14)	(7.96)	(6.31)
Leverage	0.8806***	1.0294***	0.9709***
	(27.36)	(30.61)	(30.39)
Sales Growth	-0.0043	0.0212**	0.0326***

	(-0.56)	(2.58)	(4.16)
Cash Holding	0.1663***	0.4843***	0.4643***
	(3.77)	(10.80)	(10.53)
Capital Intensity	-0.1990***	-0.1929***	-0.1886***
	(-54.09)	(-47.90)	(-51.77)
Constant	15.4689***	15.3143***	15.4411***
	(119.48)	(134.79)	(121.14)
Year	YES	YES	YES
Industry	YES	YES	YES
Province	YES	YES	YES
N	14,288	14,980	16,431
F statistics	146.54	122.34	126.55
Adjusted R^2	0.4428	0.3872	0.3734

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All p-values are two-tailed. t statistics are in parentheses.

4.5 Summary, Discussion, and Future Research

4.5.1 Discussion of Test Results

The above results show that there exists a significant and positive impact of IM adoption on Chinese listed manufacturing companies' operational performance in terms of labor productivity, and this relationship is contingent on companies' internal resources (i.e., employee human capital quality and R&D intensity) and external operating environment (i.e., industry competition). In this section, we discuss in detail about these findings as well as the similarities and differences between this study and prior IM-related empirical research.

First, our main result and the corresponding robustness checks consistently reveal that IM adoption has a positive effect on listed manufacturing firms' labor productivity in China. The operational performance implications of IM adoption have attracted OM scholars' attention in recent years (Lu *et al*., 2023). While prior conceptual articles and qualitative method-based studies have been predominantly optimistic about the performance improvement effects of IM adoption (Kiel *et al*., 2017; Tortorella *et al*., 2020), limited large-sample empirical evidence has been provided to support this assertion. One of the main obstacles for researchers to quantify the operational performance implications of IM adoption is the lack of public firm-level secondary data (Seamans and Raj, 2018). Although there do exist a few quantitative studies, they are mostly based on the data of national or industry-level usage of industrial robots or relied on data collected by questionnaires with cross-section analysis (e.g., Graetz and Michaels, 2018; Tortorella *et al*., 2020). We also notice that some firm-level IM studies using secondary data emerge in recent years. For example, both Lu *et al*. (2023) and Ying *et al*. (2022) employ text analysis method to screen IM-related keywords from listed firms' annual reports to construct the core explanatory variable (i.e., IM). Lu *et al*. (2023) find that IM has a positive effect on both short-term and long-term financial performance (i.e., ROA and Tobin's *q*), and Ying *et al*. (2022) demonstrate that IM could significantly enhance listed firms' innovativeness. These studies provide avenues for future research using secondary data to explore the impacts of IM at the firm level. We therefore follow their approach to construct the continuous IM measures in our robustness check section. However, as Mishra *et al*. (2022) suggested, this measure of new technology adoption is quite general and it in fact reflects a firm's technology focus rather than whether this firm has actually adopted this technology. Although our measure of IM in the main analysis is a binary variable, this measure derived from the exogeneous shock of IM pilot demonstration project allows us to empirically and causally examine the effect of actual IM adoption on companies' operational performance.

Moreover, our results indicate that companies' employee human capital quality and R&D intensity positively moderate the IM adoption-labor productivity relationship of listed manufacturing firms in China, indicating that manufacturers with higher level of employee human capital quality and R&D intensity will enjoy more productivity enhancement from IM adoption. Barney (1991) suggests that firms leverage resources to create competitive advantages, which in turn confer performance advantages. Previous literature points out that there is a clear distinction between competitive advantage and performance advantage. A competitive advantage is a necessary but insufficient condition for a performance advantage (Crook *et al*., 2008; Hitt *et al*., 2016). Competitive advantages in RBV are defined as value creating strategies (Barney, 1991). However, value creation inevitably includes the willingness for customers to pay, which makes it difficult for us to measure value creation in a direct way (Sirmon *et al*., 2007). Therefore, many following studies have sought to empirically relate strategic resources with firm performance (Chahal *et al*., 2020; Crook *et al*., 2008). The underlying assumption is that if resources and performance are linked, then a competitive advantage must exist. While the term competitive advantage is almost equivalent to performance in many studies (also in our work) (e.g., Chen *et al*., 2022; Lam *et al*., 2016), it is noted that we are unable to test a precise expression of the actual RBV model when exploring the resource-performance relationship. In other words, competitive advantage is not included in our model, which implies that our findings may understate the strength of support for the model (Bromiley and Rau, 2016).

