MODERATING EFFECT OF ECONOMIC POLICY UNCERTAINTY ON THE NEXUS BETWEEN EXTERNAL STAKEHOLDERS' FACTORS AND COMPANIES' DIGITAL TRANSFORMATION IN CHINA

By

SUN LE

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Chairman : Professor, Ong Tze San, PhD
School : Business and Economics

Digital transformation is essential for competitive edge in China's rapidly evolving technology landscape. However, the journey towards it is fraught with challenges, including the need to manage relationships with external stakeholders and the influence of unpredictable economic policies on strategic planning and market conditions. Despite this, the specific impacts of these factors on digital transformation remain largely unexplored. To address this gap, this study investigates the role of key external stakeholders—analysts, customers, and suppliers—in influencing digital transformation within companies, focusing on how their impact fluctuates with economic policy uncertainty. Utilizing data from 3,545 Chinese listed companies from 2011 to 2021, we find that analyst coverage positively drives digital transformation, while high concentration among customers and suppliers acts as a deterrent. Importantly, we reveal that economic policy uncertainty weakens the positive effect of analyst coverage and exacerbates the negative impact of supplier concentration on digital transformation, with no significant moderation observed on the influence of customer concentration. Our research advances Stakeholder Theory by integrating the dynamics of economic policy uncertainty, highlighting its moderating role between firms and external stakeholders in the context of digital transformation. This fills a significant gap in the literature by providing a nuanced understanding of how external pressures and uncertainties can shape corporate strategies towards digital transformation. For businesses, our findings underscore the necessity of strategically managing relationships with analysts, customers, and suppliers while navigating the challenges posed by economic policy uncertainty. For policymakers, creating a stable economic policy environment emerges as crucial to supporting digital transformation initiatives, acknowledging the complex interplay of external influences on corporate strategic decisions. This study bridges theoretical gaps and offers practical insights for enhancing digital transformation success in an unpredictable economic landscape.

Keywords: *Analyst Coverage, Customer Concentration, Digital Transformation, Economic Policy Uncertainty, Supplier Concentration.*

SDG: GOAL 9: Industry, Innovation and Infrastructure

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

KESAN PENYEDERHANAAN DASAR EKONOMI TERHADAP HUBUNGAN ANTARA FAKTOR PEMEGANG KEPENTINGAN LUAR DAN TRANSFORMASI DIGITAL SYARIKAT DI CHINA

Oleh

SUN LE

Mac 2024

Pengerusi : Professor, Ong Tze San, PhD
Sekolah : Perniagaan dan Ekonomi

Transformasi digital adalah penting untuk kelebihan daya saing dalam landskap teknologi China yang berkembang pesat. Bagaimanapun, perjalanan ke arah itu penuh dengan cabaran, termasuk keperluan untuk mengurus perhubungan dengan pihak berkepentingan luar dan pengaruh dasar ekonomi yang tidak menentu ke atas perancangan strategik dan keadaan pasaran. Walaupun begitu, kesan khusus faktor-faktor ini terhadap transformasi digital masih belum diterokai. Untuk menangani jurang ini, kajian ini menyiasat peranan pihak berkepentingan luar utama—penganalisis, pelanggan dan pembekal—dalam mempengaruhi transformasi digital dalam syarikat, memfokuskan pada cara kesannya berubah-ubah dengan ketidakpastian dasar ekonomi. Menggunakan data daripada 3,545 syarikat tersenarai China dari 2011 hingga 2021, kami mendapati liputan penganalisis secara positif memacu transformasi digital, manakala tumpuan yang tinggi dalam kalangan pelanggan dan pembekal bertindak sebagai penghalang.

Yang penting, kami mendedahkan bahawa ketidaktentuan dasar ekonomi melemahkan kesan positif liputan penganalisis dan memburukkan lagi kesan negatif penumpuan pembekal terhadap transformasi digital, tanpa penyederhanaan ketara yang diperhatikan terhadap pengaruh kepekatan pelanggan. Penyelidikan kami memajukan Teori Pihak Berkepentingan dengan menyepadukan dinamik ketidaktentuan dasar ekonomi, menonjolkan peranan penyederhanaannya antara firma dan pihak berkepentingan luar dalam konteks transformasi digital. Ini mengisi jurang yang ketara dalam kesusasteraan dengan memberikan pemahaman yang bernuansa tentang bagaimana tekanan dan ketidakpastian luaran boleh membentuk strategi korporat ke arah transformasi digital. Bagi perniagaan, penemuan kami menekankan keperluan mengurus perhubungan secara strategik dengan penganalisis, pelanggan dan pembekal sambil menavigasi cabaran yang ditimbulkan oleh ketidaktentuan dasar ekonomi. Bagi pembuat dasar, mewujudkan persekitaran dasar ekonomi yang stabil muncul sebagai penting untuk menyokong inisiatif transformasi digital, mengakui interaksi kompleks pengaruh luaran terhadap keputusan strategik korporat. Kajian ini merapatkan jurang teori dan menawarkan pandangan praktikal untuk meningkatkan kejayaan transformasi digital dalam landskap ekonomi yang tidak dapat diramalkan.

Kata Kunci: Liputan Penganalisis, Kepekatan Pelanggan, Transformasi Digital, Ketidakpastian Dasar Ekonomi, Kepekatan Pembekal.

SDG: *GOAL 9: Industry, Innovation and Infrastructure*

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Ong Tze San, PhD
Professor
Scholl of Business and Economics
Universiti Putra Malaysia
(Chairman)

Saira Binti Kharuddin, PhD
Senior Lecturer
School of Business and Economics
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Associate Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 13 June 2024

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LIST OF ABBREVIATIONS

AC	Analyst Coverage
CC	Customer Concentration
DT	Digital Transformation
DTA	Digital Technology Application
DUT	Digital Underlying Technology
EPU	Economic Policy Uncertainty
SC	Supplier Concentration
Lev	Asset-Liability Ratio
IndepRatio	The Ratio of Board Independence
LnFrimAge	The Natural Logarithm of One plus the firm Age
LnEmployee	The Natural Logarithm of One plus the Number of Employees

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

With the continuous development of technology, the digital economy is playing an increasingly important role in China's economy. In 2021, China's "14th Five-Year Plan" explicitly proposed to "accelerate digital development and build a digital China," emphasizing the drive for a transformation in production methods through digitalization. Under the guidance of national policies, China's digital economy experienced remarkable growth, doubling its size over five years. By the end of 2022, the scale of the digital economy reached 50.2 trillion yuan, up from 27.2 trillion yuan in 2017, through consistent annual increases. For a detailed quantitative analysis of the digital economy's expansion from 2017 to 2022, refer to Figure 1.1, which provides the annual growth data supporting this significant increase. This development positions the digital economy as one of the main engines driving economic growth. Against this macroeconomic backdrop, microeconomic entities have firmly seized the new opportunities presented by the digital economy era, placing digital transformation as a top priority for businesses in the ensuing period. According to statistical data from Accenture China Digital Transformation Index 2021, China's digital transformation has steadily improved, increasing from 37 points in 2018 to 54 points in 2021. The proportion of leading enterprises with significant transformation outcomes also more than doubled from 7% in 2018 to 16% in 2021 (refer to Figure 1.2). Therefore, corporate digital transformation is not just a trend, but an inevitable choice for adapting to this increasingly dynamic economic environment.

