FIRM DIGITALIZATION AND CORPORATE PERFORMANCE: THE MODERATING EFFECTS OF ORGANIZATIONAL CAPITAL

By

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ABSTRACT

This thesis examines the interplay between digital transformation and corporate performance with a special emphasis on the moderating effect of organizational capital. Utilizing textual analysis of 10-K reports, a Digital Transformation Score (DGS) is established, which quantifies the extent of a firm's digital activities. The analysis reveals that digital transformation, as represented by the DGS, is positively associated with corporate value. Furthermore, this study identifies organizational capital as a pivotal element in harnessing the value of digital initiatives. The study revolves around a unique dataset of U.S. non-technology firms, providing a novel perspective on the digitalization discourse. The findings highlight that not only is digital transformation conducive to enhanced corporate performance, as measured by Tobin's Q, but it also synergizes with high-quality organizational capital to further enhance corporate value. The evidence also suggests that governance quality, such as higher institutional ownership and superior information quality, underlines the benefits derived from digital transformation. This study contributes to digitalization research by exploring how digital transformation drives corporate performance and defining organizational capital's pivotal role. It delivers insights for both industry and academia, stressing the importance of blending digital strategies with organizational capital, and high information quality in today's digital arena. For professionals, the research offers solid evidence of the need to develop organizational capital to enhance the benefits of digital initiatives. For scholars, it offers novel insights and opens new research avenues, particularly focusing on non-technology firms in the U.S., a sector relatively underexplored in digitalization studies, thereby enriching the understanding of digitalization's impact across diverse business domains.

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CHAPTER 1: Introduction

The landscape of corporate performance is undergoing a profound transformation, driven by the persistent advance of digital technologies. Digital transformation has now become a strategic essential across various sectors; It is no longer about whether companies will adapt to this new digital era, but how effectively they can do so. In this light, the inquiry of this study begins by recognizing the growing consensus among academic scholars and business leaders regarding the necessity of integrating advanced digital tools and methodologies into firms' core operations and strategies. This thesis seeks to explore the intricate dynamics between digitalization efforts and their impact on firm performance, with a focus on the United States non-technology sectors. As companies start adopting digital transformation, they potentially face the critical task of not just adopting new technologies but embedding them within the fabric of their organizational structures, meaning that this challenge is not merely technological but also organizational. CEOs increasingly prioritize growth and cost reduction as key value drivers (PwC 2017),[1] in this context, digitalization is playing a central role. A 2017 Gartner survey finds that 56% of CEOs see digital improvements as a catalyst for revenue growth and value creation in their firms. Digital transformation, which is defined as integrating advanced information technologies like artificial intelligence, big data, cloud technology, and machine learning into a firm's processes and decision-making, aims to drive innovation-led growth and respond to the evolving needs of stakeholders such as employees and customers. This trend (visualized in Fig 1) toward digital transformation within corporations has captured the interests of academics. Emerging research demonstrates a positive link between a firm's digital initiatives and investment efficiency (Xu et al., 2023), productivity (Zhang et al., 2023), stock liquidity (Liu & Liu, 2023), reduced financial distress (Cui & Wang, 2023), ESG

[1] For instance, Zhang and Liu (2023) show that the digitalization has a positive effect on firms' centralization levels by decreasing their communication costs and improving their productivity.

performance (Zhao & Cai, 2023) and credit ratings (Panta, et al. 2023). Additionally, corporate digital transformation is associated with a reduction in stock price crash risk (Song, 2022), cost stickiness (Chen and Xu, 2023), credit spread (Cui et al., 2023), and greenwashing tendencies (Lu et al., 2023).[2]

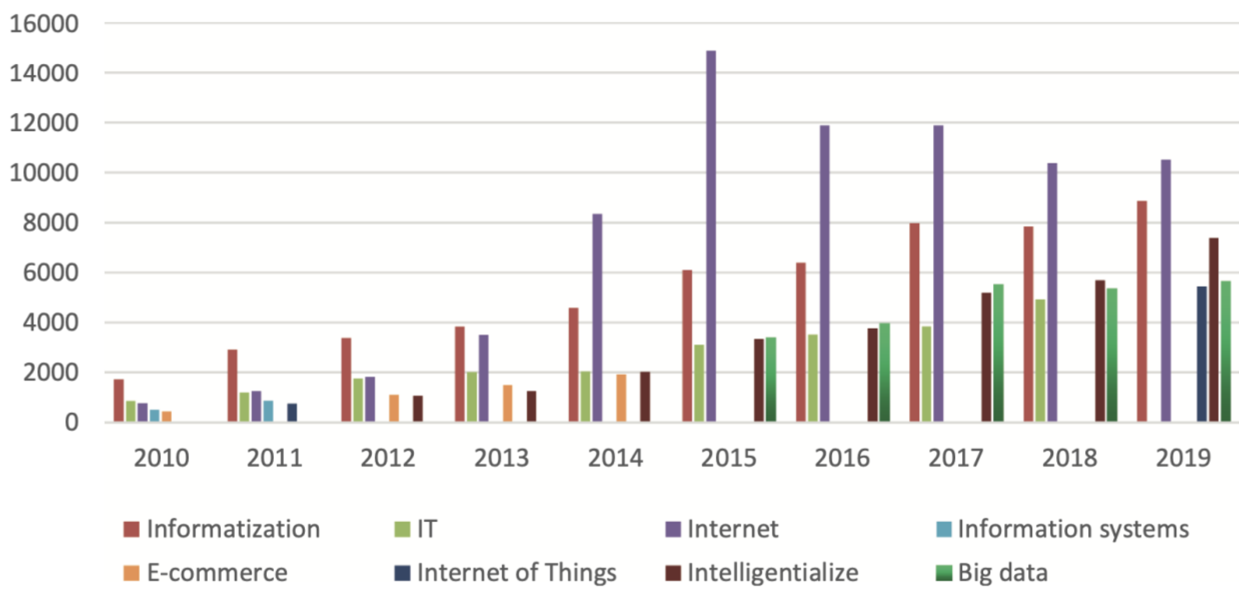

FIGURE 1: SOME CHARACTERISTICS OF DIGITAL TRANSFORMATION OVER TIME

While this developing literature refines our understanding of the relevance of digital transformation, much of its focus has been on China, calling for research attention on the economic implications of digital transformation in other countries. Further, despite evidence supporting digital transformation's

[2] In a cross-country study, Daud et al. (2022) find that FinTech promotes financial stability via artificial intelligence, cloud technology, and data technology.

role in improving firm performance (e.g. Chen & Srinivasan, 2023), many firms still struggle with successfully implementing such changes; this raises questions about the mechanisms that enable firms to achieve such value creation. Discussions on the mechanisms through which digital transformation impacts corporate performance are limited, existing literature reveals two primary gaps:

There's a noticeable absence of studies exploring the moderating effects in the sequence of digital transformation – Intangible Assets– corporate performance. It's crucial to highlight that the journey of enhancing corporate performance through digital transformation isn't straightforward. Companies often face challenges in quickly learning and adjusting to information technology; Moreover, mismanagement of digital technology can further restrict this process (Farouk and Dandago, 2015; Oh et al., 2015). Surprisingly, the finance literature has been relatively unsuccessful in explaining these mechanisms, primarily due to the challenges in their measurement and valuation. Addressing this gap, Zhang et al. (2023) present one of the first studies, to our knowledge, on the role of business model innovation in bridging the gap between corporate performance and digitization. Our study contributes to this growing body of research by exploring how organizational capital shapes this relationship.[3]

We focus on organizational capital (OC), defined by Lev and Radhakrishnan (2005, p. 75) as "an agglomeration of technologies, business practices, process and designs, and incentive and compensation systems"; OC is recognized as a key driver of firm and national growth and competitiveness (e.g., Panta and Panta 2023; Attig and El Ghoul 2018; Youndt, Subramaniam, and Snell 2004; Lev and Radhakrishnan 2005, among others), This becomes evident in how a company can acquire and retain knowledge through its organizational structures, procedures, cultural practices, and business methodologies. (Walsh and Ungson 1991). High OC will likely enhance the firm's internal capabilities (e.g., employees and managerial skills, processes) as well as its external resources (e.g., commitments

[3] Cui, et al. (2021) emphasize that organizational capital is an important determinant of corporate innovation output.

to regulations, meeting stakeholders' expectations) which are crucial in minimizing risks associated with digitization, supporting the firm's digital improvements, improving its information quality, and minimizing its financing frictions. This, accordingly, will potentially strengthen the value creation of the firm's digital initiatives.

In this thesis, we draw our main conclusions by adopting two approaches. Firstly, our methodology closely aligns with the approach Chen and Srinivasan (2023) adopted in their study. Following their strategy, we measure a firm's digital activities by analyzing the frequency of digital-related terms found within its 10-K reports. A considerable number of papers in the field have also employed similar methods to extract insights from corporate documents, highlighting the growing trend and importance of utilizing Natural Language Processing in finance research.

Secondly, we adopt a strategy in line with Eisfeldt and Papanikolaou's 2013 framework, where we assess Organizational Capital (OC) by capitalizing a firm's selling, general, and administrative expenses (SG&A) using the perpetual inventory method. By this method, we transform the traditionally viewed operational expenses into assets, giving a tangible value to intangible assets. Our findings indicate a robust and positive relationship between a firm's digital transformation and corporate value. However, our analysis also reveals that the relationship between digital transformation and corporate performance is influenced by the presence of high organizational capital (OC). We observe that the contribution of such strategies to corporate value is notably more pronounced in firms with high organizational capital (OC). Moreover, our findings offer an additional viewpoint on such mechanisms as we present that the influence of digital transformation on a firm's value is not only significant but also depends on governance quality (e.g., higher institutional ownership) and information quality (e.g., more liquid stocks, higher analyst coverage). It's important to highlight that these insights are primarily derived from our analysis of US-based firms, offering a unique perspective combined with the extant research, most of which focus on non-US samples. This geographical distinction marks the potential variations in how digital transformation impacts corporate value across different regional contexts.

In light of these considerations, by examining the interplay between digital transformation and organizational capital, this research reflects on providing valuable insights into how firms can optimize their digital strategies in line with broader economic and societal goals.

The remainder of the thesis is organized into five cohesive chapters and proceeds as follows: Chapter 2 provides a comprehensive literature review, Chapter 3 focuses on the research questions and hypothesis development, Chapter 4 outlines the data and methodology employed in the research, Chapter 5 presents the data analysis and empirical results, and Chapter 6 concludes the research by summarizing the findings and stating their theoretical and practical implications.

