IMPACT OF DIGITALIZATION ON FIRMS' OPERATIONAL, FINANCIAL AND INNOVATION OUTCOMES: THREE EMPIRICAL STUDIES

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Abstract

In the context of the rapid development of the digital economy in the Industry 4.0 era, digitalization is profoundly transforming the internal management and external competitive environment of firms. Increasingly, firms are recognizing the immense potential of digitalization and are investing heavily in digital technologies and activities. By actively engaging in digital initiatives, they aim to optimize operational efficiency, enhance financial competitiveness, and achieve higher levels of innovation, thereby gaining a competitive advantage both in the present and in the long term. However, many firms (e.g., Nokia and Blackberry) have been unable to make effective decisions regarding these initiatives or investments, thus losing opportunities to grasp critical business opportunities or achieve breakthrough improvements. Such ineffective decisions are often attributed to the lack of alignment between firms' external or internal environments and their implementation of digitalization. In this dissertation, with consideration on the alignment between digitalization and relevant environmental factors, we conduct three interrelated empirical studies to examine the effectiveness of digitalization with respect to operational, financial, and innovation outcomes.

Study 1 focuses on firms' utilization of digitalization for improving operational efficiency, a crucial indicator of a firm's internal process and resource management effectiveness. Given digitalization's unique integration with firms' existing production resources, routines, capabilities, and the creation of a distinct and valuable operational model, we utilize the Resource-based View (RBV) framework. This perspective posits that digitalization aids firms by enabling the integration of resources, the formation of routines, and the generation of capabilities, thereby fostering efficient operational models that are difficult for competitors to replicate. Following the RBV logic, we propose that the effectiveness of digitalization in enhancing operational efficiency

hinges on both the environmental stability and the firm's internal steadiness, indicating that the degree of uncertainty a firm encounter moderates digitalization's impact on operational efficiency. Using a longitudinal dataset collected from multiple sources employing innovative methodologies, including natural language processing (NLP) to analyze digitalization-related announcements from Factiva, conducting a comprehensive analysis of uncertainty by measuring it in three levels, namely, macro, industrial, and firm levels, and measuring operational efficiency based on the stochastic frontier approach (SFA), this study analyzes the impact on digitalization of 2,520 samples from 496 listed firms in North America from 2015 to 2021. The results indicate that digitalization effectively enhances firms' operational efficiency. Uncertainty of macro- and industrial-levels negatively impact digitalization's effectiveness in enhancing operational efficiency, whereas the uncertainty of firm-level does not influence the relationship significantly. To sum up, the first study offers empirical evidence on digitalization's effectiveness in operational efficiency and identifies uncertainty as a significant factor in this relationship.

Study 2 aims to understand whether and how firms' digitalization adoption is able to improve financial performance, a key metric reflecting a firm's current competitive strength in the market. Although digitalization has been widely viewed as a new tool in enhancing performance, many firms have found that the resulting financial returns sometimes was not up to the anticipated level. Under what conditions or how firms optimize digitalization's financial effectiveness is often a crucial concern for executives. Based on the Dynamic Capability View (DCV), the effective harnessing of digitalization's myriad functions to gain financial return depends on if the firm is embedded in a digitalized ecosystem. In this study we identify diversification with respect to location, product, and technology as a relevant strategy for firms to develop a digital ecosystem, thereby optimizing the effectiveness of digitalization in improving firms' financial performance. Based on DCV framework, we posit that diversification allows firms to sense, seize and synergize disparate resources, leading to enhanced financial outcomes. Using a dataset comprising 3,419 observations across 754 firms spanning from 2015 to 2021 from multiple sources (Factiva, Compustat and USPTO) and innovative analysis methods, including NLP as in Study 1, alongside conducting a unique comprehensive analysis of diversification by measuring it from geographical, product and technological perspectives, Study 2 examines digitalization's impact on financial performance and the moderating effect from the diversification strategy on this impact. The results suggest that digitalization is positively associated with firms' financial performance, and that diversification can create a conducive condition facilitating digitalization's financial effectiveness. To sum up, Study 2 provides important implications for digitalization's effectiveness, for diversification's literature and furnish recommendations for executives who consider adopting digitalization to enhance financial outcome in firms.

Study 3 investigates digitalization's impact on innovation, a vital metric for assessing a firm's potential for future growth. Although it has been incorporated into core strategies to gain a competitive edge in firms, digitalization was thought predictive in data-driven decision making but unlikely to be creative, despite its acknowledged potential. Given that digitalization serves as a bridge between the processes of recognizing, assimilating, and applying valuable external knowledge effectively which are intrinsically connected to innovation, we employ the Absorptive Capacity Theory (ACT) as the theoretical framework in Study 3. According to ACT, digitalization can identify new knowledge sources, enhance knowledge sharing for assimilation and advance information processing capabilities for its application, thereby facilitating the

absorption of external insights into innovative outcomes. Further, to delve into a nuanced understanding of how digitalization can be strategically leveraged across different types of innovation, Study 3 further differentiates innovation into two dimensions, putting forward that different innovation dimensions driven by digitalization depend on both stable resources and creative capabilities. With this conceptualization, this study identifies resource slack and learning capability as potential moderators influencing the impact from digitalization on the two innovation dimensions. Using a panel dataset of 1,430 firm-year observations spanning from 2015 to 2021 and employing various data collection methods from sources including Factiva, Compustat, and United States Patent and Trademark Office (USPTO), Study 3 offers evidence to indicate that digitalization enhances both dimensions of innovation, namely, innovation quantity and innovation quality, and that learning capability can strengthen the enhancement to both innovation quantity and innovation quality whereas resource slack can only strengthen the enhancement to innovation quantity.

Taken together, the three studies in this dissertation underscore the pivotal role of digitalization in enhancing firms' operational efficiency, financial performance and innovation outcomes, and further delves into the underlying moderating factors that make the enhancement varying across firms. The theoretical frameworks and empirical findings presented in this dissertation provide valuable insights for future studies on digitalization and guide firms in leveraging digitalization to secure a competitive edge.
Keywords: digitalization; operational efficiency; financial performance; innovation; uncertainty; diversification; organizational capability

Publications Arising from the Thesis

Published papers

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Working papers

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List of Abbreviations

AE	Firm Advertising Expenses
AGE	Firm Age
CAPX	Capital Expenditure
CF	Cash Flow
DIGI	Digitalization
DPD	Dynamic Panel Data
EPU	Macro Uncertainty
FE	Fixed Effect
FP	Financial Performance
FU	Firm Uncertainty
GD	Geographical Diversification
GMM	Generalized Method of Moments
IU	Industrial Uncertainty
IV	Instrumental Variable
LEVE	Firm Leverage
MTBR	Market-to-Book Ratio
OE	Operational Efficiency
PD	Product Diversification
R&DE	Firm R&D Expenses
R&DI	Firm R&D Intensity
RQs	Research Questions
SFE	Stochastic Frontier Estimation
SGR	Sales Growth Rate
SIC	Standard Industrial Classification
SIZE	Firm Size
TD	Technological Diversification

Chapter 1 Introduction

1.1 Research Background

With the increasingly competitive and unpredictable marketplace firms are facing (Dubey *et al.*, 2018), digitalization has become a focal activity to seek competitive advantages (Benitez *et al.*, 2023). Digitalization refers to the use of digital technologies for purposes such as improving firm performance as well as enabling enhanced decision-making, streamlined operations, and customer engagement in the context of Industry 4.0 (Stark *et al.*, 2023; Verhoef *et al.*, 2021). Digital technologies associated with this definition encompass a wide array of tools based on **A**rtificial Intelligence (such as ChatGpt); **B**lockchain (such as Bitcoin), **C**loud (such as Amazon Web Services), Big **D**ata (such as Google BigQuery), and the **I**nternet of Things (such as Nest Thermostat), which are commonly denoted as “ABCDI”. The substantial increase in investments toward digitalization, from about $1.85 trillion in 2022 to a projected $3.4 trillion by 2026 (Statista, 2022), indicates that digitalization is gaining popularity and strongly influences firms. For example, by leveraging ChatGpt, Octopus Energy automated 44% of all customer inquiries, showcasing the firm’s commitment to harnessing Artificial Intelligence for operational efficiency and enhanced customer service (Isakova, 2023). According to data by Gartner, an impressive 91% of businesses are engaged in some form of digitalization (Sultan, 2023). However, not all digitalization investments achieve the expected outcomes. A survey by the strategy and management consulting firm McKinsey & Company involving over 1,700 C-suite executives worldwide showed that nearly 45% of all digital transformation projects fall short of meeting profit expectations (Bughin *et al.*, 2019). Furthermore, according to a McKinsey study conducted in 2021, 70% of digital transformation projects ultimately fail, wasting $2.16 trillion in 2023 (George, 2023).

These data highlight the challenges firms face when executing digitalization effectively, prompting to the following questions: Can digitalization enhance firm performance? Under which conditions does digitalization strengthen or weaken the relevant enhancements? Except for the general data mentioned above, specific practical cases suggest that digitalization has enabled many firms to succeed in meeting evolving consumer demands and creating value in their business operations. For example, the implementation of advanced artificial intelligence and analytics by Amazon.com has significantly streamlined its supply chain and boosted its market efficiency (Peter, 2022). Similarly, the efforts of Tesla to integrate cutting-edge software for autonomous driving and vehicle performance solidified its leading position in the auto-drive sector (Kumari and Bhat, 2021). However, many firms have also suffered failure in their implementation of digitalization to enhance firm performance in practice. Taking Kodak and General Electric as examples, the failure of Kodak to adapt to digital photography trends resulted in its bankruptcy protection in 2012, and the struggles of General Electric with cloud technology contributed to a $7 billion loss in 2018 (Govindarajan *et al.*, 2019; Pereira, 2023). Such instances of failed digitalization in specific firms highlight the multifaceted nature of the implementation of digitalization. Therefore, the debate about the benefits of digitalization among practitioners continues and whether firms should adopt digitalization to achieve enhancements is still not entirely clear. Beyond the simple adoption of digitalization, a thorough analysis of the contextual factors influencing the impact of digitalization on different performance outcomes is also required.

1.2 Research Objectives

Although the adoption of digitalization in firms has great potential to enhance firm performance, it is associated with great challenges. To evaluate firm performance comprehensively and accurately, for this dissertation, quantitative analyses were conducted focusing on three pivotal dimensions: operational efficiency, financial performance, and innovation outcomes. Consequently, this dissertation explores two primary research questions, as follows:

RQ1: What is the impact of digitalization on firm performance regarding operational efficiency, financial performance, and innovation outcomes?

RQ2: Which contextual factors (moderators) strengthen or weaken the effectiveness of digitalization as mentioned in RQ1?

To address these questions, digitalization was first measured using secondary data. A literature review revolving around digitalization showed that although scholars are generally interested in digitalization, most studies focused on its potential outcomes utilizing survey data, only part of digital activities (e.g., Blockchain (Guo *et al.*, 2023a) and social media initiatives (Lam *et al.*, 2016)) or related investments (Karhade and Dong, 2021), thus raising concerns about the accuracy or generalisability of the obtained findings. To overcome these concerns and provide a more generalized understanding of digitalization, this dissertation conducts an examination across three separate studies, each aligned with specific objectives as outlined in the following.

The objective of Study 1 was to examine the impact of digitalization on firms' internal operations outcomes. It aimed to verify whether digitalization enhances operational efficiency and identified uncertainty as a significant moderator in the above relationship. Given the resource integrating function of digitalization, the formation of routines and the improvement of capabilities related to operations depend on production stability (Zhan *et al.*, 2023); therefore, uncertainty is considered as a contextual factor based on the resource-based view (RBV). Regarding the influence of uncertainty, prior studies posited seemingly contrasting outcomes, which may be attributed to the presence of varying forms of uncertainty that impose distinct impacts on business operations. Therefore, Study 1 explored the impact of digitalization on operational efficiency using secondary evidence collected from multiple sources, processed with innovative methodologies, while considering uncertainty from multiple levels.

The objective of Study 2 was to examine the impact of digitalization on the financial performance of firms—a critical indicator of their market competitiveness. The aim of Study 2 was to test whether digitalization enhances financial performance and to examine how diversification strategies moderate this relationship. The function of digitalization in sensing capabilities, seizing opportunities, and transforming operations related to market performance (Zeng *et al.*, 2022) depends on the collaboration and synergies of a systematic ecosystem (Bughin *et al.*, 2019). In such an ecosystem, multiple operational systems could be well integrated and transformed into revenue. Therefore, in Study 2, diversification strategy is considered as a contextual factor based on DCV. Related literature on the relationship between digitalization-related activities and financial performance have yielded inconsistent results, implying that further research on the specific impact of digitalization is needed. Regarding the influence of diversification, the varied conclusions of prior studies across various perspectives highlight the necessity to explore this topic through a more comprehensive, multidimensional lens. With such a lens, its implications can be fully understood in the context of digitalization research. Therefore, Study 2 explored the interplay between digitalization and varied diversification dimensions on financial performance, while also examining diversification from a more comprehensive perspective.

The objective of Study 3 was to examine the effectiveness of digitalization on firms' innovation outcomes, addressing the underexplored potential of digitalization to foster innovation despite its recognized capacity. The aim was to test whether digitalization enhances innovation outcomes and how resource slack and learning capability moderate this relationship. Given that acquisition, communication, and integration functions of digitalization are closely intertwined with the resources (Wang *et al.*, 2017) and capabilities (Cohen and Levinthal, 1990b) of a firm, Study 3 considered resource slack and learning capability as contextual factors of the relationship between digitalization and innovation based on ACT. A literature review related to innovation showed that although digitalization was assumed to be predictive in a data-driven decision-making context, it was unlikely to be creative (Christian and Eric, 2023). Previous studies provided theoretical discussions or empirical evidence using survey data to discuss the potential impact of digitalization on innovation; however, this approach has caused concern about the accuracy and objectivity of the findings. Additionally, most prior studies measured innovation from a single dimension only, without differentiating between varied perspectives of innovation, thus raising concerns that their findings might not align with the constraints of resource reality. Therefore, Study 3 explored the impact of digitalization on different innovation outcomes, which have been differentiated along the quantity and quality of innovation.

Table 1.1 presents the alignment between the core research questions and the respective objectives. It lays out the foundational theories underpinning the conducted analysis and identifies the specific moderators that are posited to influence the relationship between digitalization and its multifaceted impacts on firm performance. Figure 1.1 presents the overall framework of the dissertation, comprising three inter-related studies outlined above.

Table 1.1 Alignment Among RQs, Objectives and Foundational Theories

Studies	RQ 1— Digitalization's performance outcomes	RQ 2 – Moderators influencing digitalization's effectiveness	Research Objectives	Foundational Theories
Study 1	Operational efficiency	Uncertainty (Macro-level uncertainty; Industrial uncertainty; Firm-level uncertainty)	● Explore the relationship between digitalization and operational efficiency. ● How uncertainties moderate the relationship.	RBV
Study 2	Financial performance	Diversification strategies (Geographical diversification; Product diversification; Technological diversification)	● Explore the relationship between digitalization and financial performance. ● How diversification moderates the relationship.	DCV
Study 3	Innovation	Resource slack and learning capability	● Explore the relationship between digitalization and innovation. ● How resource slack and learning capability moderate the relationship.	ACT

1.3 Research Theoretical Foundations and Approaches

Digitalization fundamentally serves a multidimensional role in firms, acting as a strategic resource, a capability enabler, and an absorptive capacity, shaping operational, financial, and innovation-related outcomes. Understanding the theoretical lenses through which firms create and capture value via digitalization, along with the conditions that enable this process, is a critical priority for researchers. To examine its impact comprehensively, this dissertation integrates three key theoretical perspectives: the RBV, the DCV, and ACT. These perspectives provide a structured lens through which digitalization is analysed at different strategic levels—as a strategic resource, a dynamic capability, and an absorptive capacity. Specifically, from the RBV perspective, digitalization serves as a strategic resource as it possesses valuable, rare, inimitable, and non-substitutable characteristics, which will be explained in detail in section 3.2. From the DCV perspective, digitalization acts as a dynamic capability, enabling firms to sense opportunities, seize resources, and transform operations, as discussed in section 4.2. From the ACT perspective, digitalization functions as an absorptive capacity, enhancing firms' ability to recognize, assimilate, and apply knowledge to drive innovation, which will be explained in detail in section 5.2. This integrative approach ensures a more holistic understanding of how digitalization contributes to firm performance in diverse contexts.

This dissertation presents three empirical studies that were conducted to accomplish the above research objectives.

Study 1 focused on the impact of digitalization on operational efficiency. This study emphasized the role of digitalization in operations management, mirroring the initial intent underlying Industry 4.0 to revolutionize production processes through technology (Dalenogare *et al.*, 2018). Given that digitalization plays a pivotal role in streamlining production processes as it has become intricately intertwined with a firm's strategic assets to generate unique and valuable production barriers that are difficult to imitate, this study draws on the theoretical framework of RBV (Elia *et al.*, 2021). According to RBV—which emphasizes the strategic management of resources that are valuable, rare, inimitable, and non-substitutable—digitalization leverages technological advancements to enhance operational performance. Following the logic of RBV, this dissertation hypothesises that digitalization can improve operational efficiency by seamlessly integrating resources, forming unique operational routines, and developing distinctive capabilities within production settings. Moreover, stability emerges as a crucial element in the successful implementation of the functions of digitalization in operations and production. Consequently, this thesis postulates that uncertainty represents a significant contextual factor influencing the extent to which digitalization enhances operational efficiency.

To test the above postulations, 2,250 samples were collected from 496 listed firms in North America during 2015–2021. To remedy the lack of secondary data to measure digitalization, NLP was used to analyse digitalization announcements from Factiva, publicly issued by firms. With its capacity to process large volumes of data and its superior performance to extract accurate information from unstructured data, NLP effectively overcomes potential data inaccuracies associated with vast data size, subjective human biases, and low efficiency of traditional firm announcement analysis methods (Lingren *et al.*, 2014). Further, a comprehensive examination of uncertainty was conducted considering its multifaceted influence at macro-, industrial, and firm levels. This examination addressed issues highlighted by previous studies that suggest contrasting outcomes of the impact of digitalization, which may stem from the diverse roles of uncertainty across different business operation contexts. Based on data that were meticulously processed through the above-mentioned methods, this study implements a fixed-effect (FE) model following a hierarchical approach to explore the impact of digitalization on operational efficiency. The reasons are presented in the following. Given the unbalanced panel data spanning various years and the need to control for unobserved heterogeneities across different firms and industries in the samples used for this dissertation, the FE model was chosen because of its effectiveness in addressing these specific methodological challenges (Mundlak, 1978). This approach ensures a more accurate analysis of the impact of digitalization by controlling for time-invariant characteristics and firm-specific effects that may influence the outcome (Cui *et al.*, 2018b). To further address other potential endogeneity issues such as those imposed by reverse causality, rather than using their present values, a one-year lag was incorporated for both digitalization indicators and control variables (Hegde and Mishra, 2019). Additionally, the Heckman two-step model was employed to tackle potential sample selection bias (Kumar *et al.*, 2018), and a dynamic panel data (DPD) model was constructed to mitigate endogeneity concerns related to omitted variables (Lam *et al.*, 2016). Acknowledging the importance of temporal and sectoral differences, a heterogeneity analysis was conducted by dividing the sample into various groups based on temporal context—before and after the COVID-19 pandemic (Islam and Fatema, 2023)—and firm type, specifically distinguishing between business-to-business and business-to-consumer firms (Srinivasan *et al.*, 2011). This nuanced approach enables a deeper understanding of how the effects of digitalization may vary across different time periods and business sectors, aligning with insights from Srinivasan *et al.* (2011) on the significance of heterogeneity in business research.

Based on the digitalization data gained in Study 1, after exploring the application of digitalization in production processes, the focus of Study 2 shifted to firm performance in the market, with a specific focus on the impact of digitalization on financial performance. Financial performance is a critical indicator of the current market health of a firm and its ability to generate profits and sustain growth in a competitive landscape; therefore, financial performance is a vital measure of the strategic benefits of digitalization (Abou-foul *et al.*, 2021). As financial performance signifies a firm's market success, which is strategically enhanced by digitalization via adapting and innovating within dynamic market conditions, studying its impact on financial outcomes is consistent with DCV. According to DCV, digitalization enhances financial performance by enabling firms to swiftly adapt to changing market conditions, leveraging digital technologies as dynamic capabilities for a strategic advantage (Trujillo-Gallego *et al.*, 2022). Following DCV, it is proposed that digitalization can enhance financial performance by adeptly sensing, integrating, and transforming internal resources and capabilities to navigate evolving market conditions. During this process, the cohesion and strategic utilization of internal resources and capabilities become pivotal, as they enable the seamless integration of digitalized operational systems; this integration fosters diverse forms of collaboration and synergies that amplify the advantages of digitalization for organizations (Bughin *et al.*, 2018). Thus, Study 2 considers the diversification strategy as an influential factor in the relationship between digitalization and financial performance.

In this study, the financial outcomes of digitalization are examined using 3,419 observations across 754 companies spanning from 2015 to 2021. To overcome the limitations of previous studies that often focused on a single dimension of diversification, a comprehensive analysis of diversification is conducted. This is achieved by measuring diversification from geographical, product, and technological perspectives. This approach offers deeper insights into the nuanced ways in which diversification can influence the financial effectiveness of digitalization. As mentioned above, the data used for this dissertation are unbalanced panel data, which introduces complexities such as time and individual-specific errors; therefore, a FE model is employed to scrutinize the influence of digitalization on financial performance (Cui *et al.*, 2018b). The findings are validated with *robust t-statistics* and *bootstrap z-statistics* in the baseline regression to ensure the reliability of the obtained results (Qiu *et al.*, 2022). To mitigate the risk of endogeneity (Toh and Polidoro, 2013), including reverse causality, a one-year lag period is applied to both digitalization indicators and control variables, ensuring temporal precedence (Lam *et al.*, 2016). Further, to address concerns related to sample selection bias, the Heckman two-step model was utilized, thus enhancing the validity of inferences (Kumar *et al.*, 2018). Additionally, this study adopts instrumental variable techniques (Chari *et al.*, 2008), that were strategically selected to resolve potential endogeneity issues by isolating the exogenous variation in the impact of digitalization on financial outcomes. This approach ensures a more precise estimation of the financial effect of digitalization. Finally, in Study 2, a cross-sectional regression model was constructed to analyse the heterogeneity of the research.

Building upon the preceding exploration of the impact of digitalization on operational and market fields, Study 3 scrutinizes the relationship between digitalization and innovation—a key driver of a firm's future competitiveness. Innovation serves as a crucial indicator, signifying a firm's capacity to pioneer, adapt, and thrive in an evolving competitive landscape, thereby underpinning its long-term success. To dissect this relationship, this analysis is anchored in ACT, which clarifies how firms identify, assimilate, and apply new external knowledge to foster innovation (Cohen and Levinthal, 1990b), which is consistent with the functions of digitalization. According to ACT, digitalization catalyzes innovation by enhancing a firm's ability to recognize valuable external information, assimilate it effectively, and apply it to commercial ends. In this context, the distinction between realized and potential absorptive capacities becomes paramount, emphasizing the necessity for firms to not only acquire and assimilate new knowledge but also to transform and exploit it (Chatterjee *et al.*, 2022). Hence, in Study 3, resource slack and learning capability serve as pivotal moderators, mapping onto potential and realized absorptive capacities, to elucidate how digitalization enhances innovation optimally. Further, this nuanced examination transcends traditional one-dimensional measures of innovation by incorporating both quantity and quality perspectives to overcome prior research limitations and fully capture the multifaceted nature of innovation.

After deleting samples with missing data, an initial panel data set of 1,430 firm-year observations with a total 5,788 samples from 2015 to 2021 was obtained. This data set was used to analyse the impact of digitalization on innovation, which has been differentiated into the quantity and quality of innovation. In the analysis, a FE model was also employed, which matches the characteristics of imbalanced panel data to assess the influence of digitalization on the quantity and quality of innovation. This analytic approach reinforces the analysis with a one-year lag on digitalization measures and control variables to pre-emptively address endogeneity related to reverse causality (Lam *et al.*, 2016). To counteract potential sample selection biases related to endogeneity that may skew the results, the Heckman two-step correction technique was applied. This technique allows for a more nuanced and accurate estimation of the effect of digitalization on innovation by correcting for any systematic differences between selected and non-selected samples (Kumar *et al.*, 2018). Finally, a heterogeneity analysis is conducted utilizing alternative measurements of innovation (Woodward, 2006), enabling a deeper exploration of how digitalization impacts various aspects of innovation, from process improvements to product novelties.

1.4 Research Findings and Significance

This dissertation is subdivided into three distinct studies, each unveiling critical findings related to the multifaceted impacts of digitalization. Study 1 establishes a positive correlation between digitalization and operational efficiency, as evidenced by the results of FE models. In alignment with the argument proposed based on RBV, Study 1 finds that uncertainty generally mitigates the positive effects of digitalization on operational efficiency; both macro- and industrial level uncertainty demonstrated significant negative impacts. Conversely, uncertainty at the firm level, while also exerting a negative impact, does not show a statistically significant effect. A plausible explanation could be that at appropriate macro- and industrial- levels, the negative effects of firm-level uncertainty may be mitigated by support from partners within the supply chain.

The results of Study 2 suggest that digitalization is positively associated with firms' financial performance measured by Tobin's *Q*, showing that this positive association is more pronounced in firms with higher levels of diversification. This result matches the argument proposed based on DCV, highlighting the beneficial role of a diversification strategy. Specifically, geographical, product, and technological diversification amplify the positive impact of digitalization on financial performance. This result implies that embracing a variety of diversification strategies not only enhances a firm's adaptability and market reach, as verified by prior studies, but also significantly strengthens the financial benefits derived from digitalization efforts.

Study 3 shows that digitalization significantly bolsters innovation in both quantity and quality, supporting the hypothesis proposed based on ACT. Further, the positive impact of digitalization on innovation quantity is enhanced under conditions of both higher learning capability and higher resource slack. However, while the influence of digitalization on innovation quality is greater under higher levels of learning capability, the moderating effect of resource slack is positive but not statistically significant. The possible reason might be that higher resource slack provides firms with more flexibility and opportunities to experiment with innovative endeavours. However, this may not directly translate into improved innovation quality unless it is accompanied by targeted and accurate strategic resource management that aligns with the core objectives of the firm.

This dissertation is theoretically important in the following ways: First, this research provides empirical evidence for the effectiveness of digitalization, utilizing secondary data analysis. Although digitalization has been widely used across various sectors, its high failure rate underscores the need for a deeper examination of its nuanced applications and implications within organizations. The existing literature predominantly featured theoretical discussions and empirical findings using survey data, with a notable scarcity of empirical evidence. This examination pioneers the use of NLP to accurately quantify the extent of firms' digitalization, spanning three distinct studies (Studies 1, 2, and 3) that examine the potential of digitalization in operational management, market performance, and creativity, respectively. By constructing theoretical models based on diverse theories, this dissertation explores the multifaceted effectiveness of digitalization across various domains, thereby broadening the scope of digitalization research. Additionally, the documented results of theoretical studies provide critical empirical evidence for executives who consider the use of digitalization to achieve diverse objectives. This marks a substantial contribution to the understanding of the multifaceted effectiveness of digitalization.

Second, this dissertation comprehensively documents the direct impact of digitalization on operational efficiency, financial performance, and innovation, while also exploring the diverse factors leading to variability in these impacts across different firms. In Study 1, after considering the requirement of stability in production and operations management in firms, uncertainty at various levels is identified as a key moderating factor influencing the extent to which digitalization can enhance operational efficiency. Specifically, uncertainty is analysed from macro-, industrial, and firm levels, thereby unlocking new insights into the multifaceted nature of uncertainty and enriching the uncertainty literature. In Study 2, considering the systematic integration of digitalization and resource utilization in the marketplace, the diversification strategy is posited as a moderator of the impact of digitalization on financial performance based on DCV. More specifically, this study pioneers the assessment of diversification across geographical, product, and technological dimensions, thus shedding light on how the diversification strategy can influence the implementation of digitalization and contribute to the diversification literature. In Study 3, given that firms' innovation outcomes depend on their absorptive capacity, both realized and potential absorptive capacities are considered in the impact of digitalization on innovation based on ACT. With this approach, both resource slack and learning capability are identified as crucial factors that play different roles in the impact of digitalization on different innovation dimensions, thereby expanding the discourse on the innovation literature.

Finally, the conducted in-depth analysis of these moderators not only enriches the respective fields of study but also yields vital practical insights for executives, thus offering useful guidance for navigating the complexities of digitalization to optimize firm performance. Study 1 provides key recommendations for executives, namely that the effectiveness of digitalization in improving operational efficiency is contingent upon conditions of uncertainty. Thus, when contemplating the adoption of digitalization to improve operational efficiency, executives should be mindful of macro-level and industrial uncertainties but need not be overly cautious about firm-level uncertainty alone. Study 2 addresses concerns of executives who are skeptical about the function of digitalization in financial performance, especially considering initial investments that may not yield immediate returns. The results of Study 2 suggest that firms can leverage digitalization to improve their financial performance under a diversification strategy, capitalising on the unique attributes and advantages of different geographical locations, product line variety, and flexible technologies. Study 3 advises executives to clearly differentiate between innovation quantity and quality, as the recognition of this distinction is crucial for the effective allocation of resources and for strategizing to boost innovation within a firm under resource constraints. Study 3 further underscores the distinct roles of resource slack and learning capability as moderating factors across various dimensions of innovation; it also offers targeted recommendations for executives regarding the allocation of appropriate resources and capabilities to achieve specific innovation objectives.

1.5 Structure and Framework of the Dissertation

This dissertation consists of six chapters, including three presenting empirical studies.

Chapter 1 introduces the research background, proposes research questions and objectives, and reports the theoretical foundations and research approaches; it also illustrates the findings, discusses the research significance, and briefly summarizes the framework of the dissertation.

Chapter 2 reviews the primary literature on digitalization. Previous literature related to the definition, measurement, and potential outcomes of digitalization is searched and analysed, and existing research gaps are summarized. Chapter 2 also provides a comprehensive theoretical foundation of digitalization for the three empirical studies presented in the following chapters.

Chapter 3 explores the outcomes of digitalization in operational efficiency, emphasising stability and considering the moderating impact of uncertainty based on RBV. The purpose of Study 1 is to test whether digitalization is effective in enhancing operational efficiency and the impact of uncertainty in the above relationship.

Recommendations are provided for executives who seek to utilize digitalization in operations management under varying levels of uncertainty.

Chapter 4 verifies the effectiveness of digitalization in enhancing firms' financial performance and emphasizes the crucial role of a diversification strategy in moderating the above relationship based on DCV. The purpose of Study 2 is to identify whether and when digitalization can enhance a firm's capacity to sustain growth and profitability in a competitive marketplace. Insights are offered for executives who seek to align firm strategies with digitalization to enhance financial growth.

Chapter 5 delves into the potential of digitalization to improve innovation outcomes, considering the moderating effect of resource slack and learning capability based on ACT. Study 3 explores the conditions under which digitalization boosts a firm's creativity—a key driver of its future development—across different innovation dimensions. Targeted recommendations for resource and capability allocation are offered for executives seeking to meet specific innovation goals.

Chapter 6 summarizes the general conclusions, elaborates on theoretical contributions and managerial implications, and discusses both the limitations of this dissertation as well as promising areas of future research.

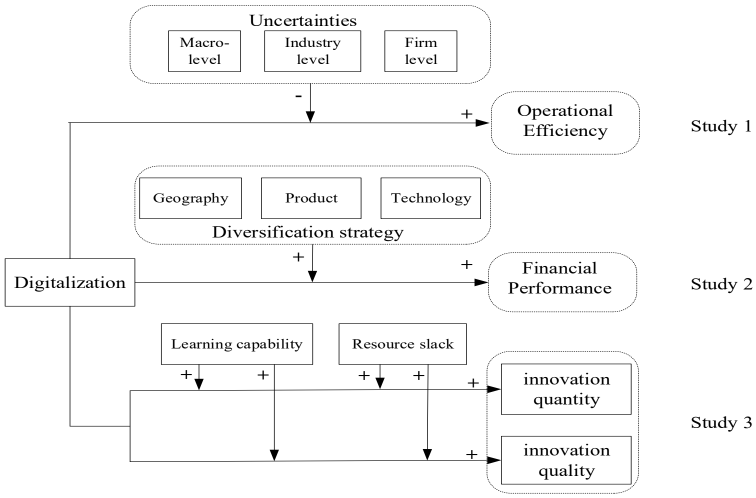


Figure 1.1 Overall Framework of The Dissertation

Chapter 2 Literature Review on Digitalization

The rising influence and popularity of digitalization across various domains has sparked considerable interest by both executives and scholars. The varying outcomes of digitalization practices across different firms have led executives to hesitate with making substantial investments into digitalization. Although empirical research is somewhat limited in this nascent field because of a lack of direct secondary data (Guo *et al.*, 2023b), many existing studies gravitate toward conceptual discussions and measurement debates. Therefore, in this dissertation, a systematic review of the literature on digitalization was conducted focusing on its 1) definitions and measurements as well as 2) performance outcomes, as shown in Table 2.1 and Table 2.2.

2.1 Definition and Measurement of Digitalization

The popularity of digitalization in both industry and academia is commonly believed to have begun since the advent of "the Industry 4.0" paradigm, which was introduced at the Hannover Messe in Germany in 2013. Nonetheless, there is no common consensus as to conceptual definitions in this emerging field, imposing certain barriers to related research and practice (Gong and Ribiere, 2021). This issue was mitigated when Verhoef *et al.* (2021) distinctly defined and differentiated digitization, digitalization, and digital transformation. In their study, digitalization was identified as the second stage of digital transformation after the stage of digitization.

Specifically, digitization is the first stage, which primarily entails encoding analogue information into a digital format, thus enabling computers to store, process, and transmit such data (Dougherty and Dunne, 2012; Leonhardt *et al.*, 2017). This process pertains to the format transformation of information, such as digitalizing internal and external documentation processes (Verhoef *et al.*, 2021), thereby preparing for digitalization in the next stage (Li *et al.*, 2016). Based on the digital documents and data gained at the digitization stage, digitalization as the second stage describes how information technologies or digital technologies are utilized to enhance existing operational patterns or processes for value creation (Li *et al.*, 2016). For instance, the utilization of information technologies and social media can update firms' traditional interactions with customers and suppliers; consequently, communication efficiency and knowledge sharing are enhanced which are important factors in value creation along supply chain (Lam *et al.*, 2016; Ramaswamy and Ozcan, 2016). Then, at the third stage, digital transformation signifies a more comprehensive and far-reaching change. At this stage, firms should not only complete the digitization of data and utilize digital tools for value creation, but also further modify their business models and organizational culture to achieve a higher comprehensive level in the era of the digital economy (Li *et al.*, 2018). For instance, the digital transformation of a traditional bookstore not only involves offering e-Books, audiobooks, and employing digital technologies in operations, but also encompasses fostering a culture of digital innovation among employees and redefining both its business model and customer engagement strategies (Montanari, 2023). Clearly, the definition of the digital transformation stage is highly sophisticated, which mostly revolves around revolutionary changes (Appio *et al.*, 2021), thereby exceeding the reality of most firms (Warner and Wäger, 2019).

Thus, “digitalization” was chosen as the research object to accurately describe the practical situation of firms. Following prior studies, digitalization is defined as the application of digital technologies in firms' existing business processes (Verhoef *et al.*, 2021).