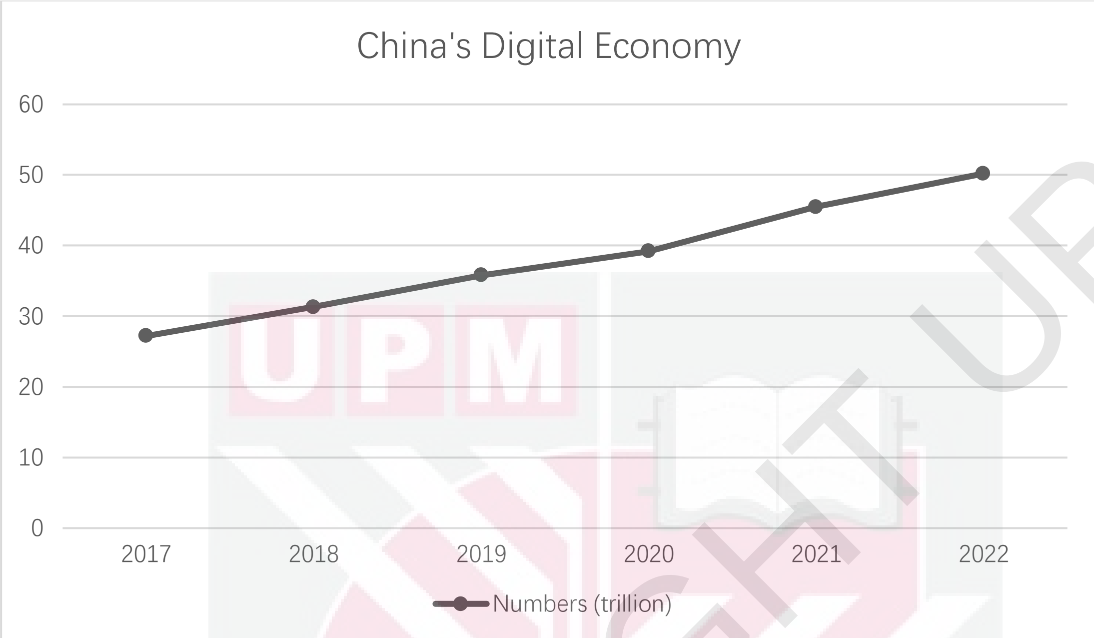

Figure 1.1: China’s Digital Economy

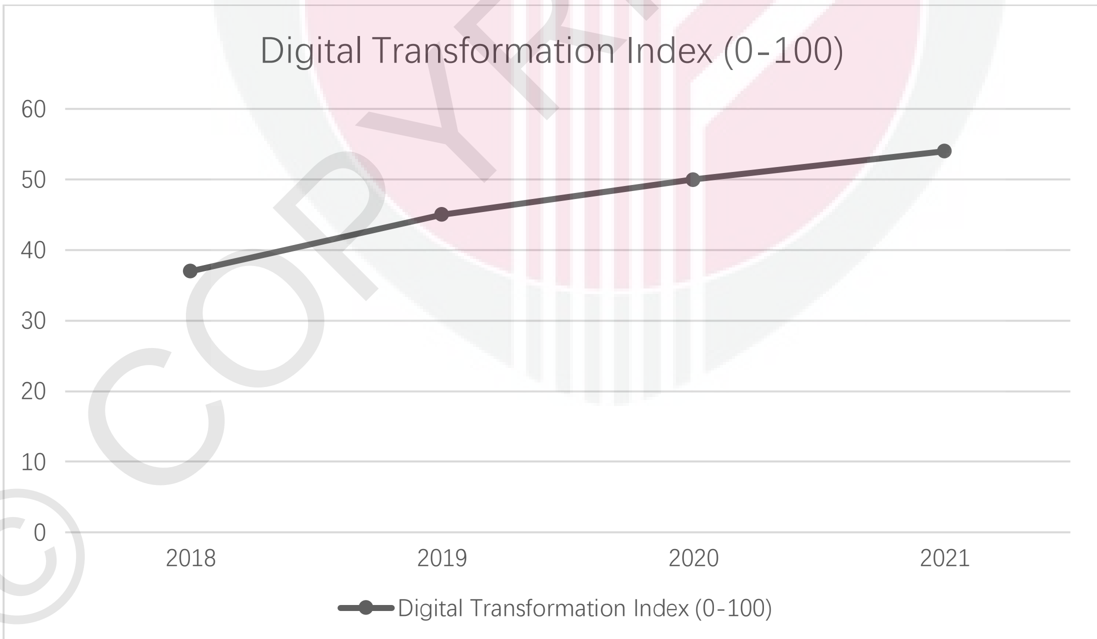

Figure 1.2: Accenture China Digital Transformation Index 2021

In embracing the modern business trend of digital transformation, the critical role of external stakeholders cannot be overlooked (Brunetti et al., 2020). External stakeholders profoundly impact corporate strategic direction and performance (Freeman & Reed, 1983). Among them, analysts, customers, and suppliers undoubtedly form the three most influential groups, as they encompass the primary external interaction domains of a business, ranging from capital markets to sales markets and supply chains. First, analysts are often viewed as representatives of capital markets (Johansson, 2007). Their forecasts and opinions reflect the views of investors and shareholders, thereby affecting stock prices (Feng et al., 2016), companies' financing costs, and investor confidence (Chang et al., 2006). Consequently, their views on a company's digital transformation strategy may directly affect the company's market performance and investment attractiveness (Jia, 2022).

Secondly, customers form the crux of the sales market and significantly reshape digital transformation through their expectations and preferences (Li et al., 2023b). In the contemporary digital economy, customer demands for innovative, efficient, and personalized services are varied (Mashalah et al., 2022). This means that, although their interactions with companies are increasingly facilitated by digital platforms, customers' attitudes towards corporate digital transformation are also changing (Hanelt et al., 2021). This necessitates businesses to closely observe and respond to these evolving preferences. In fact, in some cases, customers may impede digital transformation. For instance, digital transformation can reduce a company's reliance on major customers (Liu et al., 2022c), which often leads to dissatisfaction among these key clients. To appease important customers, enterprises may slow down the pace of their digital transformation (Li et al., 2023b).