CHAPTER 2: Literature Review

2.1 Digital Transformation

Recent academic discourse has identified three distinct phases in the process of corporate Digital Transformation: digitization, digitalization, and digital transformation (Bloomberg). The initial phase, digitization, is characterized by the transition from analog to digital formats. In other words, this phase involves converting analog information into digital data within a firm's computing systems, a process that has been known in the context of 'digitalization of information' until the early 2000s.

The next phase, digitalization, is defined by the adoption of digital technology to modify a firm's business model, thereby creating new avenues for revenue and value creation. This phase signifies a shift towards digital business practices, including the digitalization of various work processes, such as ordering and production, with a focus on operational innovation and efficiency, a trend particularly notable until the early 2010s (Bloomberg).

The final phase, digital transformation, involves the realization of strategic business innovations driven by customer needs, demanding both organizational change and the integration of digital technologies (Kim et al., 2008; Bloomberg). This stage represents a more comprehensive and profound shift, extending beyond just the adoption of digital tools, to a fundamental transformation in how firms operate and compete in the digital era.

Digital transformation has emerged as a driver in reshaping the business, improving service quality, and developing innovative digital business strategies (Fitzgerald et al, 2014). The emergence of complex digital tools, including artificial intelligence, expansive data analytics, and cloud-based solutions, is causing a transition toward a digital society that offers businesses new ways to grow (Cui & Wang, 2023).

According to the Global Digital Economy White Paper, in 2021, the digital economy's added value spanned around 47 countries, in total of $38.1 trillion, which marks a 15.6% growth rate annually and accounts for 45.0% of the GDP (Chen & Srinivasan, 2023). “In 2022, spending on digital transformation is projected to reach 1.6 trillion U.S. dollars; By 2026, global digital transformation spending is forecast to reach 3.4 trillion U.S. dollars” *(Global Digital Transformation Spending 2026, Statista)*, as shown in figure 2. In today's rapidly evolving world, digital transformation has become an essential of corporate strategy, it’s about integrating digital technology into all areas of a business, fundamentally changing how you operate and deliver value to customers. It's also a cultural change that requires organizations to challenge the status quo, experiment more, and get comfortable with failure. This sometimes means walking away from traditional business processes that companies were built upon in favor of relatively new practices that are still being defined. This shift has been significantly accelerated by the COVID-19 pandemic which forced companies to rapidly embrace digital tools and practices.

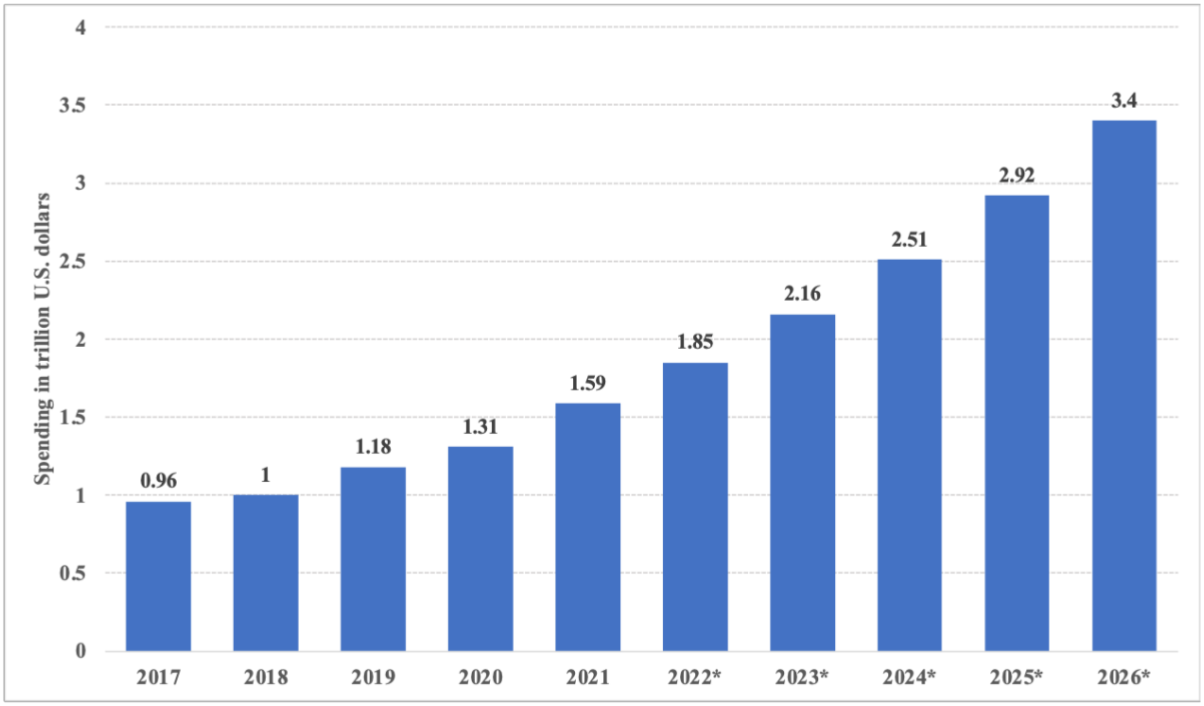

FIGURE 2: SPENDING ON DIGITAL TRANSFORMATION TECHNOLOGIES AND SERVICES WORLDWIDE FROM 2017 TO 2026 (IN TRILLION U.S. DOLLARS) SOURCE: STATISTA

U.S. companies have greatly expanded their use of digital services, tools, and frameworks over the past two years (Thoretz, 2022) This increase is due to advancements in technology that have made digital transformation tools more comprehensive. For example, U.S. firms are leveraging digital channels to engage with customers in more meaningful and interactive ways. E-commerce, mobile apps, social media, and personalized online experiences are becoming standard; such digital tools and platforms allow firms to be more agile, responsive, and efficient in their operations. For example, cloud computing, for instance, provides a scalable infrastructure that supports rapid growth and flexible resource management. The workforce is another area that is undergoing significant change because of digital transformation; there is a growing need for new skills in areas such as data science, AI, cybersecurity, and digital marketing. Companies are investing heavily in cybersecurity measures to protect their data, infrastructure, and customer information from potential violations. Sustainability and social responsibility are also being integrated into digital transformation strategies of U.S. firms; digital technologies are being used to reduce carbon footprints, manage resource utilization more efficiently, and enhance transparency in supply chains (*Agenda, World Economic Forum*, 2023). In the context of global competition, U.S. firms are leveraging digital transformation to maintain their leadership and competitiveness; this includes expanding into new markets, innovating products and services, and optimizing supply chains (Microsoft, 2022). In conclusion, digital transformation in U.S. firms is an ongoing process, deeply ingrained in the fabric of American business culture.

Additionally, the global landscape of the added value of the digital economy, and its contribution to the GDP of numerous countries highlights the importance of understanding the consequences of DT on various aspects of corporate strategies (Niu et al., 2023).

While initial investments in new digital technologies were concentrated in tech firms, recent developments have also allowed nontechnology firms to invest in such technologies at scale (Chen & Srinivasan, 2023). These transformations include a range of technologies from IT frameworks to more advanced tools like big data, cloud platforms, mobile tech, AI, IoT, and blockchain (Tu & He, 2023)

One of the key components of digital transformation is the use of data and analytics, Companies use data to drive efficiency, enhance customer experience, and create new business models. Data-driven decision-making is seen as a very important differentiator in firms nowadays. American companies are increasingly leveraging big data and advanced analytics to gain insights into customer behavior, market trends, and internal operational efficiencies (Calzon, 2023).

Another aspect of digital transformation is impacting the customer experience. Businesses are leveraging digital technologies to better understand customer behavior, preferences, and feedback so that they can customize their products and services accordingly. Today's consumers are comparatively very well-informed and have higher expectations. This boost in expectations forces companies to increase their customer service standards as well (Mihu et al., 2023). Additionally, the rise of ideas like custom-made products, additive manufacturing, and collaborative value creation has further emphasized the need for firms to digitally improve and innovate their business models (Bogers et al., 2016; Laplume et al., 2016).

Digital transformation also calls for a shift in organizational culture and mindset which requires companies to be more open to risk, and innovation. However, transitioning to this novel environment comes with its own set of challenges and potential drawbacks (Vial, 2019). Assessing the tangible benefits of digital transformation in performance enhancement and value creation is challenging due to its substantial costs, steep learning curves, and the need for organizational change (Ren & Li, 2022). There is no need to say that the successful implementation of DT is crucial for the sustainable growth and competitiveness of companies. There is historical evidence indicating the inherent challenges in navigating organizational changes (Deline, 2018), with a considerable fraction of such major shifts proving to be unsuccessful (Barrett & Stephens, 2016, 2017).

All these profound impacts have captured the attention of academics and scholars, thereby providing a ground for exploring the myriad ways in which digital transformation could influence aspects such as operational efficiency, employee engagement, and customer interactions within firms. Currently, empirical evidence on DT's impact on business performance, particularly concerning the mechanisms through which DT influences outputs and the factors that moderate this impact is limited and inconclusive. Considering the rapid integration of digital technologies in today's business practices bridging this gap is of great importance.

2.2 Digital Transformation and Corporate Performance

The ways in which digital transformation influences corporate performance are known to be complex and varied. This complexity arises from the multiple aspects that are involved in DT, which go beyond just adopting new technologies, it involves the transformation of business processes, corporate culture, and customer interactions; thus, understanding these various dimensions is crucial to fully grasp DT's impact on corporate performance. Additionally, the success of DT is not just about the technology itself but also many potential moderating factors that play a role in this context, how well a company is prepared for the change, the level of commitment from its leaders, and the skills of its employees are some of the examples (Ko et al., 2022). Exploring these areas in more detail will provide a clearer picture of when and how DT can be most beneficial for businesses and what challenges might need to be overcome in the process.
While some studies suggest a positive correlation between DT and enhanced operational efficiency, others point to the challenges and complexities involved in digital transitions, which can sometimes hinder immediate performance improvements; these arguments are important, and the subsequent paragraphs elaborate on them.

In research conducted by Li (2023), the impact of digital transformation on corporate performance and its interplay with Environmental, Social, and Governance (ESG) factors were examined, utilizing data from China's A-share listed companies from 2014 to 2021. This study focuses on understanding the dual influence of digital transformation on both enterprise performance and ESG outcomes. The results of the study demonstrated a significant positive correlation between digital transformation and enterprise performance as measured by Tobin's Q. Importantly, this study revealed a remarkable correlation between digital transformation and ESG performance, indicating that digital transformation facilitates the enhancement of ESG performance. These findings offer a deep understanding of the interplay between digital transformation, corporate performance, and ESG factors, suggesting that while digital transformation directly enhances enterprise performance, its full impact is realized when mediated through improvements in ESG performance.