Also, it is interesting to notice that the adjusted R-squared values of Model 1 (i.e., the moderating effect of employee human capital quality) in Table 4.7 is greater than that of Model 2 (i.e., the moderating effect of R&D intensity). This result suggests, to some extent, that in the context of IM adoption for Chinese listed manufacturing firms, although both employee human capital quality and R&D intensity make the IM adoption-labor productivity relationship more pronounced, the former has a higher value and is more difficult to imitate than the latter. The RBV highlights that resources should be valuable, rare, and difficult to imitate or substitute. Hoopes *et al*. (2003) also demonstrate that, in practice, value and imitability matter most. A valuable resource generates at least a temporary competitive advantage by lowering costs or commanding premium prices, and a resource that is difficult to imitate makes the advantage sustainable. Therefore, a resource that adds more value should theoretically show a higher systematic performance effect (Crook *et al*., 2008). While R&D serves as a strategic resource (Foreman-Peck and Zhou, 2023), R&D intensity seems to be a little bit distant measure for a firm’s underling R&D resources because investment levels may not totally reflect the quality of the outputs from those investments, and R&D investments are easier to copy than human capital (Crook *et al*., 2008; Rouse and Daellenbach, 1999). In fact, human capital as a strategic resource has become a critical factor in production nowadays (Bae and Kang, 2023). A large body of literature points out that companies should pay particular attention to the factor of human (especially human capital quality) in order to successfully implement new technologies (Ballestar *et al*., 2022; Li *et al*., 2023; Saldanha *et al*., 2022). While the adoption of IM does aim to automate and optimize certain tasks and enhance productivity, the value of employees' human capital quality remains significant for several reasons. For example, IM systems generate vast amounts of data, and human expertise is needed to interpret these data, make sense of patterns, and make critical decisions based on insights that machines might not capture. Even though IM reduces the need for manual intervention, human oversight is essential to monitor the performance of IM systems, ensure they are functioning correctly, and address any unexpected issues. In addition, at the current stage, while IM can handle a number of routine tasks, it is often human ingenuity that drives innovation and the development of new manufacturing processes, products, and ways of utilizing technology. One of the fundamental characteristics of IM is human-machine collaboration (Li *et al*., 2023). While the adoption of IM may reduce a company's need for labor quantity to some extent, this does not mean that the quality of employee human capital will also be replaced by IM. On the contrary, advanced manufacturing systems such as IM require employees with higher human capital quality to operate in order to facilitate effective and efficient communication, coordination, and collaboration between humans and machines. Our study joins into this research stream and demonstrates that employee human capital quality plays an important role of complementary asset for IM adoption to improve labor productivity.

Finally, our result display that industry competition also has a positive moderating effect on the IM adoption-labor productivity link. This suggests that listed firms operating in more competitive environments in China could reap more productivity enhancement benefits. Extant studies have mixed results on whether the adoption of new technology by companies results in greater performance improvement in a competitive environment. Some hold that a competitive environment is related to low level of environmental support (e.g., resources such as customer, market share, qualified labors, and capital investments) for new technology implementation (Lam *et al*., 2019), while others argue that industry competition can represent the level of environmental requirement (e.g., operational efficiency, product innovation, and new market exploration) for new technology adoption (Sharma *et al*., 2023). It is important to note that while the association between technology adoption and industry competitiveness holds true for various technological practices, there are distinct attributes of IM that accentuate its sensitivity to the competitive environment. One crucial factor that sets IM apart is its reliance on the convergence of diverse technological domains, such as AI, data analytics, and automation. In highly competitive industries, the demand for rapid, data-driven decision-making is particularly acute. IM, with its ability to harness real-time data and optimize processes, becomes a strategic advantage that aligns well with the dynamic and fast-paced nature of competitive markets. While it is acknowledged that industry competitiveness can amplify the benefits of other practices, our study underscores that the unique integration of IM with skilled human capital, R&D investment, and real-time data-driven decision-making lends it a distinctive advantage within competitive industry landscapes. By leveraging IM's adaptability, responsiveness, and resource optimization capabilities, companies can not only navigate the challenges of a competitive environment but also thrive and innovate, thereby solidifying IM's status as a catalyst for productivity enhancement. Our result thus supports the environmental requirement view and shows that IM is an effective tool for Chinese listed manufacturing companies to constantly adapt their operational strategies and improve productivity in response to a competitive operating environment.