Over the past decade, while numerous scholars have sought to measure digitalization in research, their efforts have not achieved consistency. Therefore, this dissertation conducted a review of the measurement of digitalization in empirical studies, which is shown in Table 2.1. This table illustrates the lack of a widely accepted measurement for digitalization with secondary data, as most studies rely on survey data. Specifically, some researchers measured digitalization based on examining firms’ usage of digital technologies to enhance product value or to develop new business models (Li *et al.*, 2022b); the adoption of specific digital tools such as social networks (Ribeiro-Navarrete *et al.*, 2021); examinations of firms’ digitalization capability (Anwar *et al.*, 2022; Eller *et al.*, 2020); or the usage of general digital technologies (Shi *et al.*, 2023) and special technological systems (Brivot *et al.*, 2014). Other scholars have explored the utilization of secondary data to describe the extent of the digitalization of firms. For example, certain scholars attempted to manually analyse keyword frequencies in annual reports (Guo *et al.*, 2023b) as a measure of digitalization. In summary, empirical research on digitalization currently lacks a consistent measurement approach, particularly in terms of secondary data, highlighting the need for further exploration in this area.

Table 2.1 Studies on the Definition and Measurement of Digitalization

Digitalization Literature	Content	Reference
Definition	Digitalization is the use of digital technologies to transform business processes and organizational management.	Li *et al.* (2022b)
	Digitalization is a broad sociotechnical procedure that encompasses the fusion of various technologies into everyday societal activities.	Caputo *et al.* (2021)
	Digitalization is a broad concept that encompasses the use of numerous tools.	Ribeiro-Navarrete *et al.* (2021)
	Digitalization involves the increased use of digital technologies and their integration and cross-fertilization in the firm's products and inbound and outbound activities.	Bjorkdahl (2020); Bjorkdahl and Holmen (2019)
	Digitalization refers to the application of IT or digital technologies to transform traditional business processes.	Verhoef *et al.* (2021)
Measurement	Survey data (leveraging digital tools to understand customers, guide operational choices, increase the added-value of products and services and introduce novel business models).	Li *et al.* (2022b)
	Survey data (the use of simple digital tools that are accessible to any firm, including social network updates, the corporate use of digital tools and social networks, and training in new digital tools)	Ribeiro-Navarrete *et al.* (2021)
	Survey data (evaluations of companies' digital capabilities)	Eller *et al.* (2020)
	Survey data (the usage of knowledge management systems)	Brivot *et al.* (2014)
	Survey data (the attitude to and usage of digital technologies)	Shi *et al.* (2023)
	Keyword occurrences in annual reports representing the indicators of digital transformation	Guo *et al.* (2023b)

Based on the literature review in Section 2.1, a key gap exists in the inconsistency of digitalization definitions and the lack of objective measurement methods. First, there is inconsistency in the definition of digitalization, and a lack of objective measurement methods. Specifically, the terms “digitalization”, "digitization”, and “digital transformation” are often used interchangeably in both industry and academia, leading to conceptual ambiguity and challenges in research and practice. Although scholars have attempted to refine these definitions by clarifying their evolution and distinct meanings, further empirical studies are needed to establish a more unified understanding. Additionally, current digitalization measurements primarily rely on survey data and case studies, which, while offering valuable insights, are prone to subjectivity and bias. To enhance measurement accuracy, future research should develop more scientific and objective approaches, such as analyzing enterprise system usage data and the actual impact of digitalization projects. A more precise evaluation of digitalization levels would not only support firms in better understanding and implementing digital strategies but also provide a stronger empirical foundation for academic research.

2.2 Performance Outcomes of Digitalization

Digitalization is being increasingly recognized for its pivotal role in enhancing various aspects of business performance across multiple domains. As a key aspect of Industry 4.0, the initial step in the utilization of digitalization focuses on improving production and operations management; particularly, on boosting supply chain resilience and operational efficiency across and within different sectors. For example, Shi *et al.* (2023) verified the impact of digitalization on efficiency from a supply-chain perspective. They found that digitalization is not directly related to supply chain resilience, and showed that it positively impacts the improvement of supply chain integration. Similarly, Zhao *et al.* (2023) showed how digitalization across different sectors can significantly improve supply chain cost-effectiveness, information and communication efficiency, and resilience during crises. From the perspective of firm-level operational efficiency, Tian *et al.* (2023) explored how digitalization affects a firm's operational efficiency by examining human, physical, and capital resources; they used empirical data derived from secondary sources of Chinese manufacturing firms. These studies suggest a trend toward integrating digitalization to improve operational outcomes from different perspectives. However, most previous studies were based on survey data, implying a notable gap in related research utilizing secondary data to further assess the impact of digitalization on operational efficiency.

With the increasing enthusiasm for examining digitalization, executives have experienced a variety of financial results by incorporating digitalization. Scholars have also acknowledged this phenomenon and provided controversial opinions on this issue. Specifically, Li *et al.* (2022b) and Eller *et al.* (2020) underscored the positive influence of digitalization on business-to-business exchanges and medium-sized enterprises utilizing empirical research methods based on survey data. Similarly, Pagani and Pardo (2017) and Ribeiro-Navarrete *et al.* (2021) attained the same result regarding the impact of digitalization on financial performance using a case study and qualitative comparative analysis, respectively. Conversely, Wamba *et al.* (2015) arrived at a cautionary conclusion through a case study, indicating that digitalization can lead to increased operational costs and resource wastage, thereby diminishing financial performance. Also, Sharma *et al.* (2023) found that digitalization does not improve the current accounting performance of firms. These inconsistent results between case studies and empirical studies using survey data suggests a controversial situation where the financial benefits of digitalization have been acknowledged alongside its potential drawbacks. Notably, while the published research spans various methodologies, it lacks a unified conclusion regarding the financial impact of digitalization, validated by secondary data. This lack suggests a need for further research to clarify these conflicting outcomes.

Through its profound impacts on operational processes and strategic orientations, digitalization is widely regarded as a double-edged sword for innovation. On the one hand, the functions of digitalization to provide more access to diverse resources, improving communication efficiency, and enhancing knowledge sharing are potentially beneficial for innovation. For instance, Wu *et al.* (2022) highlighted how digitalization capabilities enable firms to tap into a diverse array of innovation sources, utilizing case study methodologies to uncover detailed insights. Similarly, as evidenced by their empirical study, Lee and Roh (2023) illustrated how digitalization fosters open innovation in emerging markets by increasing collaboration frequency, accelerating opportunity evaluation, and facilitating scalable innovation. Additionally, based on survey data, Arias-Pérez *et al.* (2021) found that a strategic orientation toward digitalization enhances innovation capability across various dimensions, particularly in technology, client engagement, and marketing. On the other hand, the inherent characteristics of digitalization such as standardisation and the potential for information overload can lead to the homogenisation of ideas, thereby diminishing innovation. For example, the tendency of digitalization toward standardising processes and knowledge can inadvertently narrow the scope of creative exploration; this narrowed scope can reduce the potential for truly ground-breaking ideas that often emerge from unique resources and activities (Radicic and Petković, 2023). Additionally, high levels of digitalization can cause an explosion of information growth in firms; this information overload phenomenon may impose a burden on R&D personnel to use knowledge, which subsequently inhibits innovation (Gong *et al.*, 2023). In summary, although digitalization has been recognized for its capabilities regarding innovation, doubts remain about its capacity to be genuinely innovative. Specifically, there is a notable shortage of research employing secondary data to substantiate the relationship between digitalization and innovation across different sectors and regions.

Beyond its remarkable impacts on operational efficiency, financial performance, and innovation, digitalization crucially underpins the performance of firms or personnel, such as the development of sustainable business models (Anwar *et al.*, 2022; Broccardo *et al.*, 2023) and promotions (Brivot *et al.*, 2014). These insights collectively underscore the potential of digitalization to not only enhance traditional business metrics but also sculpt business models that are innovative, sustainable, and conducive to expansion beyond local markets. This suggests that the effectiveness of digitalization spans a broader spectrum than previously assumed. Many areas are ripe for examination, promising rich insights into how digitalization can continue to reshape the business world.

Table 2.2 Research on the Performance of Digitalization

Performance Dimensions	Main Views	Research Methodologies	References
Operational Performance	Digitalization boosts supply chain resilience and performance during crises.	Empirical study with survey data	Zhao *et al.* (2023)
	Digitalization impacts on operational efficiency analyzed through human, physical, and capital aspects.	Empirical data with secondary sources	Tian *et al.* (2023)
	The level of enterprise digitalization has a positive impact on the improvement of supply chain integration.	Empirical study with survey data	Shi *et al.* (2023)
	The adoption of a range of digital technologies affects firm productivity.	Empirical study with survey data	Gal *et al.* (2019)

Performance Dimensions	Main Views	Research Methodologies	References
Financial or Market Performance	Digitalization has a positive impact on B2B exchanges.	Case study	Pagani and Pardo (2017)
	Digitalization enhances performance via IT mediation.	Empirical study with survey data	Eller *et al.* (2020)
	Digitalization positively effects the market performance for firms in the service sector.	Qualitative comparative analysis	Ribeiro-Navarrete *et al.* (2021)
	The higher digitalization degree implies superior performance through knowledge exchange and creation.	Empirical study with survey data	Li *et al.* (2022b)
	Implementation of blockchain technology increased future earnings but did not affect current accounting performance.	Empirical data with secondary sources	Sharma *et al.* (2023)
	Digital technology led to increased operational costs and resource wastage, diminishing financial performance.	Case study	Wamba *et al.* (2015)
Innovation Performance	Digital capabilities enable diverse innovation sources.	Case study	Wu *et al.* (2022)
	Digitalization could enhance open innovation through collaboration, swift evaluation, and scalable innovation.	Empirical study with survey data	Lee and Roh (2023)
	Digitalization's strategic orientation boosts innovation capability.	Empirical study with survey data	Arias-Pérez *et al.* (2021)
	Digitalization capability has a too-much-of-a-good-thing effect on radical innovation.	Empirical study with survey data	Gong *et al.* (2023)
Others	Digitalization has potential benefits for gaining sustainable business models.	Literature review	Broccardo *et al.* (2023)
	Digital capabilities (related to digitalization) indirectly boost the internationalization of SMEs through business model innovativeness.	Empirical study with survey data	Anwar *et al.* (2022)
	Digitalization has a positive impact on a person's promotion in a large Law firm.	Empirical study with survey data	Brivot *et al.* (2014)

Based on the literature review in Section 2.2, a key gap exists in the lack of comprehensive research on the direct impact of digitalization on firm performance and the role of boundary conditions. First, there is a lack of integrated studies examining the overall impact of digitalization on firm performance, as well as the contextual factors influencing this relationship. Due to the limitations of available secondary data, most existing studies tend to analyze digitalization's impact from a single-dimensional perspective, leading to fragmented findings. While many scholars argue that digitalization enhances efficiency, fosters innovation, and strengthens competitive advantage, others highlight the "digitalization paradox", where firms fail to achieve the expected returns from digital investments. This inconsistency suggests that contextual factors may play a crucial role in shaping the digitalization-performance relationship. However, existing studies provide limited discussion on whether and under what conditions digitalization effectively contributes to outcomes, indicating a need for further investigation into the boundary conditions that influence these effects.

Chapter 3 Study 1 An empirical study on digitalization's impact on operational efficiency and the moderating role of multiple uncertainties

3.1 Introduction

Firms increasingly consider digitalization essential for their survival in the era of Industry 4.0 and are willing to make relevant investments in digital technologies substantially. Many firms such as Facebook and Google have generated unparalleled value through such investments (Costa Climent and Haftor, 2021). However, some other businesses did not achieve the expected outcomes from digitalization and took huge losses (Sjödin *et al.*, 2020), where such failure was considered in relation to a lack of attention to changes in the environment or to the inability to assess future changes (Torres, 2022). For instance, Blockbuster and Kodak's declines were attributed to the lack of foresight into changes in technologies relevant to their business contexts (Costa Climent and Haftor, 2021). Similarly, one reason for Nokia's failure was its hesitation to upgrade to Android in the early 21st century in the face of high uncertainty in the mobile industry (Salman Abdou and Hussein, 2020). One important lesson implied from these failures is that success in the adoption of digitalization hinges on firms' abilities to recognize the negative influence from environmental uncertainty and scan the relevant changes and challenges in their business environments on a regular basis. Although there have been much discussion of the negative effect of uncertainty on businesses (Leung and Sun, 2021), the understanding concerning uncertainty's impact on digitalization remains unclear.

In practice, uncertainty is widely regarded as a negative factor for firms' performance. For instance, gubernatorial elections are often considered a critical form of uncertainty for firms in the US; many firms respond by reducing investments by 5%, whereas some firms more susceptible to uncertainty reduce their relevant investments by 15% (Jens, 2017). In academia, uncertainty is also commonly believed to be negative for firms. For instance, policy uncertainty could negatively influence firms' investments (Gulen and Ion, 2016) or motivate firms to hold more cash because of precautionary considerations (Phan *et al.*, 2019). However, some research suggests that uncertainty could be a favorable condition for firms and could lead to positive outcomes such as improved innovation (Xue *et al.*, 2012) and enhanced IT ambidexterity capability and the resulted success (Syed *et al.*, 2020). One potential cause of these seemingly contrasting outcomes may be the presence of varying forms of uncertainty, which play distinct roles in business operations. Overall, there is a dearth of empirical evidence to substantiate the influence of uncertainty on the efficacy of digitalization efforts.

Scholars are interested in digitalization's effectiveness (Li *et al.*, 2023a) but face challenges caused by a lack of measurement of digitalization based on second-hand data (Axenbeck and Breithaupt, 2022). Prior research indicates that firms with higher levels of digital activities (e.g., digitalization strategic plan (Rozak *et al.*, 2023), blockchain adoption (Xiong *et al.*, 2021), and employees' digital literacy (Cetindamar *et al.*, 2022)) are associated with higher performance (Rozak *et al.*, 2023) and lower firm risk (Kim *et al.*, 2017). However, most of these studies utilize survey data or measure the adoption of digitalization with partial digital activities or based on investments, causing concern about the accuracy of the findings. Indeed, one conventional approach to measure digitalization is to count corporate announcements (Lam *et al.*, 2016), but this approach is often plagued by manual inconsistencies, time constraints, and human biases, resulting in potential data inaccuracies (Lingren *et al.*, 2014). This research attempts to address the problem by adopting a rigorous and advanced method, i.e., NLP, which is a form of the machine learning (ML) technique and is capable of capturing required announcements from bigger databases and less structured writing in comparison with conventional methods.

In this article, we test the relationship between digitalization and operational efficiency and the moderating effects of three levels of uncertainty (i.e., macro-level uncertainty (or economic policy uncertainty (EPU)), industrial-level uncertainty (IU), and firm-level of uncertainty (FU)) on this relationship. By studying 496 listed firms in North America from 2015 to 2021, we found that firms with higher digitalization levels performed better in operational efficiency. Our results also showed that different levels of uncertainty played different roles in the effect of digitalization on operational efficiency. EPU and IU hinder the enhancement of operational efficiency brought by digitalization; however, FU's moderating effect is insignificant. The three major contributions of this study are as follows: First, we measured digitalization adoption by processing objective announcement data with NLP, demonstrating the use of an advanced measurement method in text sources in the management context. Second, we verified digitalization's impact on operational efficiency. Third, we comprehensively examined the moderating effects of three levels of uncertainty on the link between digitalization and operational efficiency, thereby providing new insight to the body of knowledge on digitalization and uncertainty and to practitioners to enhance their efficiency enhancement effort via digitalization.

3.2 Theoretical Background and Hypothesis Development

3.2.1 Resource Based View

As one of the most widely accepted theory (Newbert, 2007), the RBV was put forward by Wernerfelt (1984) with an initial aim to explain how a firm's internal resources contribute to achieving a sustainable competitive advantage. According to Wernerfelt (1984) and later expanded by Barney (1991), firms with resources that are valuable and rare can enjoy enhanced performance over a short term. Moreover, resources that are valuable, rare, inimitable, and non-substitutable (VRIN) enable firms to sustain competitiveness in the long run (Barney, 1991). This perspective has gained widespread acceptance across various management disciplines, including international business, entrepreneurship, marketing, innovation/technology, and information technology (Newbert, 2007). However, RBV has been critiqued for its static definition of resources, with some scholars questioning the overlooked link between resource ownership and utilization, suggesting that the most successful firms are those that allocate their resources to maximize productivity and financial outcomes (Mahoney and Pandian, 1992). The first study of this dissertation delves into production and operations management, illustrating that the application of the RBV in this domain is logical and fitting (Bromiley and Rau, 2016). This alignment is due to the production process's emphasis on stability, which resonates with the RBV's assumption that resources are imperfectly mobile, underscoring the relevance of RBV in operational contexts.

Within the context of RBV, the definition of "resource" has evolved significantly, extending from tangible assets to include intangible routines and capabilities, particularly pertinent in the digital era (Cuthbertson and Furseth, 2022; Elia *et al.*, 2021; Knott, 2003). In line with the RBV, valuable digitalization related resources become crucial assets because they are protected by isolating mechanisms like patents or unique technological expertise, offer firms a sustainable competitive edge in the digital marketplace (Teece, 2018b). Similarly, effective routines formed through digitalization become invaluable assets as they are embedded in sticky digital knowledge and unique organizational culture, creating barriers for competitors to replicate, thus providing firms with a sustainable advantage (Knott, 2003). Furthermore, firms with advanced digitalization capabilities, such as sophisticated data analytics, AI integration, and accurate market prediction, tend to be more valuable and more difficult for competitors to imitate, because these capabilities foster unique and complex systems of customer engagement and market analysis that are deeply integrated with digitalization, making them challenging to replicate (González‐Alvarez and Nieto‐Antolín, 2005; Sánchez‐Montesinos *et al.*, 2018). Hence, this chapter utilizes RBV as the foundational theory in digitalization’s impact on operational efficiency, being consistent with the mainstream of digitalization relative studies (Huang *et al.*, 2023; Lam *et al.*, 2016; Tian *et al.*, 2023; Ye *et al.*, 2023).

3.2.2 Literature Review

The investigation into the effects of digitalization on operational performance outcomes has been diverse. Although direct empirical studies on digitalization are scarce, this body of literature has selected and summarized digitalization concepts that are similar to our definition of digitalization and has contributed to insights into outcomes such as total factor productivity (Guo *et al.*, 2023b). These direct outcomes from digitalization could also be influenced by organizational factors. For example, although digitalization enhances firm performance, this advantage may be tempered by factors such as knowledge inertia (Li *et al.*, 2022b). Similarly, digitalization can boost productivity but might concurrently impact other performance dimensions negatively (Guo *et al.*, 2023b), implying that the impact of digitalization on performance in different contexts is nuanced. To supplement this literature, new investigations into factors that strengthen the performance impact of digitalization on organizations should be conducted.

The multifaceted and volatile nature of the operational environment necessitates a more in-depth understanding of digitalization's performance impacts. The omnipresent uncertainty in general causes firms to grapple within operations (McKinsey, 2021). Specifically, ignoring uncertainty can lead to substantial risks, potentially leading firms to misalign with shifting market demands (Milliken, 1987), make suboptimal technological investments (George *et al.*, 2014), and remain unresponsive to emergent competitive dynamics (Bowman and Hurry, 1993). Consistent with the practice in the business context, the literature underscores the significant role of uncertainty in decision-making (Knight, 1921), and innovation strategy (Dunlap *et al.*, 2023), etc. Obviously, the discourse surrounding uncertainty highlights its significance in operations, an importance that becomes even more pronounced in the context of the new digital economy (Ma *et al.*, 2022). Digitalization, however, is not a monolithic entity but a layered technology strategy with implications across various strata of a firm (Bharadwaj *et al.*, 2013b). It involves a firm's capability at different levels, such as sensing total market trends (Malenkov *et al.*, 2021) and ensuring competitiveness within an industry (Lorenz *et al.*, 2020); thus, its effectiveness may vary significantly at different levels of uncertainty. In this study uncertainty is divided into three levels.

First, EPU captures the unpredictability associated with government policies and is a reflection of macro- economic and political instability (Baker *et al.*, 2016), which often has long-term impacts on businesses on a broad scale and could affect a firm's long-term decisions on digitalization (Leibrecht and Scharler, 2012). Second, IU relates to the unpredictability within industries that might spur firms to adopt digitalization to stand out in a volatile market (Swanson and Ramiller, 2004) or that might undermine the effectiveness of digitalization efforts if businesses fail to keep up with competitors (Bharadwaj *et al.*, 2013a). Finally, FU pertains to the internal unpredictability associated with fluctuations in performance that businesses face, which could hinder the smooth integration of resources with digitalization, thus affecting the potential of digitalization to achieve enhanced operational performance (Teece, 2018a). The variability and impacts posed by these distinct levels of uncertainty warrant further investigation into the role of uncertainty levels in digitalization's effectiveness. However, existing studies give scant attention to this critical research area.

3.2.3 Hypothesis Development

Digitalization has become an inevitable element of competition in the era of Industry 4.0 (Yang *et al.*, 2023). This study adopts the resource-based view (RBV) to examine the effectiveness of digitalization in enhancing operational efficiency for organizations. Prior RBV research suggests that a firm's operational efficiency depends on its 1) resources, 2) routines, and 3) capabilities from the RBV perspective (Lam *et al.*, 2016). First, digitalization works as one strategic resource and is difficult to copy because it is supposed to be closely related to a firm's specific path or trajectory (Lim *et al.*, 2011). Path-dependence leads to isolation mechanisms in firms' digitalization, hindering short-term imitation by competitors. Digitalization boosts operational efficiency by unifying tangible and intangible resources (Lam *et al.*, 2016). It optimizes access to customer data, improving understanding of their needs (Porter and Heppelmann, 2014). In addition, digitalization enables platforms and interfaces to facilitate integration of disparate yet complementary information, opening up new value creation opportunities (Yoo *et al.*, 2012). Second, as an efficient instrument that influences actual processes, digitalization improves the efficiency of managerial routines (Becker *et al.*, 2005) and is important to enhancing operational efficiency (Lam *et al.*, 2016). Third, digitalization effectively supports firms' development of their extended core capabilities (Rai *et al.*, 2006), which are regarded as those core inter-organizational processes critical to firms' performance (Hagel and Singer, 2000). Thus, we develop the first hypothesis as follows:

H1: Digitalization improves firms' operational efficiency.

Firms nowadays operate in a highly uncertain environment (Li *et al.*, 2022a). The impact of uncertainty on firms is paradoxical. On the positive side, uncertainty could be a favorable environment for firms because it may stimulate firms to adopt more flexible strategies to adapt to changes and explore new market opportunities (Tushman *et al.*, 2002). For example, firms may discover novel customer needs, products, or services, leveraging the full benefits of digitalization and improving operational efficiency and competitiveness (Rehman and Jajja, 2023). However, according to uncertainty management theory (Knight, 1921), uncertainty's negative impact may far outweigh its potential benefits in that it could expose firms to significant risks when they invest in digitalization (Bourreau *et al.*, 2021). For instance, firms may allocate substantial resources to digitalization, but because of unexpected changes in national policies, competitors' actions, or internal environments within firms, these investments may not yield the expected returns.

Considering the potentially conflicting impacts of uncertainty and firms' substantive investments in digitalization, a systematic investigation into the impacts of uncertainty on digitalization is warranted. To offer researchers and practitioners more exhaustive insights, we consider three levels of uncertainty facing firms, namely EPU, IU, and FU, in this study.

EPU is about broad societal, economic, and political fluctuations that can influence an entire industry. EPU directly affects firms' activities and performance (Li, 2020) and brings additional risks or resource requirements to firms' operations, including the effect of digitalization on operational efficiency. Specifically, higher EPU will lead firms to retain fewer resources (Zeng *et al.*, 2020), which are the core input of digitalization's integrating function. Similarly, higher EPU will reduce their human capital (Naidenova, 2022), which is essentially important in digitalization's function relative to organizational routines. Empirical evidence shows that compensation is critical in attracting and retaining digitalization professionals (Ang *et al.*, 2002) who positively impact organizational IT capabilities (Marchiori *et al.*, 2022). In addition, Nagar *et al.* (2019) asserted that during periods of heightened uncertainty, the information environment deteriorates, so there are not enough data for digitalization to identify and leverage complementary capabilities in creating value (Grover and Kohli, 2012). Accordingly, digitalization is unlikely to contribute as expected to the integration of resources to strengthen firms' routines and capabilities. With this logic, higher EPU is a negative factor in digitalization's contribution to firms' efficiency. We thus propose the following:

H2: A high level of EPU weakens the effectiveness of digitalization in enhancing operational efficiency.

IU refers to the unpredictability of various factors within industries (Yu *et al.*, 2023). Higher uncertainty within industries makes it difficult for firms to predict competitor behaviors (Lippman and Rumelt, 2003), inducing a more uncertain business environment. In industries with lower uncertainty, firms can maintain steady production and face fewer rivals (Xue *et al.*, 2012) while utilizing digitalization for resource allocation (Xue *et al.*, 2012), maintaining stable routines (Barney, 2001) and improving firms' capabilities. Limited competition ensures that digitalization can function in a knowledge exchange, optimizing processes and sensing diverse resources. In contrast, the higher the IU is, the higher is the digitalization processing ability required by organizations. We thus propose the following:

H3: A high level of IU weakens the effectiveness of digitalization in enhancing operational efficiency.

Along with external uncertainties, internal uncertainty is also an indispensable challenge facing organizations (Sinding *et al.*, 1998). Micro-level uncertainty in this study is reflected by FU, which refers to the unpredictability of internal factors impacting a firm's operations and performance (Bloom, 2009). First, firms with high FU are unlikely to have stable incomes and often suffer from high capital costs (Islam, 2012), underinvesting in digitalization and inhibiting digitalization's operational efficiency. Second, high FU creates volatile routines, complicating digitalization implementation (Tian and Xu, 2015), and firms may respond by giving up digitalization to avoid potential volatility in sales (Hunter *et al.*, 2004). Lastly, high FU incurs costs, including reduced market value and increased capital costs, posing a dilemma for firms investing in digitalization technologies and developing the necessary capabilities. We thus propose the following:

H4: A high level of FU weakens the effectiveness of digitalization in enhancing operational efficiency.

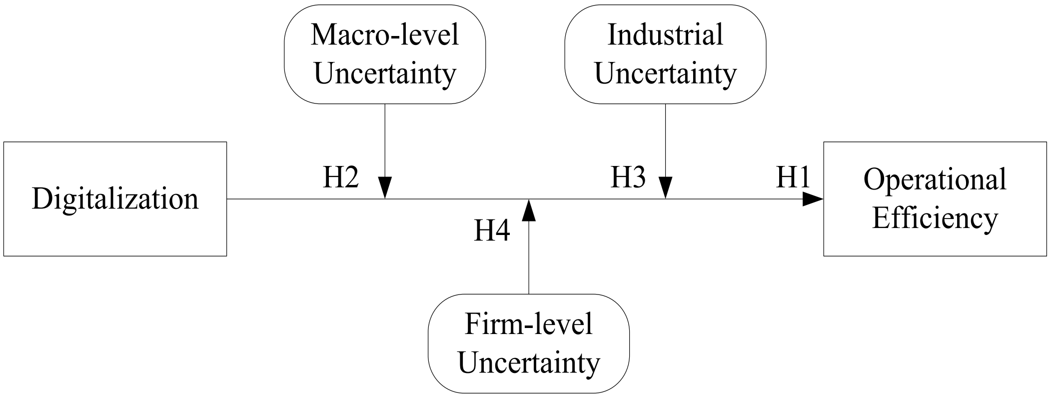


Figure 3.1 Conceptual Framework of The First Study

3.3 Data Collection and Variable Operationalization

To empirically test our hypotheses, we constructed a panel dataset on digitalization, operational efficiency, and the three levels of uncertainty from multiple sources to avoid common method bias (Mithas *et al.*, 2005). We gathered digitalization data from Factiva by identifying 1,430 firms that had made at least one announcement about digitalization during 2015-2021. After matching the announcement data with data on variables concerning operational efficiency and uncertainty from two other databases, namely Compustat and the EPU index, we secured 2,520 samples from 496 firms. A flow chart summarizing the steps in the methodology of this study, including the development of this dataset comprising 2,520 samples, is shown in Figure 3.2.

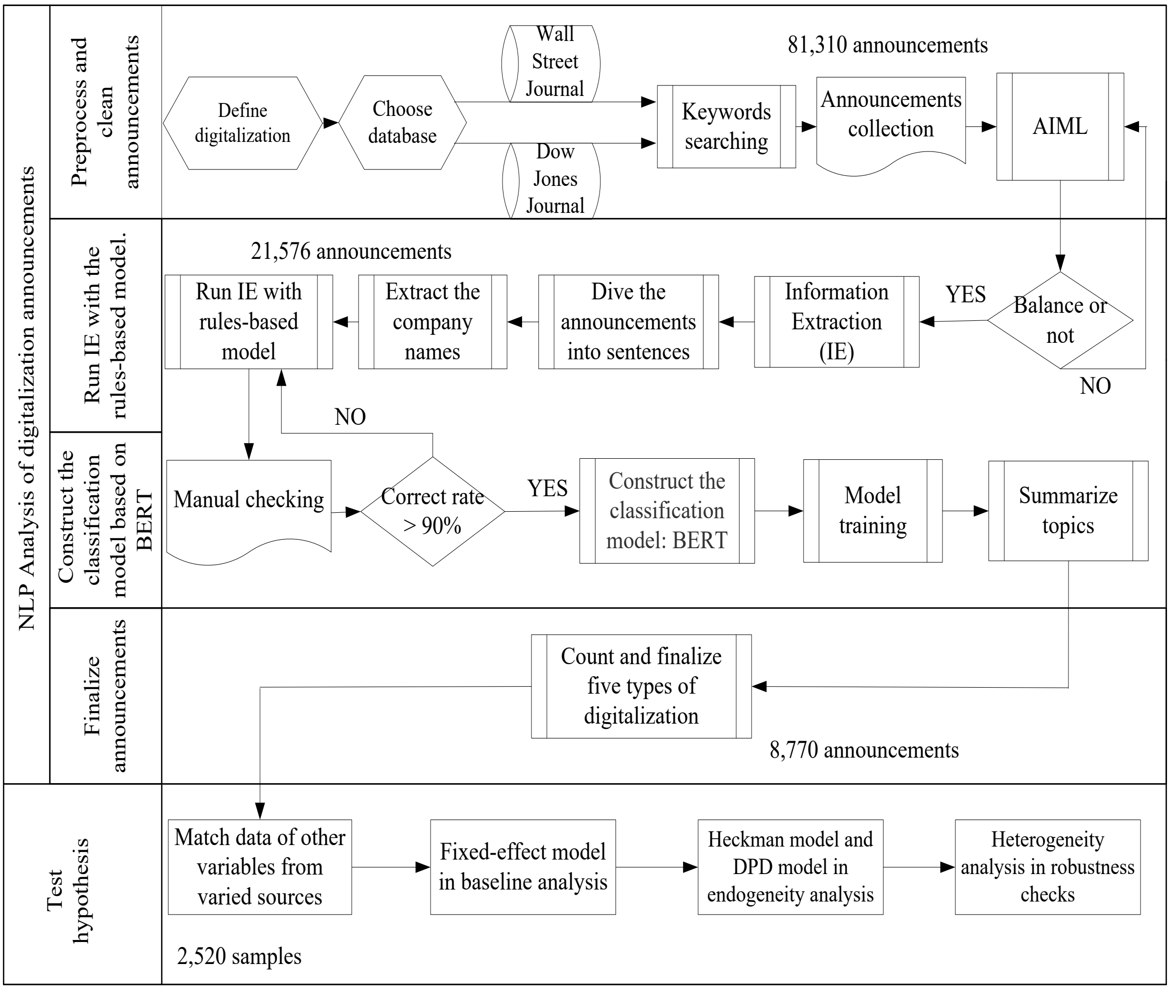


Figure 3.2 Flow Chart Summarizing The Steps in Research Methodology

3.3.1 NLP Analysis of Digitalization Announcements

To achieve better accuracy in the measurement of digitalization adoption, we analyzed digitalization announcements from Factiva using a ML technique called "topic modeling," which is a major type of NLP. Topic modeling aids in revealing the primary themes or topics embedded in unstructured documents such as texts on social media platforms, offering several advantages over existing methods in the literature. Compared to survey-based studies, which are commonly used in the literature, this approach mitigates issues such as response bias, limited sample coverage, and time lags (Bethlehem, 2010). Corporate announcements provide real-time, firm-reported digitalization activities, offering a more objective and timely measurement (Shankar and Parsana, 2022). In contrast to studies that rely on word frequency analysis in annual reports, this method addresses potential noise from generic or repetitive mentions that do not necessarily reflect strategic digitalization efforts (Abraham and Shrives, 2014). By utilizing Factiva's corporate disclosures and industry reports, this study captures more context-specific and meaningful digitalization information. Finally, unlike studies that solely rely on either manual classification or fully automated keyword-based methods, this approach reduces the subjectivity of human judgment and the rigidity of purely algorithmic identification (Sousa Lobo and Yao, 2010). By combining machine learning with human validation, this study enhances both accuracy and contextual understanding in measuring digitalization.

First, aligning with the practical considerations of data collection and informed by the literature (Verhoef *et al.*, 2021), digitalization in this study is defined as a broad concept that encompasses the use of numerous digitalization technologies or tools. With this broad definition, we derived key words to search for relevant digitalization announcements from the Factiva database. Appendix A gives the details of the announcement collection process.

After searching, gathering, and preprocessing the complete digitalization announcements from two sources within Factiva (Shankar and Parsana, 2022), the *Wall Street Journal*, and *Dow Jones Newswire*s, we classified the announcements into five types, such that four of them represented types of genuine digitalization adoption in practice (Bjorkdahl, 2020). Table 3.1 shows example announcements of these four types of digitalization. Then, we analyzed the digitalization announcements with topic modeling steps consistent with the literature (Dotzel and Shankar, 2019; Mejia *et al.*, 2019). Specifically, we adopted the latent Dirichlet allocation (LDA) model to reorganize the five types of digitalization into two topic clusters (e.g., digitalization announcements and non-digitalization announcements). The detailed process is presented in Appendix B. Note that the results obtained from the LDA model were also checked manually to achieve advantages such as scalability, discovery of hidden patterns, and consistency (Blei, 2012). In short, the combination of LDA and manual checking ensured both efficiency and accuracy in this part of the data processing and analysis.

Table 3.1 Samples of Digitalization

Category	Firms' name	Date	Samples of digitalization announcement
Use information and communication platforms of the second-party firm	SeABank	29-Dec-2021	SeABank enhances digital banking experiences with Google Cloud. Southeast Asia Commercial Joint Stock Bank has chosen Google Cloud as its primary cloud provider to enhance the service quality and customer experiences delivered on its SeAMobile/SeANet digital banking platform.
	Armis	28-Dec-2021	Armis selects Radware to deliver cloud security for AWS.
	Green-GO Digital	23-Dec-2021	Sequans Communications S.A. (NYSE: SQNS), a leading provider of cellular IoT chips and modules for massive and broadband IoT, announced that Green-GO Digital is using its Cassiopeia CB410L CBRS module to connect its new Beltpack Sports wireless intercom communications device.
Cooperate with other firms to co-construct digital infrastructures or platforms	Ardonagh and Mphasis	23-Dec-2021	Expanding on this, in 2021, Mphasis and Ardonagh agreed to set up a shared services entity to service middle and back-office functions while applying digital transformation.
	Phunware and PrimusTech	23-Dec-2021	Phunware announces partnership with PrimusTech to integrate mobile smart solutions in Asia.
	Borqs and Cheyin	22-Dec-2021	Borqs and Cheyin's cooperation plans to develop the smart digital cockpit market by deploying Qualcomm's integrated and scalable automotive solutions, including but not limited to the R&D and manufacturing of in-vehicle-infotainment systems, intelligent cockpit systems, intelligent assisted driving systems and other products based on the Qualcomm technology platform.