In exploring the nuances of digital transformation on corporate performance, the study by Teng, Wu, and Yang (2022) offers a new perspective in the context of small and medium-sized enterprises (SMEs) within China's markets from 2007 to 2020, focusing on a sample of 319 SMEs. Their approach to quantifying the intensity of digital transformation relies on analyzing the frequency of relevant terms in the companies' annual reports. The researchers examine the impact of DT across three key dimensions of company performance: operational, financial, and innovation, where operational performance is assessed through efficiency metrics such as costs and expense; Financial performance is measured using return on assets (ROA) and Innovation performance is evaluated through patent counts. As a result of their study, the positive correlation between digital transformation and operational performance suggests that digital initiatives are likely to improve process efficiencies within these SMEs. This aligns with the general understanding that digital tools can optimize operations and reduce costs. However, the study also discovered an inverted U-shaped relationship between digital transformation and innovation performance which indicates that while initial digital efforts enhance innovation, the benefits taper off after reaching a certain level of digital maturity. This could imply that there's an optimal point of digital engagement beyond which the marginal gains in innovation diminish. Interestingly, the relationship between digital transformation and financial performance, although hypothesized to be U-shaped, is not found to be significant. It raises the possibility that the initial costs and investments in digital technologies could offset short-term financial gains, with potential benefits accruing over a longer time frame. In another study, Chen & Srinivasan (2023) investigate the implications of digital technology engagement by US non-technology firms and analyze how this could affect firm value and performance. The researchers found that firms that have disclosed more about digital activities in their annual reports -a proxy for the level of digital transformation in this study- saw their market-to-book ratios increase by 8% to 26% compared to their industry peers. Their study also examined the profile of firms engaging in digital activities, finding that these firms were generally larger, and younger. In terms of financial performance, Chen and Srinivasan found that firms with higher digital activities exhibited significantly higher earnings and sales response coefficients (ERCs and SRCs) than their peers, which implies that investors placed a higher valuation on their earnings and sales. Their research also revealed that digital activities were predictive of future returns; they discovered that portfolios based on digital activity disclosure earned a significant adjusted return over three years, suggesting that continuous disclosure of digital activities is correlated with positive long-term returns, this implies that ongoing communication about digital efforts could lead to better firm valuation. However, the study also found mixed effects on other financial performance metrics. While there was some evidence of productivity gains from such technologies, as indicated by higher ROA and asset turnover, the researchers found no significant differences in profit margins and a decrease in sales growth for firms that were engaging more in digital activities. These results are informing and highlight both the potential benefits and challenges associated with digital transformation in non-tech firms suggesting that while digital activities can enhance firm valuation and predict future returns, their impact on more immediate financial performance metrics like sales growth and profit margins may be less straightforward, so it's important for firms to have strategic considerations when adopting digital technologies.

Zhang et al. (2023) explore the dynamics of how digital transformation in the manufacturing sector influences corporate performance. Their empirical analysis which is conducted on 255 Chinese manufacturing enterprises uses innovation capability as a mediator variable. Their results highlight those digital transformations enhance corporate performance, they also find Business Model Innovation as a significant mediator in this relationship, suggesting that the way digital transformation reshapes business models is crucial for its impact on performance. This highlights the importance of a firm's ability to innovate and adapt as a crucial factor in leveraging digital transformation for better performance.

Zhong & Ren's (2023) analysis of Chinese listed companies from 2008 to 2020 focuses on assessing the impact of digital transformation on the short-term performance and long-term value of firms within transitional economies. Additionally, their study also explores the moderating roles of Corporate Social Responsibility (CSR) and Corporate Social Irresponsibility (CSI) in these dynamics. Their empirical evidence offers new insights into the interplay between digital transformation and firm ethical practices. They employ Return on Assets (ROA) and Tobin's Q as the dependent variables. ROA is used to measure short-term profitability, reflecting the net short-term profit generated per unit of assets Tobin's Q, on the other hand, is an indicator of the long-term value and growth of the firm. As per moderating variables -CSR and CSI- CSR reflects a company's responsibility towards its stakeholders, including employees, consumers, communities, and the environment, and is quantified using the CSR score from the Hexun Index Score; CSI represents actions by a business that harm its stakeholders or are considered unethical, even if lawful. The correlation analysis of their study indicates an insignificant relationship between digital transformation and short-term performance (ROA), but a significant and positive correlation with long-term value (Tobin's Q). This suggests that while digital transformation might not immediately reflect long-term profitability, it contributes positively to the long-term market value of a firm. Additionally, IonIonescu al. (2022) explore the influence of digital transformation on European listed companies in the context of the European Green Deal. They examine how DT can aid companies in corporate social responsibility, particularly in environmental protection, by adopting technologies that enable efficient resource use and pollution reduction and how these efforts are rewarded in financial markets. Their study analyzes a sample of companies from major EU stock exchanges and comes to the conclusion that there is a positive correlation between digitalization efforts and corporate social responsibility, put into practice through the ESG score. They also observe that digitalization efforts are more advanced in socially responsible companies and that these efforts are recognized and rewarded by financial markets. Furthermore, Sui & Yao (2023) explore the relationship between digital transformation and corporate financialization, focusing on Chinese firms listed between 2007 and 2021. They discover that digital transformation significantly aids in corporate financialization, this is evidenced by an increase in risk-taking behaviors and a widening of the yield spread between financial and tangible assets, suggesting a strategic shift towards more financially oriented business models in the digital era. This research contributes to the understanding of the complex interplay between technological advancement and financial strategies, highlighting both the opportunities and challenges presented by digital transformation in the financial realm.

The adoption of digital technology also potentially increases firm value by increasing productivity. For example, during the information technology (IT) revolution in the 1990s, several large and diversified organizations benefited from IT adoption by improving inventory management, it also allowed firms to produce more and expand more effectively (Brynjolfsson and Hitt, 1996). Recent studies that explore the potential consequences of adopting digital technologies in productivity also find a positive correlation. Particularly Guo et al., (2023), examine the relationship between digital transformation and firm performance, with a focus on the Chinese market data from A-share listed companies between 2013 and 2020. Their study is particularly interesting due to its incorporation of the digitalization paradox and the concept of managerial myopia as moderating factors. They considered Total Factor Productivity (TFP) as a dependent variable, while firm performance was measured using financial indicators such as Return on Assets (ROA) and Return on Equity (ROE). A key concept that authors have explored in the study is "managerial myopia" which refers to the tendency of management to focus on short-term gains at the expense of long-term benefits. Their findings show that while digital transformation significantly increased TFP, indicating a positive impact on productivity, its influence on firm performance was more complex. They suggest that both low and high levels of digital transformation can be detrimental to firm performance, while a moderate level of digital transformation is more likely to yield positive results. Guo et al.'s research provides a critical examination of the complexities surrounding digital transformation in the corporate world, particularly highlighting the challenges and potential unintended consequences of these initiatives when they are not strategically balanced. Such contradictions in studies present a case that highlights the need for a nuanced understanding of digital transformation's impact on firm performance. Another value-adding aspect of digital technologies is that they potentially enhance production workflows by integrating data throughout all stages, from production to management, therefore, efficient use of this analyzed data results in better production automation and, cost savings in terms of information, time, and labor, ultimately enhancing a business's performance (Nambisan et al., 2017).

It's worth noting that much of the scholarly work has primarily explored the direct link between digital transformation and business results; as seen in several cases, it's crucial to highlight that the journey of enhancing corporate performance via digital transformation isn't straightforward. Companies often face challenges in quickly learning and adjusting to information technology. Moreover, Digital transformation has a profound effect on managerial decisions which touches every organizational aspect, from processes to communication channels, and can optimize decision-making, as suggested by Lev et al. (2009) consequently mismanagement of digital technology can further hinder this process (Farouk and Dandago, 2015).

2.3. Intangible Assets and Organizational Capital

Nakamura (1999, 2000) presents the idea that the significant rise in the importance and value of intangible capital began around the mid-1980s. This growth was around the same time as the rise of key “intangible industries” like software, biotechnology, and the internet, and this trend has continued, albeit with some fluctuations, up to today (Lev et al., 2009). McGrattan and Prescott (2007) pointed out the importance of including intangible investments in models that are trying to explain the substantial economic growth experienced in the 1990s. There is an agreement in contemporary economic research that intangible assets are principal contributors to both national and corporate value. In this context, Lev (2001) has developed a categorization framework for intangible capital, dividing these assets into four classifications:

1. Discovery/learning intangibles: Include assets like technology, patents, and other outputs from R&D and learning processes in business entities, universities, and national labs.
2. Customer-related intangibles: Include assets such as trademarks, brands, and unique distribution channels, for instance, internet-based sales platforms, that can generate abnormal earnings.
3. Human-resource intangibles: Comprises specific practices in human resource management like training and compensation systems that increase employee productivity and decrease turnover.
4. Organization capital: Refers to the exclusive structural and organizational designs and business processes that enable a firm to maintain a sustainable competitive edge.

In this research, our focus is on the last category of intangible assets, Organizational Capital (OC). Based on the paper "Organization Capital" by Lev et al. (2009) we can understand intangible assets like organizational capital are becoming increasingly important and crucial in today's economy. At its core, OC includes the arrangement of non-physical resources that a firm possesses, which can range from its internal processes and knowledge systems to the expertise and skills of its workforce. In academia, this type of capital is being increasingly recognized as a driving force behind a company's competitive edge and long-term success. Elements of OC empower companies to convert their production resources into outputs more effectively than their competitors (Martín-de-Castro et al., 2006). The concept of organizational capital is particularly interesting because it captures the essence of a company's internal dynamics that contribute to its market value and operational efficiency and since this concept is not easily mimicked or transferred by different enterprises, gives firms with strong OC a significant edge over other firms. Examples of such systems include Walmart’s supply chain management, Apple's corporate culture and product development systems, and Toyota's people-oriented and knowledge-sharing systems.

However, unlike tangible assets, such as machinery or buildings, organizational capital is not readily visible or quantifiable which makes measuring challenging; Also, investments in OC are often not fully tracked or reported, making direct measurement difficult.