4.5.2 Implications for Research

This study contributes to OM literature in three main ways. First, our research contributes to the growing discussion on emerging disruptive technologies in the OM field in general (e.g., Choi *et al*., 2022; Holmström *et al*., 2019) and the business value of IM in particular (e.g., Lu *et al*., 2023; Ying *et al*., 2022). OM scholars have long investigated emerging technology-related issues, and the focus has been shifted from the discussion of technologies' technical features and industrial applications to a more strategic view on technology adoption such as its performance effects (Lam *et al*., 2019; Chen *et al*., 2022). While prior empirical studies have well documented the operational and/or financial performance implications of some specific disruptive technologies such as artificial intelligence (Helo and Hao, 2022; Spring *et al*., 2022), big data analytics (Song *et al*., 2021; Tambe, 2014), blockchain (Klöckner *et al*., 2022; Liu *et al*., 2022), 3D printing (Lam *et al*., 2019; Schniederjans, 2017), and cloud computing (Chen *et al*., 2022; Kathuria *et al*., 2018), very limited empirical evidence has been provided about the performance effects of IM adoption and the contingency conditions of this relationship of Chinese firms. We contribute to this research stream by representing one of the first attempts to use objective secondary data to quantify the impact of IM adoption on Chinese listed manufacturing firms' operational performance in terms of labor productivity. It is expected that this study will stimulate future research to further empirically investigate the operational and financial effects of IM adoption.

Second, this paper extends the emerging IM literature by providing insights into the contingencies (i.e., firms' internal resources and external operating environment) of the linkage between IM adoption and labor productivity. A number of extant OM studies have examined the direct impacts of various resources, capabilities, and environmental characteristics on organizational behavior or performance based on the well-established resource-based view and structure-conduct-performance (SCP) paradigm (e.g., Kovach *et al*., 2015; Modi and Mishra, 2011). Lam *et al*. (2019) and Lam and Zhan (2021) thus call for future research to investigate more about the moderating effects of ex ante resources, capabilities, and environmental features on the performance effects of corporate initiatives or strategies. Our study shows that Chinese listed manufacturing firms' internal resources (i.e., employee human capital quality and R&D intensity) as well as external operating environment (i.e., industry competition) play significantly contingent roles in the IM adoption-labor productivity relationship. Also, our study responds to the calls that more efforts should be devoted to studying the impacts of human-machine interaction and collaboration (e.g., Choudhury *et al*., 2020; Saldanha *et al*., 2022) by demonstrating that employee human capital is a critical complementary asset and can significantly positively unleash the productivity benefits when adopting IM.

Finally, from a research methodology perspective, much of the prior technology management research employs an event study approach to investigate the effect of adopting a new technology on firms' short-term stock returns (Klöckner *et al*., 2022). We see great merits of event study method and fully agree that the event study approach can be leveraged as an initial attempt to quantify the value created by a novel technology. In the early stages of technology adoption, the event study approach is useful to provide a first indication for the business value related with one specific technology initiatives in OM, because this approach allows for measuring the short-run value that investors attribute to newly announced technology initiatives based on expectations of future cash flows (Bose and Leung, 2019; Ding *et al*., 2018; Klöckner *et al*., 2022). In addition to short-term stock returns, we are also interested in whether these new technologies can improve long-term operational indicators (e.g., labor productivity, operational efficiency, operating growth, operational risk, customer satisfaction). Our study demonstrates the possibility and advantages of conducting a causal inference research based on secondary data to investigate the impacts of novel technology adoption on listed firms' long-run operational performance. In addition, as a causal inference method, (quasi) natural experiment has been widely applied in the finance, accounting, and marketing literature (Armstrong *et al*., 2022; Goldfarb *et al*., 2022), but is still in its infancy in the OM discipline (e.g., Dhanorkar and Muthulingam, 2020; Lam *et al*., 2022). We therefore encourage future OM research to use this method to conduct more rigorous causal inference analyses and contribute to literature on production and operations management.