Category	Firms' name	Date	Samples of digitalization announcement
Extend the firm's business to the digitalization field through acquisition	Sage	21-Dec-2021	Sage acquired Brightpearl. This acquisition accelerates Sage's strategy for growth, including scaling Sage Intact, broadening the value proposition for mid-sized businesses, and expanding Sage's digital network.
	Oracle Corp.	21-Dec-2021	Oracle Corp. on Monday announced its largest deal ever, a roughly $28.3 billion purchase of electronic-medical-records company Cerner Corp. that vaults the business-software giant deeper into health-care technology. With this acquisition, Oracle's corporate mission expands to provide our overworked medical professionals with a new generation of easier-to-use digital tools that enable access to information via a hands-free voice interface to secure cloud applications.
	MCAP Acquisition Corporation	22-Dec-2021	MCAP Acquisition Corporation ("MCAP"; Nasdaq: MACQ), a special purpose acquisition company sponsored by an affiliate of Monroe Capital LLC ("Monroe Capital"), today announced the completion of its business combination (the "Business Combination") with AdTheorent Holding Company, LLC ("AdTheorent" or the "Company"), a leading programmatic digital advertising company using advanced machine learning technology and privacy-forward solutions to deliver measurable value for advertisers and marketers.
Develop digital technology by the company (and use it in the production or operation)	Mobiquity Technologies, Inc.	29-Dec-2021	Mobiquity Technologies, Inc. (NASDAQ: MOBQ; the "Company"), a leading provider of next-generation advertising, today announced a new end-user feature for MobiExchange (www.mobiexchange.com), the Company's SaaS platform for digital advertising and data services.
	Brain+	29-Dec-2021	Brain+ has developed a set of digital medicine technologies, which enable the Company to create a unique and differentiated product offering.
	EchoPark	22-Dec-2021	EchoPark is…and is already making its mark by earning the 2021 Consumer Satisfaction Award from DealerRater, expanding its Owner Experience Centers, developing an all-new digital ecommerce platform, and focusing on growing its brand nationwide.
	LiveFreely	22-Dec-2021	LiveFreely announces the Apple Watch version of "BUDDY," the predictive AI-driven digital health assistant for seniors and their loved ones.
	The Bank of Mexico	31-Dec-2021	Central banks need to move quickly to develop new forms of money and fully operable digital currencies amid the growing use of crypto assets and the risks they entail.

With NLP, we collected 8,770 announcements by 1,430 firms from Factiva, covering firms that made at least one digitalization announcement in the period 2015 to 2021.

3.3.2 Variables Measurement

Independent variable: Digitalization. Through the process presented in Section 3.1, we obtained announcements on digitalization. We developed our data by standardizing the announcement numbers within different industries (*j*) based on the 2-digit SIC codes as follows:

$$Digitalization_{ijt} = \frac{\begin{pmatrix} Number\ of\ digitalization\ announcements_{ijt} - \\ Mean\ of\ number\ of\ digitalization\ announcements_{jt} \end{pmatrix}}{Standard\ deviation\ of\ number\ of\ digitalization\ announcements_{jt}} \tag{3.1}$$

Dependent variable: Operational efficiency. Based on the literature (Li *et al.*, 2010), we adopted SFA to measure operational efficiency, offering a more comprehensive measurement of a firm's operational efficiency than the traditional single dimension indicator (Lam *et al.*, 2016). We calculated operational efficiency using a time varying model as follows:

$$ln(Operating\ income)_{ijt} = \beta_0 + \beta_1 ln(Number\ of\ employees)_{ijt} + \beta_2 ln(Cost\ of\ goods\ sold)_{ijt} + \beta_3 ln(Capital\ expenditure)_{ijt} + \varepsilon_{ijt} + \eta_{ijt} \tag{3.2}$$

After getting η_{ijt}, the inefficiency's corresponding frontier of operational efficiency in the same industry, we utilized Eq. (3.3) to calculate its operational efficiency, and further standardized operational efficiency with Eq. (3.4):

$$Operational\ Efficiency_{ijt} = 1 - \widehat{\eta_{ijt}} \tag{3.3}$$

$$Operational\ Efficiency_{ijt} = \frac{(Value\ of\ operational\ efficiency_{ijt} - Mean\ of\ operational\ efficiency_{jt})}{Standard\ deviation\ of\ value\ of\ operational\ efficiency_{jt}} \tag{3.4}$$

Moderators: EPU. EPU is reflected by the economic risk relative to undefined upcoming government policies and regulatory structures, and is measured by the BBD index provided by the EPU website of Baker, Bloom, and Davis (Baker *et al.*, 2016).

IU. On the basis of the literature (Chung *et al.*, 2019), we measured IU using Eq (3.5). Note that the four-firm concentration ratio is the combined market share of the four largest firms in an industry, expressed as a percentage (Chung *et al.*, 2019).

$$IU = 1 - \textit{Four-firm concentration ratio} \tag{3.5}$$

FU. The literature on FU is sparse and mostly limited by data availability (Fiori and Scoccianti, 2021). Furthermore, traditional measures, such as daily stock price volatility, have higher-frequency characteristics that may not capture the annual uncertainty faced by firms (Ilut and Schneider, 2014). Therefore, our measurement of FU is concerned with the realized or implied annual volatility of firm sales, and is obtained by computing the standard deviation of changes in earnings in sample firms as follows (Chen *et al.*, 2022):

$$FU = \sqrt{[\sum(\Delta E_{t+i+1} - E_{t+i} - \mu)^2/5]} \tag{3.6}$$

where ΔE_{t+i+1} represents the earnings before extraordinary items for year (t+i+1), where t denotes the initial year, and i ranges from 1 to 5, indicating the specific year within the 5-year period being analyzed.

Other variables. Table 3.2 provides a list of all the variables, their operationalization, and data sources.

Table 3.2 Key Variable Measurement of Study 1

Variables (Abbreviations)	Measurement	Source	Reference
	Independent Variable		
Digitalization (DIGI)	Annual firm-level count of digitalization announcements	Factiva	Dotzel and Shankar (2019)
	Dependent Variables		
Operational Efficiency (OE)	A firm's efficiency (relative to its industry peers with the same four-digit SIC code) in transforming operational inputs, i.e., EMP, CGS, and CEX, into operational output, i.e., OI, based on stochastic frontier estimation	Compustat	Lam *et al.* (2016) Li *et al.* (2022a)
	Moderating Variables		
Macro-level Uncertainty (EPU)	Policy uncertainty is measured with the BBD index developed by Baker *et al*., a monthly index that is transferred into annually data with mean value.	EPU	Baker *et al.* (2016)
Industrial Uncertainty (IU)	IU = 1-four-firm concentration ratio. A higher value of the (1-ratio) implies more competitors and a higher level of uncertainty within the industry.	Compustat	Chung *et al.* (2019); Xue *et al.* (2012)
Firm level Uncertainty (FU)	Standard deviation of change in earnings [SD(Δ*Et+1, t+5*)] is calculated based on the change in earnings before extraordinary items over the previous year for years *t+1*.	Compustat	Chen *et al.* (2022); Kobelsky *et al.* (2008)
	Control variables		
Market-to-Book Ratio (MTBR)	A firm's market value of equity divided by book value of equity.	Compustat	Hendricks *et al.* (2015); Li *et al.* (2022a)
Firm Leverage (LEVE)	A firm's total debt divided by total assets.	Compustat	Li *et al.* (2022a); Yiu *et al.* (2020)
Firm Size (SIZE)	A firm's total assets based on a logarithmic transformation.	Compustat	Li *et al.* (2022a); Li *et al.* (2010)
Firm Age (AGE)	Number of years since the firm's initial public stock offering	Compustat	Lam *et al.* (2016)
Firm R&D Expense (R&DE)	A firm's ratio of expenditures on research and development divided by the firm's sales	Compustat	Lam *et al.* (2016)
Firm Advertising Expense (AE)	Expenses associated with marketing a firm's brands, products, or services via media outlets	Compustat	Lam *et al.* (2016)

3.3.3 Summary Statistics and Correlations

The descriptions of our 2,520 samples are shown in Table 3.3 (see panels A and B). These sample firms operate in 49 industries with 2-digit SIC codes. Note that the top 20 industries are presented in panel C of Table 3.3. The correlation analysis of the variables are presented in Table 3.4, respectively.

Table 3.3 Descriptive Statistics of Study 1

Panel A: Percentage of industry based on 2-digit SIC codes

2-digit SIC code	Firm Frequency	Industry	Firm percentage
73	878	Business services	34.8%
36	196	Electronic and other electric equipment	7.8%
35	177	Industrial machinery and equipment	7.0%
48	131	Communications	5.2%
38	122	Instruments and related products	4.8%
60	122	Depository institutions	4.8%
28	112	Chemical and allied products	4.4%
37	58	Transportation equipment	2.3%
62	50	Security and commodity brokers, dealers, exchanges, and services	2.0%
87	49	Engineering, accounting, research, management, and related services	1.9%
63	48	Insurance carriers	1.9%
67	42	Holding and other investment offices	1.7%
59	40	Miscellaneous retails	1.6%
61	36	Non-depository credit institutions	1.4%
50	34	Wholesale trade e-durable goods	1.3%
99	26	Non-classifiable establishments	1.0%
13	25	Oil and gas extraction	1.0%
27	25	Printing, publishing, and allied industries	1.0%
58	25	Eating and drinking places	1.0%
78	19	Motion pictures	0.8%
Other codes	305	Other industries	12.3%
Total	2520		100%

Panel B: Percentage of industry based on sectors

Sector	Percentage
I. Services	41.4%
D. Manufacturing	31.9%
H. Finance, insurance, and real estate	11.4%
E. Transportation, communications, electric, gas and sanitary services	7.3%
G. Retail trade	4.2%
F. Wholesale trade	1.8%
B. Mining	1.1%
C. Construction	0.9%
A. Agriculture, forestry, and fishing	0.0%
Total	100%

Panel C: Industry groups of sample firms

Industry Group	Description	Firm	Percentage
01–19	Agriculture, mining, and construction	44	1.7%
20–23, 27	Other non-durable manufacturing	53	2.1%
26, 28, 29	Process manufacturing	138	5.5%
36–38	High-tech manufacturing	376	14.9%
24,25, 30–35, 39	Other durables	213	8.5%
40–48	Transportation and communications	169	6.7%
49	Utilities	18	0.7%
50–59	Retail and wholesale	160	6.3%
60–69	Financial institutions	319	12.7%
70–99	Services and others	1032	41.0%
Total		2520	100.0%

Table 3.4 Correlation Matrix of Study 1

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) $OE_{i,t+1}$	1.000											
(2) $OE_{i,t}$	0.408	1.000										
	(0.000)											
(3) $DIGI_{i,t}$	0.108	0.041	1.000									
	(0.000)	(0.087)										
(4) $EPU_{i,t}$	0.027	0.012	0.034	1.000								
	(0.259)	(0.599)	(0.162)									
(5) $IU_{i,t}$	-0.040	-0.032	-0.006	-0.005	1.000							
	(0.093)	(0.178)	(0.809)	(0.823)								
(6) $FU_{i,t}$	0.075	0.068	-0.004	0.028	0.098	1.000						
	(0.002)	(0.004)	(0.872)	(0.240)	(0.000)							
(7) $SIZE_{i,t}$	-0.152	-0.150	0.152	0.004	-0.071	-0.053	1.000					
	(0.000)	(0.000)	(0.000)	(0.865)	(0.003)	(0.024)						
(8) $AGE_{i,t}$	-0.041	-0.041	0.075	0.030	-0.015	-0.102	0.320	1.000				
	(0.086)	(0.081)	(0.002)	(0.203)	(0.523)	(0.000)	(0.000)					
(9) $LEVE_{i,t}$	-0.014	-0.011	0.000	0.014	0.013	-0.010	0.063	-0.014	1.000			
	(0.564)	(0.644)	(0.994)	(0.564)	(0.576)	(0.677)	(0.007)	(0.555)				
(10) $MTBR._{i,t}$	-0.009	-0.006	0.015	-0.155	0.025	0.006	0.036	-0.006	0.122	1.000		
	(0.695)	(0.791)	(0.537)	(0.000)	(0.293)	(0.787)	(0.133)	(0.786)	(0.000)			
(11) $AE_{i,t}$	0.017	0.005	0.208	0.048	-0.037	-0.006	0.464	0.163	0.017	0.017	1.000	
	(0.478)	(0.820)	(0.000)	(0.041)	(0.122)	(0.804)	(0.000)	(0.000)	(0.480)	(0.474)		
(12) $R\&DE_{i,t}$	0.061	0.087	0.348	0.028	-0.005	0.082	0.377	0.216	0.010	0.017	0.471	1.000
	(0.010)	(0.000)	(0.000)	(0.238)	(0.828)	(0.001)	(0.000)	(0.000)	(0.679)	(0.477)	(0.000)	

Note: n=2289; P-value in parentheses in columns

3.4 Model Development and Results Analysis

3.4.1 Model Development

We developed an equation with firm operational efficiency as the dependent variable. Note that U presents EPU, IU, and FU, which are excluded in testing H1. Subscript i denotes the firm and subscript t denotes the calendar year:

$$Operational\ Efficiency_{i,t+1} = \alpha_0 + \alpha_1 Digitalization_{it} + \alpha_2 U_{it} + \alpha_3 Digitalization_{it} \times U_{it} + \alpha_4 Firm\ Size_{it} + \alpha_5 Firm\ Age_{it} + \alpha_6 MarkettoRatio_{it} + \alpha_7 Firm\ Leverage_{it} + \alpha_8 R\&D\ Expenses_{it} + \alpha_9 Firm\ Advertising\ Expense_{it} + \sum_{k=1}^{D} \delta_k\, IND_k + \sum_{m=1}^{Y} \mu_k\, YEAR_m + \varepsilon_{it.} \tag{3.7}$$

We lagged independent variables in the equations by a year because it takes time for firms to adjust the new operational modes brought by digitalization and for these modes to take effect on operational efficiency (Dotzel and Shankar, 2019; Li *et al.*, 2022a).

The analysis controls for six firm level variables, including firm size (Qiu *et al.*, 2022), firm age (Qiu *et al.*, 2022), leverage (Li *et al.*, 2022a; Yiu *et al.*, 2020), advertising expense (Lam *et al.*, 2016), market-to-book ratio (Hendricks *et al.*, 2015; Li *et al.*, 2022a) and firm R&D expenses (Lam *et al.*, 2016). To control for unobservable time and individual effects, the current analysis added the year- and firm-fixed effects in the regression models.

3.4.2 Baseline Analysis

We constructed estimating models using Eq. (3.6) and illustrated the results of the fixed-effect (FE) model in Table 3.5, and validated the results with robust t (columns 5–8) and bootstrap z statistics (columns 9–12 (Qiu *et al.*, 2022). We utilized robust t and bootstrap z statistics to address the possibility that the model may fail to meet standard regression assumptions, and we clustered all the standard errors at the firm level.

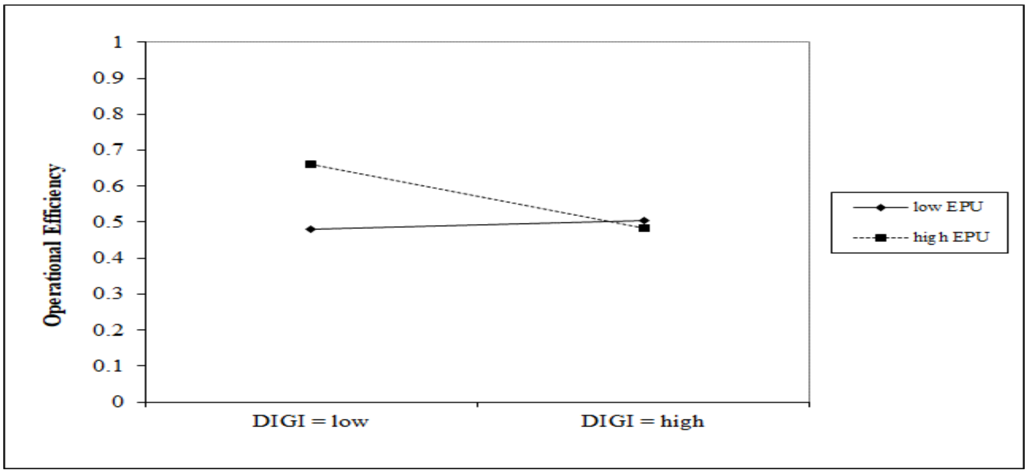
Table 3.5 Results of FE Regression Analysis of Study 1

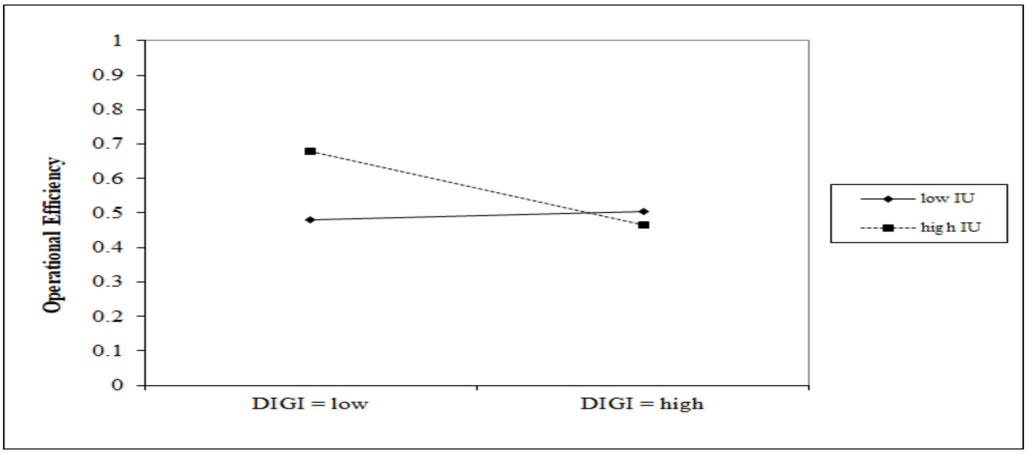
Variable	(1) $OE_{i,t+1}$	(2) $OE_{i,t+1}$	(3) $OE_{i,t+1}$	(4) $OE_{i,t+1}$	(5) $OE_{i,t+1}$ (robust t)	(6) $OE_{i,t+1}$ (robust t)	(7) $OE_{i,t+1}$ (robust t)	(8) $OE_{i,t+1}$ (robust t)	(9) $OE_{i,t+1}$ (bootstrap z)	(10) $OE_{i,t+1}$ (bootstrap z)	(11) $OE_{i,t+1}$ (bootstrap z)	(12) $OE_{i,t+1}$ (bootstrap z)
$DIGI_{i,t}$	**.0047*****	.0007	.0048***	.0046***	**.0047*****	.0007	.0048**	.0046***	**0.0047****	.0007***	.0048***	.0045**
	(4.24)	(0.50)	(4.38)	(4.17)	**(3.27)**	(0.27)	(3.45)	(3.36)	**(3.25)**	(0.25)	(4.08)	(3.33)
$EPU_{i,t}$		.0067				.0067				.0067		
		(1.52)				(1.47)				(1.29)		
$IU_{i,t}$			-.0026**				-.0026*				-.0026*	
			(-2.66)				(-1.75)				(-1.85)	
$FU_{i,t}$				.0014				.0014*				.0014
				(1.31)				(2.15)				(2.08)
$DIGI_{i,t} \times EPU_{i,t}$		**-.0117*****				**-.0117***				**-.0117***		
		(-4.63)				**(-2.49)**				**(-2.16)**		
$DIGI_{i,t} \times IU_{i,t}$			**-.0049*****				**-.0049***				**-.0049***	
			(-4.62)				**(-2.30)**				**(-2.33)**	
$DIGI_{i,t} \times FU_{i,t}$				**-.0010**				**-.0010**				-.0011
				(-1.13)				**(-1.02)**				(-0.93)
$SIZE_{i,t}$	-.0029***	-.0028***	-.0028***	-.0029***	-.0029***	-.0028***	-.0029***	-.0029***	-.0028***	-.0028***	.0029***	-.0029***
	(-5.09)	(-5.07)	(-5.14)	(-5.08)	(-6.98)	(-6.91)	(-6.69)	(-7.07)	(-6.98)	(-6.97)	(-6.84)	(-6.91)
$AGE_{i,t}$	-.0001	-.0001	-.0001	-.0001	-.0001	-.0001	-.0000	-.0001	-.0001	-.0001	.0000	-.0001
	(-0.52)	(-0.77)	(-0.42)	(-0.51)	(-0.29)	(-0.42)	(-0.23)	(-0.28)	(-0.29)	(-0.40)	(-0.23)	(-0.28)

Variable	(1) $OE_{i,t+1}$	(2) $OE_{i,t+1}$	(3) $OE_{i,t+1}$	(4) $OE_{i,t+1}$	(5) $OE_{i,t+1}$ (robust t)	(6) $OE_{i,t+1}$ (robust t)	(7) $OE_{i,t+1}$ (robust t)	(8) $OE_{i,t+1}$ (robust t)	(9) $OE_{i,t+1}$ (bootstrap z)	(10) $OE_{i,t+1}$ (bootstrap z)	(11) $OE_{i,t+1}$ (bootstrap z)	(12) $OE_{i,t+1}$ (bootstrap z)
$LEVE_{i,t}$	-.0001	-.0001	-.0001	-.0000	-.0000	-.0001*	-.0000	-.0001	-.0000	-.0000	.0000	-.0000
	(-0.67)	(-0.76)	(-0.69)	(-0.66)	(-1.60)	(-1.82)	(-1.63)	(-0.73)	(-1.60)	(-0.78)	(-0.67)	(-0.70)
$MTBR_{i,t}$	-2.91e-06	-9.15e-07	-2.58e-06	-2.85e-06	-2.91e-06	-9.15e-07	-2.58e-06	-2.85e-06	-2.91e-06	-9.15e-07	-2.58e-06	-2.85e-06
	(-0.34)	(-0.11)	(-0.30)	(-0.33)	(-1.79)	(-0.22)	(-1.49)	(-0.51)	(-1.79)	(-0.12)	(-0.41)	(-0.51)
$AE_{i,t}$	3.47e-06*	3.23e-06*	3.30e-06*	3.57e-06*	3.47e-06*	3.23e-06	3.30e-06	3.57e-06	3.47e-06	3.23e-06	3.30e-06	3.57e-06
	(2.10)	(1.96)	(2.01)	(2.16)	(1.37)	(1.34)	(1.36)	(1.31)	(1.37)	(1.28)	(1.31)	(1.35)
$R\&DE_{i,t}$	1.10e-06	8.66e-07	1.02e-06	1.17e-06	1.10e-06	8.66e-07	1.02e-06	1.17e-06	1.10e-06	8.66e-07	1.02e-06	1.17e-06
	(1.45)	(1.14)	(1.34)	(1.50)	(0.85)	(0.69)	(0.83)	(0.84)	(0.85)	(0.70)	(0.83)	(0.80)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.9427***	.9473***	.9410***	.9431***	.9427***	.9473***	.9410***	.9431***	.9427***	.9473***	.9410***	.9431***
	(115.68)	(109.44)	(116.15)	(115.71)	(194.57)	(180.84)	(189.07)	(192.66)	(186.17)	(166.33)	(183.38)	(185.01)
R^2	0.1599	0.1706	0.1733	0.1613	0.1599	0.1706	0.1733	0.1613	0.1599	0.1706	0.1733	0.1613
Adjusted R^2	0.1345	0.1446	0.1473	0.1350					0.1345	0.1446	0.1473	0.1350
F value	6.31	0.0000	0.0000	0.0000						0.0000	0.0000	0.0000
Wald chi2									4649.59	4277.01	3948.34	4465.30
Observations	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744

Note: robust t statistics in parentheses in columns (5–8), bootstrap z statistics in parentheses in columns (9–12). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ t-statistics are in parentheses.

The results in column (1) of Table 3.5 indicate that digitalization positively affects operational efficiency ($p < 0.01$), supporting H1. Then, the findings in column (2) show that EPU mitigates the enhancement effect of digitalization on operational efficiency ($p < 0.01$), supporting H2. Similarly, the findings in column (3) show that IU mitigates the enhancement effect of digitalization on operational efficiency ($p < 0.01$), supporting H3. The findings in column (4) reveal that FU does not exhibit a significant moderating influence on the effectiveness of digitalization ($p > 0.1$), rejecting H4. Figure 3.3 illustrates the moderating effect of varying levels of uncertainty on the relationship between digitalization and operational efficiency. The Figure 3.3 shows intuitively and simply that the effect of DIGI on OE is significantly different at low and high EPU and IU levels, while is not showing obvious different at low and high FU levels.





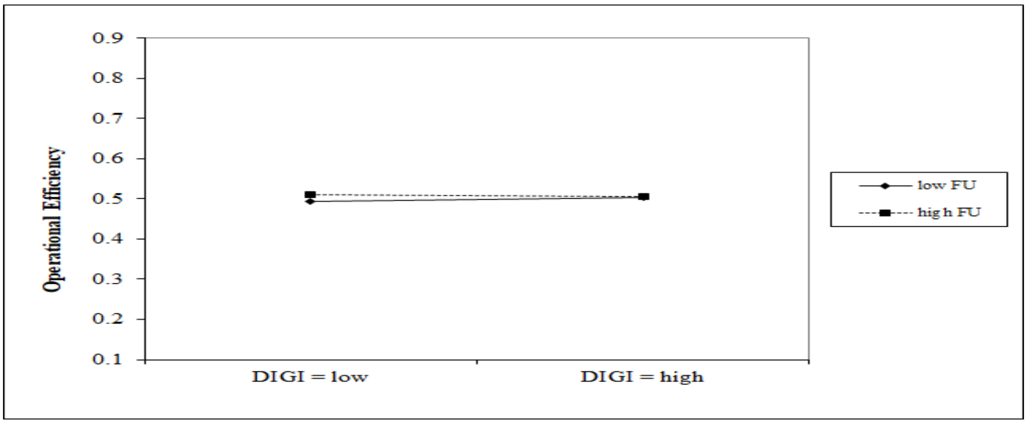


Figure 3.3 The Moderating Effect of Uncertainty on The Relationship between Digitalization and Operational Efficiency of Study 1

In addition, in order to more profound understand the impact of EPU, IU and FU on operational efficiency, this chapter has drawn the surface diagram and contour diagram of the impact of digitalization (DIGI) and three different levels of uncertainty (EPU, IU and FU) on operational efficiency (OE), as shown in Figures 3.4 to 3.6. As can be seen from the surface plots in Figures3.4 and 3.5, higher OE is observed at the higher levels of DIGI and at the lower levels of EPU and IU. In other words, when EPU and IU are low, the higher the level of DIGI of firms has a positive impact on the operational efficiency. However, in the surface figure of Figures 3.6, this study finds that with the decrease of FU, the improvement of operational efficiency is not significant with the increasing DIGI. The contour plots also depict the same result: starting from the lower left area with low uncertainty (when EPU and IU are low) to the right, it can be observed that OE increases with the level of DIGI (color changes from red to green); Similarly, starting from the upper left area with high uncertainty (when EPU and IU are high) to the right, it can be observed that OE decreases with the increasing DIGI (color changes from red to green), which further supports Hypotheses H2 and H3. However, in the contour plots in Figures 3.6, with the increase or decrease of FU, the change of OE caused by DIGI is not obvious (the color does not change much), so Hypothesis 4 is not verified.

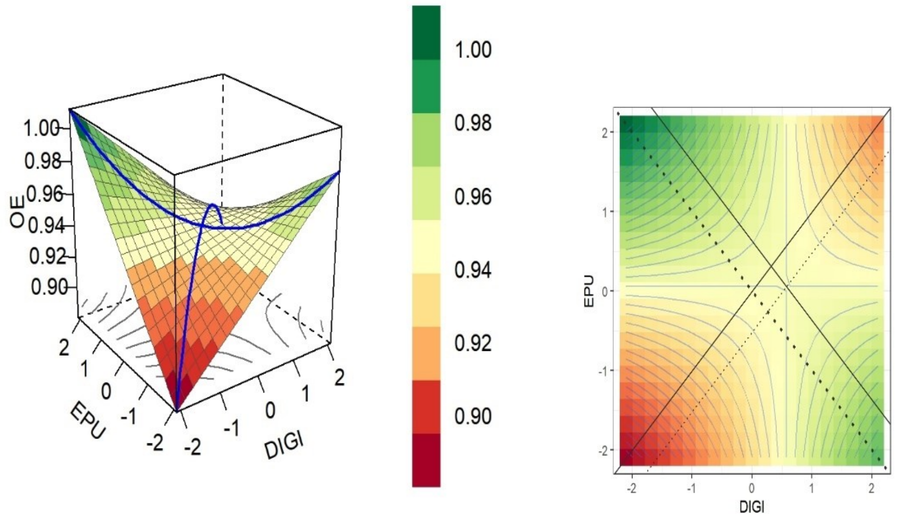


Figure 3.4 The Interaction Effect of Digitalization and Macro Uncertainty on Operational Efficiency

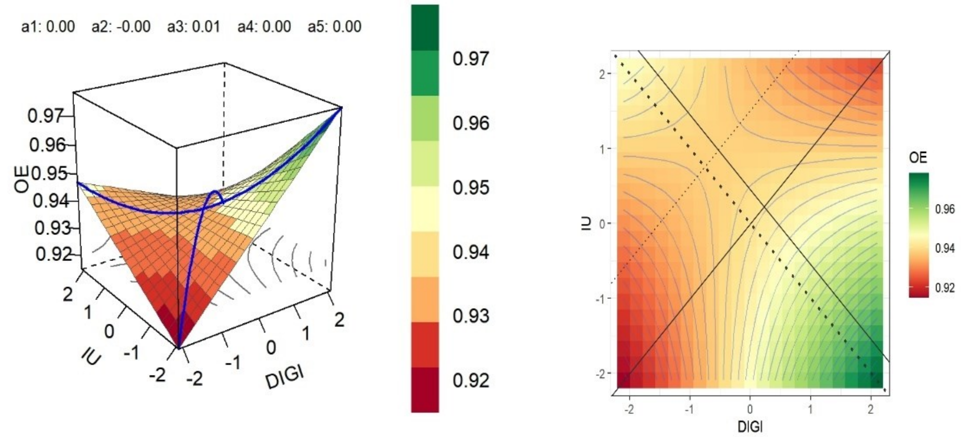


Figure 3.5 The Interaction Effect of Digitalization and Industrial Uncertainty on Operational Efficiency

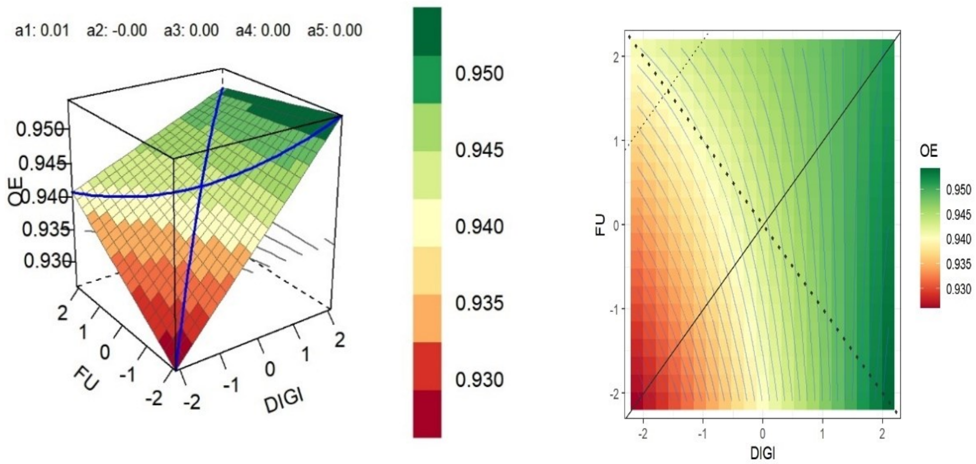


Figure 3.6 The Interaction Effect of Digitalization and Firm Uncertainty on Operational Efficiency

3.4.3 Endogeneity Concerns Analysis

The endogeneity issue that incorrect conclusions may result when one or more explanatory variables in a model are associated with the error item (Toh and Polidoro, 2013). Generally, endogeneity can stem from causes such as reverse causality, sample selection bias, and omitted variables (Toh and Polidoro, 2013).

First, the issue of reverse causality pertains to the possibility that digitalization could be endogenously determined because firms with higher operational efficiency may have more opportunities to adopt and capital to invest in digitalization. Under this situation, digitalization and the error term may be correlative, resulting in endogeneity. Based on prior studies (Hegde and Mishra, 2019), we used a one year lag of each digitalization and the control variables instead of their present values in Eq (3.7) to process the regression, which helps mitigate the potential endogeneity issue brought by reverse causality.

Second, there exists the possibility of sample selection bias in the data-collection process, so we employed the Heckman model (Kumar *et al.*, 2018) to address this potential issue. We constructed regression using Eq. (3.8) to estimate firms' probability to adopt digitalization. We next estimated the inverse mills ratio (IMR) and then estimated Eq. (3.8) by controlling IMR:

$$Probit\left(Digitalization_{i,t}=1\right)=\vartheta_0+\vartheta_1 Firm\,Size_{it}+\vartheta_2 Firm\,Age_{it}+\vartheta_3 MarkettoRatio_{it}+\vartheta_4 Firm\,Leverage_{it}+\vartheta_5 R\&D\,Expenses_{it}+\vartheta_6 Firm\,Advertising\,Expense_{it}+\sum_{k=1}^{D}\varphi_k\,IND_k+\sum_{m=1}^{Y}\omega_k\,YEAR_m+\epsilon_{it.} \quad (3.8)$$

In Eq.(3.8), we stipulated that the digitalization level equals 1 if the focal firm *i* issued at least one digitalization announcement in year *t*; the firm's size, firm's age, firm's market-to-ratio, firm's leverage, R&D expenses, and advertising expenses are considered as variables that can affect the firm's profitability. After getting the IMR value, we controlled the IMR in the second step of the Heckman model. We report the Heckman results in Table 3.6.