2.4 Moderating Role of Organizational Capital

Different studies have examined the influence of organizational capital on various aspects of firm performance. For instance, Wang, (2023) presents an advancement in the field of asset pricing by incorporating the impact of organizational capital on firm valuation and asset returns. This study modifies the existing multifactor asset pricing models, by introducing the concept of Adjusted Asset Growth (AAG) which considers the role of organizational capital in reducing the adjustment costs associated with changing physical capital levels. He finds that firms with higher organizational capital, and thus higher AAG, are valued higher by investors despite lower expected returns. This result can reflect the market's recognition of the long-term benefits of robust organizational capital, such as improved risk management, enhanced innovation capabilities, and stronger customer and supplier relationship (Wang, 2023).

In another study, Gu and Lev (2001) demonstrated that the consideration of firm-specific intangible capital can improve the correlation between market values and traditional metrics such as earnings or book values. This is because intangible assets can contribute to a firm's potential for future earnings and growth, even though they might not be directly reflected on the balance sheet. Additionally, in the field of organizational capital and its impact on corporate performance, Attig

& El Ghoul (2017) analyze the effects of organizational capital, shown through management quality practices (MQPs), on the implied cost of equity capital (ICOE) in firms. The results highlight a link between superior management practices and a decrease in the cost of equity capital. This paper argues that superior MQPs can lower a firm's underlying business risk through more efficient management of human and other firm resources. These practices are stable and do not change quickly, leading to less risk to shareholders. Moreover, they show that investments in the organizational capital lead to more productive operations, such investments allow firms to adapt to new business methods, thus lowering risk and expected stock returns in equilibrium. Superior MQPs also enable reliable data recording, processing, monitoring, and reporting, which are critical for the quality of financial reporting and disclosure, which can lead to better firm reputation, increased analyst following, and consequently, lower financing costs.

Boubaker et al. (2022) in their study of 33,618 publicly listed U.S. firms from 1992 to 2020, argue that high levels of organization capital, estimated based on selling, general, and administrative (SG&A) expenses, are associated with strong tournament incentives, as a mechanism enhancing the motivation and competitiveness among employees, which is a driver of better organizational and operating performance. In addition, Attig & Cleary (2014) explore how organizational capital, influences a firm's investment sensitivity to internal cash flows based on medium-sized U.S. manufacturing firms. Their study suggests that the presence of superior management quality practices, as a proxy for OC, decreases the sensitivity of firm investment to internal cash flow availability. This result implies that high levels of OC, through the channel of limiting the informational asymmetry and agency costs, can lead to lower investment cash flow sensitivity, meaning that firms with better management practices are less reliant on internal cash flows for investments, indicating more efficient capital allocation.

CHAPTER 3: Research Question

3.1 Hypothesis Development

The primary research question of this thesis is to understand how Organizational Capital (OC) moderates the relationship between Firm Digitalization, as measured by Digital Transformation Score (DGS), and Corporate Performance, as reflected in Tobin's Q, particularly in the context of U.S. non-technology firms. This analysis is established at the intersection of digital transformation and corporate strategy, with a focus on the role of intangible assets like OC. Digital transformation has profound implications for business models and operational strategies, which in turn affect corporate performance. The relevance of our research question is emphasized by the increasing prominence of digitalization in corporate strategies for growth and value creation. As noted by PwC (2017) and Gartner (2017), digital improvements have been recognized as key drivers for revenue growth. However, the link between digitalization and corporate performance is complex and multi-dimensional; it's not merely the adoption of digital technologies but how these technologies are integrated into and supported by the firm's existing structures, particularly OC, that determines their impact on performance. As described by Lev and Radhakrishnan (2005), OC contains the technologies, business practices, and systems unique to a firm, and forms the foundation for which digital strategies are implemented. It could be posited that the transformative potential of digital technologies, such as AI, big data, cloud computing, etc., might be more effectively realized when there is an alignment with a firm's Organizational Capital (OC). This alignment is crucial in ensuring that digital initiatives are effectively integrated into existing business processes and culture. In non-technology firms, where core business processes may not be inherently digital, the role of OC becomes even more significant and the ability of these firms to adapt to and integrate digital technologies into their operations can be a critical differentiator in performance outcomes. As suggested by the research of Attig & El Ghoul (2018) and Wang (2023), firms with robust OC might be better equipped to leverage digital transformation for enhanced performance, risk management, and innovation. Despite the acknowledged importance of digitalization in modern corporate strategy, there is a gap in existing literature regarding the specific mechanisms through which OC influences the relationship between digitalization and corporate performance. Our research question, therefore, aims to fill this gap, providing insights into how OC can act as a moderator in this relationship, especially in the context of U.S. non-technology firms where the dynamics of digital transformation might present unique challenges and opportunities.

Building on the findings of Chen and Srinivasan (2023), our first hypothesis posits a positive correlation between firm digitalization (measured by digital activities disclosed in 10-K reports) and corporate performance (assessed through Tobin's Q). This is supported by the arguments in the literature that digital transformation can strategically transform firm processes and decision-making, leading to innovation-led growth and enhanced value creation.

Hypothesis 1 (H1): Financial performance is higher for US companies that are making greater digitalization efforts.

Following the insights from Lev and Radhakrishnan (2005) and Wang (2023), our second hypothesis suggests that organizational capital (OC) moderates the relationship between digital transformation and corporate performance. OC, as a collection of business practices, by enhancing a firm's internal and external capabilities, supports digital improvements, improves information quality, minimizes digitization risks, and equips firms with the necessary tools and processes to navigate DT challenges more effectively, thereby protecting and strengthening the impact of digital transformation on corporate value creation.

Hypothesis 2 (H2): Organizational capital (OC) moderates the relationship between firm digitalization (DGS) and corporate performance (TOBINSQ), with a stronger positive relationship in firms with higher levels of OC.

Additionally, knowing that the presence of institutional investors within a firm's ownership structure is often indicative of enhanced governance and strategic oversight, in this context, Cornett et al. (2008) highlight that institutional ownership can significantly impact corporate operational performance; their findings suggest that institutional investors contribute to more efficient corporate management and strategic decision-making. Institutional investors, given their large holdings, have a significant interest in the performance and governance of the companies they invest in. They are more likely to monitor management closely and demand accountability, which can lead to better governance practices. Therefore, we can hypothesize that improved governance is important in navigating the complexities and opportunities that digital transformation brings to companies. Institutional investors, with their focus on long-term value creation, are likely to support investments in digital initiatives that enhance a firm's capabilities, thereby increasing firm value. This rationale supports hypothesis 3 that institutional ownership positively influences firm value in the context of digital transformation and this influence is moderated through improved corporate governance.

Hypothesis 3 (H3): Institutional ownership moderates the relationship between digital transformation and firm value, wherein higher levels of institutional ownership enhance the positive impact of digital transformation on firm value.

We also hypothesize that information quality, indicated by stock liquidity and analyst coverage, plays a moderating role in the relationship between digital transformation and firm value. This influence is grounded in two key aspects; Roll's (1984) measure of bid-ask spread is a widely recognized proxy for stock liquidity. Stock liquidity refers to how easily a company's shares can be bought and sold without affecting the stock price. Digital transformation in companies highlights the importance of high-quality information, as firms go through the challenges and opportunities caused by such shifts. Higher liquidity is often associated with lower information asymmetry (Liu & Liu, 2023) which is crucial for the valuation of firms, particularly firms that are integrating digitalization changes. Also, the inclusion of analyst coverage as a proxy for information quality in firms aligns with the findings of Liu, (2023) who notes that analyst coverage can reduce information asymmetry and enhance corporate environmental investment, indicating a positive role of information quality in corporate dynamics. Similarly, Naqvi et al. (2021) highlight the moderating effect of analyst coverage on the relationship between corporate social responsibility and information asymmetry. This suggests that high-quality information, facilitated through analyst coverage, can significantly impact a firm's operational and strategic outcomes. Additionally, the study by Martens & Sextroh (2021) indicates the role of analysts in facilitating business intelligence through between firms' connections. This aspect of information flow among firms suggests a critical role for information quality in shaping how firms adapt and benefit from digital transformations.

Thus, integrating these insights, we can hypothesize that information quality, as reflected in stock liquidity and analyst coverage, could be a moderator in how digital transformation affects firm value.

Hypothesis 4 (H4): Firm information quality, as evidenced by stock liquidity and analyst coverage, positively moderates the impact of digital transformation on firm value.

We have laid out clear hypotheses that connect digital transformation with firm value, considering the roles of institutional ownership, organizational capital, and information quality. These hypotheses will guide our next steps as we dive into the data and explore how these factors play out for U.S. non-tech firms and deepen our understanding of such dynamics.

CHAPTER 4: Data and methodology

4.1. Sample and Data collection

To develop a relevant and unbiased dataset, we gathered a comprehensive collection of annual reports (10-K) for all U.S. firms from Loughran-McDonald Textual Analysis Resources. We paired firms' names and CIK codes to the detailed financial and operational data from the Compustat database. Then we remove financials (SIC 6000−6999), utilities (SIC 4900−4999), and governmental and quasi-governmental entities (SIC 9000 and above), due to the unique regulatory, financial, and operational characteristics of these industries. Financial firms, for example, have different capital structure dynamics, risk profiles, and regulatory environments. Utilities are often heavily regulated and may not have the same market-driven performance incentives. Governmental entities have different accountability and performance measures that are not fully comparable. By removing these entities, our study aims to create a more homogenous sample for analysis without the noise of industry-specific factors. Key to the integrity of this study was the deliberate exclusion of technology-centric firms; following related literature (e.g. Chen and Srinivasan 2023), we focus on the digital activities of non-tech firms. This identification was carried out by examining the Standard Industrial Classification (SIC) codes associated with each firm in the initial dataset. SIC codes are widely recognized as a standard method of classifying industries based on their primary business activities. In the context of this research, firms categorized under SIC codes that represent industries related to technology — such as computer, hardware and software, electronics, communications, and internet services — were flagged as tech firms. The rationale behind this exclusion stems from the understanding that tech firms are intrinsically more engaged in digital discourse, which could potentially skew the study's findings.[4] These filters result in a final sample of 21,913 firm-year observations, covering 2011 to 2020.

4.2 Measure

4.2.1 Dependent Variable: Firm Valuation (Tobin's Q)

Tobin's Q is a widely recognized market-based measure of firm performance, reflecting the market's expectation of a firm's growth and profitability relative to its book value. Following the approach suggested by McLean, Zhang, and Zhao (2012), Rauh (2006), and Baker, Stein, and Wurgler (2003), we estimate Tobin's Q as the market-to-book ratio of firm assets. Where the market value of equity plus the book value of assets minus the sum of the book value of common equity and deferred taxes divided by the book value of assets. In order to calculate this measure, we first downloaded the data required for calculating Tobin's Q from the Compustat database. Specifically, the fields extracted contained: Total Assets, Total Liabilities, Number of Outstanding Shares, and Share Price for each firm of our sample from 2011 to 2020.