On the other hand, suppliers, as key players in supply chain management (Liu et al., 2023), impact digital transformation through their operations and interactions (Ferreira & Lind, 2023). The integration of digital solutions in supply chain processes—from procurement and logistics to inventory control—enables businesses to achieve greater efficiency and transparency. Suppliers' readiness and ability to engage in these digital exchanges and automated processes are crucial for seamless supply chain integration (Seyedghorban et al., 2019). As such, enterprises must align their digital transformation strategies with their suppliers' digital expectations to ensure that their supply chains are robust, adaptable, and capable of withstanding the challenges of a dynamic business environment (Yang & Guo, 2022).

Therefore, given the critical role of analysts, customers, and suppliers in the modern business environment, their perspectives must be incorporated into an enterprise's digital transformation strategy to ensure it is comprehensive and market aligned. A strategy that is cognizant of these external stakeholders' digital expectations is more likely to succeed and create a competitive edge in the digital economy. However, while the previous literature has widely discussed these three stakeholders' role in corporate governance and strategic decision-making, there is insufficient research on their impacts on digital transformation. Therefore, an in-depth study of their roles in digital transformation can not only provide new insights to the academic community but also have important implications for industry practitioners.

Accordingly, this study selected three proxies pertaining to the three external stakeholders—analyst coverage, customer concentration, and supplier concentration—to represent their expectations and explore how they impact an organization's digital transformation strategy. First, analyst coverage is an important source of information in the capital market, reflecting not only analysts' predictions about the company's future performance, but more importantly, the market's expectations of the company's strategy and performance (Dhiensiri & Sayrak, 2010). Past research has proven that analysts' forecasts and evaluations have a significant impact on stock prices, company financing decisions, and even senior management decisions. Therefore, understanding how analysts view companies' digital transformation strategies is critical to the understanding of this topic.

Second, against the backdrop of digital transformation, understanding customer needs and expectations is particularly crucial. In this regard, the customer concentration of a business is an important metric for measuring the strength of the relationship between a company and its main customers (Chen et al., 2023; Liu et al., 2023). Companies with high customer concentration may be more attuned to shifts in the demands of their major clients and technological trends, allowing them to adapt more quickly to market changes. However, a high degree of customer concentration could also lead to an over-reliance on a select few customers, potentially placing the company at a disadvantage during market fluctuations or technological innovations (Li et al., 2023b). Therefore, when formulating and adjusting digital transformation strategies, companies need to consider both the opportunities and risks brought about by customer concentration (Dhaliwal et al., 2016). This consideration is not only about how businesses can utilize digital technologies to improve customer service and product innovation, but also about how they can balance and diversify their customer base to reduce dependency risks and enhance market adaptability (Yang, 2023).

Similarly, supplier concentration is a key indicator of the strength of a business's relationship with its suppliers (Chen et al., 2023; Liu et al., 2023). In the process of digital transformation, the technological capability and innovation pace of suppliers directly affect the efficiency of a company's supply chain and the quality of its products (Ning & Yao, 2023). Companies with high supplier concentration may find it easier to establish close collaborative relationships with their main suppliers, jointly driving technological innovation and process optimization. Yet, this can also introduce the risk of over-dependence on a single supplier or a few ones, especially under conditions of uncertain economic policies (Kale & Meneghetti, 2014). Thus, when developing digital transformation strategies, businesses need to consider how to enhance collaboration with suppliers through technological upgrades and process improvements, while also paying attention to mitigating potential risks associated with supplier concentration (Yang & Guo, 2022). This includes seeking diversified supply chain partnerships and using digital technology to improve supply chain transparency and flexibility (Malyavkina et al., 2019).

In addition, apart from market reactions, companies must also consider the macroeconomic environment when making decisions. According to estimates, the annual average of China's Economic Policy Uncertainty Index in 2020 was 13.42 times that of 2000. Indeed, rapidly rising economic policy uncertainty (hereafter EPU) causes a series of negative impacts on economic development, such as higher market operating risks (Tsai, 2017) and economic turmoil (Kang & Ratti, 2013). Thus, EPU is a regulating variable that plays an important role in the study of digital transformation, providing an avenue to better understand how the external macroenvironment affects the internal strategic decisions of enterprises. In this study, it is anticipated that EPU moderates the influence of analyst coverage, customer concentration, supplier concentration on firms' digital transformation strategies. Specifically, when economic policy is stable, companies may rely more heavily on analyst coverage and demand from customers and suppliers to form their digital transformation strategies (Li & Huang, 2021; Liu et al., 2022a). Conversely, these relationships may change when economic policy becomes more uncertain.

Regarding analyst coverage, when EPU is high, the resulting macroeconomic instability makes forecasting more difficult, thereby challenging analysts' recommendations and forecasts (Chen et al., 2022). This may lead companies to take a more cautious attitude towards analysts' recommendations and adjust their digital transformation strategies. As for customer and supplier concentrations, EPU may affect supply and demand, causing companies to pay more attention to these two factors when considering their digital transformation strategies. For example, highly concentrated suppliers may exert greater pressure on companies under conditions of high EPU (Charoenwong et al., 2023), requiring companies to adjust their digital strategies to adapt to possible macroeconomic changes.

To summarize, in the modern business environment, enterprises are no longer isolated entities but are closely connected within a network of external stakeholders (Freeman & Reed, 1983). Among them, analysts, customers, and suppliers play key roles in corporate decision-making and strategy formation. In the context of digital transformation, the expectations and perceptions of these stakeholders directly affect the direction and speed of enterprise transformation. Especially in today's rapidly changing business environment, establishing good communication and cooperation with external stakeholders is the key to a successful digital transformation. Therefore, studying the relationship between external stakeholders and enterprise digital transformation can provide not only in-depth insights to the academic community but also key guidance for the corporate world to formulate and modify digital transformation strategies.

1.2 Problem Statement

Although microeconomic entities in the digital economy are awarding digital transformation an unprecedented degree of importance, many businesses are still hesitating to embark on this path due to the challenges and uncertain future it entails. According to the latest "White Paper on the Digital Economy of Chinese Listed Companies" (2022), in terms of the stages of corporate digital transformation, the proportion of relatively mature or fully transformed enterprises is small, accounting for only 8.7% and 0.2%, respectively. Most companies have only achieved preliminary results or are in the exploratory stage, accounting for 49.3% and 41.8%, respectively. This data indicates that despite the increasing support for digital transformation from the government and relevant institutions, enterprises encounter significant resistance in implementing this change. This is not merely a technical or resource issue; rather, the more profound challenges lie in making the strategic choices and decisions on whether to initiate this crucial transformation.