Table 3.6 Results of Heckman Correction of Study 1

Variable	(1)	(2)	(3)	(4)
	$OE_{i,t+1}$	$OE_{i,t+1}$	$OE_{i,t+1}$	$OE_{i,t+1}$
$DIGI_{i,t}$	**.0048*****	.0008	.0049***	.0047***
	(4.33)	(0.57)	(4.45)	(4.17)
IMR	.0034*	.0034*	.0025	.0034*
	(2.00)	(2.04)	(1.51)	(1.99)
$EPU_{i,t}$		.0074		
		(1.52)		
$IU_{i,t}$			-.0025*	
			(-2.54)	
$FU_{i,t}$				.0013
				(1.14)
$DIGI_{i,t}$×$EPU_{i,t}$		**-.0117*****		
		(-4.63)		
$DIGI_{i,t}$×$IU_{i,t}$			**-.0048*****	
			(-4.50)	
$DIGI_{i,t}$×$FU_{i,t}$				**-.0013**
				(-1.14)
$SIZE_{i,t}$	-.0033***	-.0033***	-.0032***	-.0033***
	(-5.09)	(-5.47)	(-5.34)	(-5.46)
$AGE_{i,t}$	.0001	.0001	.0001	.0001
	(-0.52)	(0.42)	(0.45)	(0.62)
$LEVE_{i,t}$	-.0000	-.0000	-.0000	-.0000
	(-0.62)	(-0.70)	(-0.65)	(-0.60)
$MTBR_{i,t}$	-2.54e-06	-6.94e-07	-2.32e-06	-2.47e-06
	(-0.29)	(-0.08)	(-0.27)	(-0.29)
$AE_{i,t}$	5.14e-06**	4.91e-06**	4.57e-06*	5.26e-06*
	(2.78)	(1.96)	(2.48)	(2.83)
$R\&DE_{i,t}$	1.75e-06*	1.54e-06*	1.51e-06	1.87e-06
	(2.12)	(1.86)	(1.84)	(2.19)
Year-fixed effect	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES
Constant	.9268***	.9317***	.9290***	.9272***
	(81.50)	(80.54)	(82.10)	(81.21)
R^2	0.1618	0.1706	0.1744	0.1633
Observations	1744	1744	1744	1744

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ t-statistics are in parentheses.

The results show that the coefficient of digitalization remains significantly positive (p<0.01), whereas the moderating effects of EPU (p<0.01) and IU (p<0.01) are still significantly negative, and the moderating effect of the coefficient of FU is the same, i.e., insignificant (p>0.1).

Last, the issue of omitted variables is common in econometric models because it is impossible to make sure that a model can cover all the relevant variables. Referring to prior research on operational efficiency (Lam *et al.*, 2016; Qiu *et al.*, 2022), we considered that operational efficiency has the persistent influence of past operational efficiency. We built a dynamic panel data (DPD) model using Eq. (3.9) as follows:

$$
\begin{aligned}
&Operational\ Efficiency_{i,t+1} \\
&\quad = \beta_0 + \beta_1 Operational\ Efficiency_{i,t} + \beta_2 Digitalization_{it} + \beta_3 U_{it} \\
&\quad + \beta_4 Digitalization_{it} \times U_{it} + \beta_5 Firm\ Size_{it} + \beta_6 Firm\ Age_{it} \\
&\quad + \beta_7 MarkettoRatio_{it} + \beta_8 Firm\ Leverage_{it} + \beta_9 R\&D\ Expenses_{it} \\
&\quad + \beta_{10} Firm\ Advertising\ Expense_{it} + \sum_{k=1}^{D} \varphi_k IND_k + \sum_{m=1}^{Y} \omega_k YEAR_m \\
&\quad + \epsilon_{it.}
\end{aligned}
\tag{3.9}
$$

Indeed, results of Table 3.4 indicate that the operational efficiency of a firm is very significantly associated with its performance in the previous year (R=0.408, p<0.01). Table 3.7 reports the results of the DPD model, in which the findings are consistent, i.e., H1, H2, and H3 are supported, and H4 is rejected.

Table 3.7 Results of DPD Analysis of Study 1

Variable	(1) $OE_{i,t+1}$	(2) $OE_{i,t+1}$	(3) $OE_{i,t+1}$	(4) $OE_{i,t+1}$	(5) $OE_{i,t+1}$ (robust t)	(6) $OE_{i,t+1}$ (robust t)	(7) $OE_{i,t+1}$ (robust t)	(8) $OE_{i,t+1}$ (robust t)	(9) $OE_{i,t+1}$ (bootstrap z)	(10) $OE_{i,t+1}$ (bootstrap z)	(11) $OE_{i,t+1}$ (bootstrap z)	(12) $OE_{i,t+1}$ (bootstrap z)
$OE_{i,t}$	**.3252*****	**.3275*****	**.3215*****	**.3244*****	.3252*	.3276**	.3215*	.3244*	.3252*	.3276*	.3215*	.3244*
	(13.42)	**(13.61)**	**(13.34)**	**(13.39)**	(2.44)	(2.43)	(2.45)	(2.43)	(2.26)	(2.25)	(2.26)	(2.25)
$DIGI_{i,t}$	**.0045*****	.0003	.0046***	.0045***	.0045**	.0003	.0046**	.0045**	0.0045**	.0003	.0046**	.0045**
	(4.30)	(0.24)	(4.45)	(4.24)	(3.27)	(0.13)	(3.49)	(3.38)	(3.24)	(0.12)	(4.08)	(3.34)
$EPU_{i,t}$		.0056				.0056				.0056		
		(1.35)				(1.40)				(1.25)		
$IU_{i,t}$			-.0019*				-.0026*				**-.0019***	
			(-2.66)				(-1.61)				**(-1.69)**	
$FU_{i,t}$				.0012				.0011*				.0012
				(1.13)				(1.85)				(1.77)
$DIGI_{i,t} \times EPU_{i,t}$		**-.0123** ***				**-.0124****				**-.0123***		
		(-4.63)				**(-2.65)**				**(-2.32)**		
$DIGI_{i,t} \times IU_{i,t}$			**-.0048*****				**-.0048***				**-.0047***	
			(-4.72)				**(-2.39)**				**(-2.42)**	
$DIGI_{i,t} \times FU_{i,t}$				.0009				-.0010				-.0009
				(-1.01)				(-0.92)				(-0.86)
$SIZE_{i,t}$	-.0020***	.0019***	-.0020***	-.0020***	-.0020***	-.0019***	-.0020***	-.0020***	-0.0020***	-.0020***	.0020***	-.0020***
	(-3.66)	(-3.61)	(-3.67)	(-3.66)	(-4.68)	(-4.52)	(-4.59)	(-4.60)	(-4.46)	(-4.31)	(-4.37)	(-4.35)
$AGE_{i,t}$	-.0000	-.0001	-.0000	-.0001	-.0000	-.0001	-.0000	-.0000	-.0000	-.0001	.0000	-.0000
	(-0.36)	(-0.60)	(-0.29)	(-0.36)	(-0.19)	(-0.30)	(-0.15)	(-0.18)	(-0.18)	(-0.29)	(-0.14)	(-0.18)
$LEVE_{i,t}$	-.0000	-.0000	-.0000	-.0000*	-.0000	-.0000*	-.0000*	-.0000*	-.0000	-.0000	.0000	-.0000
	(-0.54)	(-0.64)	(-0.57)	(-0.53)	(-1.78)	(-2.08)	(-1.82)	(-1.71)	(-0.56)	(-0.61)	(-0.53)	(-0.54)

Variable	(1) $OE_{i,t+1}$	(2) $OE_{i,t+1}$	(3) $OE_{i,t+1}$	(4) $OE_{i,t+1}$	(5) $OE_{i,t+1}$ (robust t)	(6) $OE_{i,t+1}$ (robust t)	(7) $OE_{i,t+1}$ (robust t)	(8) $OE_{i,t+1}$ (robust t)	(9) $OE_{i,t+1}$ (bootstrap z)	(10) $OE_{i,t+1}$ (bootstrap z)	(11) $OE_{i,t+1}$ (bootstrap z)	(12) $OE_{i,t+1}$ (bootstrap z)
$MTBR_{i,t}$	-2.38e-06	6.15e-08*	-2.22e-06	-2.85e-06	-2.38e-06*	6.15e-08	-2.22e-06	-2.33e-06*	-2.38e-06	-6.15e-07	-2.22e-06	-2.33e-06
	(-0.29)	(0.01)	(-0.27)	(-0.28)	(-1.66)	(0.01)	(-1.45)	(-1.67)	(-0.41)	(0.01)	(-0.35)	(-0.41)
$AE_{i,t}$	2.92e-06	2.68e-06	2.76e-06	3.57e-06	2.92e-06*	2.68e-06	2.76e-06	3.01e-06	2.92e-06	2.68e-06	2.76e-06	3.01e-06
	(1.86)	(1.72)	(1.77)	(1.91)	(1.24)	(1.22)	(1.22)	(1.28)	(1.22)	(1.20)	(1.20)	(1.26)
$R\&DE_{i,t}$	1.42e-07	-1.20e-07	6.89e-08	1.17e-06	1.42e-07	-1.20e-07	6.89e-08	2.10e-07	1.42e-06	-1.20e-07	6.89e-06	2.10e-06
	(0.20)	(-0.17)	(0.10)	(0.28)	(0.11)	(-0.09)	(0.06)	(0.15)	(0.10)	(-0.09)	(0.05)	(0.14)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.6328***	.6345***	.6346***	.6340***	.6328***	.6345***	.6346***	.6340***	.6328***	.6345***	.6346***	.6340***
	(25.99)	(26.00)	(26.20)	(26.03)	(5.05)	(4.98)	(5.14)	(15.05)	(4.64)	(4.60)	(4.71)	(4.65)
R^2	0.2408	0.2526	0.2521	0.2418	0.2408	0.2526	0.2521	0.2418	0.2408	0.2526	0.2521	0.2418
Adjust R^2	0.2174	0.2287	0.2282	0.2175					0.2174	0.2287	0.2282	0.2175
F value	10.31	10.57	10.54	9.97						0.0000	0.0000	0.0000
Wald chi2									5312.22	4833.66	4815.33	5142.43
Observations	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744

Note: robust t statistics in parentheses in columns (5), (6), (7), and (8), bootstrap z statistics in parentheses in columns (9), (10), (11), and (12). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ t-statistics are in parentheses.

3.4.4 Robustness Checks

To test for robustness, we verified our hypothesis findings by conducting heterogeneity analysis. We considered both time and firm-type factors. Specifically, we first divided the samples into two groups, namely before COVID-19 and after COVID-19. To compare digitalization's effect on operational efficiency in these two groups, we reported the results of FE Models (1) to (8) in Table 3.8. Then we further divided the samples into two groups based on firm-type, namely the B2B and B2C groups (Srinivasan *et al.*, 2011). We report the results of FE Models (9) to (16) in Table 3.8. Overall, all the model results in Table 3.8 indicate that the hypothesis findings are robust in all the groups.

Table 3.8 Heterogeneity Analysis of Study 1

								$OE_{i,t+1}$								
Variables		**Before Covid-19**				**After Covid-19**				**B2B**				**B2C**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$DIGI_{i,t}$	**.0052***	-.0074	.0041*	.0052**	**.0036****	.0011	.0042***	.0038**	**.0043****	-.0003	.0048***	.0043**	**.0079***	.0040	.0096**	.0072*
	(2.29)	(-1.29)	(1.85)	(2.31)	**(3.09)**	(0.86)	(3.59)	(3.17)	**(3.41)**	(-0.19)	(3.78)	(3.37)	**(2.28)**	(1.92)	(2.73)	(2.04)
$EPU_{i,t}$		.0101				.0052				.0019				.0300*		
		(1.14)				(1.08)				(0.36)				(2.37)		
$IU_{i,t}$			-.0022**				-.0031**				-.0032**				-.0028	
			(-1.21)				(-2.87)				(-2.78)				(-0.27)	
$FU_{i,t}$				.0021*				.0013				.0009				.0010
				(1.04)				(1.02)				(0.75)				(0.21)
$DIGI_{i,t} \times EPU_{i,t}$		**-.0242***				**-.0106*****				**-.0128*****				**-.0153*****		
		(-2.38)				**(-4.38)**				**(-4.07)**				**(-2.72)**		
$DIGI_{i,t} \times IU_{i,t}$			**-.0058****				**-.0045**				**-.0057*****				**-.0067***	
			(-2.63)				**(-4.01)**				**(-4.73)**				**(-2.02)**	
$DIGI_{i,t} \times FU_{i,t}$				-.0033				.0004				.0009				-.0047
				(-2.04)				(0.33)				(-0.85)				(-0.76)
$SIZE_{i,t}$	-.0031	-.0033**	.0004*	-.0032**	-.0027***	-.0026***	-.0028	-.0032***	-.0025***	-.0025***	-.0025***	-.0025***	-.0048	-.0051***	-.0049**	-.0047**
	(-3.00)	(-3.15)	(-1.85)	(-3.06)	(-4.35)	(-4.27)	(-4.43)	(-1.37)	(-3.67)	(-3.66)	(-3.68)	(-3.69)	(-3.31)	(-3.57)	(-3.35)	(-3.30)
$AGE_{i,t}$	-.0004	-.0004	.0031	-.0004	.0001	.0001	.0002	.0001	-.0001	-.0001	-.0001	-.0001	.0000	-.0002	.0001	.0000
	(-1.84)	(-2.18)	(-3.05)	(-1.84)	(1.21)	(1.09)	(1.37)	(1.24)	(-0.85)	(-0.91)	(-0.84)	(-0.85)	(0.17)	(-0.69)	(0.29)	(0.18)

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ *t*-statistics are in parentheses

	$OE_{i,t+1}$															
Variables	**Before Covid-19**				**After Covid-19**				**B2B**				**B2C**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$LEVE_{i,t}$	-.0000	-.0000	-.0000	-.0000	-.0000	-.0000	-.0000*	-.0000	-6.77e-06	-.0000	-8.61e-06	-5.93e-06	-.0002	.0001	-.0002*	-.0003
	(-0.30)	(-0.35)	(-0.29)	(-0.30)	(-0.10)	(-0.25)	(-0.20)	(-0.12)	(-0.14)	(-0.25)	(-0.17)	(-0.12)	(-0.52)	(-0.39)	(-0.64)	(-0.79)
$MTBR_{i,t}$	-.0000	-.0000	-.0000	-.0000	-7.87e-07	1.28e-06	-1.08e-07	-8.00e-07	-7.88e-07	3.04e-06*	-2.17e-07	-7.86e-07	-5.27e-07	-1.94e-06	1.13e-06	6.82e-06
	(-0.27)	(-0.46)	(-0.60)	(-0.52)	(-0.10)	(0.17)	(-0.01)	(-0.10)	(-0.08)	(0.31)	(-0.02)	(-0.08)	(-0.02)	(-0.06)	(0.04)	(0.21)
$AE_{i,t}$	8.55e-06(1.84)	8.33e-06(2.36)	8.09e-06*	8.60e-06	9.41e-07	9.04e-07	9.94e-07	9.00e-07	4.29e-06	4.20e-06	3.99e-06*	4.39e-06	.0000*	.0000*	.0000*	.0000*
			(2.29)	(2.43)	(0.55)	(0.54)	(0.59)	(0.53)	(2.39)	(2.35)	(2.25)	(2.44)	(2.06)	(1.99)	(1.97)	(2.07)
$R\&DE_{i,t}$	2.44e-06	2.08e-06	2.66e-06	3.29e-06	8.01e-07	4.82e-07	5.80e-07	6.59e-07	8.76e-07	6.39e-07	7.07e-07	9.55e-07	7.97e-06	6.96e-06	.0000	8.44e-06
	(1.50)	(1.28)	(1.64)	(1.95)	(1.02)	(0.62)	(0.75)	(0.82)	(1.07)	(0.78)	(0.87)	(1.14)	(0.84)	(0.74)	(1.07)	(0.88)
Year-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	.9459***	.9548***	.9381***	.9464***	.9406***	.9444***	.9392***	.9409***	.9402***	.9412***	.9381***	.9405***	.9438***	.9722***	.9340***	.9550***
	(64.22)	(59.12)	(98.82)	(98.00)	(104.13)	(99.10)	(104.99)	(103.98)	(50.03)	(92.88)	(98.82)	(98.00)	(49.69)	(44.39)	(49.56)	(15.05)
R^2	0.1568	0.1646	0.1667	0.1627	0.2093	0.2246	0.2278	0.2102	0.1273	0.1389	0.1476	0.1282	0.4125	0.4288	0.3502	0.4141
Adjust R^2	0.1004	0.1061	0.1084	0.1040	0.1696	0.1840	0.1873	0.1688	0.0941	0.1048	0.1138	0.0936	0.3448	0.3585	0.2429	0.3421
F value	2.78	2.81	2.86	2.77	5.27	5.53	5.63	5.08	3.84	4.06	4.36	3.70	6.08	6.11	3.26	5.75
Observations	719	719	719	719	1025	1025	1025	1025	1284	1284	1284	1284	339	339	339	339

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ t-statistics are in parentheses.

3.5 Discussion and Conclusions

3.5.1 Discussion

Numerous studies have examined the outcomes of digitalization in various contexts. However, whether uncertainty provides a favorable (Rehman and Jajja, 2023) or unfavorable environment (Mathews and Russell, 2020) for using digitalization to enhance operational efficiency is unclear. Our study employed NLP to analyze Factiva data to objectively measure digitalization and then to regress digitalization against operational efficiency, finding that digitalization enhances operational efficiency. In addition, we identified uncertainty as a highly relevant factor affecting the effectiveness of digitalization, and we comprehensively measured uncertainty at macro-, industrial, and firm levels using objective data including the EPU index and Compustat. Our results indicate that different uncertainty levels influence digitalization's impact on operational efficiency differently. Unlike firm-level uncertainty, the other two levels of certainty pose significant challenges for organizations implementing digitalization strategies. This research highlights the complex interplay between digitalization, operational efficiency, and uncertainty, providing valuable insights for researchers and practitioners.

3.5.2 Theoretical Implications

First, this research extends the literature on digitalization in the Industry 4.0 era. Indeed, many prior studies have recognized the necessity of researching digitalization's impact on firm outcomes (Ribeiro-Navarrete *et al.*, 2021; Yang *et al.*, 2023). Although data on direct measurement of digitalization are lacking, myriad studies have found positive contributions of specific digital instruments and activities on firm performance. For instance, Lam *et al*. (2016) elucidated the advantages rendered by social media initiatives, Kozjek *et al*. (2018) highlighted the positive outcomes of integrating new digital processes, and Xiong *et al*. (2021) demystified the operational benefits of blockchain adoption. Cumulatively, these studies ratified the overwhelmingly positive imprint of specific facets of digitalization on business outcomes. Our research provides further empirical evidence with objective data on digitalization's positive impact from an operational perspective, generating new insights to the literature on digitalization and operations management.

More importantly, our research not only corroborates earlier insights but also but also enriches the empirical evidence by employing NLP for data analysis of digitalization. The survey data or data of specific technologies utilized in prior studies (Gomez *et al.*, 2017) are fraught with challenges, such as respondent biases (Speklé and Widener, 2018) or accuracy concern because of the limited technologies covered in the measurement (Brynjolfsson and Hitt, 2000). To improve the accuracy of the data of digitalization, this study employs NLP, a more advanced approach for soliciting insights from secondary data. Aligning with our study's reliance on the textual characteristic of announcements as a key source of digitalization, this methodological advancement allows for a more nuanced understanding of digitalization and demonstrates to researchers the use of a new approach for measuring a concept via unstructured and/or voluminous data.

Second, this study delves into the role of uncertainty as a critical context influencing the effectiveness of digitalization. Previous research on the relationship between uncertainty and digitalization has been inconclusive, with some studies suggesting positive effects (Tushman *et al.*, 2002) and others emphasizing negative consequences (Bourreau *et al.*, 2021; Knight, 1921). Indeed, these mixed findings could be related to the assumption that uncertainty is a single-dimension factor. Our findings contribute to this ongoing debate by examining uncertainty at three levels, i.e., firm-, industrial- and macro-level uncertainty. We demonstrated that uncertainty, except for FU, presents a significant challenge for organizations implementing digitalization strategies. Specifically, we revealed that EPU and IU pose significant challenges for organizations implementing digitalization strategies, whereas FU has a negligible effect. This result is in line with the notion that digitalization's impact is highly conditional and challenging to manage (Kobelsky *et al.*, 2008). Overall, our results contribute to the literature on digitalization and uncertainty by offering empirical evidence of their interaction with respect to the outcome of operational efficiency.

3.5.3 Practical Implications

Our study offers clear practical implications for businesses seeking to implement digitalization strategies to improve operational efficiency. These implications provide guidance on both whether and when (not) to pursue digitalization for firms.

First, our findings emphasize the importance of recognizing digitalization as a strategic tool for enhancing operational efficiency rather than merely viewing it as a generic method for imitating the practices of competitors. With this insight into the link between digitalization and operational efficiency, firms with the strategic goal of enhancing operational efficiency should invest more substantially in digitalization. When selecting the specific technologies and considering the use of the resulting insights, extra attention should be paid to the potential technologies' relevancy to operational efficiency.

Second, our research highlights the need for executives to understand that digitalization's effectiveness is conditional. They should assess and identify the types of uncertainty their organizations face and adjust their digitalization strategies accordingly. Specifically, our results indicate that high levels EPU and IU are unfavorable for digitalization. With the recognition that it is inevitable that firms should continue to invest in digitalization, firms must be very cautious in the relevant actions and decisions. For instance, the selected technologies must be pertinent to the business's short-term operational goals. In addition, more sensitivity analysis on broader areas such as social, economic, or market changes should be carried out while making long-term investments concerning digitalization. In addition, after making digitalization investments, firms must monitor their external environments closely and adjust their adoption strategies or relevant decisions accordingly.

In summary, our research offers valuable practical guidance for businesses aiming to harness the power of digitalization to improve operational efficiency. By understanding the context-specific nature of digitalization's effectiveness and tailoring their strategies to address different levels of uncertainty, organizations can better position themselves for success in an increasingly digital and uncertain business landscape.

3.5.4 Limitations and Future Research

There are at least three limitations in this research. First, our sample only covers listed companies in North America. Although this sample helps us establish an important and relevant dataset, our findings may not be generalizable to firms in other contexts. Second, the endogeneity issue raised by omitted variables is also a great challenge to our research. We employed lagged variables, the Heckman model, and the generalized method of moments (GMM) to mitigate the possible endogeneity issues due to reverse causality, sample selection bias, and omitted variables, respectively. However, the use of GMM only addresses the endogeneity concerns in the relationship between digitalization and operational efficiency, without considering all three levels of uncertainty. Finally, we only tested the digitalization's effectiveness on operational efficiency, but it could also impact other important performance dimensions such as innovation, financial performance, and firm risks.

Future studies could verify the results developed in this study with a larger sample scope, such as unlisted firms in the US or listed firms in Asian or European countries. Furthermore, to tackle the endogeneity issue caused by potential omitted variables, future studies should prioritize the identification of strictly exogenous instrumental variables, a solution that is widely considered to be effective for testing endogeneity due to omitted variables. Finally, future research may provide extra empirical evidence on the performance implications of digitalization with respect to different performance outcomes and to different moderating factors such as supply chain complexity or innovation capability.

Chapter 4 Study 2 Digitalization's Impact on Financial Performance Under Diversification

4.1 Introduction

As firms seek to manage increasingly complex organizational structures and integrate into dynamic ecosystems (Lütjen *et al.*, 2019), digitalization has become a focal approach for them to seek market competitive advantage (Benitez *et al.*, 2023). Digitalization refers to the use of digital technologies with purposes of improving firm performance (Verhoef *et al.*, 2021). Indeed, a raft of successful cases suggest that digitalization and its associated technologies can improve firm market competitiveness and financial performance. For example, Amazon's implementation of advanced AI and analytics has significantly boosted its market efficiency and customer reach (Peter, 2022). While many other firms have found that though digitalization in general can enhance firm performance, the enhancement is not up to the anticipated level of financial returns. In this study we attempt to examine the financial impact of digitalization and if a relevant strategy, namely diversification, influences this expected impact.

The diversification strategy refers to the strategic expansion into new markets, products, or technologies to exploit potential synergies and integration, fostering overall business growth (Ahuja and Novelli, 2017). Indeed, the recent developments in the global environment, such as the COVID-19 pandemic and geopolitical conflicts, have prompted many firms to adopt the diversification strategy (Wenzel *et al.*, 2021; Yaya *et al.*, 2024). McKinsey's report validates the trend that over 70% of large global companies operate in multiple industries, underscoring diversification as a key strategy for expansion and value enhancement (Caudillo *et al.*, 2015). In regard to the relevancy of this strategy to digitalization, McKinsey offers insight explaining that the effectiveness of digitalization hinges on whether an organization operates within a digitalized ecosystem, where multiple digitalized operational systems could be well integrated and adopt differing forms of collaboration and synergies, maximizing the benefits of digitalization to the organization concerned (Bughin *et al.*, 2018). In this study we consider diversification as the relevant strategy supporting organizations to develop a digitalized ecosystem because it can provide organizations with ample opportunities to digitalize and integrate their diversified business activities at the business unit level, operational level, or in events concerning product or technology development. Nonetheless, studies on the role of the diversification strategy in the performance impact of digitalization are virtually non-existent in the literature.

From a theoretical perspective, the DCV provides a framework to understand why the diversification strategy is pertinent to digitalization's impact on financial performance. DCV emphasizes the ability of firms to adapt, integrate, and reconfigure internal and external resources in rapidly changing environments (Teece *et al.*, 1997). The literature on DCV suggests that the diversification strategy can enhances a firm's dynamic capability by expanding its range of markets and/or products (Lee and Kang, 2015; Sambharya and Lee, 2014), implying that the expansion induced by diversification allows the firm to better leverage the advantages of digital technologies through better access to varying resources, more options in integrating the resources across multiple business units, and greater agility in transforming and reconfiguring operations to respond to changing situations. Taking geographical diversification as an example, studies on digitalization adopted by multinational corporations (MNCs) confirm that digitalization enables these firms to leverage their resources and capabilities more efficiently because of better scrutiny of the emerging market trends and more effective reallocation of resources to diverse operations (Anand and Singh, 1997). Thus, the literature and related concepts of DCV suggest that diversification is a relevant strategy for enhancing the effectiveness of diversification in enhancing organizational performance.

Diversification is a complicated strategy that occurs when a firm moves into a new location, market, or other fields, and often appears with distinct dimensions (Ansoff, 1958). These multiple facets of diversification frequently exist within firms' dynamic ecosystems, offering flexibility and adaptability for their operations (Delios and Beamish, 1999; Hashai and Delios, 2012). For example, Apple has adopted the diversification strategy through broadening its product range, expanding operations and retail networks globally, and leveraging technologies such as AI and cloud computing (Gao, 2021). Companies also diversify by expanding product lines to meet varied consumer demands, building operations in new geographical areas to enhance market integration (Delios and Beamish, 1999), and developing new technologies for enhanced operations or new product development (Ceipek *et al.*, 2019). However, previous studies have frequently overlooked the technological dimension of diversification (Kistruck *et al.*, 2013; Levine *et al.*, 2021; Su and Tsang, 2015). In this research we adopt a comprehensive perspective, assessing diversification across geographical, product, and technological aspects, labelled as geographical diversification (GD), product diversification (PD), and technological diversification (TD), respectively, to investigate the boundary condition of digitalization in improving financial performance.

In this study we aim to ascertain if digitalization enhances firms' financial performance and how diversification moderates this relationship. To meet our aims more rigorously, we employ NLP to analyze pertinent announcements from Factiva and estimate the adoption levels of digitalization in sample firms, utilizing a more comprehensive approach to measure diversification with data from Compustat and the USPTO. This results in a dataset with 3,419 observations across 754 companies from 2015 to 2021. Upon testing our hypotheses, all the postulated outcomes of digitalization and the moderating effect of diversification are primarily supported. We contribute to research and practice in three ways. First, we offer empirical evidence on the positive impact of digitalization on firms' financial performance. Second, we identify diversification as a favorable strategy for digitalization, enriching the literature on diversification and furnishing practical recommendations for organizations adopting digitalization to enhance financial performance. Finally, through measuring digitalization with NLP and diversification in three dimensions, we advance research on these concepts and methodology.

4.2 Theoretical Background and Hypothesis Development

4.2.1 Dynamic Capability View

DCV has emerged as a pivotal extension of the RBV (Trujillo-Gallego *et al.*, 2022), addressing criticisms of RBV's static nature and its limited explanation for sustaining competitive advantages related to the fluctuating markets (Barreto, 2010; Gupta *et al.*, 2020a). Originating from Teece's innovative framework (Teece *et al.*, 1997), DCV highlights the importance of firms' abilities to integrate, build, and reconfigure internal resources and external competencies, thus achieving sustainable market competitiveness (Teece, 2007; Winter, 2003). This conceptualization has evolved to emphasize processes including sensing, seizing, and transforming opportunities and resources in response to environmental changes in empirical studies, underscoring DCV's broad applicability in management research (Ambrosini *et al.*, 2009; Bag *et al.*, 2020; Teece, 2018a). However, debates arise regarding how firms can effectively develop these capabilities to ensure long-term sustainability and competitive edge (Bari *et al.*, 2022). These debates highlights a significant gap in the specification of the DCs construct and points to a pressing need for more empirical evidence to understand DCV in antecedents, mechanisms, and effects (Barreto, 2010; Schilke *et al.*, 2018), calling for further empirical evidence which can provide concrete insights into how DCs are developed and deployed across different contexts.

This study focuses on financial performance — a reflection of a firm's profitability, growth and shareholder value (Perinpanathan, 2014) —and utilizes DCV as a robust framework. DCV underscores how a firm's ability to navigate market volatility and leverage opportunities from technological advancements, regulatory changes, and competitive dynamics significantly influences its financial outcomes (Karaboga *et al.*, 2023). For instance, Fosso Wamba (2022) utilizes the DCV framework to investigate the impact of AI assimilation on a firm's financial performance, arguing that integrating AI technologies can enhance business processes, allowing firms to adapt more effectively to dynamic market conditions (Fosso Wamba, 2022). Additionally, Ariadi *et al.* (2020) argue that DCs brought by strategic integration with suppliers and customers enable firms to navigate sustainability challenges and secure financial returns through the continuous integration, recreation, renewal, and reconfiguration of resources . Clearly, the DCV framework elucidates the complex interplay between a firm's DCs, shaped by various tools or strategies, and its financial outcomes, underscoring the adaptability and relevance of the DCV in research focused on financial performance.

The adaptability brought by DCs also provides guidance to identify how digitalization capabilities might perform under varying conditions (Tallon, 2008). More exactly, serve as higher-order dynamic capabilities, digitization enables firms to respond agilely to market changes through capturing, transforming, sharing, and analyzing data (Witschel *et al.*, 2019), further enhancing decision-making efficiency and facilitating the transformation, reconciliation, and reconfiguration of existing diversified resources and capabilities (Gupta *et al.*, 2020b; Gupta *et al.*, 2020c). This is consistent with Teece's latest research that emphasizes firms' DCs related to search/selection and configuration/deployment of key assets or diversified resources (Sohvi *et al.*, 2022). Obviously, based on these extended ideas, digitalization could sense, seize and reallocate resources (Sohvi *et al.*, 2022) from diversified sections to react to changes in the market, fitting to the framework of DCV (Chondrakis and Sako, 2020; Sohvi *et al.*, 2022), as shown in Table 4.1.

Table 4.1 Schema of Dynamic Advantages Brought by Diversification to Financial Performance

Geographical Diversification	Product Diversification	Technological Diversification
Sensing: Firms with operations in different geographical locations communicate and interact with diversified suppliers, employees and stakeholders (e.g., governments, NGOs, etc.), enabling them to learn or sense opportunities effectively.	**Sensing**: Firms with diversified projects have specialized knowledge on wider products and their customers, enabling them to identify product-specific (or customer-specific) opportunities.	**Sensing**: Firms with a narrow technological competence could be badly affected by disruptive technologies or unsuccessful R&D results. In contrast, firms with a broad portfolio of technologies are less affected by such problems and more likely to achieve critical technological breakthroughs.
Seizing: Firms with operations in different locations can mobilize their resources (e.g., engineers, IT equipment) among locations to enhance the efficiency in seizing the opportunities.	**Seizing**: By using their broad knowledge base on products and customers, these firms can analyze their opportunities to come up with better applications insights.	**Seizing**: When technological advancements occur, firms with expertise in wider technologies are more likely to have similar existing expertise to help explore and learn the new technologies.

Geographical Diversification	Product Diversification	Technological Diversification
Transforming: Such firms in general are MNCs which more likely afford resources in investing in sizable or risky projects for the opportunities.	**Transforming**: When attempting to fully exploit the opportunities, these firms have more products or production processes for them to choose from.	**Transforming**: After acquiring new technologies, these firms can consider integrating the new technologies with their wide range of existing technologies in order to develop future technological advancements.

4.2.2 Literature Review

As a novel technology strategy in practice leading to varied outcomes, there is no consistent view of digitalization's financial effectiveness in academia. Obviously, authors of major studies on related activities as a portfolio of digital technologies tend to see digitalization's financial effectiveness from a positive perspective. For example, Yang and Yee (2022) demonstrated that the process digitalization initiative can effectively obtain accurate data and reduce the consumption of energy and shipping costs, thereby improving corporate profitability. Wang *et al.* (2020) also found that adopting the digital transformation strategy reaps benefits such as promoting intelligent operations and achieving business model innovation, thereby having a positive relationship with firms' short-term and long-term financial performance. Similarly, Lee and Roh (2023) provided empirical evidence on digitalization's capability in increasing productivity and reducing cost, creating firms' sustainable competitive advantage in financial performance. However, some researchers have found a mixed relationship between digitalization (or the associated technologies) and financial performance. For example, Sharma *et al.* (2023) indicated that while the implementation of blockchain can increase future earnings but it has no relation to current accounting performance. Also, Guha and Kumar (2018), and Wamba *et al.* (2015) showed that digital technologies can increase the operational cost and organizational resources waste, diminishing corporate financial performance. The mixed evidence on the effectiveness of digitalization in enhancing corporate performance implies that further studies on the performance implications of digitalization are warranted. Table 4.2 lists the major recent studies on digitalization's impacts on firms' financial outcomes.

Table 4.2 Major Findings of Literature Relative to Digitalization's Financial Outcomes

Basic View	Findings	Author and Year
Positive	Process digitalization initiative led to improved data accuracy, energy and cost savings, improving profitability in Chinese firms.	Yang and Yee (2022)
Positive	Digital transformation strategy enhanced intelligent operations and business model innovation, positively impacting both short-term and long-term financial performance.	Wang *et al.* (2020)
Positive	Digitalization increased productivity and reduced costs, leading to a sustainable competitive advantage in financial performance.	Lee and Roh (2023)
Mixed	Implementation of blockchain technology increased future earnings but did not affect current accounting performance.	Sharma *et al.* (2023)
Negative	Digital technology led to increased operational costs and resource wastage, diminishing financial performance.	Guha and Kumar (2018); Wamba *et al.* (2015)

In addition, prior studies related to technological strategies suggest that companies operating in different environments and with different resources and strategies are unlikely to gain the same benefits from their innovative technology adoption (Lam *et al.*, 2019). Thus, further research is needed to understand the context in which digitalization will have a beneficial financial impact (Lee and Roh, 2023). Most current researchers consider environmental factors as influential for digitalization's functioning, including institutional conditions (Liu *et al.*, 2023b), the development level of regional science and technology (Xie *et al.*, 2023), and country development and sector technology intensity (Oduro *et al.*, 2023). Besides, some researchers are interested in the impacts of internal resources and capabilities, such as managers' characteristics (Ribeiro-Navarrete *et al.*, 2021), cognitive conflict (Wang *et al.*, 2020), and absorptive capacity (Yang and Yee, 2022), on the success of digitalization. As researchers delve deeper, corporate strategy is considered increasingly important because it shapes the way firms integrate and leverage digital technologies (Yang and Yee, 2022). In this study we adopt a similar perspective and focus on understanding diversification's interplay with digitalization. In a globalized and highly competitive market, diversification serves as a core strategy for enhancing financial performance by providing firms with stable revenue streams and greater market adaptability (Chakrabarti *et al.*, 2007). It influences market performance through market identification, adaptability, and resource responsiveness, which are critical for leveraging digitalization effectively. Diversified firms can better distribute digitalization resources, capture new opportunities, and mitigate market risks (Caputo *et al.*, 2021), thereby strengthening the financial impact of digitalization. Therefore, this study selects diversification as a key boundary condition to examine how different diversification strategies amplify the financial benefits of digitalization. In fact, researchers have diverse views about diversification. Some suggest that diversification can have a negative impact on performance (Chakrabarti *et al.*, 2007) by asserting that diversification can increase dynamic operation expenditure, deepen managerial and organizational complexity, and limit a firm's ability to quickly react to external changes (Theuvsen, 2004). In contrast, other researchers have explored the positive impact of diversification on firms' financial performance (Ravichandran *et al.*, 2009) by asserting that firms with diversification capitalize on economies of scale to realize enhanced performance gains, especially when combined with IT capability (Chari *et al.*, 2008). The complex findings underscore the necessity for examining how firms' diversification strategy interacts with digitalization.