4.5.3 Implications for Practices

The empirical results of this study allow us to derive several practical implications for operations managers. First, although IM has received widespread attention from academia and industry, it is still in its nascent stages of development and its adoption rate is still low, especially in emerging markets (e.g., China). This low adoption rate may be attributed in part to the relatively low level of technology development, as well as the lack of knowledge about IM and the difficulty in quantifying the value that IM creates. This study is a solid step forward in empirically examining the impact of IM adoption. Our analyses show that the IM implementation can indeed improve Chinese listed manufacturers' labor productivity, which helps to dispel operations managers' doubts about the value of IM and encourage listed manufacturers in China to explore this smart production system. Manufacturing is a substantially data-intensive industry, which requires firms to have strong information processing as well as operations and production ability (Yiu *et al*., 2021). IM is a powerful tool to be applied into manufacturing sector to solve diverse organizational issues and to ultimately enhance firms' operational capabilities and competitive advantages.

Second, our results suggest that the identification of appropriate use cases for IM remains an important issue. Although IM may not be the "silver bullet" for all challenges in the OM field, the potential of IM can be unfolded under certain application characteristics. Our findings help operations managers better understand the circumstances under which the benefits of IM adoption may be maximized and the type of firms that should actively engage into IM business. For example, we suggest managers pay particular attention to investing in employee human capital development. Firms looking to adopt IM should prioritize investing in their employees' human capital quality. This includes training programs, upskilling initiatives, and fostering a culture of continuous learning. Skilled and adaptable employees are crucial for effectively utilizing and maximizing the benefits of IM. We also recommend that manufacturers increase their R&D investments to reap more benefits from implementing IM, as R&D investments not only lead to the creation of innovative processes, products, and technologies that align with the goals of IM, but also facilitate the search for the knowledge that needed for IM and enhance organizational learning capabilities (Thakur-Wernz and Samant, 2019). In addition, we advise firms customizing IM adoption strategies. Our results indicate that the impact of IM on productivity varies based on industry competitiveness. In highly competitive industries, the benefits of adoption are more pronounced. Companies therefore should tailor their adoption strategies based on the level of competition in their specific industries.

Considering that our variable of interest is based on the government policy, this study also has the implication for policymakers. Our research indicates that the IM pilot policy is effective in the Chinese market. Policymakers may consider extending this pilot policy to more companies to improve the intelligence of Chinese listed manufacturing firms. Previous studies have shown that financial constraint is a key restriction to firms' development, especially in developing countries (Farre-Mensa and Ljungqvist, 2016; Whited and Wu, 2006). The implementation of IM demands long-term and substantial capital investment. Policymakers thus could consider providing corresponding policy support, such as preferential tax policies, R&D subsidies, and credit support, to firms selected into pilot projects, so that these firms could have sufficient capital and resources to invest in IM and complete the intelligent transformation.

In addition, policymakers can support firms that plan to leverage IM by incentivizing and funding skill development programs aimed at enhancing employees' human capital quality. These programs could focus on improving technical competencies, adaptability, and data literacy. What's more, policymakers may consider tailoring support mechanisms based on industry competitiveness. For instance, additional incentives or support could be provided to firms operating in highly competitive industries to encourage the adoption of IM. Policymakers can also conduct regular assessments of industry competitiveness and IM adoption rates. This information can inform policy adjustments and interventions to further support IM implementation.

4.5.4 Limitations and Future Research Directions

This study has several limitations, which also offer meaningful directions for future research. First, while the quasi-natural experimental design and the staggered DID approach enable robust causal inference regarding the effect of IM adoption, the operationalization of IM adoption as a binary variable may oversimplify the inherently complex and multidimensional nature of IM implementation. This dichotomous treatment does not capture variation in the intensity, scope, or depth of firms' engagement with IM practices.