First, we calculate the Market Value of Equity as follows:

$$MV_{Equity,it} = P_{it} \times S_{it} \quad [1]$$

[4] We exclude from our sample of firms those operating the industries with the following SIC codes: 3570, 3571, 3572, 3575, 3576, 3577, 3578, 3579, 3661, 3663, 3669, 3670, 3672, 3674, 3675, 3675, 3677, 3678, 3679, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7376, 7377, 7378 and 7379.

This equation represents the market capitalization of firm *i* at time *t*; where P_t is the Share price of firm *i* at time *t,* and S_t is the number of outstanding shares of firm *i* at time *t.*

Then by using the total liabilities and total assets of each firm, we calculate Tobin's Q as follows:

$$Q_{\ it} = \frac{MV_{Equity,it} + BV_{Assets,it} - (BV_{CE,it} + DT_{it})}{BV_{Assets,it}} \quad [2]$$

Where$Q_{\ it}$ is the Tobin's Q of firm *i* at time *t*, $BV_{CE,it}$ is the book value of common equity for firm *i* at time *t*, DT is the deferred taxes for firm *i* at time *t*, and$BV_{Assets,it}$ is the book value of assets for firm *i* at time *t*.

We chose this measure for several reasons. Firstly, Tobin's Q, as a market-based indicator, is forward-looking and captures the market's expectations about the firm's future performance. Secondly, it's less susceptible to fluctuations caused by changes in accounting practices, providing a more stable and reliable measure of firm performance (Chen and Srinivasan, 2023; Fauver, Hung, Li, & Taboada, 2017). Lastly, Tobin's Q, with its emphasis on the equity aspect, is particularly suited to our study's focus on how OC influences firm value through various potential channels.

4.2.2. Independent Variable: Digital transformation score (DGS)

To construct DGS, we utilized Python to conduct a textual analysis of the 10-K reports of the selected firms. The decision to utilize 10-K reports is a critical one, because of their detailed disclosures, their text presents an analysis of the company's business performance and an outlook of the future growth during the reported period of a company, this approach has been widely acknowledged in academic research (Loughran & Mcdonald, 2011). In other words, annual reports are official records that not only outline a company's financial health and performance over a fiscal year but also highlight significant events, such as strategic shifts toward digital transformation. Thus, the specific focus of a company is often mirrored in the prevalence of specific keywords within its annual reports (Teng et al., 2022). In the field of digital transformation research, quantifying this concept through traditional metrics is a challenge. The need for precision and the public nature of these reports imply that companies are very cautious in their language use. Prior studies (Huang et al., 2023; Zhang & Zhao, 2023; Teng et al., 2022) have developed a specialized dictionary for digitally related terminology in corporate reporting, which is a groundwork for identifying digital transformation narratives from such reports and documents.

The frequency rate of specific terms in annual reports is often indicative of their significance to the company (Liu & Liu, 2023). Given the large volumes of data in these reports, the method of analyzing word frequency emerges as the most effective tool for this examination, reflecting the company's commitment to digital initiatives.

A fundamental aspect of this research was developing a unique and novel digitalization dictionary, a list of terms related to various aspects of digital transformation. We developed this dictionary through reviewing a wealth of studies and articles that are well-known and highly recognized in our area of research, each contributing unique perspectives and terminologies associated with digital transformation. By examining these studies, we identified a diverse range of terms reflecting the multifaceted nature of digital transformation. These terms include key areas such as analytics, automation, artificial intelligence, cloud computing, digitization, big data, blockchain, and machine learning. Eventually total of 120 keywords were carefully selected within this dictionary. Notably, the selection of terms was informed by the work of Chen & Srinivasan (2023). Their research provided a foundational understanding of the key terminologies used in this context. Similarly, the studies by other scholars (e.g. Huang et al., 2023; Zhang & Zhao, 2023; Teng et al., 2022; Zhong & Ren, 2023; Liu & Liu, 2023; Li et al., 2023) offered further insights into our selection of keywords. Not to mention that this dictionary, goes beyond just the merge of digital terms; it represents terms particularly relevant to the landscape of U.S. firms. This relevance is crucial, especially since the journey that U.S. companies take in digital transformation can be quite different from places like China, which is where a lot of studies concentrate. These differences are often due to the unique ways markets work and the rules they follow in each country. While existing literature provides a foundational understanding of digital terms, there was a gap in resources that specifically addressed the context of the US market. Our development also involved an evaluation of existing terms and the inclusion of emerging concepts that were neglected in some studies, so that we can be sure that our dictionary is not only comprehensive but also contemporary, reflecting the latest developments and trends in digital technology and, therefore, contributes to the academic literature from this perspective. The full list of keywords used to build our dictionary of digital transformation is provided in the appendix section of this study.

As the next step, to identify these keywords within the text of the 10-K filings of the companies within our sample, we employed regular expressions (regex) – a powerful tool for text pattern recognition. For each keyword in our dictionary, a regex pattern was created. We count the frequency of digital terms from the 10-k reports, following Chen and Srinivasan (2023). The occurrences of each of these keywords are summed to establish the total number of occurrences in one report. Finally, considering the different lengths of each annual report, for a robust outcome we scale the sum of the frequency of digital keywords by dividing by the total number of words in each annual report. The mathematical expression is shown in Eq. 3.

$$DGS_{i,t} = \frac{DigitalKey\_Num_{it}}{TotalWord\_Num_{it}} \times 1000 \quad [3]$$

As a first step in our investigation, we aim to analyze the trend of digital transformation within non-tech, US companies. Therefore, we plot in Figure 3 which shows the time trend of DGS, the upward trajectory observed in the plot over the sample period represents an increasing focus on digital transformation initiatives within these companies. Each data point corresponds to the average frequency of digital transformation-related keywords for a given year, providing a quantifiable measure of the level of digital transformation activities undertaken by these companies. This trend, consistent with increases year over year, highlights not only the growing importance of digital transformation in the corporate sector but also aligns with related studies.

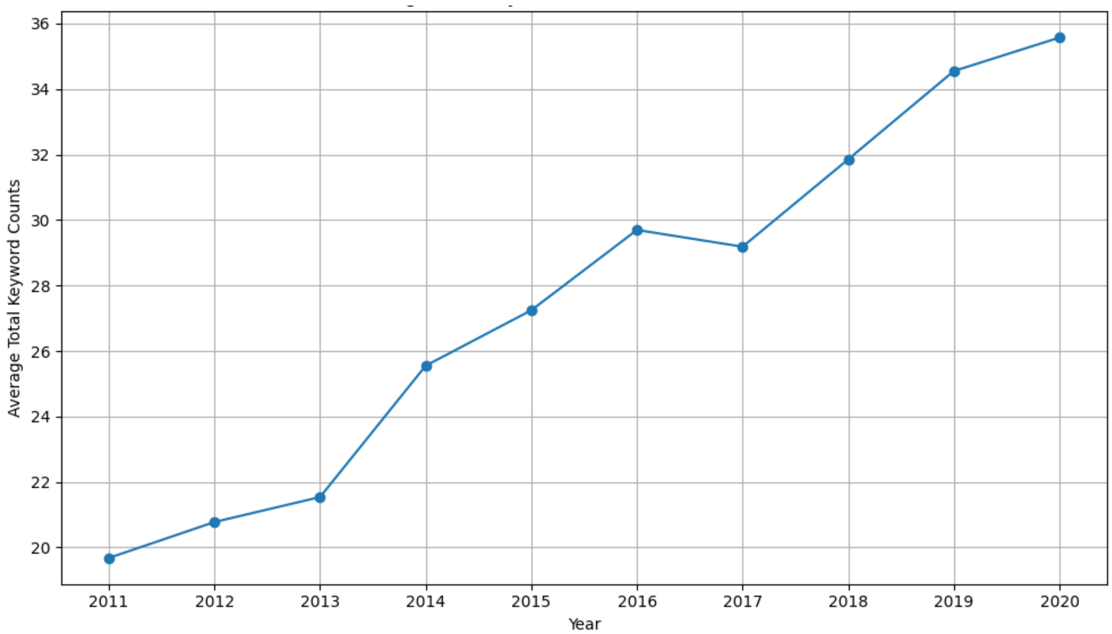

FIGURE 3: YEARLY TRENDS IN DIGITAL TRANSFORMATION SCORES (DGS) FOR US NON-TECH COMPANIES, 2011- 2020

This trend towards digital transformation in U.S. companies is highly informative for several reasons. First, it highlights the increasing adoption of digital strategies as an essential and integral component of business operations. As we know this shift is not just about adopting new technologies, but reflects a deeper, more fundamental change in how companies operate and strategize in the digital age. Second, this trend provides insight into the evolution of corporate innovation and adaptability; as businesses are trying to respond to the challenges and opportunities of this digital age, they are redefining the landscape of their corporate innovation. Third, this trend confirms the validity of using keyword frequency as a proxy for measuring digital transformation progress. This method of quantifying corporate communications and reports is proving to be a reliable indicator of the depth and breadth of digital integration in business operations. This correlation could also highlight the potential of this approach as a predictive metric as more companies increasingly mention digital technologies and strategies in their public disclosures.