When companies actually undergo digital transformation, they may encounter various challenges, including: misunderstandings, distrust, and poor standards (Klein & BİBer, 2022); digital skill insufficiencies as well as organizational and cultural barriers (Lei et al., 2023); limited resources (Li, 2023); external crises like the COVID-19 pandemic (Kutnjak, 2021); and the struggle to achieve equilibrium in relationships with external stakeholders (Cui et al., 2022). Moreover, inappropriate attempts at digital transformation can lead not only to a lack of anticipated advantages for enterprises but also to transformation failures, putting the enterprises in a more passive position. Hajli et al. (2015) pointed out that, due to the asynchronous development of enterprise management capabilities and rapid digital technological advancements, the performance of enterprises post-digital transformation has not improved significantly. Accenture's "2020 China Enterprise Digital Transformation Index Study" supports this conclusion, finding that the proportion of enterprises achieving performance improvements through digital transformation only increased from 7% in 2018 to 11% at present. This implies that despite knowing the substantial advantages of digital transformation and investing considerable resources and effort into it, the actual effectiveness of transformation has not met expectations, instead bringing greater disadvantages. This further exacerbates enterprises' hesitation and concerns about digital transformation.

Meanwhile, the challenges of managing relationships with external stakeholders during a digital transformation are multifaceted and significant, making it crucial to balance relationships with them (Broekhuizen et al., 2021). External stakeholders such as customers, suppliers, and analysts each have their own set of expectations, demands, and thresholds for change, which can vary widely and change over time, especially during periods of rapid technological evolution. This discrepancy between stakeholder expectations and a company's digital transformation efforts can lead to misunderstandings and a breakdown in trust (Candelo et al., 2021; Faruquee et al., 2021). The lack of standardized protocols for digital operations further exacerbates this issue (Butt, 2020), as stakeholders are left without clear guidelines on how to interact with the transforming entity.

Moreover, it is clear that the unpredictable nature of economic policy can exacerbate these challenges. The volatility associated with EPU can lead to hesitation in investment decisions (Hoang et al., 2023), including those related to digital transformation. When policies are uncertain, organizations may struggle to formulate a coherent digital strategy, anticipate the regulatory landscape, or commit to long-term technological investments. This hesitancy can be particularly detrimental in a digital context, where agility and decisiveness are paramount (Schiuma et al., 2021).

Furthermore, managing relationships with external stakeholders becomes even more critical against a backdrop of EPU. Stakeholders' expectations are likely to shift as they respond to policy changes, affecting their interactions with the firm (Yuan et al., 2022). Companies must navigate these shifts by engaging closely with stakeholders, understanding their concerns and expectations, and integrating this feedback into their digital transformation strategies.

In conclusion, the biggest challenge Chinese businesses currently face is not knowing how to properly implement digital transformation, especially by balancing their relationship with stakeholders in an unconventional environment, which causes them to hesitate, put off, or forgo implementing digital transformation strategies altogether. Therefore, exploring the drivers of digital transformation in different economic environments is particularly important.

The existing literature on digital transformation focuses mainly on its economic impact on enterprises and the strategic choices enterprises make during such transformations. However, there's a gap in understanding the role of external factors, especially the influence of external stakeholders like analysts, customers, and suppliers, on digital transformation strategies. This gap is significant, considering the profound impact of EPU and stakeholder expectations on corporate strategies.

This study addresses this overlooked area by investigating how analyst coverage, customer concentration, and supplier concentration affect firms' digital transformation efforts in uncertain environments. By shedding light on the interaction between enterprises and their external stakeholders amidst EPU, this research aims to provide new empirical insights and practical recommendations, helping businesses navigate digital transformation more effectively.

1.3 Research Questions

To attain an in-depth understanding of the determinants of digital transformation in China, the current study raised two main questions to be answered using a set of methodological approaches, as stated below:

1. What is the relationship between external stakeholders (analyst coverage, customer concentration, supplier concentration) and digital transformation in Chinese listed companies?

2. How does EPU moderate the relationship between external stakeholders (analyst coverage, customer concentration, supplier concentration) and digital transformation in Chinese listed companies?

1.4 Research Objectives

The main aim of this study was to investigate the antecedent and moderating factors of digital transformation in China. The specific objectives were as follows:

1. To examine the relationship between external stakeholders (analyst coverage, customer concentration, supplier concentration) and digital transformation in Chinese listed companies.
2. To examine the moderating role of EPU in the relationship between external stakeholders (analyst coverage, customer concentration, supplier concentration) and digital transformation in Chinese listed companies.

1.5 Significance of the Study

This research work contributes significantly to three key aspects, namely theoretical significance, practical significance and policy significance.

1.5.1 Theoretical Significance

Firstly, while Stakeholder Theory has been widely explored and applied in the literature on corporate governance, research connecting it with digital transformation remains relatively scarce. This study systematically examined how three major external stakeholders - analysts, customers, and suppliers -

influence, facilitate, or constrain a firm's digital transformation. In doing so, it provides a new theoretical framework for applying Stakeholder Theory in the context of digital transformation, further enriching current research in this area.

Secondly, by introducing EPU as a moderating variable, the study underscores its importance in digital transformation. This not only adds a new dimension to research in the field of digital transformation but also highlights the critical role of the external macroeconomic environment in corporate governance and strategic decision-making. It offers researchers a new perspective to deeply understand the interaction between the external environment and internal corporate strategies, which is significant for both academia and practice. Moreover, the impact of EPU on corporate digital transformation strategies and their interactions with stakeholders offers a new direction for future research.

Furthermore, this study breaks away from the traditional focus of digital transformation research, which is often one-dimensional. While extant research primarily focuses on technology and strategy, this study emphasizes the complex interactions between multiple external stakeholders and a firm's digital transformation. This not only provides a more comprehensive and integrated paradigm for studying digital transformation but also deepens the understanding of digital transformation.

In summary, this research not only expands the application of Stakeholder Theory in the context of digital transformation but also provides new perspectives and frameworks for research in this field, thus offering valuable references for future studies.

1.5.2 Practical Significance

This study offers valuable practical guidance for enterprises on the path towards digital transformation. It reveals how corporate decision-makers can better balance and consider the expectations and needs of multiple stakeholders, ensuring that digital transformation meets internal demands while forming effective synergies with external stakeholders. In an environment of EPU, enterprises can refer to the conclusions of this study to develop more flexible and adaptive strategies, ensuring the continual advancement of digital transformation with minimal disruption from the external environment.

1.5.3 Policy Significance

This research underscores the critical role of stable economic policies, diversified supply chains, and informed analyst coverage in enabling digital transformation. Governments should strive for policy stability to mitigate the impacts of economic policy uncertainty, creating a conducive environment for digital initiatives. Encouraging supply chain diversification can alleviate risks tied to customer and supplier concentration, thereby fostering resilience and innovation. Furthermore, policies that enhance the quality and reach of analyst coverage can contribute to a more transparent and informed market environment, encouraging firms to undertake digital transformation strategies.

Together, these recommendations aim to address key challenges in digital transformation, promoting the healthy and sustainable development of the digital economy.