The decision to use a binary variable in the present study was primarily driven by data availability and the need for a clean identification strategy under the quasi-experimental framework. At the time of this research, comprehensive and reliable firm-level data capturing the continuous or granular dimensions of IM implementation, such as the extent of technology integration, staff training, or IM-related workforce development, were not systematically available for a sufficiently large sample of firms. Moreover, using a binary indicator allowed for a more straightforward application of the staggered DID approach, minimizing concerns related to functional form misspecification or endogeneity that often arise with continuous treatment variables.

Nevertheless, future studies are encouraged to explore continuous or multidimensional proxies for IM implementation to enrich the understanding of its heterogeneous effects. For example, firm-level labor market data, such as the number or proportion of IM-related job postings, could be used to approximate firms' intensity of IM investment. This approach has been applied effectively in related contexts; for instance, Darendeli *et al*. (2022) utilized green skill-related job postings to proxy for firms' investment in environmental capabilities. Employing such continuous indicators may provide a more nuanced understanding of how varying levels of IM engagement influence firm- and supply chain-level outcomes. Furthermore, future research could broaden the scope of inquiry by investigating the implications of IM adoption for a wider range of outcomes beyond those examined in this study. Potential areas include operational efficiency, cost stickiness, risk management (both operational and financial), customer satisfaction, supplier selection, and supply chain transparency. Such investigations would deepen our understanding of the multifaceted role of IM in shaping firm competitiveness and supply chain performance.

Second, our research concentrates on Chinese publicly listed manufacturing firms, which may limit the generalizability of our results to private firms and firms operated in other industries, countries or regions. In general, non-listed firms possess less resources compared with listed firms, which may influence their IM adoption to some extent. Also, it may not be suitable to adopt IM for some firms with large non-standard stock keeping units (SKUs). Future research could investigate the benefits of IM adoption in private firms or firms operating in other contexts (e.g., other economies or industries).

Third, in this study, we observe a direct, linear association between IM adoption and firm performance, which to some extent ignores the adaptive nature of IM strategy (Nair and Reed-Tsochas, 2019). Future research could use the complex adaptive system (CAS) lens to explore the dynamic process of IM adoption, which enables the models to be more realistic and makes it more likely that the empirical models be understood and used in a practical business setting.

Chapter 5 Conclusion

5.1 Summary of the Findings

Drawing upon the resource-based view, upper echelons theory, attention-based view, and natural-resource-based view, this thesis empirically investigates the impact of digital transformation on firms' financial, operational, and environmental performance from multiple perspectives, including digital technology, digital talent, and digital policy. Specifically, it comprehensively examines the influence of digital technology deployment, the role of chief CDOs, and the effects of intelligent manufacturing pilot projects on firms' digital transformation journeys. The research aims to address three primary questions: (1) How does the deployment of digital technology affect firms' environmental performance? (2) To what extent does the appointment of CDOs influence firms' financial performance? (3) Can the implementation of intelligent manufacturing initiatives enhance firms' labor productivity? Through three interrelated studies, this thesis employs rigorous methodologies to provide solid empirical evidence on these questions and contributes to the understanding of the impact of digital transformation on firm-level outcomes. The findings of the three studies are summarized below.

In Study 1, we examined the direct impact of digital technology deployment on firms' environmental performance. We found a significant positive relationship between digital technology deployment and firms' environmental performance. We then tested the moderating effects of hard and soft lean practices (i.e., inventory leanness and environmental leadership) to determine if firms could derive greater environmental benefits from integrating a human-centered lean production paradigm into digital technologies. The results indicated that both inventory leanness and environmental leadership positively moderate the relationship between digital technology deployment and environmental performance.

In Study 2, we investigated the effect of CDO appointments on firms' financial performance, specifically using Tobin's q as a measure. We found that the appointment of a CDO improves a firm's financial performance, and this relationship remains robust after conducting several tests. Further analysis revealed that the positive impact is more pronounced when the CDO is recruited externally, is a generalist, and when the firm has greater board diversity. These findings suggest that the effectiveness of CDO appointments is influenced by individual and board-level contingencies.