4.2.3. Moderator variables:

Organizational Capital (OC)

We construct Eisfeldt and Papanikolaou's (2013) measure of organizational capital. Lev and Radhakrishnan (2005) and Lev (2001) have argued that spending recorded in SG&A leads to improvements in areas like employee incentives, internal communication, and distribution systems. Eisfeldt and Papanikolaou's (2013) method, which focuses on investment in intangible capital, creates a direct measure of organizational capital by capitalizing firms' SG&A expenses, using the perpetual inventory method. The method continuously updates the value of organizational capital in a way that each period's value is calculated based on the previous period's value, after accounting for depreciation, and the current period's investment. The Bureau of Economic Analysis (BEA) employs a comparable approach in building up a stock of research and development (R&D) capital (see Sliker, 2007). A significant portion of SG&A includes labor and Information Technology (IT) related expenses (Eisfeldt & Papanikolaou, 2013). The first component of SG&A, selling expenses, refers to costs directly and indirectly associated with the sales process. This includes not only the expenses that happen in the direct act of selling – like commissions and shipping – but also in broader activities such as advertising and promotional efforts. Next is general expenses that cover the operational costs of running a business; these are the expenses that an organization goes through regardless of its level of production or sales. For instance, rent for office space, utility bills, office supplies, etc. Finally, administrative expenses are those related to the overall management and administration of a company; this includes the salaries of executive staff and costs associated with corporate functions like accounting and legal services. While these expenses might seem distant from the direct process of selling a product or service, they are crucial for maintaining a structured, and effectively governed organization and indirectly contribute to building the company's intangible assets. It's essential for management to keep a careful watch on these expenses, as they can significantly influence the financial health and strategic direction of the business. (Attig & El Ghoul, 2018)

The stock of organization capital for firm *i* at time *t* is given by the following equation:

$$OC_{it} = (1 - \delta_0) \times OC_{it-1} + \frac{SG\&A_{it}}{cpi_t}, \qquad [4]$$

where *SG&A* is selling, general, and administrative expenses, *cpi* is the consumer price index at time *t*, OC_{it-1} is an organizational capital index of firm *i* for the previous period, δ_0 is the depreciation rate of 15%, matching the rate used by the Bureau of Economic Analysis (BEA) for R&D capital in 2006. Similar to physical assets, organizational capital is subject to depreciation as well; we calculate the deflated value of SG&A expenses by adjusting them with the consumer price index. The CPI measures the average change over time in the prices paid by consumers for a basket of goods and services and is a common measure of inflation. By adjusting SG&A expenses with the CPI, we are aligning these costs with the general price level changes in the economy, so it helps in understanding the real change in these expenses.

Since this is a recursive process, the first observation is not defined. We define the first observation as follows:

$$OC_0 = \frac{SG\&A_1}{g + \delta_0}. \qquad [5]$$

Where *g* mirrors the average real growth rate of firm-level SG&A expenses, which according to the literature is set to 10 percent. Following Eisfeldt and Papanikolaou (2013) we deflate organization capital by total assets, this adjustment is done to normalize the value of organization capital relative to the size of the company, allowing for more accurate comparisons across firms or over time within the same firm.

Institutional ownership (IOWN)

It's well-established in corporate finance literature that the presence of institutional investors can lead to enhanced corporate governance and strategic oversight (Cornett et al. 2007). In our study, the moderator variable, institutional ownership, is meticulously calculated to reflect the proportion of a company's shares that are held by institutional investors. This includes entities such as pension funds, mutual funds, insurance companies, and investment banks. We express Institutional ownership as a percentage, calculated by dividing the number of shares held by institutional investors by the total number of outstanding shares of the company. To obtain accurate and comprehensive data on institutional ownership for U.S. companies, we use the Compustat database.

Bid-ask spread (BAS)

In our analysis, we utilize stock liquidity as a proxy for information quality, quantified through the bid-ask spread calculated via Roll's method. Roll's model offers a sophisticated approach to estimating the bid-ask spread by analyzing the serial covariance of stock price changes, rather than relying on direct observations of bid and ask prices. This method infers the spread from the variance of the observed price changes. By employing Roll's method, we are able to approximate the stock liquidity of U.S. non-tech firms, with the underlying assumption being that higher liquidity, indicated by a lower bid-ask spread, reflects higher information quality available in the market. This measurement of stock liquidity as a proxy for information quality is important for our study as it captures the efficiency and transparency of the market in pricing the stocks, which are key indicators of the availability and quality of information to investors.

Number of analysts (NA)

In our study, we also employ the number of analysts covering a firm as an additional proxy for information quality. As mentioned in Chapter 3, a higher number of financial analysts tracking a firm indicates greater availability of information regarding that firm's activities and performance. Therefore, the extent of analyst coverage can be seen as a reflection of the degree to which a company is scrutinized and the amount of information that is readily available to the public and investors. For obtaining reliable data on the number of analysts covering U.S. firms, we turn to the Institutional Brokers' Estimate System (IBES). IBES is renowned for its extensive database of analyst coverage, forecasts, and recommendations.

4.2.4 Control Variables

In our regression model, we incorporate a comprehensive set of control variables at the firm level to ensure robustness and to account for factors that might influence our primary variable of interest, the Digital Transformation Score (*DGS*). Each of these control variables is selected based on its relevance and the established practices in financial research.

Firm Size (*SIZE*), measured by the natural logarithm of total assets, is a fundamental control variable. *SIZE* is crucial as larger firms might have different market valuations, risk profiles, and operational characteristics compared to smaller firms. The logarithmic transformation helps in stabilizing variance and making the relationship more linear. The Leverage Ratio (*LEVR*), calculated as the ratio of total debt to total assets, is included to control for the firm's capital structure. *LEVR* is an essential indicator of the firm's financial health and its ability to access resources for growth and development, as discussed by Brammer and Millington (2008), It also reflects the firm's risk profile, as higher leverage might increase financial risk. Research and Development expenses (*RD*), scaled by assets, are included to account for the firm's investment in innovation and technology; *RD* is a critical factor in value creation, especially in industries where innovation is a significant driver of competitive advantage; scaling *RD* by assets helps to normalize this variable across firms of different sizes and asset bases. Capital Intensity (*CINT*), represented by the ratio of net property, plant, and equipment divided by total assets, is included to consider the effects of capital-intensive industries, this helps to differentiate between firms that rely heavily on physical capital and those that do not, as capital-intensive firms might have different financial and operational characteristics. Dividend Payment (*DIVD*) is included to account for the firm's dividend policy, which is an important aspect of corporate finance. The decision to pay dividends may indicate a firm's financial stability and its ability to generate sufficient cash flow; also reflects on financial constraints and resource availability, affecting the firm's investment decisions and growth potential. Institutional Ownership (*IOWN*) is included to control aspects of corporate governance. The presence of institutional investors can signify better governance practices, as these investors often influence management decisions and policies. Firm Age (*AGE*) is controlled for as it represents the maturity and historical background of the firm as older firms might have different operational efficiencies, market perceptions, and financial structures compared to newer firms. Sales Growth (*SGR*), the year-over-year change in sales, is a measure of a firm's growth opportunities and reflects the aspect of the firm's operational performance and its ability to expand in the market. We control for industry effects defined at the two-digit SIC level (μ_j) and year-fixed effects (μ_t).

4.3. Model construction:

By analyzing the data of 21,913 firm-year observations, spanning the period from 2011 to 2020, this study performs a correlation test of panel data. The initial phase, involves adjusting the data, using Stata and Python, a key step in preparing our data involved applying filters to ensure the accuracy and relevance of our sample. To mitigate the impact of outliers, which can skew results and interfere with the robustness of statistical analysis, we winsorize non-categorical control variables at the 1% level at each tail of the distribution to ensure a more standardized and reliable dataset for our analysis. Then we conduct a descriptive statistical analysis to grasp the fundamental characteristics of the variables. Following this, we carry out a correlation analysis which is crucial for identifying initial correlations between the dependent variables and those on the right-hand side of our model and in detecting any potential issues with multicollinearity among the explanatory variables. Finally, a robustness check is performed to validate our findings.

The start of our empirical analysis is centered around addressing the main question: Does digital transformation create value for firms? To explore this, we structure our analysis around the following multiple regression model:

$$TOBINSQ_{i,t} = \alpha_0 + \alpha_1 DGS_{i,t} + \alpha_2 FIRMCTRL_{i,t} + \varepsilon_{i,t}, \qquad [6]$$

Where i denotes individual firms, t denotes years, $TOBINSQ$ indicates the firm's market value relative to its asset value, DGS indicates the Digital Transformation Score for firm i in year t, $FIRMCTRL$ includes range of firm-level control variables that were mentioned earlier.

To further clarify the dynamics of digital transformation in the context of Organizational Capital

(OC), our study extends the analysis by incorporating OC and its interaction with DGS into our primary regression model. This extension of the model is critical for understanding the moderating effect of OC on the relationship between digital transformation and firm value; the augmented model is a moderated multiple regression shown in Eq. 7:

$$TOBINSQ_{i,t} = \beta_0 + \beta_1 DGS_{i,t} + \beta_2 OC_{i,t} + \beta_3 (DGS_{i,t} \times OC_{i,t}) + \beta_4 FIRMCTRL_{i,t} + \mu_{i,t} \qquad [7]$$

In this model, $\beta_3 (DGS_{i,t} \times OC_{i,t})$ captures the interaction effect between Digital Transformation Score (DGS) and Organizational Capital (OC), providing insights into their combined impact on firm's value.

Similarly, the equations for testing our Hypotheses 3 and 4 are as follows:

$$TOBINSQ_{i,t} = \gamma_0 + \gamma_1 DGS_{i,t} + \gamma_2 IOWN_{i,t} + \gamma_3 (DGS_{i,t} \times IOWN_{i,t}) + \gamma_4 FIRMCTRL_{i,t} + \epsilon_{i,t} \qquad [8]$$

Where $\gamma_1, \gamma_2, \gamma_3$ are the coefficients for *DGS*, Institutional Ownership ($IOWN$), and their interaction term, respectively, and $FIRMCTRL$ includes a range of firm-level control variables.

$$TOBINSQ_{i,t} = \mu_0 + \mu_1 DGS_{i,t} + \mu_2 BAS_{i,t} + \mu_3 (DGS_{i,t} \times BAS_{i,t}) + \mu_4 FIRMCTRL_{i,t} + \epsilon_{i,t} \qquad [9]$$

Where μ_1, μ_2, μ_3 are the coefficients for *DGS*, Bid-Ask Spread (BAS), and their interaction term, respectively, $FIRMCTRL$ includes range of firm-level control variables.

Similarly, we have the following moderated multiple regression for the other proxy of information quality, which is the number of analysts:

$$TOBINSQ_{i,t} = \mu_0 + \mu_1 DGS_{i,t} + \mu_2 NA_{i,t} + \mu_3 (DGS_{i,t} \times NA_{i,t}) + \mu_4 FIRMCTRL_{i,t} + \epsilon_{i,t} \quad [10]$$

Where μ_1, μ_2, μ_3 are the coefficients for DGS, the Number of analysts (NA), and their interaction term, respectively, and $FIRMCTRL$ includes range of firm-level control variables.

CHAPTER 5: Data Analysis and Empirical Results

5.1. Sample statistics

The descriptive statistics, as presented in Panel A of Table 1, offer insightful observations about the key variables used in our baseline regression. Panel B's correlation matrix offers additional dimensions; The Pearson correlation coefficients are generally low, indicating that multicollinearity is unlikely to pose significant concerns in our regression analyses. The positive correlation between RD and TOBINSQ might suggest a link between higher R&D spending and greater market valuation. The positive correlation between AGE and DIVD may indicate a tendency for older firms to pay dividends.