1.6 Scope of the Study

The rapid advancement of the digital economy, coupled with growing environmental uncertainty, motivated this research. This study aimed to explore the impact of expectations from three external stakeholders - analysts, customers, and suppliers - on the digital transformation strategy of firms, along with the moderating role of policy uncertainty in this relationship. The scope of the research encompassed panel data of listed A-share companies on China's Shanghai and Shenzhen stock exchanges, spanning a decade from 2011 to 2021.

1.7 Definition of Terms

This section presents brief definitions of the terms used throughout the current study. More detailed explanations are presented in subsequent chapters.

1.7.1 Digital Underlying Technology

It captures the extent to which a company is invested in the foundational aspects of digital transformation. It is measured by the frequency of terms related to artificial intelligence, blockchain, cloud computing, and big data technologies within the management discussion and analysis section of annual reports. A higher frequency of these terms suggests a deeper integration of digital infrastructure within the company's strategic framework. The variable is quantified using the natural logarithm of one plus the total count of relevant keywords (Wu et al., 2021).

1.7.2 Digital Technology Application

It assesses the application level of digital transformation within a company. It is determined by the frequency of terms associated with the practical use of digital technologies, such as mobile internet, e-commerce, and fintech, in the management discussion and analysis section of annual reports. The frequency of these terms is indicative of the company's commitment to implementing digital technologies in its operations. The measurement is the natural logarithm of one plus the keyword count (Wu et al., 2021).

1.7.3 Analyst Coverage

It is quantified as the natural logarithm of one plus the annual number of analyst teams tracking the company (Khatri, 2023). This serves as a gauge for the external financial community's attention and is indicative of the company's visibility and informational transparency in the marketplace (Chang et al., 2006).

1.7.4 Customer Concentration

It is measured by the sales proportion from the company's top five customers, reflecting the dependency on key customers and potential risks associated with customer diversification (Li et al., 2023b; Patatoukas, 2011).

1.7.5 Supplier Concentration

It is assessed by the ratio of purchases from the company's top five suppliers, signifying the level of dependency on main suppliers and the associated supply chain risks (Liu et al., 2022b; Liu et al., 2023).

1.7.6 Economic Policy Uncertainty (EPU)

It is measured using the China Economic Policy Uncertainty Index, which is calculated as the ratio of South China Morning Post articles containing specified keywords to the total number of articles, averaged annually, and adjusted by a factor of 100 (Baker et al., 2016).

1.7.7 Asset-Liability Ratio

It is calculated as the ratio of year-end liabilities to total year-end assets, reflecting the company's financial leverage and capacity to sustain debt (O'Brien, 2003).

1.7.8 Board Independence

It is measured by the ratio of non-executive directors to the total board size, which is considered to influence the company's governance quality and strategic decisions (Adamas & Ferreira, 2007).

1.7.9 Firm Age

It is calculated as the natural logarithm of the current year minus the year of establishment plus one, capturing the firm's experience and market tenure (BarNir et al., 2003).

1.7.10 Number of Employees

It is measured by the natural logarithm of the total number of employees plus one, indicating the firm's size and complexity (McKelvie & Davidsson, 2009).

1.8 Structure of the Thesis

This thesis comprises five chapters, organized as follows: Chapter 1 introduces the research topic and provides an overview of the thesis. Chapter 2 presents a review of the existing literature, followed by the development of the research framework and hypotheses. Chapter 3 elucidates the research methodologies employed and the various measures for the dependent and independent variables. Subsequently, Chapter 4 interprets and discusses the results, while Chapter 5 concludes with the study’s implications, limitations, and recommendations for future research.

1.9 Summary

This chapter has laid the groundwork by setting the contextual backdrop of the study. It introduced the problem statement, laid out the research questions and corresponding objectives, and expounded upon the significance, both theoretical and practical, of this study on digital transformation and its various factors. Lastly, it outlined the scope of the study, the definitions of key terms, and the structure of this thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter focuses on the literature review, research framework, and hypotheses development. The primary objective of this study was to investigate the impact of major external stakeholders' expectations on digital transformation, specifically analyzing the influences of analyst coverage, customer concentration, and supplier concentration. Additionally, the study examined the moderating role of EPU in these relationships. Six hypotheses are proposed to test these relationships. The organization of this chapter is as follows: Section 2.2 discusses the underpinning theory, Sections 2.3 to 2.7 present reviews of related research, Section 2.8 introduces the conceptual framework, Section 2.9 discusses the development of the study's hypotheses, and Section 2.10 provides a summary of the chapter.

2.2 The Underpinning Theory - Stakeholder Theory

Stakeholder Theory emerged around the 1960s in countries like the United States and the United Kingdom that traditionally adhered to an external control model of corporate governance. The theory represents a significant shift from the conventional shareholder-centric business theory. It posits that shareholders, creditors, employees, suppliers, and other stakeholders who invest “specific capital” in a firm and bear its risks are integral to the sustainable development of the enterprise. Thus, a firm should serve not only the interests of its shareholders but also protect the interests of its other stakeholders.

Indeed, considering the rights and interests of stakeholders in corporate governance and encouraging their appropriate participation has become a widely accepted concept. In the early 1980s, economists and management scholars like Freeman analyzed the subjects of corporate governance structures from the perspectives of corporate strategic management and business ethics, conducting empirical studies on stakeholder phenomena (Freeman & Reed, 1983). Blair (1996) argued that a corporation should have social responsibilities, serving the interests of all stakeholders, not just shareholders. Shareholders, having only limited liability, transfer a portion of the residual risk to creditors and others. The risks borne by shareholders can be mitigated through diversification, as they can include shares as a part of their total investment portfolio. Therefore, the crux of corporate governance reform is that more rights and control should not be given to shareholders alone; “Management should be separated from shareholder pressure and more rights should be given to other stakeholders.”

Additionally, significant corporate governance principles like the "OECD Principles of Corporate Governance" launched in June 1999 by the Organization for Economic Co-operation and Development (OECD) and corporate governance statements from the Business Roundtable in the United States place stakeholders in a considerably important position. In European countries such as Germany, the Netherlands, and Switzerland, the participation of typical stakeholders like employees, customers, and suppliers in corporate governance is quite common.

However, constrained by factors such as corporate resources and capabilities, firms cannot equally and comprehensively provide the products and services needed by every stakeholder. That is, they cannot equitably fulfill every stakeholder's expectations. Instead, they might prioritize fulfilling the expectations of those stakeholders who have a higher impact on the enterprise (Levitas, 2013). Indeed, the interests of external stakeholders encompass various elements, including demands, expectations, rationales, requirements, and values (Lukes, 2005).

In summary, the key lesson of Stakeholder Theory for digital transformation is that a business does not exist solely for its shareholders. Numerous stakeholders are affected by, and in turn, influence the decisions made in a firm’s digital transformation. Moreover, treating these stakeholders equally is not necessary; allocating different levels of attention to different stakeholders based on varying scenarios is an inevitable and rational choice for enterprises to scientifically and effectively undertake digital transformation. This study thus integrates the expectations of external stakeholders regarding the comprehensive needs and performance of digital transformation.