4.2.3 Hypothesis Development

According to the DCV, organizations can leverage digitalization as a technological resource to sense market changes and potential opportunities, seize these opportunities through strategic decision-making, and reconfigure existing assets to develop products and services that meet market demands (Karaboga *et al.*, 2023). This process enables firms to adapt to market changes, enhance their dynamic capabilities, and ultimately improve their financial performance (Fosso Wamba, 2022). First, digitalization has functions in promoting firms' capabilities such as in sensing market demand changes (Pagani and Pardo, 2017), enabling firms increase financial performance (Abou-foul *et al.*, 2021) Second, digitalization provides tools and platforms that facilitate firms in seizing market trends and responding rapidly, leading to more cohesive and efficient operations. This includes the restructuring of digital business models (Bonnet and Westerman, 2015), and the transformation of operating flows (Elia *et al.*, 2021), ultimately resulting in enhanced financial performance. Third, digitalization plays a key role in the processes of reconfiguring and optimizing resources through crucial activities, such as gathering data and information, thereby improving operational efficiency (Lam *et al.*, 2016), reducing costs (Karhade and Dong, 2021) and improve business scope (Westerman *et al.*, 2011), contributing to value creation (Ribeiro-Navarrete *et al.*, 2021).Thus, given digitalization's function in sensing, seizing, and transforming market opportunities and resources, we propose the following hypothesis:

H1: Digitalization positively affects financial performance.

Based on DCV, firms with higher diversification could sense diverse market opportunities; seize strategic advantages; and transform insights and resources from different locations, business segments, and technological fields into innovative solutions and competitive strengths (Teece *et al.*, 1997). This enhanced capability to navigate and capitalize on a variety of scenarios in the environment underpins their agility in adapting to rapid market changes and technological advancements.

GD refers to the process of expanding into new geographic locations such as markets beyond a firm's current borders (Hitt *et al.*, 1994). To access new resources (Porter, 1998) and lower production costs (Sun and Govind, 2018), a strategy that not only bolsters traditional business expansion but also supplies a wealth of resources from varied regions is crucial for the effective functioning of digitalization. First, as an index to measure the extent of firms' sales in different countries, GD enhances operational flexibility and positions firms to effectively sense opportunities within larger, more varied markets (Kogut, 1983). This expanded market presence allows the firm to engage with a diverse array of stakeholders (Hitt *et al.*, 2016), enabling them to anticipate and respond to shifts in global market demands, thus maintaining a competitive edge. Second, firms with GD can efficiently seize and utilize different resources from different locations for digitalization to integrate, helping to achieve economies of scale (Bühner, 1987; Kostova and Zaheer, 1999; Pan and Chao, 2010). Such geographical synergy allows firms to optimize their digitalization efforts to better match the demands and resources present in each geographical market, thus deriving greater value from their digitalization investments. Last, firms operating across diversified locations are better positioned to undertake significant or high-risk projects that are beneficial to optimizing digitalization's functionality and mitigating its risks, because the multi-location approach affords them access to substantial funding and a wide array of resources (Heady, 1952). That is, GD can work in sensing, seizing, and transforming capability, which is beneficial to digitalization's impact on financial performance.

H2: GD positively moderates the impact of digitalization on financial performance.

PD is the extent to which firms expand into product markets new to them(Hitt *et al.*, 1994). The increasingly customized demands require firms to develop more diversified products to satisfy heterogonous customer needs (Sun and Govind, 2018), in turn providing a flexible environment for digitalization to effectively enhance product development. First, firms with diversified products provide a broader platform for digitalization to capture extensive market data, facilitating its identification of new opportunities for accurate customization, thereby enhancing firms' competitive edge (Ketchen Jr *et al.*, 2007). Second, as an index to measure the extent of firms' sales in different product segments, PD allows optimization of resource allocation across different segments, leveraging digitalization for data-driven decision-making, and capturing and responding to a wide range of market opportunities (Batsakis *et al.*, 2022). Finally, the practice of product diversification grants firms strategic flexibility to implement "winner-picking," whereby they dynamically reallocate resources from underperforming product segments to those with higher potential (Stein, 1997). This process of resource reallocation underscores the transformative potential of digitalization in diversified firms, aligning with researchers' insights on leveraging internal resources for sustainable competitive advantage (Penrose, 2009). Thus, we propose that:

H3: PD positively moderates the impact of digitalization on financial performance.

TD refers to the expansion of a firm's technological competence and its diversity or breadth of the technology base, and works as a measurement of capturing the degree of variation in the types of technologies that the firm possesses or utilizes (Granstrand *et al.*, 1997). With large investment in a range of related technologies development (Lim *et al.*, 2011), firms can scan for new opportunities arising from disruptive technologies, explore these new technologies with a strong technological foundation, and transform them into commercial applications by leveraging their existing expertise. First, an array of technological resources and capabilities act as a cornerstone for digitalization (Nason and Wiklund, 2018), which renders firms less affected by disruptive technology problems and more likely to scan new technological opportunities to achieve critical technological breakthroughs, aligning with the “sense” function of DVC (Teece *et al.*, 1997). Second, a higher TD level signals firms’ superior capabilities and available resources in facilitating exploration and exploitation of new products (Krammer, 2016). This explains why many large firms maintain highly diversified technology portfolios, with their TD levels often exceeding the diversification levels of their product portfolios (Leten *et al.*, 2007). This diversified technological support allows firms to be better equipped to leverage digitalization for capturing and capitalizing on new ventures, enabling them to seize new opportunities in the market. Last, the advantage of firms with higher TD lies not only in strategically integrating diversified technologies into a diverse product portfolio and transforming them into commercial applications to respond to and anticipate demands, but also in providing a robust expertise foundation for firms to develop new technological advancements. Thus, TD can work in sensing, seizing, and transforming capability, which is beneficial to digitalization’s impact on financial performance.

H4: TD positively moderates the impact of digitalization on financial performance.

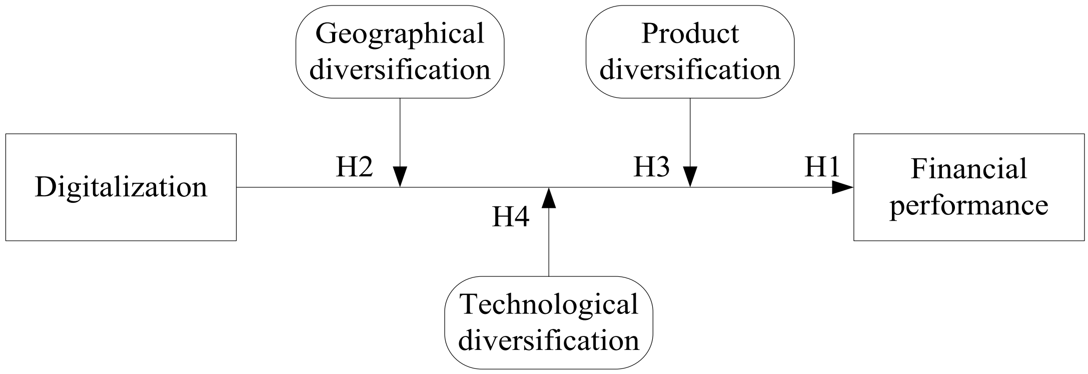


Figure 4.1 Conceptual Framework of the Second Study 2

4.3 Methods

4.3.1 Samples and Data Collection

We obtain the necessary data from separate sources: We collect data on the independent variable (digitalization) from Factiva; we collect data on the dependent variable (financial performance) from Compustat; we collect data on two of the moderating variables (GD and PD) from Compustat, and data on another moderating variable (TD) from USPTO. After matching data from these diversified sources, we build an unbalanced data panel containing 754 companies from 2015 to 2021, with 3,419 samples in all.

4.3.2 Variables Measurement

Table 4.3 illustrates the definitions, variable constructions, and sources for the variables.

Dependent variable: Financial Performance. Financial performance can be reflected from different perspectives (Richard *et al.*, 2009). Compared with profit, Tobin's *Q*, an accounting indicator, is more popularly accepted as the market value indicator to reflect firms' financial performance (Kohli *et al.*, 2012; Mithas and Rust, 2016). Specifically, profit represents a firm's short-term annual operating situation and profitable growth (Dehning *et al.*, 2006), whereas Tobin's *Q* is a classic proxy to measure a firm's market value (Kohli *et al.*, 2012) and is believed more comprehensive and stable. So we use Tobin's Q as the measurement of financial performance, which is calculated with data from Compustat.

Independent variable: Digitalization. Consistent with our first study, we define digitalization as the usage of digital technologies with the purposes of improving both business performance and scope (Verhoef *et al.*, 2021; Westerman *et al.*, 2011). Followed by a strict NLP processing (as shown in Appendix B), we standardized digitalization data following prior studies (Lam *et al.*, 2016), which sees the Eq. 3.1.

Moderating variables: GD. GD is the extent to which a firm conducts business in different countries. To remain consistent with the prior literature (Hendricks *et al.*, 2009), we collect GD data from the Compustat Business Segment dataset. A number of researchers have adopted this dataset for measuring GD (e.g., Yegmin and Howard (1989);Denis *et al.* (2002);Hitt *et al.* (1997)). Companies are obligated to disclose information on geographic areas that contribute more than 10% to their total sales, profits, or assets. Geographic segments in Compustat are defined based on country-level operations (the number of geographic segments is limited to four, including the domestic segment). To measure geographic diversification, we calculate the Geographic Herfindahl Index (HHI) based on sales in different geographic segments, which is the sum of the square of the ratio of the annual sales of individual geographic segments to the total sales of the firm as follows:

$$G_{Hrf(i,t)} = \sum_{i=1}^{N} \left(\frac{S_{i,t}}{S_i}\right)^2 \tag{4.1}$$

$$GD_{i,t} = 1 - G_{Hrf(i,t)} \tag{4.2}$$

where S_i is the annual sales of ith geographic segment, S is the total annual sales of the firm, and N is the number of geographic segments reported in Compustat.

PD. PD is measured by the diversified extent of a firm in business segments. Based on prior research (Sun and Govind, 2018), we use information from the Compustat business segment data to measure PD through the entropy index. The concept of PD refers to the number of sectors in which a firm has a business presence, and its measurement is dependent on the industry it belongs to, in that different industries have varying product and service varieties (Amit and Livnat, 1988; Kim and Pantzalis, 2003). To standardize the measurement of PD across industries, we scale the number of sectors by the industry average, a common practice in the existing literature. Thus, we calculate PD as the magnitude of the deviation between a firm's number of products and service sectors from the industry mean as follows:

$$PD=\sum P_i \ln 1/P_i \tag{4.3}$$

TD. TD is measured by the diversified extent of a firm in technology or knowledge. Based on prior research (Ndofor *et al.*, 2011), we adopted HHI method to measure TD. After conducting an initial search for all patents filed at the USPTO, we measured the extent of TD of the firm in a given year (t) by computing the HHI based on its primary patent classes at the three-digit level (Garcia-Vega, 2006), as shown in Eq. 4.4 and 4.5:

$$T_{Hrf(i,t)} = \sum_m \left(\frac{\text{Pat}_{\ tm}}{\text{Pat}_{\ t}}\right)^2 \tag{4.4}$$

$$TD_{i,t} = 1 - T_{Hrf(i,t)} \tag{4.5}$$

where Pat_{tm} stands for the number of patents in patent class *m* granted to the partnering firm up to the year *t*, and Pat_t represents the total number of patents granted up to the year *t*.

Table 4.3 Key Variable Measurement of Study 2

Variables (Abbreviations)	Measurements	Sources	References
Independent Variable			
Digitalization (DIGI)	Annual firm-level count of digitalization announcements	Factiva	Dotzel and Shankar (2019)
Dependent Variables			
Financial Performance (FP)	Tobin's *Q*: Ratio of the market value of the firm divided by the replacement cost of assets.	Compustat	Mithas and Rust (2016) Sabherwal *et al.* (2019) Deb *et al.* (2019) Wang and Choi (2013)
Moderating Variables			
Technological Diversification (TD)	We calculated the degree of TD of the partnering firm in a specific year using the Herfindahl Index (TD_{Hrf}) based on its three-digit main patent classes.	USPTO	Garcia-Vega (2006) Natalicchio *et al.* (2017)
Product Diversification (PD)	The component of related diversity is the weighted average of the firms' degree of diversification within related business segments. We use the Standard Industrial Classification (SIC) codes to distinguish related from unrelated PD.	Compustat	Hitt *et al.* (1997) Chan Kim *et al.* (1989) Palepu (1985)
Geographical Diversification (GD)	We use reciprocal ($1/GD_{Hrf}$) of geographic Herfindahl Index (GD_{Hrf}) to measure the geographic diversification.	Compustat	Hendricks *et al.* (2009)
Control variables			
Market-to-Book Ratio (MTBR)	A firm's market value of equity divided by book value of equity	Compustat	Li *et al.* (2022a) Hendricks *et al.* (2015); Lu and Shang (2017)
Firm Leverage (LEVE)	A firm's total debt divided by total assets	Compustat	Yiu *et al.* (2020) Li *et al.* (2022a)
Firm Size (SIZE)	A firm's total employees based on a logarithmic transformation	Compustat	Lam *et al.* (2016);
Firm Age (AGE)	Calculated by a firm's initial public stock offering	Compustat	Lam *et al.* (2016);
Firm R&D Expense (R&DE)	A firm's expenses on research and development.	Compustat	Lam *et al.* (2016);
Firm Advertising Expense (AE)	expenses associated with marketing a firm's brand, product, or service via media outlets	Compustat	Lam *et al.* (2016);

4.3.3 Model Development

We test the hypotheses utilizing fixed effects models, which have superior controls for time-invariant variables and an effective approach to mitigating the potential endogeneity problems (Cui *et al.*, 2018b). Specifically, we develop a system of three equations with firms' financial performance as the dependent variable (Eqs (4.6), (4.7), and (4.8)). First, financial performance is the endogenous variable and measured by Tobin's Q (a long-term comprehensive proxy of financial performance, which is widely used for measuring the operating performance in finance of firms (Brainard and Tobin, 1968); digitalization; GD, PD, and TD; and controlling variables (size, age, R&D expenses, leverage, advertising expenses, and market-to-book ratio) are exogenous variables that are supposedly correlative with the models; α, β, and γ are parameters to be estimated; and ε, ω, and θ are the error terms associated with the samples. Second, in the three equations, the endogenous variable is lagged by 1 year after the exogenous variables, which is consistent with the prior literature concerning the outcomes of technologies or related strategies (Lam *et al.*, 2016; Xue *et al.*, 2012). Finally, we include business segments and time effects in our models to account for the potential influence of industry-specific characteristics and temporal dynamics on the findings.

$$Financial\ performance_{i,t+1} = \beta_0 + \beta_1 Digitalization_{i,t} + \beta_2 GD_{i,t} + \beta_3 Digitalization_{i,t} \times GD_{i,t} + \beta_4 Firm\ Size_{i,t} + \beta_5 Firm\ Age_{i,t} + \beta_6 MarkettoRatio_{i,t} + \beta_7 Firm\ Leverage_{i,t} + \beta_8 R\&D\ Expense_{i,t} + \beta_9 Firm\ Advertising\ Expense_{i,t} + \sum_{k=1}^{D} \varphi_k\, IND_k + \sum_{m=1}^{Y} \omega_k\, YEAR_m + \epsilon_{i,t} \tag{4.6}$$

$$Financial\ performance_{i,t+1} = \beta_0 + \gamma_1 1 Digitalization_{i,t} + \gamma_2 PD_{i,t} + \gamma_3 Digitalization_{i,t} \times PD_{i,t} + \gamma_4 Firm\ Size_{i,t} + \gamma_5 Firm\ Age_{i,t} + \gamma_6 MarkettoRatio_{i,t} +$$

$\gamma_7 Firm\ Leverage_{i,t} + \gamma_8 R\&D\ Expense_{i,t} + \gamma_9 Firm\ Advertising\ Expense_{i,t} +$

$$\sum_{k=1}^{D} \pi_k\, IND_k + \sum_{m=1}^{Y} \rho_k\, YEAR_m + \theta_{i,t} \tag{4.7}$$

$Financial\ performance_{i,t+1} = \alpha_0 + \alpha_1 Digitalization_{i,t} + \alpha_2 TD_{it} +$

$\alpha_3 Digitalization_{i,t} \times TD_{i,t} + \alpha_4 Firm\ Size_{i,t} + \alpha_5 Firm\ Age_{i,t} + \alpha_6 MarkettoRatio_{i,t} +$

$\alpha_7 Firm\ Leverage_{i,t} + \alpha_8 R\&D\ Expense_{i,t} + \alpha_9 Firm\ Advertising\ Expense_{i,t} +$

$$\sum_{k=1}^{D} \delta_k\, IND_k + \sum_{m=1}^{Y} \mu_k\, YEAR_m + \varepsilon_{i,t} \tag{4.8}$$

4.4 Data Analysis and Results

4.4.1 Baseline Analysis

In this section we test the digitalization's effect on financial performance under different dimensions of diversification including GD, PD and TD. We initially constructed estimating models as shown in Eqs. (4.6), (4.7), and (4.8). Before reporting the regression results, we report the descriptive characteristics and correlations of variables in Table 4.4 and Table 4.5, respectively.

Table 4.4 Characteristics of the Core Variables of Study 2

Variables	Observations	Mean	SD	Min	Max
OE	2289	.922	.038	0	.983
DIGI	2289	.516	1.399	0	21
EPU	2289	182.04	61.118	142.396	464.243
IU	2289	.823	.206	.257	1
FU	2289	.365	.481	.01	4.246

Table 4.5 Correlation Matrix of Study 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) $FP_{i,t}$	1.000										
(2) $DIGI_{i,t}$	0.296	1.000									
	(0.000)										
(3) $GD_{i,t}$	-0.063	-0.018	1.000								
	(0.000)	(0.296)									
(4) $PD_{i,t}$	-0.010	-0.002	0.019	1.000							
	(0.552)	(0.909)	(0.264)								
(5) $TD_{i,t}$	0.023	0.038	0.497	0.018	1.000						
	(0.184)	(0.027)	(0.000)	(0.281)							
(6) $SIZE_{i,t}$	-0.035	-0.022	0.049	0.032	0.022	1.000					
	(0.039)	(0.205)	(0.004)	(0.059)	(0.205)						
(7) $AGE_{i,t}$	-0.097	-0.027	0.021	0.156	0.002	0.151	1.000				
	(0.000)	(0.116)	(0.213)	(0.000)	(0.923)	(0.000)					
(8) $MTBR_{i,t}$	0.040	0.020	0.001	0.022	0.018	-0.004	-0.016	1.000			
	(0.019)	(0.248)	(0.952)	(0.204)	(0.296)	(0.807)	(0.347)				
(9) $LEVE_{i,t}$	0.007	0.019	-0.019	0.002	-0.003	0.007	-0.007	0.602	1.000		
	(0.684)	(0.257)	(0.266)	(0.919)	(0.875)	(0.670)	(0.690)	(0.000)			
(10) $AE_{i,t}$	0.022	0.014	0.068	0.021	0.069	0.366	0.155	0.014	0.011	1.000	
	(0.202)	(0.422)	(0.000)	(0.209)	(0.000)	(0.000)	(0.000)	(0.430)	(0.533)		
(11)$R\&DE_{i,t}$	0.116	0.061	0.005	0.012	-0.012	0.152	0.124	0.021	-0.002	0.258	1.000
	(0.000)	(0.000)	(0.753)	(0.490)	(0.476)	(0.000)	(0.000)	(0.229)	(0.897)	(0.000)	

Note: n=3419; P-value in parentheses in columns

Given that it takes time for digitalization to take effect on firms' financial performance by identifying and integrating firms' resources, our dependent variable is lagged in one year (financial performance$_{i,t+1}$ means financial performance for firm i in year t+1).

We illustrate the regression results of the FE model in Table 4.6. It can be seen that the coefficient is significantly positive in digitalization's impact on financial performance (coef.=0.3406, p<0.001), suggesting that a higher digitalization level in a firm will enhance its financial performance significantly, supporting H1. We also verify the moderating effects of GD, PD, and TD as significantly positive, with the coefficients being 0.2276 (p<0.001), 0.0923 (p<0.005), and 0.1346 (p<0.001), respectively, supporting H2-H4. Following Qiu *et al.* (2022), we report the results with robust t (columns (5)-(8)) and bootstrap z statistics (columns (9)-(12)). Both robust t and bootstrap z statistics can address the issue that the model may fail to meet standard regression assumptions, and all the standard errors are clustered at the firm level. According to the results in columns (5)-(12), all the coefficients are significantly positive, supporting H1-H4 further.

Table 4.6 Results of FE Regression Analysis of Study 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$	$FP_{i,t+1}$
					(robust t)	(robust t)	(robust t)	(robust t)	(bootstrap z)	(bootstrap z)	(bootstrap z)	(bootstrap z)
$DIGI_{i,t}$	$.3406^{***}$	$.3056^{***}$	$.3333^{***}$	$.3469^{***}$	$.3407^{***}$	$.3049^{***}$	$.3336^{***}$	$.3469^{***}$	$.3392^{***}$	$.0258^{***}$	$.3318^{***}$	$.3469^{***}$
	(11.75)	(10.35)	(11.48)	(12.01)	(8.05)	(6.38)	(7.81)	(7.91)	(8.04)	(3.95)	(7.78)	(7.71)
$GD_{i,t}$		-.0683				$-.0676^{*}$				-.0010		
		(-1.80)				(-1.84)				(-0.17)		
$PD_{i,t}$			.0353				.0100				.0323	
			(1.33)				(0.36)				(1.13)	
$TD_{i,t}$				.0404				$.0404^{*}$				$.0404^{*}$
				(1.51)				(1.79)				(1.84)
$DIGI_{i,t} \times GD_{i,t}$		$.2276^{***}$				$.2283^{**}$				$.0324^{**}$		
		(5.30)				(3.23)				(3.25)		
$DIGI_{i,t} \times PD_{i,t}$			$.0923^{**}$				$.0896^{*}$				$.0935^{*}$	
			(2.99)				(1.77)				(1.89)	
$DIGI_{i,t} \times TD_{i,t}$				$.1346^{***}$				$.1346^{**}$				$.1346^{**}$
				(4.78)				(3.14)				(3.09)
$SIZE_{i,t}$	$-.0005^{*}$	-.0005	$-.0006^{*}$	-.0005	-.0005	-.0005	$-.0005^{*}$	$-.0005^{*}$	$-.0005^{*}$	-.0000	-.0005	$-.0005^{*}$
	(-1.78)	(-1.75)	(-1.78)	(-1.67)	(-2.42)	(-2.39)	(-2.40)	(-2.29)	(-2.12)	(-1.450	(-2.09)	(-2.02)
$AGE_{i,t}$	$-.0182^{***}$	-.0186	$-.0183^{***}$	$-.0182^{***}$	-.0182	-.0187	$-.0182^{***}$	$-.0182^{***}$	$-.0182^{***}$	$.0021^{***}$	-.0183	$-.0182^{***}$
	(-6.42)	(-6.57)	(-6.46)	(-6.43)	(-6.17)	(-6.34)	(-6.19)	(-6.17)	(-6.00)	(4.50)	(-6.01)	(-6.06)

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$	(5) $FP_{i,t+1}$ (robust t)	(6) $FP_{i,t+1}$ (robust t)	(7) $FP_{i,t+1}$ (robust t)	(8) $FP_{i,t+1}$ (robust t)	(9) $FP_{i,t+1}$ (bootstrap z)	(10) $FP_{i,t+1}$ (bootstrap z)	(11) $FP_{i,t+1}$ (bootstrap z)	(12) $FP_{i,t+1}$ (bootstrap z)
$LEVE_{i,t}$	-.0031	-.0038	-.0031	-.0031	-.0031	-.0036	-.0030	-.0031	-.0046	.0009*	-.0045	-.0046
	(-1.47)	(-1.79)	(-1.43)	(-1.47)	(-1.44)	(-1.62)	(-1.41)	(-1.47)	(-0.73)	(2.10)	(-0.72)	(-0.59)
$MTBR_{i,t}$	.0046*	.0051	.0045*	.0046*	.0046	.0050	.0045	.0046*	.0068*	-.0006**	.0067	.0068*
	(2.32)	(2.60)	(2.26)	(2.34)	(1.68)	(1.78)	(1.64)	(1.70)	(2.02)	(-3.11)	(1.99)	(1.50)
$AE_{i,t}$	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0000***	.0000	.0001
	(0.88)	(0.91)	(0.84)	(0.91)	(1.26)	(1.35)	(1.20)	(1.33)	(1.17)	(4.49)	(1.11)	(1.19)
$R\&DE_{i,t}$	.0002***	.0002***	.0002***	.0002***	.0002***	.0002***	.0002***	.0002***	.0002***	.0000***	.0001	.0002***
	(6.94)	(7.27)	(7.06)	(7.13)	(7.87)	(8.21)	(7.92)	(8.06)	(7.85)	(7.16)	(7.93)	(7.82)
Year-fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	2.4258***	2.405***	2.427***	2.416***	2.425***	2.4391***	2.423***	2.416***	2.426***	.0601***	2.427***	2.416***
	(25.06)	(24.88)	(25.10)	(25.03)	(24.30)	(24.35)	(24.35)	(24.25)	(23.35)	(3.69)	(23.32)	(23.17)
R^2	0.1312	0.1417	0.1346	0.1398	0.1312	0.1424	0.1340	0.1398	0.1319	0.1187	0.1352	0.1398
Adjust R^2	0.1155	0.1255	0.1182	0.1236					0.1163	0.1022	0.1190	0.1236
F value	8.36	8.76	8.25	8.62								
Observations	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,650

Note: robust t statistics in parentheses in columns (5)(6)(7)(8), bootstrap z statistics in parentheses in columns (9)(10)(11)(12). $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$ t-statistics are in parentheses

To further visualize the moderating effect of varying perspectives of diversification on the relationship between digitalization and financial performance, this study presents Figure 4.2. The illustration indicates that the moderating roles of GD, PD and TD are positive, providing additional validation for Hypotheses 2-4.

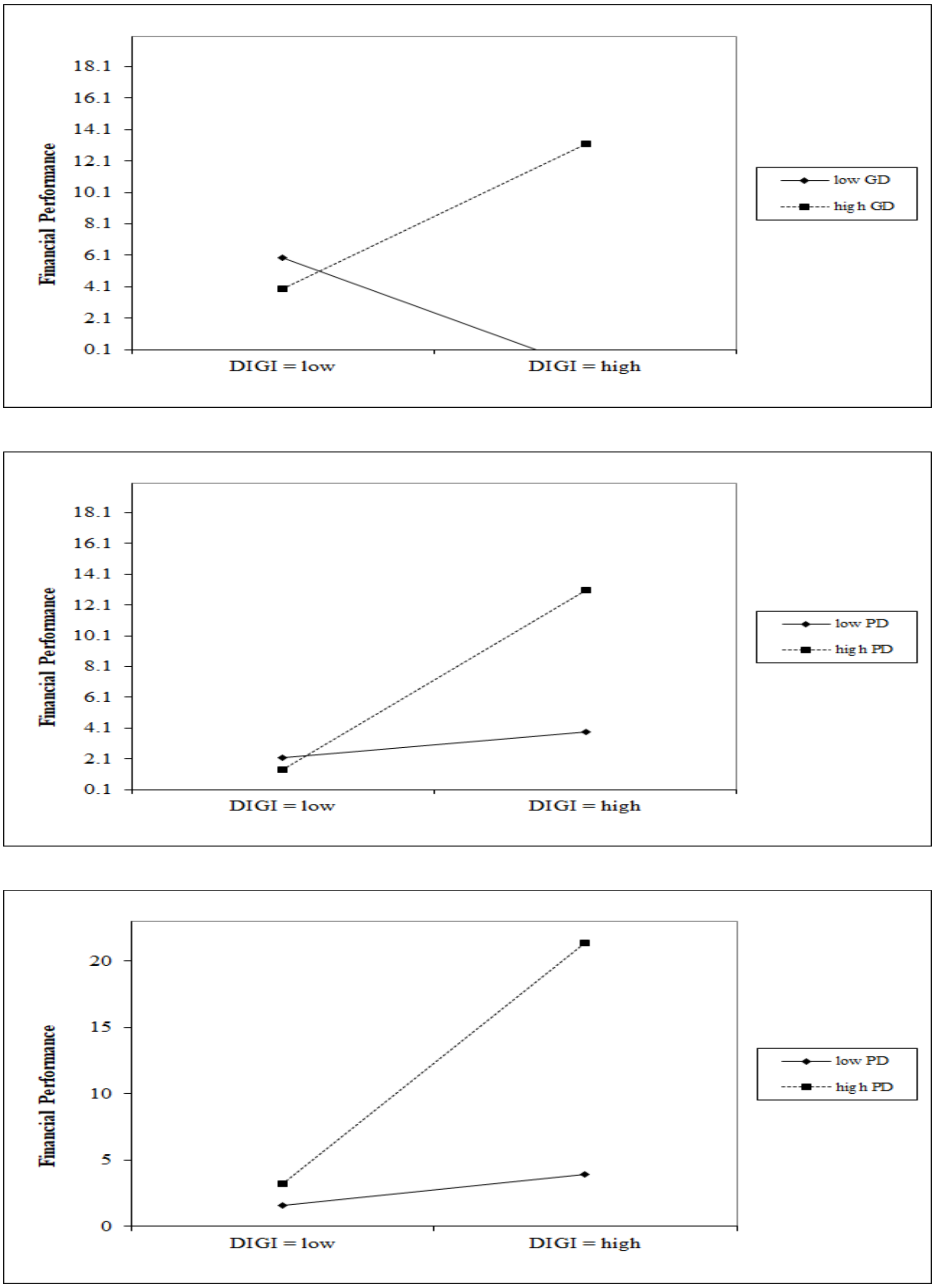


Figure 4.2 The Moderating Effect of Diversification on The Relationship between Digitalization and Financial Performance of Study 2

In addition, to more intuitively understand the impact of GD, PD and TD on the relationship between digitalization (DIGI) and financial performance (FP), we created surface and contour plots of the interaction effects, as shown in Figures 4.3-4.5. The surface plots show that higher levels of FP are associated with higher levels of DIGI and diversification strategy (GD, PD, TD). The contour plots also validate these moderating effects: moving from the bottom left corner (where the levels of GD, PD, TD and DIGI are low) to the top right corner (where the levels of GD, PD, TD and DIGI are high), there is an observable increase in FP (where the color changes from red to orange or green). This evidence supports Hypotheses 2–4.

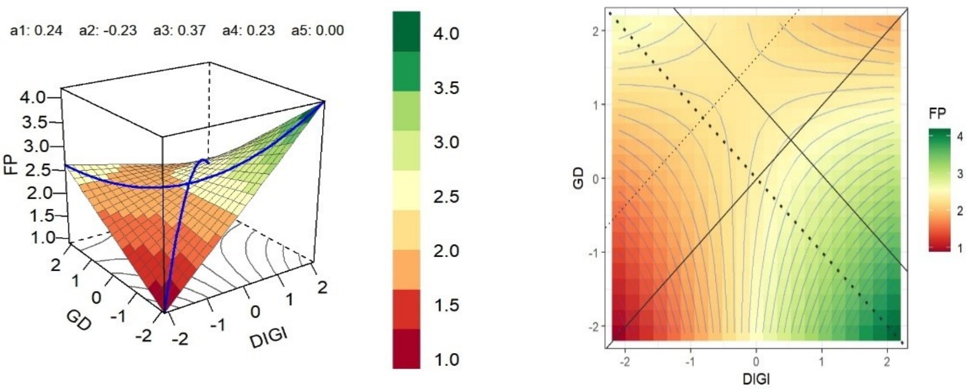


Figure 4.3 The Interaction Effect of Digitalization and Geographical Diversification on Financial Performance

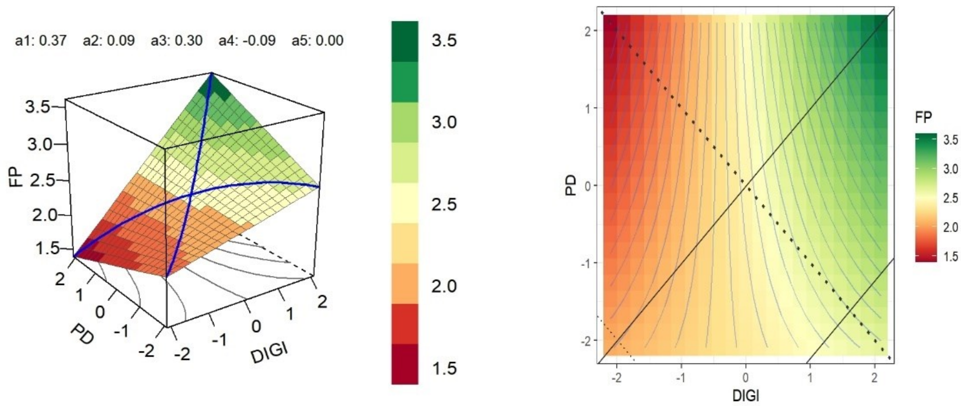


Figure 4.4 The Interaction Effect of Digitalization and Product Diversification on Financial Performance

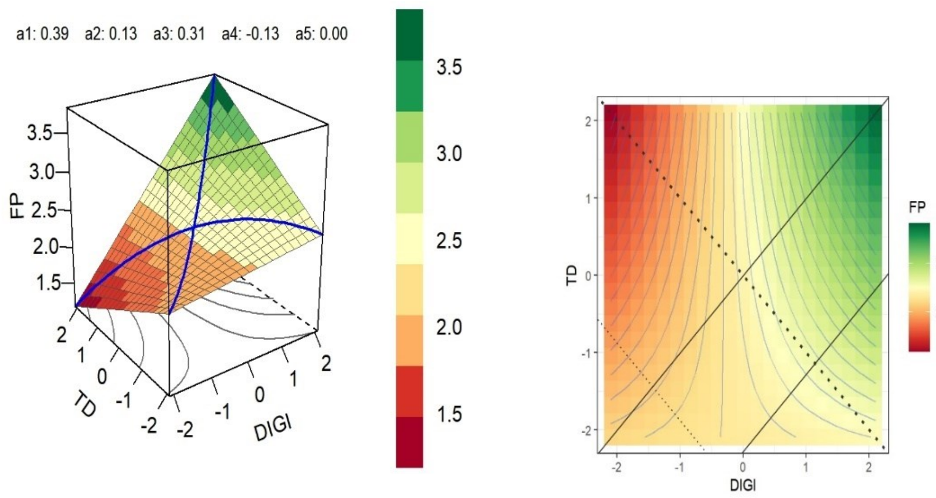


Figure 4.5 The Interaction Effect of Digitalization and Technological Diversification on Financial Performance

4.4.2 Endogeneity Concerns Analysis

Because we employ an unbalanced panel dataset spanning different years, the sample may be subject to potential endogeneity issues. First, the issue of reverse causality may exist, resulting in an endogeneity problem. We use a one-year lag of digitalization and each control variable instead of their present values in models (4.6), (4.7), and (4.8) to process the regression, which helps mitigate the potential endogeneity problem caused by reverse causality.