TABLE 1: DESCRIPTIVE STATISTICS FOR KEY VARIABLES

Panel A: Descriptive Statistics

	TOBINSQ	*DGS*	*OC*	*SIZE*	*LEVR*	*RD*	*CINT*	*DIVD*	*IOWM*	*AGE*	*SGR*
Mean	2.20	0.45	16.72	6.58	0.27	0.07	0.27	0.44	0.55	2.9	0.07
p25	1.17	0.08	0.49	5.06	0.06	0	0.07	0	0.17	2.3	-0.08
p50	1.61	0.19	2.25	6.63	0.24	0	0.18	0	0.65	3.0	0.03
p75	2.49	0.47	9.50	8.06	0.41	0.04	0.40	1	0.88	3.5	0.14
SD	1.76	0.73	74.08	2.12	0.24	0.17	0.25	0.50	0.36	0.8	0.69

Panel B: Correlation Matrix

	TOBINSQ	*DGS*	*OC*	*SIZE*	*LEVR*	*RD*	*CINT*	*DIVD*	*IOWM*	*AGE*	*SGR*
TOBINSQ	1										
DGS	0.00	1									
OC	-0.01	0.04	1								
SIZE	-0.20	0.03	0.34	1							
LEVR	-0.06	-0.04	0.04	0.31	1						
RD	0.42	-0.07	-0.06	-0.42	-0.12	1					
CINT	-0.24	-0.17	0.00	0.22	0.26	-0.29	1				
DIVD	-0.11	-0.02	0.16	0.39	0.06	-0.25	0.15	1			
IOWM	0.01	0.05	0.06	0.44	0.03	-0.17	-0.04	0.09	1		
AGE	-0.16	-0.03	0.20	0.37	0.00	-0.30	0.06	0.37	0.21	1	
SGR	0.06	0.00	-0.01	0.03	0.02	-0.02	-0.01	-0.02	0.04	0.00	1

Panel A of this table presents the descriptive statistics of our key regression variables. Our test variable is *DGS*, a firm's digital score, calculated by the ratio of digital keywords to the total words in the firm's annual report. Panel B reports the correlation matrix among our main variables: Tobin's Q (*TOBINSQ*), firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). All continuous variables are winsorized at the 1% and 99% levels.

5.2. Empirical Results On The Impact of Digital Transformation on Corporate Value

We start our empirical analysis by addressing whether DGS creates value. To this end, we run the following model:

$$TOBINSQ_{i,j,t} = \alpha_0 + \alpha_1 DGS_{i,t} + \alpha_2 FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

The results of this model are shown in Table 2. We run two specifications. In the first (column 1), we present the regression results without time-variant firm characteristics. In the second (column 2), we augment our model with time-variant firm characteristics. In column 3, we have clustered errors at the firm level. For all regressions, the *DGS* coefficient remains positive and significant. In the first column, the coefficient 0.121 implies that a one-unit increase in the digital score is associated with an increase of 0.121 units in Tobin's Q. In the second and third columns, the coefficient is 0.069, the significance level in the second column remains at 1%, while in the third column, it is significant at the 5% level. Notably, in both models (1 & 2), the *DGS* coefficient is positive and significant at the 1 percent level, suggesting that digital transformation is beneficial to firm value. Similarly in column 3, with clustered errors at the firm level, the *DGS* coefficient remains positive and significant, indicating a slight reduction in confidence but still a strong relationship. Based on the results presented in Table 2, we find substantial evidence supporting

Hypothesis 1, which proposes that financial performance, as measured by Tobin's Q (TOBINSQ), is higher for U.S. companies that are making greater digitalization efforts.

TABLE 2: DIGITAL TRANSFORMATION AND CORPORATE VALUE

	(1) TOBINSQ	(2) TOBINSQ	(3) TOBINSQ
DGS	0.121***	0.069***	0.069**
	(6.764)	(4.039)	(2.008)
SIZE		-0.058***	-0.058***
		(-8.363)	(-3.550)
LEVR		0.263***	0.263*
		(5.465)	(1.915)
RD		3.158***	3.158***
		(39.103)	(14.542)
CINT		-0.932***	-0.932***
		(-14.829)	(-6.022)
DIVD		0.175***	0.175***
		(7.200)	(3.638)
IOWM		0.531***	0.531***
		(15.709)	(7.969)
AGE		-0.085***	-0.085***
		(-5.586)	(-2.875)
SGR		0.156***	0.156***
		(10.339)	(5.980)
Constant	2.145***	2.368***	2.368***
	(158.050)	(42.130)	(18.985)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Clustered Errors	NO	NO	YES
Observations	21,913	21,910	21,910
R-squared	0.165	0.255	0.255

This table reports the results of multivariate regression analysis examining the link between a firm's *DGS* and corporate value, measured by Tobin's Q (*TOBINSQ*). We control for the following variables: firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). We control for industry and year-fixed effects in all our regression specifications. Column 3 clusters the standard errors at the firm level. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We next run robustness tests to validate the evidence of a positive association between *DGS* and *TOBINSQ* and report the results in Table 3. While our empirical setting does not provide a natural experiment allowing us to attribute causality to our results, we attempt to limit the endogeneity bias arising from omitting unobservable heterogeneity by repeating our analysis after replacing *TOBINSQ* with future *TOBINSQ* as the dependent variable. Future *TOBINSQ* refers to Tobin's Q calculated for a period after the one used for the initial analysis. This approach tests whether the observed positive impact of digital transformation on firm value persists into the future. By using future *TOBINSQ* as the dependent variable, we are attempting to limit the endogeneity bias arising from unobservable heterogeneity; while unmeasured factors might influence current *TOBINSQ*, their impact on future *TOBINSQ* might be less direct or immediate. Therefore, if the independent variables (DGS) still predict future *TOBINSQ*, it strengthens the argument that the observed relationships are not merely due to omitted variables. Across all specifications, as shown in columns 1–3, the positive and significant *DGS* coefficient reinforces the value-creating impact of digital transformation. So far, in our regression models, we control only for the time and industry-fixed effects. In columns 4 (TOBINSQ) and 5 (future *TOBINSQ*), we control for firm fixed effects to account for unobserved time-invariant heterogeneity across different firms. These results show that the *DGS* coefficient remains positive and significant at 10 percent. However, it's important to be careful when interpreting these results, as including firm fixed effects in the analysis can absorb much of the cross-sectional variation.

TABLE 3: ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)
	Future TOBINSQ			TOBINSQ	Future TOBINSQ
DGS	0.106***	0.063***	0.063**	0.051*	0.049*
	(6.069)	(3.688)	(1.969)	(2.157)	(2.124)
SIZE		-0.041***	-0.041***	-0.373***	0.117***
		(-5.961)	(-2.629)	(-5.521)	(3.392)
LEVR		0.223***	0.223*	-0.165*	-0.141
		(4.677)	(1.746)	(-1.951)	(-1.503)
RD		2.266***	2.266***	1.659***	0.065
		(28.400)	(11.711)	(15.003)	(0.326)
CINT		-0.908***	-0.908***	-0.728***	-0.759***
		(-14.628)	(-6.013)	(-4.508)	(-5.547)
DIVD		0.120***	0.120***	0.098*	0.080**
		(5.021)	(2.585)	(2.169)	(2.594)
IOWM		0.535***	0.535***	0.395***	0.596***
		(16.007)	(8.202)	(10.273)	(9.345)
AGE		-0.032**	-0.032	-0.637***	-0.060
		(-2.138)	(-1.139)	(-3.261)	(-0.573)
SGR		0.312***	0.312***	0.089***	0.203***
		(20.839)	(11.597)	(6.520)	(6.649)
Constant	2.095***	2.128***	2.128***	6.343***	1.383**
	(158.627)	(38.320)	(17.965)	(6.828)	(2.844)
Industry FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	NO	NO
Clustered Errors	NO	NO	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES
Industry x Year FE	NO	NO	NO	YES	YES
Observations	21,913	21,910	21,910	21,529	21,529
R-squared	0.147	0.216	0.216	0.750	0.696

In this table, we report the results of robustness tests. In columns 1 through 3 we use future (i.e. next year) *TOBINSQ* as the dependent variable. In all our model specifications, we control for firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). In columns 4 and 5, we control for firm-fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Empirical Results on the Organizational Capital as a Moderating Factor

After we have established that firm digitization correlates with enhanced corporate value, we now focus on the influence of OC in this dynamic, as detailed in our results in Table 4. We categorize firms into two groups: those with high OC (above the sample median) and those with low OC (below the sample median). Our findings, reported in columns 1 and 2, reveal that the positive link between *DGS* and *TOBINSQ* is observable predominantly in high OC firms. To determine the role of OC, we include *OC* and its interaction with *DGS* (*OC* × *DGS*) into our main regression model as shown below:

$$TOBINSQ_{i,t} = \beta_0 + \beta_1 DGS_{i,t} + \beta_2 OC_{i,t} + \beta_3 (DGS_{i,t} \times OC_{i,t}) + \beta_4 FIRMCTRL_{i,t} + \mu_{i,t}$$

Analyzing the regression results, we observe that the coefficient of DGS in firms with high OC (0.107 in column 1) has a positive and statistically significant interaction effect, supporting our Hypothesis 2, which states that OC boosts the value creation from corporate digitization. This suggests that in firms with high OC, an increase in digitization correlates with a notable increase in TOBINSQ. In contrast, for firms with low OC, the coefficients for DGS are negative (-0.026 and -0.015) and not statistically significant. In columns 4–6, we replicate this analysis using future TOBINSQ as the dependent variable and by having a positive and statistically significant coefficient for DGS (0.094 in column 4), we can confirm our findings on the relevant role of OC in shaping the relationship between *DGS* and *TOBINSQ*.