In addition, previous research has engaged with Information Asymmetry Theory to investigate the determinants of digital transformation. The concept of information asymmetry, pivotal in understanding market mechanics and decision-making processes, has been extensively explored in economic and management research. It means in market economic activities, various types of personnel have different understandings of relevant information; those with sufficient information are often in a more advantageous position, while those with poor information are in a relatively disadvantaged position (Bergh et al., 2018).

Akerlof (1984) seminal work on the 'market for lemons' elegantly frames how disparities in information among market participants can precipitate adverse selection. Bromberg (1970) analysis furthers this discourse, scrutinizing the broader economic implications of information asymmetry on resource allocation, an understanding that is increasingly relevant in the strategic deployment of digital transformation initiatives. Li and Zhao (2008) exploration of information asymmetry's influence on dividend policy intimates the broader implications of information imbalances on corporate financial strategies. Graham et al. (2010) treatise on fluctuating asymmetry, albeit in a different context, underscores the ubiquity and relevance of asymmetrical dynamics. Lastly, Bergh et al. (2018) provided a meta-analysis of information asymmetry's role within management research, encapsulating its diverse applications and reinforcing its pertinence to organizational decision-making, such as digital transformation strategy.

While Information Asymmetry Theory is touched upon within this study, it is not the central theoretical framework. The essence of this research is to adopt a holistic perspective in examining how multiple stakeholders—including analysts, customers, and suppliers—collectively impact the digital transformation strategies of enterprises.

For instance, analysts mitigate information asymmetry between investors and firms by providing in-depth market and corporate analyses (Brauer & Wiersema, 2018), which may in turn incentivize enterprises to intensify their digital transformation efforts. Suppliers, by sharing extensive inventory and operational data, assist businesses in better forecasting demand and reducing surplus (Nikoofal & Gümüş, 2018), further facilitating digital transformation through the reduction of information asymmetry. However, these influences are not isolated; they occur within a network of stakeholder interactions.

Given that the focus of this study extends to how multiple external stakeholders influence corporate digital transformation, not only under normal conditions but also against the backdrop of macroeconomic uncertainties such as EPU, the Stakeholder Theory provides a more appropriate analytical framework. This framework allows researchers to explore and understand how the convergence of various stakeholder forces within complex macro environments affects the formulation and execution of corporate strategies. Through such analysis, the research can offer practical guidance on how to balance relationships with external stakeholders, respond to economic policy uncertainties, and make informed decisions regarding digital transformation. Additionally, these findings can also assist governments in formulating clearer policies to foster the development of the digital economy.

2.3 Digital Transformation

This section first presents a definition of digital transformation, followed by an introduction to related research on the topic of digital transformation. China's digital transformation has been marked by strategic governmental planning and robust growth, particularly since the early 2000s. The "Internet Plus" strategy, introduced in the 12th Five-Year Plan (2011-2015), and the subsequent "Made in China 2025" initiative, have been pivotal in harnessing digital technologies for economic development. By the end of 2021, under the guidance of the "14th Five-Year Plan," China's digital economy reached a staggering 45.5 trillion-yuan, accounting for 39.8% of GDP and surpassing the nominal GDP growth rate by 3.4%. This significant growth demonstrates China's effective policy implementation and its rapid adaptation to digital advancements. Despite regional disparities and the need for data security enhancements, China continues to invest in new infrastructure, such as nationwide 5G networks, to cement its status as a global leader in the digital era.

2.3.1 The Definition of Digital Transformation

Despite scholars' extensive discussions, there is still no consensus on a unified definition of digital transformation. Existing studies primarily focus on four aspects: the subject, the technological scope, the domain of transformation, and the effects of transformation. At the subject level, research is divided into micro and macro perspectives. The micro perspective considers enterprises as the research subjects (Earley, 2014; Eller et al., 2020; Reinartz et al., 2019; Schwarzmüller et al., 2018; Vollero et al., 2020; Zhuo & Chen, 2023), whereas the macro perspective takes a societal approach, focusing on nations, markets, industries, and so on as research subjects (Popkova et al., 2022; Scott & Orlikowski, 2022).

In terms of technological scope, debates revolve around what technologies constitute digital transformation. Bharadwaj (2013) initially described digital technology as a combination of information, computing, connection, and connectivity technologies. Sebastian et al. (2017) summarized the new generation of digital technologies as SMACIT, namely social, mobile, analytics, cloud, and Internet of Things technologies. Chinese scholars tend to define digital technology as ABCD, which stands for Artificial Intelligence, Blockchain, Cloud Computing, and Big Data. Vial (2019) proposed a unified concept, defining it as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies." Despite differences in details, the core essence of these definitions is similar.

From the perspective of the domain of transformation, there are two views adopted in studies on enterprises: the first sees digital transformation primarily as a way to improve business operations through digital technology, focusing on enhancing a specific business function (Earley, 2014; Eller et al., 2020; Reinartz et al., 2019; Schwarzmüller et al., 2018; Vollero et al., 2020; Zhuo & Chen, 2023); the second posits that digital transformation is a holistic organizational change driven by new technology and information science, elevating it to a strategic level (Verhoef et al., 2021; Vial, 2019). The latter perspective seems to garner more support, and this research also adopts the view of digital transformation as a strategic decision.

Regarding the effects of transformation, studies bifurcate into examining enterprise subjects and macro-level perspectives. Scholars focusing on enterprise subjects believe that digital transformation can facilitate the restructuring of business models, improve performance, and transform organizational frameworks (Vial, 2019). Those studying the macro perspective, on the other hand, argue that digital transformation enhances quality of life, fosters overall industry development, and stimulates national economic growth (Popkova et al., 2022; Scott & Orlikowski, 2022; Senhao, 2022). Disputes in this area mainly arise from the differing emphases of each part.

In summary, there is no unified view on the concept of digital transformation, and the variety of definitions contributes to its conceptual diversity. This study, building on Vial (2019), concludes that digital transformation is a comprehensive organizational reform at the strategic level, centered around enterprises and realized through the integration of artificial intelligence, blockchain, cloud computing, and big data. Specifically, digital transformation is a significant strategic change, deeply integrating digital technology with business strategy by leveraging technologies (e.g., artificial intelligence, blockchain, cloud computing, and big data) to drive systemic evolution and digital transformation in organizational structures, business models, and external ecosystems. Consequently, after identifying the subject and domain of transformation, this study establishes two indicators of digital transformation: the underlying digital technology, addressing the technological scope controversy to an extent; and digital practical applications, responding to the debates on the effects of transformation to a certain degree.

2.3.2 Research on Digital Transformation

Digital transformation, as a significant strategic reform, represents a deep integration of digital technologies with corporate strategies. Leveraging technologies such as artificial intelligence, blockchain, cloud computing, and big data, it induces systemic evolution and transformation in organizational structure, business models, and external ecological environments (Verhoef et al., 2021; Vial, 2019).