In Study 3, we explored the influence of intelligent manufacturing on firms' labor productivity. By analyzing the staggered implementation of intelligent manufacturing pilot projects among Chinese listed manufacturing firms, we found a significant positive impact on firms' labor productivity. Subsequently, we investigated the conditions under which firms could benefit more from the adoption of intelligent manufacturing. We examined the moderating roles of firms' internal resources (i.e., R&D intensity and employee human capital quality) and external operating environments (i.e., industry competition). Our results demonstrated that the positive impact of intelligent manufacturing implementation on labor productivity is more significant for firms with higher R&D intensity and employee human capital quality, and firms operating in more competitive industries also experience a greater productivity enhancement effect from adopting intelligent manufacturing.

5.2 Implications for Research

The thesis contributes to the literature in several significant ways. First, it provides new empirical evidence on the impact of digital technology deployment on firms' environmental performance in an emerging economy. Previous findings regarding this relationship have been inconsistent, partly due to variations in research contexts, including data sources, samples, and backgrounds. To address this gap, the thesis utilizes large-scale secondary data from Chinese listed firms and conducts multiple robustness tests, offering solid empirical evidence supporting the positive effect of digital technology deployment on firms' environmental performance. Furthermore, while previous conceptual articles argued that data-driven digital transformation could enhance organizational performance when combined with a human-centered production paradigm (i.e., lean), limited empirical evidence has been provided to date. Building on this concept, the thesis demonstrates that inventory leanness and environmental leadership positively moderate the link between digital technology deployment and environmental performance. This finding suggests that firms can achieve greater environmental benefits by integrating digital technologies with lean practices. Consequently, the thesis provides inspiration for future studies to delve deeper into the integration of digital technology and lean practices to gain further insights.

Second, the thesis extends research on CDOs by analyzing the financial performance implications of CDO appointments and the factors influencing their effectiveness. While prior literature mainly focused on the antecedents of CDO appointments, understanding the performance implications of CDOs remained limited. Drawing on upper echelons theory and the attention-based view, the thesis explains how the presence of a CDO can improve firms' forward-looking performance. Additionally, it investigates various individual and board-level factors influencing the effectiveness of CDOs, thus complementing existing studies. Notably, the thesis reveals that the effectiveness of CDOs does not rely on the CIO, suggesting that the CDO role is relatively independent in leading enterprise-wide digital transformation initiatives.

Third, the thesis contributes to the intelligent manufacturing literature by providing empirical evidence of the productivity improvement effect of intelligent manufacturing adoption. While previous conceptual studies highlighted the potential benefits of intelligent manufacturing adoption, empirical evidence was lacking due to data availability constraints. By analyzing the staggered implementation of intelligent manufacturing pilot projects among Chinese manufacturing companies, the thesis causally demonstrates the significant positive impact of intelligent manufacturing on firms' labor productivity. Furthermore, it explores various boundary conditions, such as R&D intensity, employee human capital quality, and industry competition, to determine whether firms can experience enhanced productivity under these circumstances.

Overall, while previous literature on digital transformation primarily focused on digital technologies, the thesis emphasizes the importance of considering other critical elements such as people and government policies. By comprehensively analyzing the performance implications of digital transformation and considering the roles of technology, people, and government policy, the thesis not only provides a more holistic understanding of its impact but also enriches future research perspectives in digital transformation studies. The empirical evidence provided in the thesis contributes to bridging gaps in the literature, including inconsistencies in understanding the impact of digital technology deployment on environmental performance, the performance implications of CDO appointments, and the productivity improvement effect of intelligent manufacturing adoption. By addressing these gaps and highlighting the moderating factors influencing these relationships, the thesis offers valuable insights for both academia and industry practitioners seeking to navigate and capitalize on the complexities of digital transformation.