TABLE 4: THE MODERATING ROLE OF ORGANIZATIONAL CAPITAL

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	TOBINSQ			Future *TOBINSQ*		
	High *OC*	Low *OC*	Full Sample	High *OC*	Low *OC*	Full Sample
DGS	0.107**	-0.026	-0.017	0.094**	-0.015	-0.027
	(2.233)	(-0.715)	(-0.469)	(2.051)	(-0.448)	(-0.830)
OC			0.102			-0.021
			(1.628)			(-0.359)
DGS x High OC			0.166***			0.179***
			(3.193)			(3.565)
SIZE	-0.040*	-0.187***	-0.086***	-0.028	-0.100***	-0.051***
	(-1.657)	(-5.870)	(-4.583)	(-1.241)	(-3.343)	(-2.897)
LEVR	-0.187	0.635***	0.258*	-0.191	0.572***	0.225*
	(-0.909)	(3.828)	(1.884)	(-0.988)	(3.719)	(1.771)
RD	6.114***	2.672***	3.130***	5.783***	1.790***	2.245***
	(6.735)	(11.605)	(14.388)	(6.366)	(8.853)	(11.586)
CINT	-0.270	-1.177***	-0.896***	-0.228	-1.275***	-0.903***
	(-1.254)	(-5.684)	(-5.797)	(-1.143)	(-6.145)	(-5.958)
DIVD	0.132**	0.229***	0.181***	0.096	0.200***	0.127***
	(2.080)	(3.414)	(3.787)	(1.571)	(3.025)	(2.726)
IOWM	0.250***	0.984***	0.517***	0.264***	0.873***	0.529***
	(3.048)	(8.890)	(7.767)	(3.361)	(8.064)	(8.132)
AGE	-0.046	-0.146***	-0.094***	-0.042	-0.016	-0.033
	(-1.155)	(-3.461)	(-3.178)	(-1.102)	(-0.406)	(-1.169)
SGR	0.611***	0.117***	0.163***	0.758***	0.259***	0.314***
	(6.442)	(4.355)	(6.225)	(8.539)	(9.417)	(11.639)
Constant	2.148***	3.102***	2.517***	2.017***	2.420***	2.198***
	(9.885)	(15.797)	(19.091)	(9.959)	(13.317)	(17.710)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES	YES	YES
Observations	11,081	10,828	21,910	11,081	10,828	21,910
R-squared	0.239	0.288	0.257	0.243	0.237	0.218

In this table, we examine the extent to which a firm's organizational capital shapes the effect of *DGS* on *TOBINSQ*. We use Eisfeldt and Papanikolaou's (2013) measure of organization capital (OC). In columns 1–3, *TOBINSQ* is the dependent variable, whereas in columns 4–6, future (i.e. next year) *TOBINSQ* is the dependent variable. In all our model specifications, we control for firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). In all our regression specifications, we control for industry and year-fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To further understand the relationship between *DGS* and *TOBINSQ*, we explore the influence of other firm-level characteristics, with results presented in Table 5. Initially, we examine the impact of institutional ownership, a measure of firm governance quality as represented by the proportion of outstanding shares of a company that are held by institutional investors. Our analysis, shown in columns 1 and 2, indicates that the positive relation between *DGS* and *TOBINSQ* primarily occurs in firms with high institutional ownership. Subsequently, we assess the role of firm information quality using two proxies. First, employing Roll's (1984) average bid-ask spread over the fiscal year, we find, as depicted in columns 3 and 4, that *DGS* significantly and positively affects *TOBINSQ* in firms with low bid-ask spread (i.e., low stock illiquidity). Furthermore, we analyze the effect of the analyst coverage, observing a positive link between *DGS* and *TOBINSQ* in firms with a higher analyst following. These results support hypotheses 3 & 4 on the moderating role of governance and information quality in the Digital transformation and firm value dynamic. Models used for these analyses are listed below:

$$TOBINSQ_{i,t} = \gamma_0 + \gamma_1 DGS_{i,t} + \gamma_2 IOWN_{i,t} + \gamma_3 (DGS_{i,t} \times IOWN_{i,t}) + \gamma_4 FIRMCTRL_{i,t} + \epsilon_{i,t}$$

$$TOBINSQ_{i,t} = \mu_0 + \mu_1 DGS_{i,t} + \mu_2 BAS_{i,t} + \mu_3 (DGS_{i,t} \times BAS_{i,t}) + \mu_4 FIRMCTRL_{i,t} + \epsilon_{i,t}$$

$$TOBINSQ_{i,t} = \mu_0 + \mu_1 DGS_{i,t} + \mu_2 NA_{i,t} + \mu_3 (DGS_{i,t} \times NA_{i,t}) + \mu_4 FIRMCTRL_{i,t} + \epsilon_{i,t}$$

TABLE 5: THE MODERATION EFFECTS OF CORPORATE GOVERNANCE AND INFORMATION QUALITY

	(1)	(2)	(3)	(4)	(5)	(6)
	TOBINSQ		*TOBINSQ*		*TOBINSQ*	
	Institutional Ownership		Bid-Ask Spread		Number of Analysts	
	High	Low	High	Low	High	Low
DGS	0.131**	0.008	-0.011	0.120**	0.170***	-0.008
	(2.515)	(0.214)	(-0.372)	(2.091)	(2.841)	(-0.259)
SIZE	-0.055**	-0.073***	-0.233***	-0.238***	-0.144***	-0.174***
	(-2.198)	(-3.536)	(-8.016)	(-8.283)	(-5.278)	(-6.332)
LEVR	-0.083	0.516***	0.622***	-0.184	0.039	0.444***
	(-0.372)	(3.208)	(4.574)	(-0.833)	(0.190)	(2.975)
RD	4.959***	2.875***	2.635***	5.526***	3.366***	2.757***
	(10.385)	(12.024)	(11.510)	(10.315)	(7.913)	(11.292)
CINT	-0.593***	-1.182***	-0.948***	-0.711***	-0.629**	-1.032***
	(-2.794)	(-5.984)	(-6.165)	(-2.976)	(-2.561)	(-6.155)
DIVD	0.105	0.282***	0.238***	0.069	0.057	0.313***
	(1.606)	(4.423)	(4.591)	(1.018)	(0.801)	(5.685)
AGE	-0.043	-0.086**	-0.138***	-0.022	0.035	-0.089**
	(-1.129)	(-2.115)	(-3.842)	(-0.535)	(0.859)	(-2.263)
SGR	0.223***	0.114***	0.095***	0.220***	0.166***	0.127***
	(4.666)	(3.680)	(3.552)	(3.868)	(4.200)	(3.855)
Constant	2.097***	2.535***	3.220***	4.319***	3.063***	2.867***
	(8.307)	(16.130)	(17.818)	(15.813)	(12.615)	(16.346)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES	YES	YES
Observations	10,956	10,954	10,954	10,955	10,936	10,974
R-squared	0.291	0.260	0.313	0.321	0.283	0.282

In this table, we examine the extent to which the quality of a firm's corporate governance and its information quality shape the effect of *DGS* on *TOBINSQ*. We use the shareholdings of intuitional investors to proxy for the quality of corporate governance. We use stock illiquidity measured by Roll's (1984) bid-ask spread and analyst coverage as proxies for firm information quality. We use sample median to distinguish between firms with high and low indicators. In columns 1–3, *TOBINSQ* is the dependent variable, whereas in columns 4–6, future (i.e. next year) *TOBINSQ* is the dependent variable. In all our model specifications, we control for firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), firm age (*AGE*), and sales growth (*SGR*). In all our regression specifications, we control for industry and year-fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

CHAPTER 6: Conclusion and Discussion

Corporate digitization is usually associated with efficiencies in the firm processes, culture, and operational methods. These efficiencies contribute to cost reduction, optimized resource use, and an enhanced ability to meet dynamic internal and external demands, potentially leading to innovation-led value creation and growth. This thesis has delved into the intricate relationship between firm digitalization, corporate performance, and the moderating role of organizational capital (OC). Our analysis, based on a robust empirical framework, reveals several key findings that contribute to our understanding of how digital transformation shapes corporate value, particularly in the context of U.S. non-technology firms. Firstly, our study supports the hypothesis that digital transformation, as measured by the Digital Transformation Score (DGS), positively influences corporate performance; this relationship emphasizes the importance of integrating digital technologies into corporate strategies. However, more significantly, it highlights the critical role of organizational capital as a moderating factor. As shown by our results, firms with higher levels of organizational capital tend to leverage digital transformation more effectively. Secondly, this thesis presents novel insights into the interaction between digital transformation and firm characteristics such as governance quality and information transparency. Firms with higher institutional ownership and better information quality were found to benefit more from digital transformation efforts, indicating that these elements play a supportive role in enhancing the value derived from digital initiatives. Moreover, our findings offer a unique perspective by focusing on U.S.-based firms; this geographical distinction provides valuable insights into how digital transformation's impact might vary in different regional contexts, given the unique nature of each market dynamics and digitalization approach.

In light of these empirical results, this thesis makes a contribution to the literature on digital transformation and corporate performance. We not only validate the positive relationship between digital transformation and corporate value but also bring to light the pivotal role of organizational capital in this dynamic. Future research in this area is certainly called for. For instance, investigating the role of organizational capital in moderating the linkage between corporate digitization and other corporate outcomes, particularly in a cross-country context, seems appropriate. Further, an empirical examination of the role of corporate leadership in shaping the valuation effect of firm digital transformation is beyond the scope of this study, but it points to a promising direction for future research.

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Appendix: List of Keywords

Artificial intelligence
Artificial reality
App
3D print
5G
Augmented reality
Automation
Autonomous driving
Autonomous technology
Big data
Biometric
Biometrics
Bitcoin
Blockchain
Bots
Business intelligence
Click-through rate
Cloud
Cloud collaboration
Cloud computing
Cognitive computing
Converged infrastructure
Cryptocurrency
Data analytics
Data architecture
Data capturing
Data integration
Data lake
Data mining
Data monetization
Data processing system
Data science
Data visualization
Decentralized Finance
Deep learning
DevOps
Differential privacy
Digital
Digital currency
Digital marketing
Digital twin
Digitalization
Digitally
Digitization
Distributed computing
Ebusiness
E-business
Ecatalogue
E-catalogue
Ecommerce
E-commerce
Edge Computing
Elearning
E-learning
Emobility
E-mobility
E-procurement
Epublishing
E-publishing
Eservice
E-service
Face recognition
Fintech
Green computing
Heterogeneous data
Hightech
High-tech
Human cloud
Image recognition
Image understanding
Industry 4.0
Influencer
In-memory computing
Intelligent systems
Internet
Internet of Things
IoT
Machine learning
Metaverse
Mobile internet
Mobile payment
Natural language processing
Neural network
New economy
Newsfeed
NFC payment
NLP
Office automation
Online
Open banking
Open source
Organizational capital
Platform
Quantum computing
Robotics
Robots
Selfdriving car
Semantic search
Sentiment analysis
Serverless computing
Sharing economy
Smart agriculture
Smart content
Smart contracts
Smart devices
Smart factory
Smart healthcare
Smart home
Smart investment
Smart transportation
Smartphone
Social media
Software
Speech recognition
Text mining
Unmanned
Virtual reality
Voice recognition
Web 3.0
Web based