Second, the issue of selection bias may exist, resulting in endogeneity. In this study we study digitalization's impact on financial performance and find that the impact is positive. Meanwhile, it is possible that those firms with higher digitalization also perform well in other aspects such as human capital(Crook *et al.*, 2011), which is also essential to financial performance. Consistent with the prior literature (Wooldridge, 2001), we adopt the Heckman model, a two-step process, to handle endogeneity. It can be seen from Table 4.7 that the Inverse Mills Ratio (IMR) is not significant (p<0.1), implying the selection bias does not exist in models (4.6), (4.7), and (4.8). Thus, it is appropriate to utilize Heckman's two-stage model to handle endogeneity here. After adding IMR in the regression model, we re-estimate the effect of digitalization on financial performance after correcting the selection bias. The results in Table 4.7 also show that the outcomes are still consistent with the hypotheses in the second stage of Heckman's model.

Table 4.7 Results of Heckman Correction of Study 2

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
$DIGI_{i,t}$	.3415***	.3083***	.3357***	.3486***
	(11.74)	(10.37)	(11.49)	(11.99)
IMR	.0089	-.0119	-.0121	-.0161
	(0.36)	(-0.51)	(-0.52)	(-0.70)
$GD_{i,t}$		-.0341		
		(-0.93)		
$PD_{i,t}$			.0028	
			(0.10)	
$TD_{i,t}$				.0461*
				(1.74)
$DIGI_{i,t-1} \times GD_{i,t}$		.2257***		
		(5.23)		
$DIGI_{i,t-1} \times PD_{i,t}$			.0887**	
			(2.85)	
$DIGI_{i,t-1} \times TD_{i,t}$				.1314***
				(4.64)
$SIZE_{i,t}$	-.0006	-.0004	-.0004	-.0003
	(-1.45)	(-0.96)	(-0.95)	(-0.75)
$AGE_{i,t}$	-.0183***	-.0190***	-.0187***	-.0187***
	(-6.42)	(-6.71)	(-6.56)	(-6.58)
$LEVE_{i,t}$	-.0031	-.0035*	-.0029	-.0029
	(-1.47)	(-1.65)	(-1.37)	(1.38)
$MTBR_{i,t}$	.0046*	.0051*	.0046*	.0047*
	(2.32)	(2.57)	(2.29)	(2.34)
$AE_{i,t}$	.0001	.00003	.0000	.0000
	(0.91)	(0.66)	(0.63)	(0.67)
$R\&DE_{i,t}$	.0002***	.0002***	.0002	.0001***
	(6.51)	(6.54)	(6.31)	(6.37)

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
Year-Fixed	YES	YES	YES	YES
Industry-Fixed	YES	YES	YES	YES
Constant	2.392^{***}	2.701^{***}	2.688^{***}	2.692^{***}
	(18.24)	(25.93)	(25.78)	(25.89)
R^2	0.1295	0.1326	0.1258	0.1315
Adjust R^2	0.1147	0.1189	0.1120	0.1178
F	8.77	9.68	9.11	9.59
Observations	2638	2638	2638	2638

Note: models (1)-(4) are built with Tobin's *Q* as dependent variable robust t statistics in parentheses*p<0.1, **p<0.05, ***p<0.01

Third, the issue of omitted variables may exist and result in the endogeneity issue. Although we consider six controlling variables, there exist the possibility of omitting variables that have impacts on the link between digitalization and financial performance. Following prior studies (Chari *et al.*, 2008; Lev and Sougiannis, 1996), we calculate the industry average value based on 2-digit SIC to create instruments for digitalization. Then we test and find that there is no weak instrument variable problem (F=19.65>10). Finally, we utilize the predicted digitalization value to estimate the regression models and report the results in Table 4.8. All the estimated results remain consistent with the hypothesis that digitalization is positively and significantly related to financial performance (coef.=1.101, p<0.01), with GD (coef.=0.586, p<0.05), PD (coef.=0.256, p<0.1), and TD (coef.=0.4063, p<0.05) moderating the relationship positively.

Table 4.8 Results of IV Regression of Study 2

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
$DIGI_{i,t}$	1.101^{***}	$.937^{***}$	1.054^{***}	1.024^{***}
	(6.78)	(5.25)	(6.31)	(6. 02)
$GD_{i,t}$		-.0369		
		(-0.89)		
$PD_{i,t}$			.0405	
			(1.34)	

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
$TD_{i,t}$				$.0714^{*}$
				(2.35)
$DIGI_{i,t}\times GD_{i,t}$		$.586^{**}$		
		(2.77)		
$DIGI_{i,t}\times PD_{i,t}$			$.256^{*}$	
			(1.82)	
$DIGI_{i,t}\times TD_{i,t}$				$.4063^{**}$
				(3.06)
$SIZE_{i,t}$	-.0003	-.0003	-.0003	-.0003
	(-0.98)	(-0.91)	(-1.09)	(-0.98)
$AGE_{i,t}$	$-.0151^{***}$	$-.0153^{***}$	$-.0157^{***}$	$-.0154^{***}$
	(-4.71)	(-4.97)	(-4.91)	(-4.89)
$LEVE_{i,t}$	-.0051	-.0060	-.0057	-.0052
	(-1.30)	(-1.59)	(-1.45)	(-1.35)
$MTBR_{i,t}$	.0018	.0022	.0019	.0018
	(0.76)	(0.97)	(0.82)	(0.78)
$AE_{i,t}$	.00001	.00002	.0000	.00001
	(0.31)	(0.35)	(0.36)	(0.21)
$R\&DE_{i,t}$	$.00001^{**}$	$.0001^{***}$	$.0001^{***}$	$.0001^{***}$
	(3.32)	(3.69)	(3.64)	(3.71)
Year-Fixed	YES	YES	YES	YES
Industry-Fixed	YES	YES	YES	YES
Constant	2.818^{***}	2.816^{***}	2.832^{***}	2.821^{***}
	(25.85)	(26.99)	(26.29)	(26.47)
Wald chi2	242.38	289.53	259.75	275.51
Observations	2,650	2,650	2,650	2,650

Note: t statistics in parentheses $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

4.4.3 Robustness Analysis

To validate the robustness of the results, we tested our hypothesis with samples in groups: 2-digit SIC industry (Lam *et al.*, 2016). All the samples could be divided into 52 groups, the top ten industries are shown in Table 4.9.

Table 4.9 Percentage of Sample Firms in Additional Analysis of Study 2

2-digit SIC codes	Firm Frequency	Industries	Firm Percentage
73	224	Business services	29.7%
36	56	Electronic & other electric equipment	7.43%
35	50	Industrial machinery & equipment	6.63%
38	41	Instruments & related products	5.44%
60	41	Depository institutions	5.44%
28	40	Chemical & allied products	5.31%
48	37	Communications	4.91%
63	18	Insurance carriers	2.39%
37	16	Transportation equipment	2.12%
87	16	Engineering; accounting; research; management; and related services	2.12%

It can be seen from Table 4.10 that digitalization impacts financial performance positively at a significant level (coef.=0.3253, p<0.01), and does the same under the moderating effects of GD (coef.=0.2237, p<0.05), PD (coef.=0.1026, p<0.05), and TD (coef.=0.1438, p<0.01), suggesting that our model performs well in the robustness test.

Table 4.10 Results of Cross-sectional Regression Analysis of Study 2

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
$DIGI_{i,t}$	$.3253^{***}$	$.2930^{***}$	$.3172^{***}$	$.3323^{***}$
	(11.06)	(6.38)	(10.7)	(11.34)
$GD_{i,t}$		$-.0687^{*}$		
		(-1.79)		
$PD_{i,t}$			.0143	
			(0.50)	
$TD_{i,t}$				.0494
				(1.79)
$DIGI_{i,t}$×$GD_{i,t}$		$.2237^{**}$		
		(5.24)		

Variables	(1) $FP_{i,t+1}$	(2) $FP_{i,t+1}$	(3) $FP_{i,t+1}$	(4) $FP_{i,t+1}$
$DIGI_{i,t} \times PD_{i,t}$			$.1026^{**}$	
			(3.29)	
$DIGI_{i,t-1} \times TD_{i,t}$				$.1438^{***}$
				(5.04)
$SIZE_{i,t}$	$-.0005^{*}$	-.0005	$-.0005^{*}$	-.0005
	(-1.66)	(-1.63)	(-1.69)	(-1.53)
$AGE_{i,t}$	$-.0130^{***}$	$-.0136^{***}$	$-.0132^{***}$	$-.0132^{***}$
	(-5.12)	(-5.35)	(-5.21)	(-5.24)
$LEVE_{i,t}$	-.0032	$-.0039^{*}$	(-.0031)	-.0032
	-1.51	-1.83	(-1.48)	(-1.49)
$MTBR_{i,t}$	$.0051^{*}$	$.0057^{**}$	$.0051^{*}$	$.0052^{*}$
	2.58	(2.84)	(2.53)	(2.58)
$AD_{i,t}$	.0001	.0001	.0001	.0001
	1.13	(1.10)	(1.13)	(1.08)
$R\&DE_{i,t}$	$.0002^{***}$	$.0002^{***}$	$.0002^{***}$	$.0002^{***}$
	5.94	(6.33)	(6.05)	(6.25)
Year-Fixed effect	YES	YES	YES	YES
Industry-Fixed effect	YES	YES	YES	YES
Constant	4.259^{***}	2.4391^{***}	4.118^{***}	3.652^{***}
	(6.18)	(5.84)	(5.975)	(5.26)
R^2	0.1497	0.1598	0.1532	0.1593
Adjust R^2	0.1286	0.1383	0.1316	0.1378
F value	7.11	7.44	7.08	7.42
Observations	2,650	2,650	2,650	2,650

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ t-statistics are in parentheses.

4.5 Discussions and Conclusions

4.5.1 Discussion

This study is an attempt to investigate digitalization's effect on financial performance with consideration of the impact of the diversification strategy using secondary data from multiple sources, i.e., Factiva, Compustat, and USPTO. The financial performance implications of digitalization have attracted research attention in recent years (Oduro *et* *al.*, 2023). Although the majority of the existing studies are theoretical discussions and their authors are predominantly optimistic about the performance improvement effects of digitalization adoption (Verhoef *et al.*, 2021), the limited empirical studies show mixed results (Sharma *et al.*, 2022; Wamba *et al.*, 2015). Using a large-sample secondary dataset containing digitalization data processed with NLP, we find that digitalization can improve organizations' financial performance effectively, which is consistent with prior survey-based studies (Abou-foul *et al.*, 2021; Gu *et al.*, 2023). Specifically, the results suggest that digitalization remains positively associated with firms' financial performance, as measured by Tobin's *Q*. This positive impact on financial performance remains stable and significant in the results of endogeneity and robustness tests.

Moreover, our results indicate that the diversification strategy positively moderates the digitalization-financial performance link, indicating that firms with a higher level of the diversification strategy will enjoy more financial enhancement from digitalization. Specifically, compared with previous single-dimensional measurements (Levine *et al.*, 2021; Su and Tsang, 2015), we examine diversification on three dimensions, i.e., GD, PD, and TD, with data from Compustat and USPTO, providing a more comprehensive view of firms' diversification strategy. The results show that all three dimensions of diversification are effective in strengthening digitalization's positive impact on financial performance. Firms exhibiting greater geographical diversification, with expanded product portfolios, and a more diverse technological base, gain significant financial improvement by adopting digitalization.

4.5.2 Theoretical Implications

This study makes the following three contributions to the existing literature on the effectiveness of implementing digitalization in firms.

First, we establish a conceptual framework concerning digitalization and financial performance based on DCV, exploring the critical impact of digitalization on improving firms' financial performance. The previous literature on digitalization focused on its specific forms, such as social media initiatives (Lam *et al.*, 2016), software libraries (Fink *et al.*, 2020), process digitalization initiatives (Yang and Yee, 2022), and blockchain technology (Guo *et al.*, 2023a). More recently, researchers have shown growing interest in exploring the overall impact of digitalization on firm performance. However, most of these studies provide empirical evidence of digitalization's impact on firm performance using survey data (Issah and Calabro, 2024; Li *et al.*, 2023a); the actual impact of digitalization on financial performance remains mixed and warrants further investigation with more objective data. Our research supplements this body of knowledge in that we examine digitalization's effect through analyzing secondary data of listed companies in North America and applying a pioneering methodology in measuring digitalization, enriching the relevant body of knowledge with more objective and valid evidence.

Second, we identify the diversification strategy as a beneficial contextual factor that enhances the impact of digitalization on financial performance. Within the DCV framework, diversification is identified as crucial for enhancing a firm's ability to leverage digitalization efforts by broadening its resource base and enabling swift re-alignment in response to environmental changes. Historically, diversification has been associated with benefits such as market expansion (Ayal and Zif, 1979; Tang *et al.*, 2019), risk management (Zamore *et al.*, 2019), and optimizing the financial structure (Mehmood *et al.*, 2019). However, its role in enhancing technological adaptability and effectiveness has been relatively overlooked. Given that companies operate under varying environments, resources, and strategies, the benefits derived from innovative technology adoption can differ significantly. The previous literature emphasizes the significance of environmental factors (e.g., institutional conditions, country development, sector technology intensity, and regional science and technology levels) (Liu *et al.*, 2023b; Oduro *et al.*, 2023; Xie *et al.*, 2023) and internal resources and capabilities (e.g., managers' characteristics and organizational factors) (Ribeiro-Navarrete *et al.*, 2021; Yang and Yee, 2022). This study contributes to the literature in that we examine a corporate strategy as a moderating factor, delving into the nuanced dynamics between diversification and digitalization and offering fresh insights into how strategic choices can support leveraging digitalization to enhance organizational performance.

Finally, this chapter broadens the conceptual boundaries of diversification, introducing the technological dimension, providing reference for more intricate future explorations in the domain. Specifically, the majority of existing research on diversification is predominantly confined to the geographical (Pan and Chao, 2010) and product perspectives (Su and Tsang, 2015). Traditionally, firms have prioritized geographical and product diversifications in their strategic planning (Wood *et al.*, 2017). However, the evolving technological landscape now necessitates the consideration of technological diversification, driven by the need for rapid technology iteration (Wanasinghe *et al.*, 2023), applicability across various market settings (Gambardella and McGahan, 2010), adaptability to emerging needs (Kholiavko *et al.*, 2021), and agility in adoption (Troise *et al.*, 2022), compelling firms to continuously update and diversify their technological portfolio. By introducing technological diversification into the diversification strategy, with this chapter we significantly enrich research on diversification, suggesting that incorporation of technological diversification is relevant for researchers working on new insights within the diversification domain.

4.5.3 Managerial Implications

This study offers executives practical insights on leveraging digitalization to enhance their firms' financial performance.

First, the results indicate that firms could introduce and apply digitalization more substantially in their operations to enhance financial performance. Given the concern of limited benefits or returns from early-stage digital investments (Dalenogare *et al.*, 2018) and the perception of digitalization as a significant financial commitment with potential risks (Yang *et al.*, 2021), the so-called "digitalization paradox" leads some executives to hesitate to pursue digitalization (Tian *et al.*, 2023). After verifying digitalization's impact on financial performance, we suggest that executives should recognize the critical financial value of digitalization and increase investments in the associated practices and technologies accordingly.

Second, executives should recognize that diversification can enhance the effectiveness of digitalization in enhancing financial performance. In many cases, the main reason why firms fail to realize the expected benefit from digitalization is that executives blindly implement digitalization without scrutinizing if their firms operate within a conducive environment (Ye *et al.*, 2023). Our findings imply that there are at least three forms of diversification with which firms could make efforts to support digitalization's financial outcomes. To start, firms implementing digitalization should tilt resources to expand foreign operations outside boundaries, exploiting synergies between digitalization and the resources from operations in new geographical areas and/or economies of scale through the expanded operations. Furthermore, executives should invest in developing new product segments together with implementing digitalization, thereby providing flexibility and opportunities for digitalization to shift knowledge and resources to more diverse product segments and optimizing digitalization's resulting knowledge and capabilities. Last, to diversify technologically, firms should be willing to recruit employees with different professional backgrounds and cooperate with universities or research institutes that have relevant technical expertise in both digitalization and other new technological fields.

4.5.4 Limitations and Future Research

Despite much effort, this study has limitations that need to be addressed. First, the sample is listed companies in North America, and the results may not be generalized to smaller companies or those outside North America. Further research is needed to verify digitalization's effectiveness with data from small- and medium-sized enterprises or businesses in other regions. Second, we focus on examining the diversification strategy's moderating effect on digitalization's impact on financial performance. Future researchers may examine the moderating effect of other relevant practices such as supply chain diversity and internal resource slack. Finally, we explore diversification through three dimensions, i.e., geographical, product, and technological diversification. While the global business environment evolves rapidly, new dimensions of diversification may emerge in the future. Considering the strategic importance of diversification in businesses, future researchers can identify such new diversification dimensions and offer insight on their relevance accordingly.

Chapter 5 Study 3 Prolific and Profound? Unraveling the Effects of Digitalization on Innovation Quantity and Quality

5.1 Introduction

In the fast-paced and disruptive business environment, digitalization is widely regarded as one of the key approaches for organizations to gain a long-term competitive edge (Bharadwaj *et al.*, 2013a; Broccardo *et al.*, 2023). In practice, organizations have incorporated digitalization into their core strategies and allocated significant resources to address the dynamic demands, such as Amazon (Armonk, 2023) and IBM (Dfreight, 2023). In literature, the significance of digitalization is well recognized and there has been a lot of evidence on the potential benefits in areas including supply chain profit (Xin *et al.*, 2023), environmental performance (Ye *et al.*, 2023), production (Ku *et al.*, 2020), etc. However, digitalization was thought predictive in data-driven decision making but unlikely to be creative (Christian and Eric, 2023). Despite extensive theoretical discussions, data analysis indicates a scarcity of businesses that have explicitly stated or demonstrated the use of digitalization to enhance innovation. More exactly, out of the initial 81,310 announcements issued in Factiva from 2015-2021 related to digitalization, only 828 explicitly mentioned innovation (3917 mentioned efficiency, 2272 mentioned profit). This practical data indicates a limited focus among businesses on leveraging digitalization for innovation, despite its acknowledged potential. Similarly, the academic research witnesses a parallel trend, with some studies focusing only on theoretical discussions of digitalization's potential to improve innovation (Hendriksen, 2023), with a handful of studies offering empirical evidence of its innovation benefits through survey data (Gaglio *et al.*, 2022; Radicic and Petković, 2023). However, there is scarce evidence on the impact of digitalization on innovation, particularly empirical findings from secondary data (Hendriksen, 2023). This study aims to fill this gap by investigating digitalization's influence on innovation with objective data, addressing the oversight in both practice and academic research.

The rapid data connectivity, effective information sharing, and the virtual and experimental capabilities of digitalization empower organizations to unlock the potential in different innovation outcomes. For instance, Zara actively harnesses digitalization to collect and analyze consumers information to enable real-time market insights, and to realize it's fast fashion value with fast and vast new product development, implying digitalization's potential in innovation quantity (Bharadwaj *et al.*, 2013a). On the other hand, Tesla significantly emphasizes the integration and collaborative aspects of digitalization through a digital twin platform to enhance high-quality innovation (Purdy *et al.*, 2020). These examples highlight digitalization's dual potential in enhancing both the quantity and quality of innovations. Innovation quantity involves expanding the scope and quantity of innovative products, services, or technologies, whereas innovation quality emphasizes the uniqueness and creativity (Edwards-Schachter, 2018). Differentiating between innovation quantity and quality is crucial for grasping digitalization's full impact on innovation (Guo *et al.*, 2020), as failing to do so and misaligning resources could lead to suboptimal innovation outcomes (Li *et al.*, 2023b) or significant inefficiencies (Falkenberg *et al.*, 2022). Consequently, given the constraints of resources and strategic decision-making, achieving a comprehensive measurement and clear understanding of innovation quantity and quality is pivotal. Thus, this study delves deeper into the influence of digitalization on both innovation quantity and innovation quality, seeking to uncover how organizations can harness digitalization to simultaneously boost innovation quantity and quality.

In exploring the relationship between digitalization and innovation quantity (quality), the ACT provides a theoretical framework. ACT sheds light on how firms identify, absorb and utilize external resources and knowledge, processes that are closely intertwined with the acquiring, communicating and integrating functions of digitalization (Cui *et al.*, 2018a), playing a crucial role in enhancing innovation (Cohen and Levinthal, 1989). It also emphasizes that a firm's resources and capabilities greatly affect process effectiveness, underlining the need to consider the firm's organizational contextual factors when assessing how digitalization influences innovation outcomes. According to Zahra and George's understanding of ACT which divides the concept into realized and potential capacities, this chapter specializes the context with two moderators: resource slack and learning capability (Zahra and George, 2002). Specifically, resource slack serves as a marker of realized absorptive capacity, essential for digitalization's integration (Liu *et al.*, 2023a), while learning capability reflects potential absorptive capacity, crucial for new knowledge acquisition and application in digitalization (Sheng, 2019). In summary, digitalization's enhancement of a firm's knowledge processing, along with the consideration of resource slack and learning capabilities, aligns with interpretations of ACT of Cohen and Levinthal (1989) and Zahra and George (2002) respectively, indicating its suitability as this research's theoretical framework.

The primary aim of this chapter is to empirically test digitalization's effectiveness on different innovation dimensions considering the moderating effect of resource slack and learning capability. To test our arguments, we collected a sample of 1475 list firms from North America who announced at least one digitalization announcement during 2015–2021, matched with other variables measured by secondary data from other databases. More specifically, this chapter identifies and processes digitalization announcements from Factiva with NLP, an emerged method that effectively addresses the subjectivity and challenges of manual identification in large volumes of unstructured text data (Shankar and Parsana, 2022). Subsequently, it matches the data of innovation from US Patent and Trademark Office (USPTO), and that of moderators and controlling variables from Compustat, obtaining a specific panel dataset for this study. The result shows that digitalization improves firms' innovation outcome in both quantity and quality. More importantly, this chapter identifies that learning capability is significant in helping digitalization's positive impact on both innovation quality and quantity; while resource slack could only help in improving digitalization's positive impact on innovation quantity. Additional tests with alternative measurements and analytical methods are performed to ensure the robustness of the results.

5.2 Theoretical Background and Hypothesis Development

5.2.1 Absorptive Capacity Theory

ACT traces its roots back to the innovative work of Cohen and Levinthal in 1990, which introduced the concept as a critical determinant of a firm's innovative capacity and long-term performance (Cohen and Levinthal, 1990a). According to ACT, a firm's ability to recognize the value of external information, assimilate it, and apply it is essential for achieving sustainable innovation and competitive advantage (Cohen and Levinthal, 1990a). The three-stage process involves the acquisition of external knowledge, its assimilation into the organization's existing knowledge base, and the application of this assimilated knowledge in new or improved products, services, or processes. Considering its focus on strategic knowledge management for competitive advantage, ACT has broadened applied various domains significantly, such as strategic management (Lenox and King, 2004), information management (Roberts *et al.*, 2012), and innovation studies (Zhao *et al.*, 2021).

This study concentrates on innovation, a pivotal indicator of a firm's future competitive advantage, representing an outcome of a process of leveraging absorptive knowledge and resources. This emphasis of process aligns with the three-stage process outlined by ACT, highlighting the significance of translating continuously external knowledge into competitive innovation. More specifically, to shape firms' innovation strategies, companies need to absorb new information from the environment and use it internally (Kranz *et al.*, 2016a). For instance, a study by Wu *et al.* (2013) explores how a firm's openness strategies influence its innovation capabilities based on the three stages of ACT (Wu *et al.*, 2013). Consequently, ACT emerges as a highly relevant theoretical lens for examining innovation processes, illuminating how firms leverage the absorptive capacity process to secure sustained competitive advantage and achieve innovation success.

However, Cohen's sequential emphasis on knowledge absorption process is controversial especially when these different stages co-existing in a firm (Todorova and Durisin, 2007). For instance, a perspective posits that the stages of absorptive capacity could indeed happen concurrently, rather than in a linear sequence (Chatterjee *et al.*, 2022; Yeoh, 2009). To weaken the sequence and develop the ACT's explanation further, Zahra and George introduced a nuanced perspective, describing absorptive capacity as realized and potential absorptive capacities (Chatterjee *et al.*, 2022). This refinement avoids the sequence controversial but highlights different types of organization's absorbing capacities in fostering innovation (Gebauer *et al.*, 2012), offering a more flexible understanding of how firms leverage external resources and knowledge for innovation. For instance, the study by Cui *et al.* (2022) exemplifies the application of realized and potential absorptive capacity in classifying searching approaches to enhance innovation under the context of information technology usage. It aligns with the process of innovation generation, elucidating why companies with varying resources and capabilities can achieve different levels of absorption effectiveness (Duan *et al.*, 2020). Consistent with these studies, our research utilizes ACT as the theoretical foundation in considering the contextual factors of digitalization's impact on innovation, focusing on resource slack and learning capability as realized and potential capacity.

5.2.2 Literature Review

Innovation quantity and quality. Innovation refers to organizations' ability to introduce or develop new products or services as well as create R&D outputs and patents (Ko and Choi, 2019). Earlier literature tends to utilize one single dimension, such as the number of patents that a firm applied for, to measure innovation (Schilling and Phelps, 2007). Later, the abundance of patents that lack practical application has sparked skepticism among scholars regarding the validity of this measure. Research indicates that patents not only reflect a firm's innovative efforts but also fulfill broader strategic roles, such as providing defense against infringement lawsuits during cross-licensing negotiations (Hall and Ziedonis, 2001), or serving as a tool for strategic positioning to exert pressure on competitors (Lemley and Shapiro, 2005). These strategic motivations lead firms to engage in "patent portfolio races", resulting in accumulating vast numbers of patents with less value (Cantrell, 2009). Therefore, rather than being described by a single dimension, innovation is a complex and comprehensive concept that encompasses multiple dimensions (Gupta, 2021). Some scholars have started to make efforts through dividing innovation into different types, such as exploratory and exploitative innovation (Cui *et al.*, 2022); products and services innovation (Nijssen *et al.*, 2006), and continuous and breakthrough innovation (Morris, 2013).

In their efforts, researchers not only classify innovation to capture its multifaceted complexity but also prioritize data accessibility and authorization, establishing patents to construct some tangible and widely accepted measurement proxies of innovation in academic research, which could be classified generally into two mainstreams: innovation quantity and quality (Ahuja and Katila, 2001; Chu *et al.*, 2019; Hu *et al.*, 2020; Rosenkopf and Almeida, 2003). For innovation quantity, prior research has highlighted drivers that underscore the importance of a broad range of resources, including R&D subsidy (Bronzini and Piselli, 2016), gender diversity on the board (Ain *et al.*, 2022), outward foreign direct investment (Dong *et al.*, 2021), supply network structures (Bellamy *et al.*, 2014), etc. Regarding the determinants of innovation quality, emphasis is placed on intensifying external knowledge integration and deepening learning, illustrated by practices such as balancing exploratory and exploitative knowledge search (Zhou *et al.*, 2022), deepening alliance partnerships (Zheng and Yang, 2015), and leveraging unique and super-modular complementarities of knowledge (Wang *et al.*, 2024) etc. Recent studies have explored factors that could enhance innovation quantity and quality simultaneously, such as supplier-customer proximity (Chu *et al.*, 2019), independent boards (Balsmeier *et al.*, 2017), technological resource divestiture (Kim *et al.*, 2021), etc. Consistent with these studies, this chapter also endeavors to explore drivers to enhance innovation and suggests that specific resource and capability allocation based on distinct innovation output goals, providing firms targeted recommendations to enhance their innovation outputs effectively in the industry 4.0.

Resource slack and learning capability. The various innovation outcomes necessitate a consistent application of firms' resources and capabilities (Cui *et al.*, 2022). First, innovation outcome emphasizes that organizational resource slack provides the necessary flexibility and buffer for experimentation in innovation (Cohen and Levinthal, 1989). In this process, resource slack offers material support for digitalization, facilitating a broader scope and scale of digital innovation initiatives. This buffer allows organizations to experiment with new digital technologies (Duan et al., 2020) without jeopardizing core operations. By enabling multiple trials within a short period and providing opportunities to adjust innovation strategies, resource slack increases firms' tolerance for innovation risks (Nohria and Gulati, 1996), thereby promoting higher-quality and deeper innovation exploration. Second, innovation performance relies on the accumulation of knowledge and the ability to support technological breakthroughs through strong learning capabilities. The innovation process is closely tied to organizational learning and knowledge transfer, which align with the core functions of learning capability—absorbing, integrating, and utilizing knowledge (Valaei et al., 2017). Digitalization facilitates the flow of information and knowledge, and a firm's learning capability enhances this process, ensuring that knowledge is effectively utilized across the organization. This fosters cross-departmental and cross-team collaboration, accelerating the innovation process (Hanelt et al., 2021).Thus, this study examines resource slack and learning capability as contextual factors in the relationship between digitalization and innovation, corresponding to the realized and potential capacities in ACT.

Resource slack, was introduced by Cyert and March in 1956 (Cyert and March, 1956) and further defined by George in 2005, refers to “potentially utilizable resources that can be diverted or redeployed for the achievement of organizational goals” (George, 2005). These resources may remain underutilized within a firm’s possession (Bradley *et al.*, 2011) and shows various types (Lecuona and Reitzig, 2014; Yang and Jiang, 2023), among which, financial slack is the most popular proxy for its flexibility in conversion into different resources (Bradley *et al.*, 2011; George, 2005). In terms of the influence of resource slack on firm performance, the conclusion is complex and controversial. Some argue that abundance of slack resources facilitates experimentation, innovation, and risk-taking (George, 2005). Conversely, others posit that more financial resources makes managers less motivated to react to competitive attacks (Debruyne *et al.*, 2010), harming firm performance (Baker and Nelson, 2005; Mosakowski, 2017). Recently, scholars have tried to examine the slacks’ role combining with different factors to verify when and how these resources slacks influence which perspective of firms’ performance (Nguyen *et al.*, 2023).

On the other hand, learning capability develops from organizational field and now refers to an organization’s capacity to acquire, assimilate, and utilize knowledge for growth and improvement (Sancho-Zamora *et al.*, 2022). It embodies an intrinsic organizational aptitude that directly impacts the efficacy of the entity and its potential to stimulate innovation (Chiva and Alegre, 2009). In prior studies, learning capability was multifaceted and can be described as different types, such as market-focused learning, internally-focused learning (Weerawardena *et al.*, 2006), exploitative learning and explorative learning (Valaei *et al.*, 2017). Considering its ability to encapsulate both the depth and breadth of an organization's commitment to learn, R&D intensity has become a widely accepted indicator of learning capability (Lee *et al.*, 2014). In terms of the studies related to learning capability and innovation, prevailing literature predominantly underscores a positive association between them (Chiva and Alegre, 2009; Curado *et al.*, 2018).

To sum up, considering the impacts of resource slack and learning capability is essential in the realm of digitalization-innovation research. These elements serve as critical levers in influencing the benefits of digitalization on both innovation quantity and quality, providing a nuanced understanding of how firms can navigate and leverage digitalization to be innovate effectively.

5.2.3 Hypothesis Development

When ACT was originally proposed, it identified three critical stages: recognizing valuable external knowledge, assimilating it, and applying it effectively, all of which are intrinsically connected to innovation processes (Cohen and Levinthal, 1990b). The advent of digitalization serves as a bridge between the processes that it fosters enhanced access to external knowledge, facilitate efficient assimilation of this knowledge, and expedite its application to innovative processes. First, digitalization provides the technological infrastructure that enables firms to effectively sense and identify new knowledge sources (Arias-Pérez *et al.*, 2021). It makes organizational boundaries more porous, fostering the inflow of external knowledge, a crucial factor for innovation as highlighted by the absorptive capacity theory (Cohen and Levinthal, 1989; Cui *et al.*, 2018a). However, the benefits of external knowledge are not automatic (Laursen and Salter, 2006). Firms need to recognize the value of this information, assimilate it through knowledge sharing (Cohen and Levinthal, 1990b). Obviously, digitalization has a superior function in knowledge sharing and communication across sections (Audretsch *et al.*, 2023; Lam *et al.*, 2016). Finally, digitalization facilitates the apply stage of ACT through enhancing information processing capabilities, enabling the knowledge application (Saldanha *et al.*, 2017). Thus, digitalization effectively facilitates all three stages of ACT—knowledge acquisition, assimilation, and application—thereby leading to enhanced innovation.

Consistent with section 5.2.2, this chapter describes innovation in both quantity and quality. By bolstering firms' absorptive capability through recognition, integration and application processes, digitalization is expected to not only increase the volume of innovative output (innovation quantity) but also enhance the impact of those patents (innovation quality). Consequently, we posit the following hypotheses:

H1a: Digitalization could improve firms' innovation quantity.

H1b: Digitalization could improve firms' innovation quality.

Although we have argued that digitalization could enhance firms' innovation outcomes, it should be realized that the degree of the improvement may also depend on the richness and the effectiveness of the absorbed capacities, realized and potential as outlined in ACT. Realized absorptive capacity, involving the transformation and exploitation of capabilities within firms' resources and knowledge (Cepeda-Carrion *et al.*, 2012), requires clear order and stability to be effective. That is, realized absorptive capacity calls for clear and stable conditions conducive to deriving novel insights and outcomes from the amalgamation of existing and newly acquired knowledge (Yeoh, 2009). Considering its significant role as a buffer against uncertainties and the flexibility to pivot in response to new information, this chapter identifies financial slack as a key representative of realized capacity. First, financial slack, essentially a stable surplus of financial resources (Herold *et al.*, 2006), equips firms to effectively implement innovative insights into practical business applications, aiding the stable exploration of digitalization with large investment, further to enhance the innovation. Furthermore, a surplus of resources provides firms with the capability to freely explore and assimilate vast swathes of digitalization knowledge and tools without restriction, empowering firms in their digitalization endeavors, and ensuring the efficient identification and internalization of these insights into innovation (Chatterjee *et al.*, 2022). That is, resource slack provide a cushion for digitalization's experimentation, internalizing and risk-taking (George, 2005), enhancing a firm's successful rate of breakthrough innovation.

To sum up, as firms engage in the assimilation with digitalization, resource slack may act as a crucial enabler, allowing firms to allocate more resources and enhance their innovation volume, allowing them to navigate the associated challenges and setbacks, maintaining their commitment to acquiring high-quality knowledge.

Thus, we propose the following hypothesis:

H2a: Resource slack could moderate digitalization's impact on innovation quantity positively.

H2b: Resource slack could moderate digitalization's impact on innovation quality positively.