5.3 Implications for Practices

The findings in this thesis offer several practical implications. First, managers can strategically leverage the positive impact of digital technology deployment on firms' environmental performance, particularly when complemented by lean practices such as inventory leanness and environmental leadership. Aligning digital transformation initiatives with environmental sustainability goals is paramount, requiring organizations to integrate environmental considerations into their digital strategies from the outset. Additionally, the integration of lean principles alongside digital initiatives presents an opportunity to amplify environmental benefits. This necessitates investment in employee training to cultivate skills in lean practices and foster environmental leadership within the organization. Revising performance metrics to encompass both operational efficiency and environmental sustainability objectives is essential for tracking progress effectively. Continuous monitoring and evaluation are imperative to ensure the ongoing effectiveness of digital technology deployment and lean practices in achieving environmental goals. By integrating these findings into strategic planning and operational processes, firms can better achieve gains in environmental sustainability, thereby driving long-term success.

Second, firms contemplating the adoption of a CDO role should acknowledge its potential value addition to financial outcomes. The robustness of this relationship across various tests underscores its reliability and significance. Furthermore, identifying specific factors that amplify this impact—such as external recruitment, generalist expertise, and board diversity—highlights the nuanced nature of CDO effectiveness. Managers should recognize the strategic importance of these factors in optimizing the performance of their appointed CDOs. It is imperative to prioritize the recruitment of CDOs with diverse skill sets and experiences, particularly those equipped with a comprehensive understanding of digital technologies and their strategic implications for the organization. Additionally, fostering greater diversity within the boardroom can enhance the effectiveness of CDOs in driving financial performance improvements. By proactively considering and leveraging individual and board-level contingencies, firms can strategically position themselves to maximize the impact of CDO appointments and capitalize on the transformative potential of digital technologies.

Third, firms considering the adoption of intelligent manufacturing should recognize its potential to substantially enhance labor productivity, thereby improving overall operational efficiency and competitiveness. Moreover, understanding the moderating roles of internal resources, such as R&D intensity and employee human capital quality, as well as the external operating environment, particularly industry competition, is paramount for maximizing the benefits of intelligent manufacturing adoption. Managers should prioritize strategic investments in R&D and human capital development to cultivate a workforce equipped with the skills and knowledge necessary to leverage intelligent manufacturing technologies effectively. Additionally, firms operating in highly competitive industries stand to benefit significantly from embracing intelligent manufacturing practices as a means to gain a competitive edge. By proactively aligning internal resources with external competitive dynamics, firms can derive the greatest productivity enhancement effects from intelligent manufacturing adoption, fostering sustained growth and success in the ever-evolving marketplace.

In short, the culmination of the three studies underscores the transformative potential of digital technologies, CDO appointments, and intelligent manufacturing adoption for firms seeking to enhance their performance across various dimensions. The positive impact of digital technology deployment on environmental performance highlights the importance of integrating sustainability considerations into digital transformation strategies. The moderation of this relationship by lean practices emphasizes the need for a holistic approach that combines technological innovation with lean principles to maximize environmental benefits. The findings regarding the financial performance implications of CDO appointments underscore the strategic value of this role in driving forward-looking performance. Managers should carefully consider individual and board-level contingencies, such as recruitment strategies and board diversity, to optimize the effectiveness of CDO appointments. Finally, the significant positive impact of intelligent manufacturing adoption on labor productivity, particularly in competitive industries and firms with high R&D intensity and employee human capital quality, underscores the critical role of internal resources and external operating environments in shaping the productivity gains from technological advancements. Collectively, these findings offer practical insights for managers navigating the complexities of digital transformation, highlighting the importance of strategic alignment, resource allocation, and adaptation to external dynamics in driving organizational success in the digital age.

5.4 Limitations and Future Research Directions

As with any empirical study, this thesis has several limitations, which also present opportunities for future research. First, generalizability is a concern. While Study 1 and Study 3 focused on Chinese listed firms, Study 2 utilized secondary data from US listed companies. Future studies could reexamine our findings in different contexts, such as in other countries or with private firms, to uncover new insights. Second, our measures of certain variables have limitations. For example, we measured intelligent manufacturing using a binary variable. While this approach facilitated causal inference regarding the impact of intelligent manufacturing adoption on firms' labor productivity, it restricted our ability to observe diverse characteristics of intelligent manufacturing. Future research could employ multiple methods, such as surveys and case studies, to address this limitation. Additionally, more attention could be given to investigating moderating factors in future research to further enhance the understanding of potential mechanisms and provide more practical insights.

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