With the continuous expansion of enterprise digital transformation, related academic research has also been increasing. Current literature primarily focuses on the internal and external factors influencing corporate digital transformation, as well as its economic consequences. Internally, technology, managerial characteristics, and resources and capabilities are critical dimensions. First, regarding technology, the capability of digital technologies to integrate resources significantly impacts how firms formulate transformation strategies and seek new avenues for value creation, proving crucial for digital transformation (Vial, 2019). Second, managerial characteristics such as leadership style influence the choice of digital transformation strategies

(Porfírio et al., 2021). Leaders need to have a clear digital vision and understanding of digital technologies, as well as the ability to empower and manage diverse teams (Wrede et al., 2020). Third, for resources and capabilities, small and medium-sized enterprises can utilize the power of digital platforms to develop dynamic management and organizational capabilities, thereby driving digital transformation (Eller et al., 2020). Other studies have shown that customer expectations (Earley, 2014) also influence the choice of digital transformation strategies.

External factors affecting the choice of digital transformation strategy include macroeconomic policies and micro-market environments. At the macroeconomic policy level, government tax incentives or fiscal subsidies play a significant role in the process of corporate digital transformation. In promoting digital transformation policies, Nosova et al. (2021) noted that nations need to formulate rational economic policies to foster digital transformation, thereby mitigating the adverse effects caused by COVID-19. This perspective is also supported by Gabryelczyk (2020), who highlighted the pandemic's role in accelerating digital transformation. At the micro-market level, Mithas et al. (2013) pointed out that the micro-market environment significantly affects the implementation of corporate digital strategies, suggesting that firms should pay attention to the digital business competitive environment and respond accordingly.

Regarding the economic consequences of corporate digital transformation, first, digital transformation has implications beyond individual organizations; it drives industry-wide changes by disrupting traditional business models and creating new opportunities for innovation and growth (Scott & Orlikowski, 2022). It also has societal impacts, such as improving access to services, promoting sustainability, and addressing significant challenges in sustainable development (Popkova et al., 2022). Second, research has found that digital transformation significantly impacts all aspects of an organization, primarily by reducing operational costs, increasing operational efficiency (Vial, 2019), streamlining processes, and enabling organizations to deliver personalized and seamless customer experiences (Reinartz et al., 2019). It also facilitates data-driven decision-making and provides organizations with valuable insights for strategic planning (Schwarzmüller et al., 2018). Additionally, corporate digital transformation has been shown to significantly promote corporate social responsibility (Vollero et al., 2020), innovation (Zhuo & Chen, 2023), human resource management (Purwanto et al., 2023), supply chain management (Guo et al., 2023), and corporate performance (Melo et al., 2023; Tsou & Chen, 2023).

However, digital transformation is not without its challenges. Organizations may face resistance to change, cultural barriers, and the need for upskilling and reskilling employees to adapt to new technologies and ways of working (Barišić et al., 2021; Vial, 2019). Additionally, there may be concerns around data privacy and security, as well as ethical considerations related to the use of emerging technologies (Dziuba et al., 2022).

In summary, existing research on the performance results of corporate digital transformation is quite comprehensive. However, theoretical and empirical investigations of its influencing factors and driving mechanisms are relatively lacking, with the limited available literature focusing on technological and economic levels while neglecting the roles of various stakeholders. This gap hinders a complete explanation of the decision logic and behavioral mechanisms of this core strategy in the digital economy era. This study, selecting analysts, customers, and suppliers as external stakeholders, therefore holds theoretical value and practical significance in exploring the influencing factors of digital transformation.

2.4 Stakeholders – Internal and External

In the fields of corporate governance and strategic management, stakeholders are broadly categorized into internal and external entities (Mazur & Pisarski, 2015). Internal stakeholders typically encompass shareholders, employees, and management, whose interests are directly tied to the internal operations and governance of the company. Their influence is exerted through ownership rights, operational roles, and decision-making capacities (Ahmad et al., 2005). The perspective and influence of internal stakeholders are crucial for the alignment of business objectives with operational capabilities and organizational culture.

External stakeholders, on the other hand, include analysts, customers, suppliers, regulators, competitors, and the community at large. These groups interact with the firm from outside its organizational boundaries but have significant impacts on the business's strategic direction and performance (Chan & Oppong, 2017). They offer valuable insights, indicate market signals, and can influence the firm's reputation and market position. Among external stakeholders, analysts, customers, and suppliers play particularly influential roles in the context of digital transformation.

This study chose to focus on external stakeholders—specifically analysts (Zhou et al., 2023), customers (Li et al., 2023b), and suppliers (Zhang et al., 2020)—because they represent the interface of the firm with its market and industry. Their perspectives and actions provide a lens through which the company's digital transformation efforts are evaluated and necessitated. Moreover, these three groups encapsulate a broad range of external influences, offering a comprehensive view of the market-driven factors that can promote or impede a firm's digital transformation.

Focusing on these external stakeholders allowed this research to concentrate on the market dynamics and external perceptions that are critical for the success of digital transformation strategies. While internal stakeholders are undoubtedly important, the external stakeholders chosen for this study provide the competitive and market pressures that often serve as catalysts for digital transformation. This narrowed focus is justified by the pivotal role these stakeholders play in the rapidly evolving digital landscape and their capacity to provide actionable insights that can be directly related to market performance and strategic outcomes. It aligns with the research objective to analyze and understand the external market forces and expectations that shape and drive digital transformation within firms.

Furthermore, this study specifically targets analysts, customers, and suppliers as the primary external stakeholders due to their direct, quantifiable impact on a company's strategic decisions and digital transformation outcomes. Unlike regulatory bodies, competitors, or technological partners, whose influences might be more indirect or challenging to measure, analysts, customers, and suppliers undoubtedly form the three most influential groups, as they encompass the primary external interaction domains of a business, ranging from capital markets to sales markets and supply chains. Focusing on these groups allows the research to delve into the complex interplay between market dynamics and firm strategies, providing a clear, measurable connection between external stakeholder behavior and digital transformation efforts.

2.5 Analyst Coverage

This section first introduces the definition of analyst coverage, then introduces related research on this concept.

2.5.1 The Definition of Analyst Coverage

Broadly, an analyst is someone who, by researching data indicators and real-world events, expresses their investment opinions. This study focused on analysts in the narrow sense, defining them as those with appropriate qualifications and expertise who issue research reports and opinions on either a whole industry or specific companies (Barth et al., 2001). These analysts can be further classified into two categories: buy-side analysts and sell-side analysts. Buy-side analysts are employed by fund companies to conduct research and provide confidential decision-making opinions internally. Sell-side analysts, on the other hand, are employed by securities firms and other institutions to conduct research and provide publicly available reports that guide investors in making informed investment decisions (Cheng et al., 2006). This study examined only sell-side analysts.