Potential absorptive capacity, refers to the ability of an organization to identify, value, and acquire new external knowledge (Zahra and George, 2002). This capacity is pivotal in the critical stages of the knowledge absorption process, where organizations internalize knowledge from external sources and accumulate to innovate (Cepeda-Carrion *et al.*, 2012). A critical characteristic of potential absorptive capacity is its demand for change and creativity (Cepeda-Carrion *et al.*, 2012). Learning capability fits the requirement that enables firms to synthesize new, external knowledge with their existing knowledge reservoir. With the more external knowledge and resources brought by digitalization that firms cannot generate internally, learning capability allows firms to identify, integrate and develop a more diverse knowledge base, generating creative ideas (Sancho-Zamora *et al.*, 2022). More exactly, to develop innovation, companies need to absorb new external information and use it internally through learning capability (Kranz *et al.*, 2016b), which could be divided into exploitative and exploratory learning processes (Gebauer *et al.*, 2012). On one hand, the exploitative learning capability enables firms' digitalization to effectively assimilate and utilize the vast array of external knowledge, integrating it with internal resources and expertise, generating efficient innovation. This effective integration of knowledge from both internal and external sources is pivotal in digitalization's increasing the volume of innovative output, allowing firms to rapidly expand their innovation portfolio in response to evolving competence trends (Killen *et al.*, 2008). On the other hand, exploratory learning capability extends beyond mere integration and portfolio of knowledge, emphasizing digitalization's actionable deployment of this synthesized knowledge. Here, exploratory learning capability ensures that the blend of internal and external knowledge through digitalization is strategically channeled into breakthrough innovation processes.

Thus, we propose the following hypothesis:

H3a: A firm's learning capability strengthens the positive effect of digitalization on innovation quantity.

H3b: A firm's learning capability strengthens the positive effect of digitalization on innovation quality.

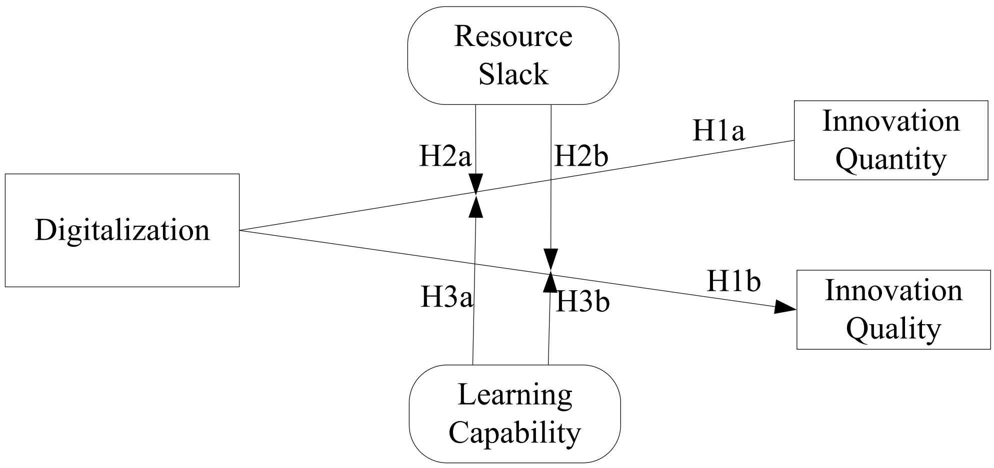


Figure 5.1 Conceptual Framework of The Third Study 3

5.3 Methodology

5.3.1 Data

Our study utilized a multi-database to generate a comprehensive sample of listed firms in North America, drawn from various industries, that have engaged in digitalization activities from 2015 to 2021. We chose 2015 as the baseline year due to the significant growth in digitalization activities two years after the introduction of the Industry 4.0

concept in 2013, in contrast to the steady trend observed prior, with digitalization announcements around 96,500. To elaborate further, our initial data of digitalization is from Factiva, a renowned global news database, which identified 5,737 announcements from a pool of 1,475 firms that issued at least one announcement related to digitalization between the research period. Subsequently, we identified the firms' GVKEY Code manually, and matched digitalization data with financial data from Compustat. Then, to gain insights into these firms' innovation activities, we further cross-referenced the list of 1,475 firms with data obtained from the USPTO. This provided us with a matched panel of 1,461 firms. After deleting the samples with missing data, we got an initial panel data set of 1,430 firm-year observations with a total 5,292 digitalization announcements, as shown in Table 5.1.

Table 5.1 Descriptive Statistics of Study 3

Panel A: Distribution of samples firms which issued digitalization announcements across year

Year	Frequency	Percentage
2015	612	11.56%
2016	617	11.66%
2017	722	13.63%
2018	728	13.76%
2019	711	13.44%
2020	820	15.50%
2021	1082	20.45%
Total	5292	100%

Panel B: Firm Characteristics

Variables	Unit	Mean	SD	Min	Max
Total Assets	Millions of dollars	31943.877	163583.83	0	3169495
Number of Employees	Thousands	20.3	46.0	0	470.2
Firms age	Years	20.856	9.499	1	80
Cash Flow	Millions of dollars	-1.14	27.904	-2254	178.8
ROA		-.03	.5	-10.9	.5

Panel C: Percentage of industry based on division

DIVISION	Percentage
I. Services	34.90
D. Manufacturing	32.05
H. Finance, insurance, and real estate	14.42
E. Transportation, communications, electric, gas, and sanitary service	7.77
G. Retail trade	5.78
F. Wholesale trade	1.64
B. Mining	2.69
C. Construction	0.17
J. Public administration	0.58
A. Agriculture, forestry, and fishing	0
Total	100

5.3.2 Variables Measurement

The measurement of the variables utilized in this research, including the focal variables and control variables are summarized in Table 5.2.

Independent variable: Digitalization. Consistent with prior research (Verhoef *et al.*, 2021), we define digitalization as the firms' behavior of utilizing digital technologies. After applying a strict NLP method (Shankar and Parsana, 2022) to process the unstructured announcements issued in Factiva, we collected statistics of digitalization data accurately and standardized the digitalization data by industry (SIC-2 codes) due to the varying distribution of product digitalization scores across different industries (Ashouri *et al.*, 2022).

Dependent variable: Innovation. Innovation refers mainly to organizations' ability to introduce or develop new products or services as well as create R&D outputs and patents (Ko and Choi, 2019). Realizing that using solely the quantity of patents as an indicator of a firm's innovative capability does not paint a comprehensive picture (Lemley and Shapiro, 2005), this chapter considers both the amount and the substantial impact of the patents, which reflects innovation quantity and innovation quality (Hu *et al.*, 2020). More exactly, to measure innovation quantity, we use the number of patent applications as a proxy (Balsmeier *et al.*, 2017; Lee and Chung, 2022). For assessing innovation quality, we rely on the number of citations a patent receives, indicating its significance and impact in the domain (Lee and Chung, 2022).

Moderating variables: Resource Slack. Resource slack refers to the surplus resources at a firm's disposal, allowing it flexibility in strategic decision-making and the ability to pursue potential investments without external financing. As a predominant form of internal resource, financial slack plays an indispensable role in buttressing a firm's adaptability in the face of market dynamics and ensuring uninterrupted innovation trajectories. This concept is empirically gauged using the liquidity ratio, defined as the ratio of a firm's total current assets to its total liabilities (Lin *et al.*, 2009; Yang *et al.*, 2011).

Learning Capability. Learning capability embodies a firm's ability to absorb, adapt, and apply new knowledge in a manner that furthers its competitive advantage. It serves as the bedrock upon which companies base their efforts to innovate, evolve, and outmaneuver competitors. This capability's empirical manifestation is often assessed via R&D intensity, which is calculated as the ratio of a firm's research and development (R&D) expenditures to its sales or revenue. Such a metric provides a lens through which one can gauge the firm's investment vigor in R&D activities—activities inherently linked with the pursuit of new knowledge, the genesis of groundbreaking technologies, and the nurturing of innovation. Consequently, an escalated R&D intensity stands as a beacon of a company's resolute commitment to continuous learning, adaptability, and sustaining a vanguard position within its industry.

Controlling variables. In elucidating the relationship between digitalization and innovation, it becomes paramount to account for other variables that can significantly influence this dynamic. Firstly, Firm Size often correlates with innovation capabilities, as larger organizations may possess better infrastructure for innovation but may also face bureaucratic hurdles. Firm Age plays a role, as older organizations may have entrenched routines, affecting their agility in adopting innovative practices, whereas newer entities might be more adaptable. The Capital to Labor ratio (K/L) is critical, as an optimal balance between technology and human capital can pivotally influence innovation outcomes. Firm Leverage offers insights into financial decisions, with higher leverage potentially restricting firms' capacity to invest in innovative projects due to debt obligations. The Market-to-Book Ratio is indicative of market valuation and its perspective on a firm's growth prospects, possibly acting as an innovation catalyst or deterrent. ROA is a telltale of a firm's operational efficiency and may influence its capability and intent to channel resources toward innovation. Sales Growth and Sales Growth Rate are harbingers of a firm's market trajectory and its profitability, which can either amplify or suppress its innovative pursuits. Lastly, Cash Flow and Capital Expenditure offer financial health snapshots, with sufficient liquidity often being a prerequisite for sustained innovative ventures.

Table 5.2 Key Variable Measurement of Study 3

Variables (Abbreviations)	Measurements	Sources	References
	Independent Variables		
Digitalization (DIGI)	Annual firm-level count of digitalization announcements	Factiva	Dotzel and Shankar (2019)
	Dependent Variables		
Innovation Quality (IQL)	The number of forward citations a patent gets.	Uspto	Singh (2008) Jia *et al.* (2019) Kumar and Zaheer (2019)
Innovation Quantity (IQT)	the number of patents that a firm has applied for (and are granted eventually) each year.	Uspto	Krolikowski and Yuan (2017) Tan *et al.* (2014) Jia *et al.* (2019)
	Moderating Variables		
Resource Slack (RS)	Resource slack is excess inputs for the same level of output, i.e., lower efficiency, to evaluate if increasing levels of resource efficiency lead to diminishing financial returns for firms.	Compustat	Bourgeois (1981); Hendricks *et al.* (2009)
Learning Capability (LC)	R&D intensity is typically calculated as the ratio of a company's research and development (R&D) expenditures to its sales or revenue.	Compustat	Cohen and Levinthal (1990a) Lee *et al.* (2010) Escribano *et al.* (2009) Bellamy *et al.* (2014))
	Control variables		
Firm Size (SIZE)	Total asset	Compustat	Jia *et al.* (2019) Lu and Wang (2018)
Firm Age (AGE)	Calculated by a firm's initial public stock offering	Compustat	Lam *et al.* (2016) Wang and Zatzick (2019)
Firm Leverage (LEVE)	A firm's total debt divided by total assets (account for the effect of capital structure)	Compustat	Zhong (2018) Lu and Wang (2018)
Market-to-Book Ratio (MTBR)	A firm's market value of equity divided by book value of equity	Compustat	Zhong (2018) Jia *et al.* (2019) Lu and Wang (2018)
Sales Growth Rate (SGR)	measured by the difference of an organization's sales in year t and year t–1 divided by its sales in year t–1.	Compustat	Wang and Zatzick (2019)
Cash Flow (CF)	Cash flow from operating activities	Compustat	Lu and Wang (2018)
Capital Expenditure (CAPX)	Capital expenditure divided by total assets	Compustat	Lu and Wang (2018)

5.3.3 Model Development

Our first aim is to estimate the impact of digitalization on the innovation. We adopt the following Eq. (5.1) for estimation:

$$Innovation_{\,i,t+1} = \alpha_0 + \alpha_1 Digitalization_{it} + \alpha_2 M_{it} + \alpha_3 Digitalization_{it} \times M_{it} + \alpha_4 Firm\ Size_{it} + \alpha_5 Firm\ Age_{it} + \alpha_6 Firm\ Leverage_{it} + \alpha_7 MarkettoRatio_{it} + \alpha_8 Sale\ growth_{it} + \alpha_9 Cash\ Flow_{it} + \alpha_{10} Capital\ Expenditure_{it} + \sum_{k=1}^{I} \delta_k\, Firm_k + \sum_{m=1}^{Y} \mu_k\, YEAR_m + \varepsilon_{it} \qquad (5.1)$$

Here subscript *i* represents the firm and subscript *t* represents the calendar year, α_0 to α_{10} denote scalars, *M* presents Moderators, including Resource Slack and Learning Capability, both are excluded in testing H1. The equation concludes a vector of control variables which explain innovation outcomes might be influenced by firm size, age, leverage, market to book ratio, sale growth rate, cash flow and capital expenditure, GVKEY firm code and year.

It is important to recognize that, since patents from different years have different "windows of opportunity" to be cited in our dataset, a direct comparison of patent citations across patents from different years would be inappropriate. To overcome this issue, we follow Jaffe and Trajtenberg (2002) (Chapter 13) in including year fixed effects in all regressions, so that systematic cross-year differences arising from this "truncation bias" are taken into account. Similarly, as described below, technology fixed effects help overcome systematic cross-technology differences in citation rates. Following previous studies (e.g., Kiss *et al.* (2018); Lam *et al.* (2016)), we lag the variables by one year to address potential endogeneity associated with digitalization.

5.4 Empirical Results

5.4.1 Baseline Results

Table 5.3 and Table 5.4 presents the means, standard deviations, and correlation coefficients. Since high coefficients of correlation were found between some of the studied variables, we followed the procedures suggested by Aiken and West to standardize the independent variables of the original terms and their interaction terms to mitigate the potential problem of multicollinearity (Aiken and West, 1991). Because all values of the variance inflation factor (VIF) were smaller (from 1.01 to 1.38) than the suggested ceiling of 10, there was no evidence of multicollinearity.

Table 5.3 Characteristics of The Core Variables of Study 3

Variables	Observations	Mean	SD	Min	Max
DIGI	8409	0.629	1.767	0	58
IQT	8409	32.677	84.07	1	2580
IQL	8409	745.224	415.77	0	190510
RS	8409	50.857	560.88	0	27130.5
LC	8409	6.577	11.95	0	88.66

Table 5.4 Correlations Matrix of Study 3

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) $DIGI_{i,t}$	1.000											
(2) $IQT_{i,t}$	0.297	1.000										
	(0.000)											
(3) $IQL_{i,t}$	0.073	0.120	1.000									
	(0.000)	(0.000)										
(4) $RS_{i,t}$	0.074	0.153	0.035	1.000								
	(0.000)	(0.000)	(0.004)									
(5) $LC_{i,t}$	0.101	0.065	0.016	0.004	1.000							
	(0.000)	(0.000)	(0.188)	(0.730)								
(6) $SIZE_{i,t}$	-0.005	-0.005	-0.004	-0.005	0.002	1.000						
	(0.681)	(0.671)	(0.711)	(0.661)	(0.891)							
(7) $AGE_{i,t}$	0.063	0.121	0.003	-0.003	0.166	0.047	1.000					
	(0.000)	(0.000)	(0.780)	(0.826)	(0.000)	(0.000)						
(8) $LEVE_{i,t}$	-0.010	-0.017	-0.015	-0.040	0.016	0.026	-0.006	1.000				
	(0.406)	(0.149)	(0.198)	(0.001)	(0.179)	(0.027)	(0.640)					
(9) $MKBR_{i,t}$	0.027	-0.046	0.004	0.008	0.047	0.028	-0.083	0.104	1.000			
	(0.023)	(0.000)	(0.762)	(0.498)	(0.000)	(0.019)	(0.000)	(0.000)				
(10) $SGR_{i,t}$	-0.002	-0.001	-0.011	0.003	0.032	-0.008	-0.011	-0.012	-0.003	1.000		
	(0.876)	(0.950)	(0.368)	(0.810)	(0.007)	(0.502)	(0.375)	(0.322)	(0.815)			
(11) $CF_{i,t}$	0.008	0.018	0.008	0.001	0.004	0.014	0.029	-0.004	-0.007	0.016	1.000	
	(0.494)	(0.137)	(0.489)	(0.961)	(0.763)	(0.245)	(0.016)	(0.745)	(0.585)	(0.190)		
(12) $CAPX_{i,t}$	-0.006	0.004	0.001	0.012	-0.015	0.234	0.023	0.038	0.011	-0.009	0.021	1.000
	(0.586)	(0.716)	(0.935)	(0.323)	(0.214)	(0.000)	(0.058)	(0.002)	(0.370)	(0.441)	(0.083)	

Note: n=7061; P-value in parentheses in columns

Table 5.5 reports the regression results. Model 1 tests the relationship between digitalization and innovation. We find that digitalization has a positive effect on innovation quantity (0.113, $p<0.01$) and on innovation quality (0.098, $p<0.01$). More specified, this impact remains consistently and significantly positive across all models, reinforcing the robustness of this relationship. Hence, our hypotheses H1a and H1b are supported.

H2a and H2b predict that the positive relationship between digitalization and innovation (innovation quantity and innovation quality) becomes stronger in firms with higher resource slack. In Model 2, the interaction term between digitalization and resource slack exhibits a significant positive impact on innovation quantity (0.077, $p<0.01$), while its effect on innovation quality is not statistically significant. The results suggest that resource slack does moderate the impact of digitalization on innovation quantity, supporting H2a. However, the influence of digitalization on innovation quality shows positive but not significant (0.004, $p>0.1$), suggesting that H2b is not supported. The possible reason might be that resource slack, might inadvertently foster a complacent organizational culture or encourage suboptimal allocation to various projects due to perceived abundance (Tan and Peng, 2003). Conversely, innovation quality involves sophisticated, focused projects which demand a more precise, directed use of resources and alignment with core objectives innovation (Jansen *et al.*, 2005)

H3a and H3b predict the important moderating role of learning capability that suggest the positive relationship between digitalization and innovation (innovation quantity and quality) could be strengthened in firms with higher learning capability. In

Model 3, the interaction between digitalization and learning capability is noteworthy. It presents significant results for both innovation quantity (0.033, $p<0.05$) and quality (0.063, $p<0.01$). This signifies that learning capability indeed plays a role in enhancing the positive effects of digitalization on innovation, in line with hypotheses H3a and H3b. That a surplus of resources provides the necessary bandwidth and flexibility for firms to rapidly test, iterate, and scale innovative endeavors; Simultaneously, learning capability plays a crucial role in assimilating precise and sophisticated knowledge, thus amplifying the effects of digitalization on innovation quantity.

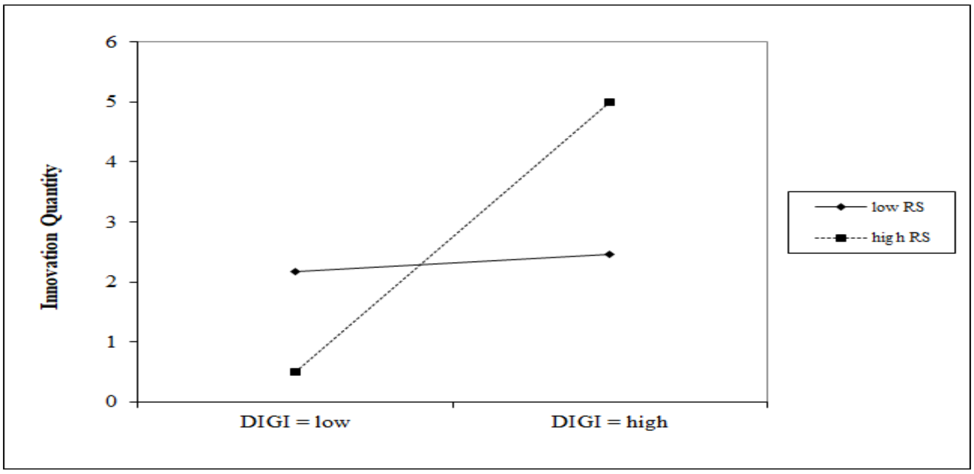
Table 5.5 Results of FE Regression Analysis of Study 3

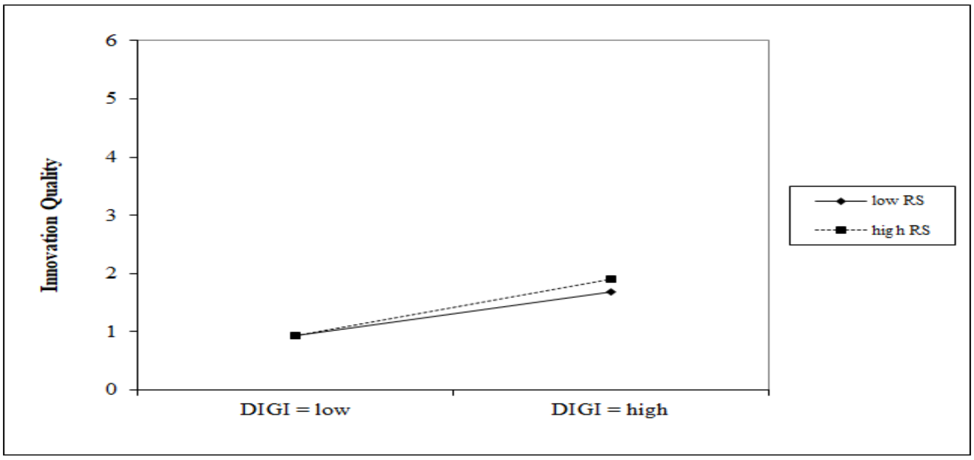
Variables	Model 1		Model 2		Model 3	
	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$
$DIGI_i$	0.113^{***}	0.098^{***}	0.112^{***}	0.098^{***}	0.108^{***}	0.083^{***}
	(0.015)	(0.017)	(0.014)	(0.017)	(0.015)	(0.019)
$RS_{i,t}$			-0.198^{***}	0.002	-0.201^{***}	0.004
			(0.019)	(0.016)	(0.019)	(0.016)
$LC_{i,t}$			0.090	0.084	0.102	0.091
			(0.137)	(0.137)	(0.141)	(0.137)
$DIGI_{i,t}\times RS_{i,t}$			0.077^{***}	0.004		
			(0.013)	(0.013)		
$DIGI_{i,t}\times LC_{i,t}$					0.033^{**}	0.063^{***}
					(0.014)	(0.020)
$SIZE_{i,t}$	-0.093	-0.036	-0.091	-0.040	-0.094	-0.039
	(0.072)	(0.082)	(0.069)	(0.083)	(0.071)	(0.082)
$AGE_{i,t}$	0.062	-0.056	0.047	-0.068	0.049	-0.066
	(0.073)	(0.093)	(0.067)	(0.093)	(0.068)	(0.093)
$LEVE_{i,t}$	-0.825	-0.614	-0.922	-0.615	-0.936	-0.480
	(1.166)	(1.285)	(1.091)	(1.284)	(1.097)	(1.279)
$MTBR_{i,t}$	-0.843	4.648	-1.885	4.308	-1.481	4.142
	(2.914)	(3.683)	(2.997)	(3.763)	(3.009)	(3.771)

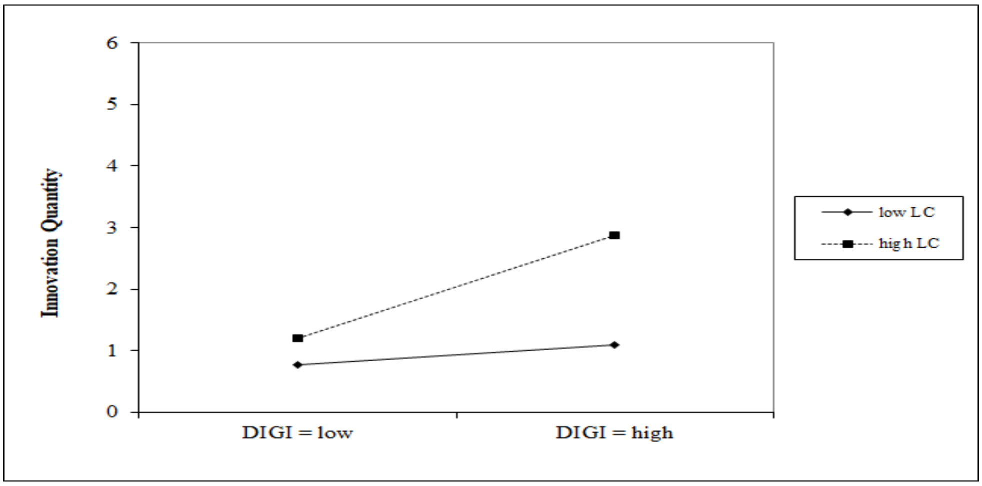
Variables	Model 1		Model 2		Model 3	
	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$
$SGR_{i,t}$	-0.000	-0.006	0.001	-0.006	0.001	-0.006
	(0.002)	(0.012)	(0.003)	(0.012)	(0.003)	(0.012)
$CF_{i,t}$	0.052	-0.132	0.093	-0.121	0.087	-0.109
	(0.141)	(0.226)	(0.150)	(0.226)	(0.147)	(0.229)
$CAPX_{i,t}$	0.113	0.028	0.122*	0.030	0.122*	0.031
	(0.074)	(0.106)	(0.069)	(0.106)	(0.068)	(0.104)
Constant	0.028	-0.107	0.089	-0.102	0.074	-0.109
	(0.058)	(0.071)	(0.058)	(0.072)	(0.058)	(0.072)
Year-fixed effect	YES	YES	YES	YES	YES	YES
Firm-fixed effect	YES	YES	YES	YES	YES	YES
Observations	5788	5788	5788	5788	5788	5788
R^2(within)	0.0227	0.0096	0.1026	0.0097	0.0912	0.0131
F statistic	6.24	3.10	13.20	2.60	11.72	4.39

Note: *p<0.1, **p<0.05, ***p<0.01 Robust standard errors

To further visualize the moderating effect of resource slack (RS) and learning capability (LC) on the relationship between digitalization (DIGI) and innovation (IQT and IQL) more intuitively and simply, this study presents a standard moderation effect graph (see Figure 5.2). The illustration indicates that the moderating roles of LC are positive in digitalization's enhancement on both IQT and IQL, thereby providing additional validation for Hypotheses 3a and 3b; the moderating of RS on DIGI and IQT is also positive, validating the Hypothesis 2a, however, it's moderating effect on DIGI and IQL is not significant.







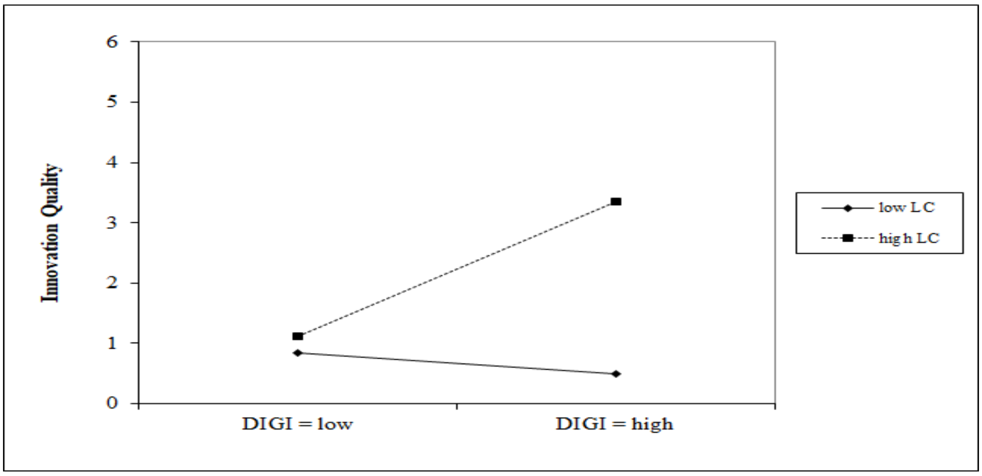


Figure 5.2 The Moderating Effect of Resource Slack and Learning Capability on The Relationship between Digitalization and Innovation of Study 3

In addition, in order to more intuitively and comprehensively understand the impact of resource slack (RS) and learning capability (LC) on digitalization's impact on innovation (IQT and IQL), this chapter has drawn the surface diagram and contour diagram of the impact of digitalization (DIGI) and interaction between DIGI and RS, LC respectively, as shown in Figures 5.3 to 5.6.

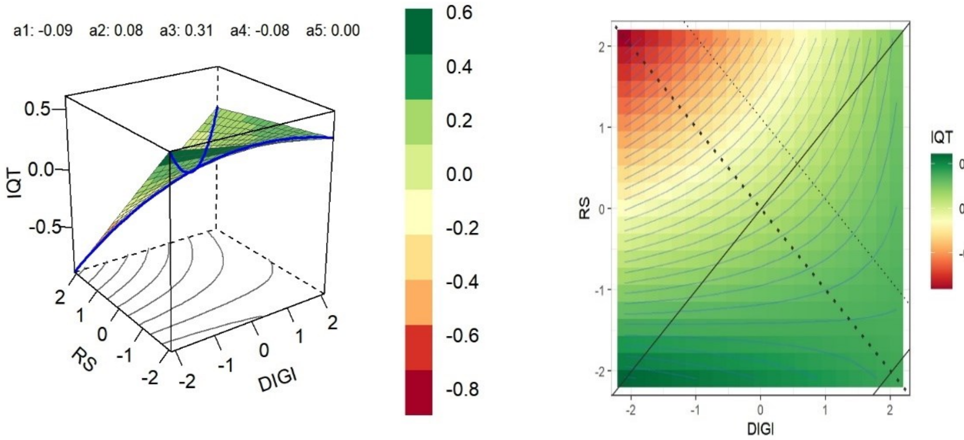


Figure 5.3 The Interaction Effect of Digitalization and Resource Slack on Innovation Quantity

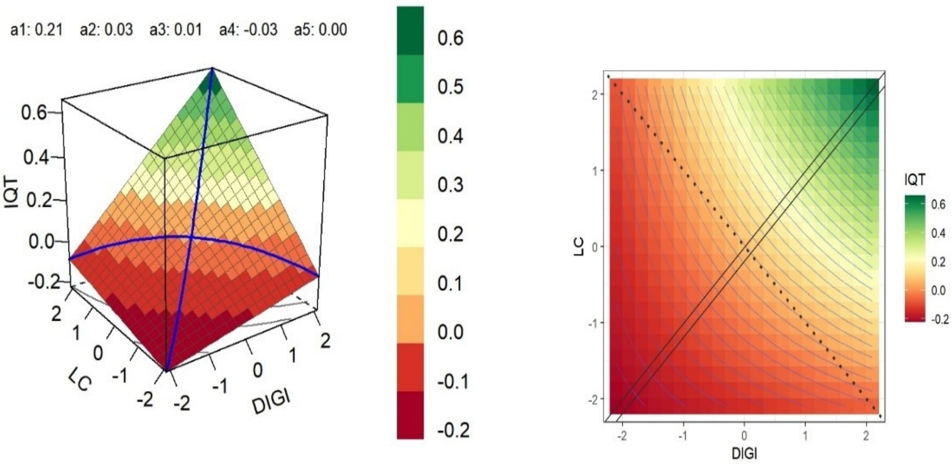


Figure 5.4 The Interaction Effect of Digitalization and Learning Capability on Innovation Quantity

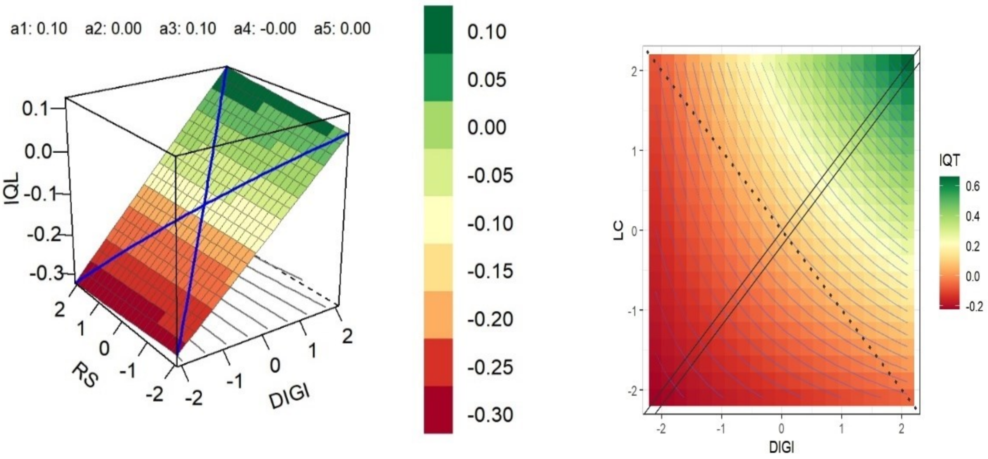


Figure 5.5 The Interaction Effect of Digitalization and Resource Slack on Innovation Quality

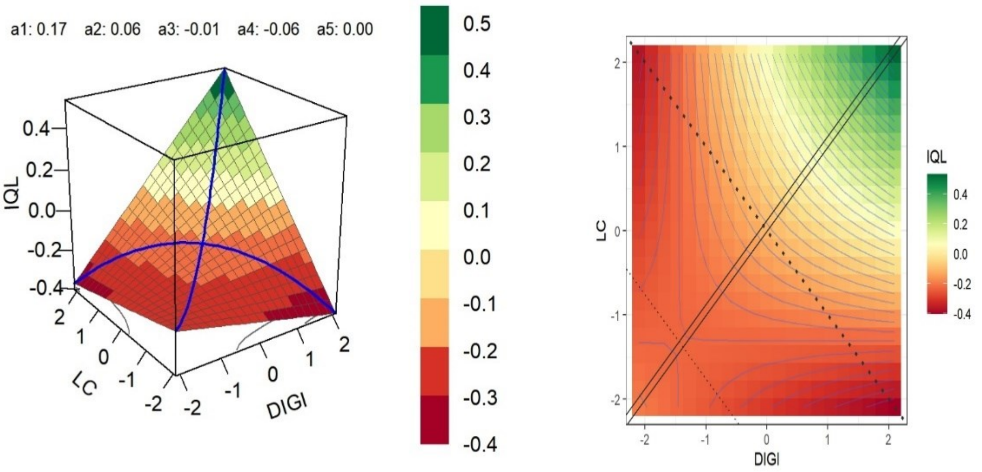


Figure 5.6 The Interaction Effect of Digitalization and Learning Capability on Innovation Quality

As can be seen from the surface plots in Figures 5.3 and 5.4, a higher level of innovation quantity (IQT) can be observed in higher level of digitalization (DIGI) and in higher level of RS and LC. In other words, when RS and LC are higher, DIGI has a more positive impact on the IQT of a firm. Hypotheses 2a and 3a of study 3a are verified. The contour plots in Figures 5.3 and 5.4 also depict the same results: starting from the lower left side with RS and LC to the right side, it can be observed that the IQT increases with the increasing DIGI (color changes from red to green), further supporting hypotheses 2a and 3a.

Also in Figures 5.6, higher IQL can be observed in the case of higher DIGI level and higher LC. In other words, when LC is high, the DIGI has a positive impact on IQL of the firms. Hypothesis H3b of study 3 is verified. The contour plots in Figures 5.6 also depict the same information: starting from the lower left side where LC is low to the right side, it can be observed that IQL increases with the increasing DIGI (color changes from red to green), further supporting Hypothesis 3b. However, in the surface diagram and contour diagram in Figure 5.5, the interaction effect of DIGI and RS on IQL is not significant, thereby Hypothesis 2b is not supported.

5.4.2 Endogeneity Tests

Endogeneity issue is a problem of incorrect conclusions that results from one or more explanatory variables in a model are associated with the error item (Toh and Polidoro, 2013). Generally, endogeneity can stem from causes such as reverse causality, sample selection bias, and omitted variables (Toh and Polidoro, 2013)

First, reverse causality. The digitalization could be endogenously determined because firms with higher innovation level may have more opportunities and motivation to invest and adopt digitalization. Under this situation, the digitalization and the error term maybe correlative, resulting to endogeneity problem. Based on prior studies (Hegde and Mishra, 2019; Shou *et al.*, 2020), we use one year lag of each digitalization and control variables instead of their present values in models to process the regression, which will help to mitigate potential endogeneity problem caused by reverse causality.

Second, selection bias. There still exists possibility of sample selection bias in the data colleting process. Thus we process the Heckman model (Kumar *et al.*, 2018). we also estimate a two-step Heckman selection model to account for potential sample-induced endogeneity. The first stage (selection equation) uses a Probit model to estimate digitalization propensity. The second stage (ultimate equation) uses maximum likelihood estimation to predict digitalization intensity with the inclusion of inverse Mills ratio (IMR) that accounts for potential sample-induced endogeneity (Clougherty *et al.*, 2016). Table 5.6 reports the full results of the Heckman correction models. More exactly, the IMR for each regression about innovation quantity is -0.765, -0.711 and -0.752 at $p<0.01$. This implies that unobserved factors have affected the process and outcomes of sample selection. After Heckman correction, the regression results of digitalization and innovation quantity keeps positive and significant ($p<0.01$), and the relationship could be strengthened in firms with higher resource slack ($p<0.01$) and with higher learning capability ($p<0.05$), which is consistent with the baseline results, supporting H1a, H1b, H2a and H3a. additionally, the IMR for each regression about innovation quality is -0.087, -0.100 and -0.112 at $p>0.1$, indicating that the selection bias does not affect the regression results, which is consistent with baseline results, supporting H1b, H3b. The H2b keeps unsupported.

Table 5.6 Results of Heckman Correction of Study 3

Variables	Stage 1	Stage 2					
	DIGI Dummy	Model 1		Model 2		Model 3	
	Coef.	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$
$DIGI_{i-1}$		0.112^{***}	0.098^{***}	0.111^{***}	0.098^{***}	0.106^{***}	0.083^{***}
		(0.015)	(0.017)	(0.014)	(0.017)	(0.015)	(0.019)
IMR		-0.765^{***}	-0.087	-0.711^{***}	-0.100	-0.752^{***}	-0.112
		(0.196)	(0.248)	(0.181)	(0.250)	(0.181)	(0.247)
$RS_{i,t}$	$-.022^{*}$			-0.197^{***}	0.002	-0.200^{***}	0.004
	(.018)			(0.019)	(0.016)	(0.019)	(0.016)
$LC_{i,t}$	$.074^{***}$			0.130	0.089	0.144	0.097
	(.018)			(0.134)	(0.137)	(0.138)	(0.137)
$DIGI_{i,t} \times RS_{i,t}$				0.076^{***}	0.004		
				(0.012)	(0.013)		
$DIGI_{i,t} \times LC_{i,t}$						0.034^{**}	0.063^{***}
						(0.014)	(0.020)
$SIZE_{i,t}$	-.005	-0.078	-0.034	-0.079	-0.038	-0.082	-0.037
	(.018)	(0.073)	(0.083)	(0.070)	(0.083)	(0.071)	(0.082)
$AGE_{i,t}$	.031	-0.165^{*}	-0.082	-0.169^{*}	-0.098	-0.180^{**}	-0.100
	(.018)	(0.100)	(0.115)	(0.091)	(0.116)	(0.092)	(0.116)
$LEVE_{i,t}$	-1.55^{*}	2.315	-0.254	1.991	-0.204	2.150	-0.021
	(.975)	(1.434)	(1.590)	(1.317)	(1.588)	(1.346)	(1.579)
$MTBR_{i,t}$	3.52^{*}	-9.663^{***}	3.639	-10.222^{***}	3.130	-10.313^{***}	2.829
	(2.21)	(3.433)	(4.495)	(3.465)	(4.605)	(3.467)	(4.584)
$SGR_{i,t}$	-.010	0.020^{***}	-0.004	0.020^{***}	-0.004	0.021^{***}	-0.003
	(.016)	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)	(0.013)
$CF_{i,t}$	.408	-2.111^{***}	-0.379	-1.912^{***}	-0.404	-2.035^{***}	-0.425
	(.397)	(0.599)	(0.825)	(0.569)	(0.830)	(0.572)	(0.825)
$CAPX_{i,t}$	.006	0.109	0.028	0.120^{*}	0.030	0.120^{*}	0.031
	(.021)	(0.073)	(0.106)	(0.068)	(0.106)	(0.067)	(0.104)
Constant	$-.611^{***}$	2.847^{***}	0.216	2.710^{***}	0.268	2.849^{***}	0.304
	(-10.42)	(0.724)	(0.916)	(0.668)	(0.923)	(0.669)	(0.912)
Year-fixed Effect	YES	YES	YES	YES	YES	YES	YES
Firm-fixed Effect	NO	YES	YES	YES	YES	YES	YES
Observations	5788	5,788	5,788	5,788	5,788	5,788	5,788
R^2	-	0.027	0.0131	0.0131	0.0131	0.095	0.013
F statistic	-	7.59	2.88	14.28	2.44	12.94	4.14
Censored Observations	2,189	2,189	2,189	2,189	2,189	2,189	2,189
Uncensored Observations	4,872	4,872	4,872	4,872	4,872	4,872	4,872

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ Robust standard errors

5.4.3 Robustness Test

As a robustness check, we utilized the data of granted patents to instead of applied patents in baseline regression. Exactly, we measure innovation quantity with the amount of granted patents and innovation quality with the citations of granted patents. We depicted in the Table 5.7 for the impact of digitalization on innovation via granted patents, have been grounded in the FE model framework. To maintain rigorousness, all standard errors were clustered at the firm level.

From the outset, the results from the initial columns manifestly demonstrate the positive repercussions of digitalization on innovation quantity (coef.=0.086, $p<0.01$) and innovation quality (coef.=0.211, $p<0.01$). This evidence robustly supports Hypotheses H1a and H1b. Delving deeper, the moderating role of resource slack surfaces. The findings indicate that while resource slack positively moderates the impact of digitalization on innovation quantity (coef.=0.034, $p<0.01$), bolstering Hypothesis H2a. However, the resource slack's impact on the relationship between digitalization and innovation quality was positive but still not significant (coef.=0.004, $p>0.1$), Hypothesis H2b was not supported by the empirical evidence, which is consistent with the result of baseline results. Lastly, we put all the moderating variables into Model 3 and found the firm's learning capability emerges as a significant player, substantially intensifying digitalization's positive effect on innovation quantity (coef.=0.024, $p<0.05$) and innovation quality (coef.=0.063, $p<0.01$), affirming Hypothesis H3a and 3b.

Table 5.7 Results of Robustness Test of Study 3

Variables	Model 1		Model 2		Model 3	
	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$
$DIGI_{i-1}$	0.086^{***}	0.211^{***}	0.085^{***}	0.210^{***}	0.081^{***}	0.083^{***}
	(0.011)	(0.020)	(0.011)	(0.020)	(0.010)	(0.019)
$RS_{i,t-1}$			-0.004	0.018	-0.005	0.004
			(0.007)	(0.013)	(0.007)	(0.016)
$LC_{i,t-1}$			-0.023	0.107	-0.017	0.091
			(0.071)	(0.096)	(0.071)	(0.137)
$DIGI_{i,t} \times RS_{i,t}$			0.034^{***}	0.004		
			(0.011)	(0.021)		
$DIGI_{i,t} \times LC_{i,t}$					0.024^{**}	0.063^{***}
					(0.010)	(0.020)
$SIZE_{i,t}$	-0.039	-0.013	-0.036	-0.019	-0.037	-0.039
	(0.043)	(0.074)	(0.044)	(0.075)	(0.044)	(0.082)
$AGE_{i,t}$	0.048^{*}	-0.088	0.051^{*}	-0.103	0.052^{*}	-0.066
	(0.026)	(0.067)	(0.027)	(0.071)	(0.026)	(0.093)
$LEVE_{i,t}$	0.114	0.221	0.150	0.231	0.164	-0.480
	(0.363)	(0.848)	(0.376)	(0.848)	(0.365)	(1.279)
$MTBR_{i,t}$	-2.220^{*}	2.275	-2.375^{*}	1.863	-2.226	4.142
	(1.329)	(2.436)	(1.396)	(2.459)	(1.372)	(3.771)
$SGR_{i,t}$	-0.001	0.001	-0.001	0.000	-0.001	-0.006
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.012)
$CF_{i,t}$	0.039	0.068	0.043	0.080	0.042	-0.109
	(0.040)	(0.092)	(0.043)	(0.091)	(0.044)	(0.229)
$CAPX_{i,t}$	-0.013	0.011	-0.013	0.014	-0.013	0.031
	(0.041)	(0.081)	(0.043)	(0.079)	(0.041)	(0.104)
Constant	-0.039	-0.132^{***}	-0.033	-0.129^{***}	-0.041	-0.109
	(0.028)	(0.046)	(0.029)	(0.046)	(0.028)	(0.072)
Year-fixed Effect	YES	YES	YES	YES	YES	YES
Firm-fixed Effect	YES	YES	YES	YES	YES	YES
Observations	5,788	5,788	5,788	5,788	5,788	5,788
R^2(within)	0.069	0.080	0.082	0.0883	0.0883	0.013
F statistic	5.29	9.39	4.66	7.97	4.72	4.39

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ Robust standard errors

To refine these insights, we ushered in an additional analysis, weaving both moderators into a single model. This enriched perspective divulged consistent outcomes. Resource slack plays a favorable factor in digitalization's impact on innovation quantity, but remains inert for firms anchoring with digitalization for quality enhancement. Meanwhile, learning capability keeps robust positive in both innovation quantity and quality enhancement by digitalization, reinforcing its pivotal role in magnifying the effects of digitalization on innovation.

In our preceding analyses, we probed into the individual moderating effects of resource slack and learning capability in the relationship between digitalization and innovation outcomes. Initial results keep stable in the further investigations in additional test, as shown in Table 5.8. More specifically, resource slack significantly influenced innovation quantity with a coefficient of 0.078 ($p<0.01$) in Model 4, rendering it an invaluable asset for firms keen on ramping up their innovation volume. However, its impact on innovation quality appeared negligible, with a mere coefficient of 0.006 ($p>0.1$) in the full model, indicating that sheer investment in resources might not guarantee superior innovative quality.

Learning capability, on the other hand, showcased its universal appeal across both dimensions of innovation. In Model 4, it amplified the effects of digitalization on innovation quantity and quality with coefficients of 0.036 ($p<0.01$) and 0.063 ($p<0.01$) respectively. This buttresses the preliminary conclusion that its influence on innovation quality might slightly eclipse its impact on quantity.

Table 5.8 Additional Analysis of Study 3

Variables	Model 4 (applied patents)		Model 5 (granted patents)	
	$IQT_{i,t+1}$	$IQL_{i,t+1}$	$IQT_{i,t+1}$	$IQL_{i,t+1}$
$DIGI_{i,t}$	0.104***	0.083***	0.079***	0.195***
	(0.014)	(0.019)	(0.010)	(0.019)
$RS_{i,t}$	-0.197***	0.004	-0.003	0.020
	(0.019)	(0.016)	(0.007)	(0.013)
$LC_{i,t}$	0.094	0.090	-0.020	0.114
	(0.137)	(0.137)	(0.070)	(0.097)
$DIGI_{i,t}\times RS_{i,t}$	0.078***	0.006	0.034***	0.006
	(0.013)	(0.013)	(0.011)	(0.021)
$DIGI_{i,t}\times LC_{i,t}$	0.036***	0.063***	0.025***	0.064***
	(0.013)	(0.020)	(0.009)	(0.021)
$SIZE_{i,t}$	-0.090	-0.038	0.051*	-0.101
	(0.069)	(0.082)	(0.026)	(0.073)
$AGE_{i,t}$	0.048	-0.066	0.206	0.377
	(0.067)	(0.093)	(0.379)	(0.832)
$LEVE_{i,t}$	-0.841	-0.473	-2.455*	1.654
	(1.093)	(1.279)	(1.400)	(2.419)
$MTBR_{i,t}$	-2.002	4.103	-0.001	0.001
	(3.003)	(3.770)	(0.001)	(0.002)
$SGR_{i,t}$	0.001	-0.006	0.048	0.093
	(0.003)	(0.012)	(0.045)	(0.099)
$CF_{i,t}$	0.100	-0.108	-0.012	0.015
	(0.151)	(0.229)	(0.045)	(0.074)
$CAPX_{i,t}$	0.123*	0.031	-0.035	-0.017
	(0.070)	(0.104)	(0.044)	(0.075)
Constant	0.085	-0.108	-0.036	-0.135***
	(0.058)	(0.072)	(0.029)	(0.045)
Year-fixed Effect	YES	YES	YES	YES
Firm-fixed Effect	YES	YES	YES	YES
Observations	5788	5788	5,788	5,788
R^2(within)	0.0629	0.0530	0.086	0.088
F statistic	12.75	4.14	4.69	7.45

Note: *p<0.1, **p<0.05, ***p<0.01 Robust standard errors

5.5 Discussion and Conclusions

5.5.1 Discussion

This study is based on panel data from the listed companies in North America spanning the years from 2015 to 2021. Through theoretical analysis and empirical examination, this chapter extends digitalization's potential in improving firms' innovation quantity and quality. In this light, several crucial finds and implications are unveiled: (1) Digitalization will significantly promote the quantity and quality of firms' innovation. This conclusion remains valid after a series of robustness tests. (2) As a potential absorptive capability, the learning capability will strengthen digitalization's positive function in improving both innovation quantity and quality. (3) As a realized absorptive capability, the resource slack will only strengthen digitalization's impact on innovation quantity.

5.5.2 Theoretical Implications

First, echoing Radicica's call for further use of secondary panel data instead of survey data to study the impact of digitalization on innovation, this chapter identifies digitalization as a key driver for both innovation quality and quantity based on Cohen and Levinthal's perspective of ACT (Radicic and Petković, 2023). In prior studies of researching factors contributing to innovation, scholars have identified internal organizational structures, behaviors, resources, and capabilities (i.e. senior management characteristics (Lee and Chung, 2022), inter-organizational cooperation (Liu *et al.*, 2023c), resource slack (Wiersma, 2017), and research collaboration (Zhang *et al.*, 2019) respectively)) and external technological advancements (Liu *et al.*, 2022). As digitalization progresses, encompassing technologies such as artificial intelligence, blockchain, big data, cloud computing, and the internet of things, there is increasing interest in their potential to drive innovation. This research provides empirical evidence for digitalization's impact on innovation quality and quantity, exploring digitalization as a driver of innovation with secondary empirical evidence.

Second, this chapter enriches the innovation studies through describing it from two dimensions: quantity and quality, highlighting the significance of differentiating them based on the limited-resource practice. More specifically, by establishing clear innovation objectives, this study aims to circumvent blind innovation and underscores the importance of a holistic approach to measuring innovation, thereby enhancing the multidimensionality of innovation literature. Prior studies have noticed the issue of "innovation blindness", which includes the phenomenon where different departments within an organization fail to share ideas due to a lack of awareness or understanding of each other's perspectives (Leonardi, 2011), and the situation of large firms which fail to adequately respond to disruptive changes but continue to invest heavily in innovation in its traditional areas of business (Neus *et al.*, 2017). These studies underscore the importance of having well-communicated and clear innovation goals within a firm but only focus on innovation quantity or innovation quality, ignoring the pivotal role of comprehensive description. This research contributes to this area of study by emphasizing the importance of distinguishing innovation aims into quantity and quality. Such a distinction is crucial for firms with limited resources and capabilities, as it aids in appropriately allocating resources and capabilities to the most pertinent areas (Hall and Andriani, 2003). By incorporating both two dimensions, our study paves the way for a more comprehensive and nuanced exploration of innovation.

The third theoretical implication is associated with the moderating roles of resource slack and learning capability in digitalization's function on both innovation quantity and quality, identifying their nuance difference in the relationship between digitalization and different innovation outcomes. Although some prior studies have pointed out that the two factors are influential in promoting innovation (Demirkan, 2018; Weerawardena *et al.*, 2006), few literature has analyzed their nuance subtle differences in varied innovation dimensions. This research verifies their distinct effects when delving into the subtle distinctions between innovation's quantity and quality. Specifically, both resource slack and learning capability act as catalysts for firms striving to enhance innovation quantity via digitalization. Conversely, when a firm aims to enhance innovation quality through digitalization, it is the learning capability that plays a more active moderating role, rather than resource slack. The possible reason might be that the inherent characteristics of resource slack do not align well with the rigorous requirements typically associated with enhancing innovation quality. Thus, while resource slack provides a breadth for multiple innovative endeavors, it might lack the necessary depth and strategic focus in enhancing innovation quality, potentially explaining the non-confirmation of H3b in empirical tests. This nuance underscores the importance of aligning strategies with the specific goals of digitalization in enhancing innovation, and the necessity of recognizing the differential roles played by contextual elements.

5.5.3 Managerial Implications

Our study provides some policy implications regarding utilizing digitalization in firms innovation. First, for firms which strive to concurrently chase innovation quantity or quality with their limited resources and capabilities, this chapter suggests that they could leverage digitalization as an effective driver in their innovation strategy. Prior comments given to executives focused on traditional R&D processes, such as participating in collaborative innovation networks (Benhayoun *et al.*, 2020), enhancing R&D collaborations (Kafouros *et al.*, 2020) and etc. This chapter explores digitalization's critical function in enhancing firms' innovation outcomes. Thus, we recommend that executives seeking to enhance their innovation should pay more attention in adopting digitalization, harnessing its potential to drive both the innovation quantity and quality.

Second, this chapter suggests executives to recognize the multidimensional aspects of innovation. It is essential for business leaders to understand that innovation encompasses both quantity and quality, each requiring distinct resources and focus (De Rassenfosse, 2013). Recognizing this distinction is vital for the effective allocation of resources and strategic planning in enhancing innovation within a firm. The innovation goals should align with the broader corporate strategy to ensure cohesive progress towards the organization's overarching objectives. Firms aiming to boost innovation quantity at a reduced cost should prioritize innovation quantity, drawing inspiration from companies like Zara. Conversely, firms striving for market differentiation should place a greater emphasis on the quality of their innovations, mirroring the approach of companies like Tesla. This targeted approach to innovation allows firms to better align their resources and capabilities with specific innovation goals and market demands.

Third, executives need to be aware of the favorable contextual factors of digitalization's impact on different innovation aims, balancing resource slack and learning capability for quantity-driven innovation goals with digitalization. With the aim around ramping up innovation quantity through digitalization, it is crucial for firms to efficiently allocate resource slack and prioritize learning capability in conjunction with their digitalization efforts. For example, on one hand, firms could first reallocate their slacked financial fund towards technological-relative resources such as extending strategic partnerships and collecting more information and resources; on the other hand, they could invest in comprehensive training programs that enhance employees' digitalization literacy and capability as the suboptimal context for digitalization's impact on innovation quantity. For executives aimed to enhance firms' innovation quality, they should pivot their focus and resources towards strengthening learning capability in their digitalization journey. For example, firms could hold more training programs, set up incubator programs and establishing skill-building workshops to cooperate with digitalization's functioning process in improving innovation quality.

5.5.4 Limitations and Future Research

There are at least three limitations in this research. First, as we utilized the listed companies embedded in North America area as a sample unit of this analysis, which limits the generalizability of our findings to private firms and firms located in other counties. Compared with publicly listed firms, unlisted firms often have less resources and more flexible structures which may affect digitalization’s absorptive capability in enhancing innovation. Similarly, firms located in different countries may encounter varying levels of governmental and infrastructural support to implement digitalization, leading to diverse innovation outcomes. Therefore, it would be necessary and interesting for future studies could verify the results developed in this study with a larger sample scope, such as unlisted firms in North America or other firms in Asian or European countries.

Furthermore, this research calls for more measurement of innovation dimensions. This chapter utilized the number of patent application and citations of patents as the measurement of innovation quantity and quality respectively, providing a relatively comprehensive understanding of innovation. However, it is crucial to recognize that innovation is multifaceted and can manifest in ways beyond just patents outcome. For example, directions in innovation quality research might duly consider metrics that better reflect quantity scope and quality gradations, such as trademarks and breakthrough innovations. Integrating such measures can offer a more nuanced and depth-filled perspective on innovation.

Finally, the innovation literature identifies many factors influencing the innovation process. While this study only incorporates two factors (resource slack and learning capability) in digitalization’s impact on innovation. To gain a more holistic understanding of the factors influencing digitalization’s impact on innovation, future research could delve into the exploring other variables, such as strategic alliance, supply chain diversifications. A comparative analysis considering diverse factors would provide a richer perspective on the function of digitalization in driving innovation.

Chapter 6 Conclusions and Future Works

6.1 Conclusions

Since the introduction of Industry 4.0 at the Hannover Messe (Hannover Fair) in Germany in 2013, digitalization has rapidly evolved and has been widely adopted across various sectors (Yang and Gu, 2021). Despite this widespread adoption of digitalization for numerous purposes, the substantial failure rate associated with these initiatives underscores the complexity and challenges firms face in effectively leveraging digitalization. This phenomenon highlights a critical gap in understanding whether and under what conditions digitalization is beneficial for firms. Thus, three empirical studies were conducted in this dissertation to address this gap by examining digitalization within listed North American firms. The results offer empirical evidence regarding its impacts on several dimensions of firm performance.

Study 1 addresses the research question of whether and when firms benefit from digitalization in product and operations management. Study 1 focuses on the impact of digitalization on operational efficiency and explores the uncertainty of different levels as influential factors based on RBV. The findings indicate that digitalization enhances the operational efficiency of firms through the integration of production resources, the formation of efficient product routines, and the cultivation of analytical and design capabilities for productivity. Moreover, Study 1 identifies that uncertainty generally undermines the positive effects of the above relationship. For instance, macro-level uncertainty (e.g., the emergence of global events or economic policy changes within countries) as well as industrial uncertainty (e.g., sudden shifts in competitors' supply and market demand) can hinder the ability of digitalization to enhance operational efficiency. Conversely, the impact of firm-level uncertainty (e.g., unexpected changes in profit or income) is negative but not significant. A plausible explanation for this result is that the negative effects of firm-level uncertainty can be mitigated through the potential collaboration of the focal firm with its partners within supply chains. Overall, Study 1 shows that while digitalization fosters operational efficiency, the extent of its effectiveness is contingent upon prevailing levels of uncertainty. This result offers pivotal insight for enhancing operational management through digitalization.

Study 2 further explores whether and when firms experience financial benefits from digitalization. Previous empirical studies have discussed the financial returns obtained from digitalization through theoretical discussion and empirical research on the utilization of survey data (Guha and Kumar, 2018; Wang *et al.*, 2020). However, the inconsistent and varied results observed in practice suggest that further examination is needed to understand the complexities of the impact digitalization has on financial performance (Sharma *et al.*, 2023). Therefore, Study 2 focuses on the impact of digitalization on financial performance and further explores diversification strategy as an important moderating factor based on DCV. The conducted analysis shows that digitalization significantly improves financial performance, and that this positive impact can be further strengthened by firms' diversification strategy. Specifically, firms' expansions into new geographical locations (e.g., multinational companies), product markets (e.g., multidivisional corporations), and technological domains (e.g., technological companies) provide more accesses for digitalization to accurately sense customer demands, seize potential opportunities, and synergize operations with flexible technological support. Overall, Study 2 highlights how digitalization, coupled with strategic diversification, can drive financial improvement, thus providing valuable insights for firms aiming to harness digitalization for financial gains.

Study 3 addresses whether and when firms benefit from digitalization under different innovation dimensions. Existing research related to digitalization generally explored its functions in production systems (Ye *et al.*, 2023), personnel promotion (Brivot *et al.*, 2014), and marketing performance (Yang and Yee, 2022). However, its potential functions in driving innovation have received less attention. Study 3 therefore focuses on the impact of digitalization on innovation outcomes and explores both resource slack and learning capability as important moderating factors based on ACT. The findings uncover a substantial positive impact of digitalization on innovation outcomes, which is further differentiated between innovation quantity and quality. Further, the impact of digitalization on various innovation dimensions diverges under different contexts. Specifically, learning capability (e.g., professional extent of research employees) provides a conducive context for the influence of digitalization on both innovation quantity and quality; however, resource slack (e.g., surplus financial resources) significantly bolsters the effect on innovation quantity but does not markedly enhance innovation quality. This distinction underscores the nuanced relationship between digitalization and innovation, highlighting the importance of strategic resource allocation and emphasising learning to optimize the benefits of digitalization. Consequently, Study 3 enriches the discourse on innovation management in the digital era, providing key insights on how to leverage digitalization to effectively foster innovation.

6.2 Theoretical and Practical Implications

This dissertation has important theoretical implications for research on the impact of digitalization across different performance dimensions. Firstly, by employing NLP to measure digitalization, this dissertation overcomes the challenges of term ambiguity, mixed usage, and unclear measurement; in the past, these have led to a predominance of theoretical discussions or empirical studies that rely on survey data. The utilization of NLP to process extensive announcements issued by listed firms fills a key gap by providing a secondary data-based measurement of digitalization. With these accurate data, this research examines the effectiveness of digitalization in operational efficiency, financial outcomes, and innovation dimensions, thus offering a solid foundation for future research related to digitalization. Secondly, this dissertation explores varying contextual factors that influence different performance outcomes of digitalization, anchored in distinct theoretical frameworks. Specifically, uncertainty is identified as a significant factor in the digitalization-operational efficiency relationship based on RBV; according to DCV, diversification is a crucial element in the digitalization-financial performance nexus; according to ACT, resource slack and learning capability are key moderators in the digitalization–innovation outcomes relationship. These applications of classic management theories in digitalization research, which extend their relevance for contemporary technological contexts, underscore the enduring utility of these frameworks in navigating the complexities of the modern business landscape. Thirdly, this dissertation offers a comprehensive exploration of uncertainty, describing it from macro-, industrial-, and firm levels, thereby enriching uncertainty research. Additionally, diversification is measured from geographical, product, and technological perspectives, thus enhancing the conceptual discourse and offering nuanced insights for future studies.

This dissertation has several managerial implications that are crucial for firms embarking on or navigating through digitalization. Despite substantial investments, many firms encounter challenges or even fail in their digitalization efforts. Such failure has sparked pressing queries among executives about the efficacy of digitalization, the conditions under which it benefits organizations, and the potential barriers to its successful implementation. The findings of this dissertation first emphasize the importance of recognising digitalization as a strategic tool to enhance operational efficiency, financial performance, and innovation outcomes rather than merely perceiving it as a generic method for imitating the practices of competitors. With this insight into the link between digitalization and operational efficiency as well as financial performance and innovation dimensions, firms with the strategic goal to enhance different organizational purposes should invest more substantially in digitalization. This dissertation also highlights the importance of recognising the multidimensional aspects of the effectiveness of digitalization for executives, each requiring distinct resources and foci. Regarding the managerial implications derived from individual studies, Study 1 underscores the importance for executives to assess and identify the types of uncertainty their organizations face when attempting to leverage digitalization to enhance operational efficiency and adjust their digitalization strategies accordingly. Specifically, executives should carefully assess macro- and industrial-level uncertainties when leveraging digitalization to enhance operational efficiency; they should also recognize that firm-level uncertainties may not significantly impact the effectiveness of digitalization because of cooperative partnerships. Study 2 suggests that executives seeking financial returns from digitalization should specifically pay attention to their diversification strategy. Effectively synchronizing diversification with digitalization strategies can significantly amplify financial returns. Specifically, executives should leverage diversification to enhance the implementation of digitalization, integrate resources across various markets, exploit the unique advantages of different geographical locations, and flexibly utilize technological support from a robust technology base. Study 3 elaborates on the impact of digitalization on the multifaceted nature of innovation, emphasising the importance to recognize its various dimensions for strategic resource allocation and learning capability. Specifically, executives should efficiently allocate resource slack or learning capability in conjunction with their digitalization efforts to improve the quantity of innovation; simultaneously, they should prioritise learning capability to improve innovation quality within their organizations.

6.3 Limitations and Future Work

In addition to the limitations of the three individual studies discussed above, overall, this dissertation has two major limitations that open avenues for future research. First, the utilized sample only covers listed companies in North America. Although this sample was utilized to establish a unique and relevant dataset, the findings may not be generalizable to non-listed firms in other regions. Compared with listed firms, non-listed firms often have less resources and more flexible structures, both of which may affect the absorptive capability of digitalization in enhancing innovation. Similarly, firms located in different countries may encounter varying levels of support from governments and infrastructure to implement digitalization, leading to diverse outcomes. Therefore, it would be necessary and interesting for future studies to test the results obtained by this dissertation with a larger sample scope, such as non-listed firms in North America or other firms in Asian or European countries.

Second, this dissertation explores the contextual factors influencing the impact of digitalization on operational efficiency, financial performance, and innovation outcomes considering the contextual factors of uncertainty, diversification strategy, resource slack, and learning capability based on RBV, DCV, and ACT, respectively; however, other possible operational factors have been ignored. Given that the effectiveness of digitalization can manifest differently under different operational contexts (such as the diversity of the external supply chain or internal governance characteristics), it is essential for subsequent studies to deepen the research into digitalization.

Appendix A

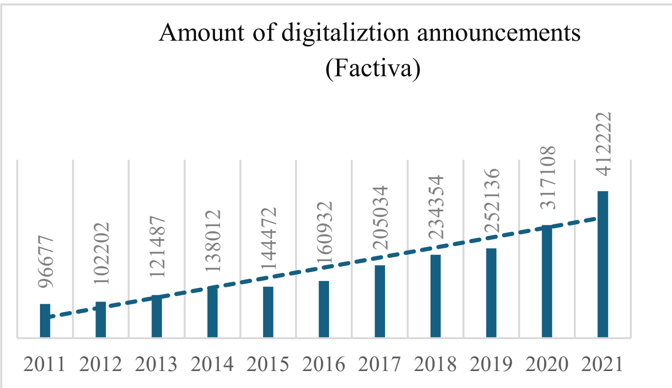
We used broad search terms including “digit!” (to capture any word that starts with “digit,” such as “digitalization,” “digitalise,” or “digital”) and a number of relevant verbs (such as “adopt” and “implement”) to ensure the announcements identified were pertinent to making changes or adopting new practices. One key parameter that needed to be determined was the number of words between “digit!” and the relevant verb. Following the approach of Dotzel and Shankar (2019), we experimented with setting this parameter from 8 to 12 and manually inspected the outcomes. The results indicated that a search specifying no more than ten words between “digital” and the relevant verb was the most effective setting to obtain relevant announcements accurately.

With this setting and the search terms discussed above, we input the following to Factiva,

> *“(digit or digits or digitization or digitalization or digitalisation or digitize or digitise or digital or digitally or AI or big data or cloud or blockchain or internet of things) near 10 (construct or constructs or constructing or constructed or construction or adopt or adopts or adopted or adopting or adoption or use or uses or using or used or usage or usages or utilize or utilizes or utilizing or utilized or utilization or develop or develops or developing or developed or development or exploit or exploits or exploiting or exploiting or exploitation or apply or applies or applying or applied or application or equip or equips or equipping or equipped or equipment or establish or establishes or establishing or established or establishment).”*

This search resulted in 81,310 announcements. We then followed the steps of Shankar and Parsana (2022) to employ LDA, which is an ML algorithm particularly useful for analyzing large volumes of text data, to classify files into different groups with distinct digitalization types. We also supplemented the LDA analysis with manual inspection to ensure accuracy in the classification.

We also paid attention to make sure we collected announcements from accurate sources. Factiva is a comprehensive database comprising data from various sources. This study followed prior literature (e.g., Hendricks and Singhal (2003)) to gather announcements from two major sources, namely Dow Jones and the *Wall Street Journal*. To ensure the accuracy of the data from these two sources, we compared the search results of Dow Jones and the *Wall Street Journal* against those from the whole Factiva database (see Figure I). The number of digitalization announcements in Factiva showed a linear trend and maintained a steady increase over the years. In contrast, trends in Dow Jones and the *Wall Street Journal* were more consistent with practice—the jump in 2013 is partly related to the proposition of "Industry 4.0" that promotes the rapid development of digitalization; the valleys in 2019 and 2020 are consistent with the outbreak of COVID-19, supporting the accuracy and representativeness of the data from these two resources.



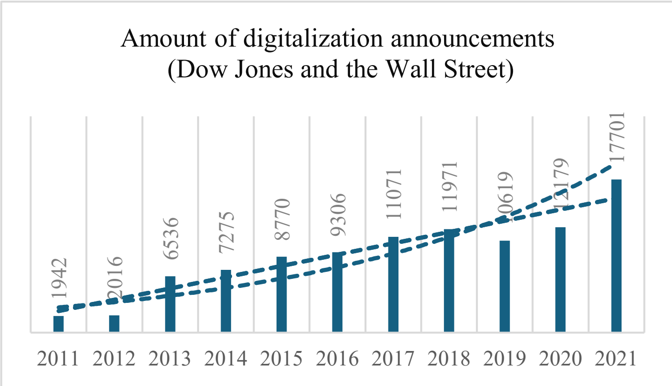


Figure I Trends of Digitalization Announcements from Factiva (all sources), Dow Jones and the Wall Street Journal

Appendix B

We completed a four-stage collection process (Dotzel and Shankar, 2019; Shankar and Parsana, 2022) to develop the digitalization data. The details are presented in Table I.

Table I Steps of Digitalization Data Collection Using NLP

Steps	Description
Stage 1: Preprocess and clean announcements	►Tokenize the corpus in whitespaces. ►Convert each character to its lowercase form. ►Remove numbers at the beginning or end of the sentence or passage. ►Remove stop words. ►Remove punctuations, single character words, and very high frequency words that offer little inference. ►Lemmatize all words.
Stage 2: Run information extraction (IE) with the rules-based model.	► Extract the companies' names. ► Opt for a rules-based model, using text documents of the characteristics and structures to find rules for extraction. ►Construct the regular expression to classify the digitalization announcements into five types that are distinct in the announcements. Type 1: A company announced acquisition of another company to obtain new expertise of digital technologies. Type 2: A company announced the appointment of a senior manager to carry out specific digitalization-related tasks or with an emphasis on their prior experience in digitalization. Type 3: A company announced development or launched new digital technologies. Type 4: A company announced co-design or co-development with third parties in digital technologies. Type 5: Other announcements that were obtained through the approach in Appendix I but could not be clarified into Types 1 to 4. In this classification, the levels of restrictions are controlled carefully to make sure announcements only fall correctly into their corresponding types of categories. ►Match each sentence of the announcements with regular expression to gain short but information-rich paragraphs, thereby reducing the data volume and enabling the manual checking process. ►Manually check half the classified announcements and correct the errors identified. The five groups of checked and corrected announcements serve the training purposes in the subsequent stage.
Stage 3: Construct the classification model based on a pre-trained language model: BERT	►Split the dataset by randomly assigning 90% and 10% to the training set and validation set, respectively. ►Train the classification model by the BERT model and linear layers using the training data set. ► Test the classification model by using the validation data set and evaluate the result's accuracy. The accuracy in the result is considered unsatisfactory because the number of Type 5 announcements is markedly higher than any of the the other four types of announcements, making the learning process ineffective. ►To address this problem, data were reclassified into two groups. Group 1 comprises announcments of Types 1 to 4 whereas Group 2 comprises anouncements of Type 5. We used this classification of data to retrain the classification model by BERT and linear layers. The result of this clssification model achieved an accuracy rate of 91.667%.
Stage 4: Collect statistics	► Employ the announcements of Group 1 as the data to reflect the digitalization variable of this study.

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