Barth et al. (2001) described an analyst as a financial professional who conducts research and analysis on companies, industries, and financial markets. Extending from this definition, existing research suggests that analysts are key professionals who address information asymmetry in the market. They not only rely on technical expertise and professional strengths but also accumulate substantial practical experience. Analysts assess financial statements and specialized information of their own companies and the industries in which they operate, subsequently making professional forecasts and providing valuable information to the market.

Security analysts primarily engage with enterprises by collecting market information and conducting field research to write analytical reports. These reports cover a range of aspects, including strategy, mergers and acquisitions, research, ratings, and earnings forecasts. This focus is termed "analyst coverage." Existing studies have shown that the more analysts track and research a company, the higher the degree of analyst attention it receives. Following He and Tian (2013), this study used the number of analysts making earnings forecasts for a company in each complete year as a proxy variable for the degree of analyst coverage.

2.5.2 Research on Analyst Coverage

As evidenced by prior literature, analysts play a pivotal role in financial markets, significantly influencing a range of strategic decisions and outcomes. Due to the rapid development of the analyst profession, scholars have begun to explore analyst attention as a critical external governance mechanism. Within the scope of corporate strategy, scholarly inquiries are examining the link between analysts and corporate governance, specifically focusing on how their coverage and recommendations influence perceptions of corporate behavior.

Consequently, analyst coverage has emerged as a substantially important study area within strategic management. Analyst coverage refers to the extent of research and recommendations financial analysts provide for specific companies (Chang et al., 2006; He & Tian, 2013). It plays a vital role in financial markets, as analysts act as intermediaries between companies and investors, conveying information and influencing investment decisions (Jia, 2022; Zhou et al., 2023). Gentry and Shen (2013) elaborated on this, discovering that failure to meet analysts' earnings forecasts is associated with cuts in research and development (R&D) spending to improve short-term performance. The study also suggested that companies exceeding analysts' earnings predictions might similarly reduce R&D expenditure to hedge against further upward adjustments in analysts' forecasts. Interestingly, the study indicated that for companies failing to meet analysts' predictions, higher analyst coverage might help mitigate agency problems related to R&D investment. This is because managers anticipate enhanced oversight and may thus avoid making cuts in R&D for fear of penalties from analysts and investors.

The research by Liu et al. (2020) similarly supports the view that analyst coverage helps curtail agency problems, suggesting that it can deter corporate fraud by increasing information transparency and investor awareness. This means that companies with higher analyst coverage are more likely to be scrutinized and monitored, thus reducing the motivation for fraudulent activities. To et al. (2018) also shows that analyst coverage supports improving the quality of corporate investment decisions by increasing information transparency and strengthening external supervision. In summary, analyst coverage significantly influences corporate strategic decisions. Furthermore, the level of analyst coverage can have a profound impact on various aspects of corporate performance and market dynamics.

Another line of research has examined the relationship between analyst coverage and stock price synchronicity. Feng et al. (2016) reported that analyst coverage is positively associated with stock return. This suggests that analyst coverage contributes to the dissemination of information and the incorporation of market-wide factors into stock prices. In addition to its impact on market dynamics, analyst coverage also affects the value of covered firms. Dhiensiri and Sayrak (2010) revealed a significant and positive price reaction at the time of the announcement of analyst coverage initiations. This suggests that analyst coverage adds value to covered firms by providing information and attracting investor attention. However, the price impact of coverage initiations is not related to the reputation of the analyst firm or other factors such as the exchange listing or whether the analyst firm is also the IPO underwriter.

Furthermore, analyst coverage has implications for the stability of financial markets. Jia (2022) examined the relationships between financial market stability, corporate strategic radicalization, and analyst coverage, finding that corporate strategic radicalization negatively affects analyst coverage, and this effect is exacerbated by the risk of corporate stock price crash. This suggests that unstable market conditions and radical corporate strategies can reduce analyst coverage, potentially leading to information asymmetry and increased market volatility.

There are also some studies that focus on the relationship between analyst coverage and current hot topics. Barber and Odean (2000) examined the investment performance of individual investors and found evidence of a "herding" behavior, where investors tend to follow the crowd and invest in popular stocks. This supports that analysts are more likely to focus on topics that are currently popular in the market. In addition, Baker and Wurgler (2007) investigated investor sentiment in the stock market and revealed that sentiment can have a significant impact on stock prices. They concluded that analysts may be influenced by prevailing market sentiment and, as a result, may be more inclined to chase hot topics that are in line with the prevailing sentiment.

Overall, research on analyst coverage highlights its importance in various aspects of financial markets. Analyst coverage can influence corporate strategic decisions by improving information transparency, alleviating agency problems between investors and companies, and optimizing corporate financing environments (Zhou et al., 2023). It also adds value to the companies covered and impacts market stability.

2.6 Customer Concentration and Supplier Concentration

This section first collectively introduces the definition of customer concentration and supplier concentration, then reviews their related research. This structural design is underpinned by both Supply Chain Logic and Stakeholder Theory, which together support a holistic examination of these parties' influence on an enterprise's digital transformation.

From the Supply Chain Logic perspective, customer and supplier concentration metrics address the impact of supply chain actors' expectations on digital transformation. These concentrations reflect a firm's dependency on key stakeholders for sales and supplies, indicating how susceptible the firm is to the demands and capabilities of these pivotal actors (Chen et al., 2023; Liu et al., 2023). The pursuit of advantageous positions by customers and suppliers along the continuum from supplier to business to customer is a dynamic that directly influences the firm's approach to digitalization (Guo et al., 2023).

Stakeholder Theory provides an additional rationale for this combined discussion. It suggests that all stakeholders, including customers and suppliers, have the ability to significantly influence the strategic direction of a firm (Kale & Meneghetti, 2014). When considering digital transformation, the expectations, readiness, and demands of these stakeholders can become drivers or barriers to change (Vial, 2019). Their influence is particularly potent given the accelerated pace and increased scope of digital transformation initiatives required to compete in today's economy.

By discussing customers and suppliers in unison, this study acknowledges their interrelated impact on the firm's digital transformation. This approach is consistent with previous literature that often considers customer and supplier concentrations together within the context of supply chain concentration. Such a comprehensive discussion allows for a nuanced understanding of how these stakeholders' concentrations can shape a firm's digital strategy, offering vital insights into the balancing act firms must perform between stakeholder influence and digital agility. This balanced approach is crucial for firms aiming to navigate the complexities of digital transformation in a way that is aligned with both their immediate operational needs and long-term strategic goals.

2.6.1 The Definitions of Customer Concentration and Supplier Concentration

Customer concentration refers to the degree of a company's revenue dependence on a few customers. It has been measured as the ratio of sales to the company's most significant customers to total sales (Patatoukas, 2011). In existing studies, the primary indicator of customer concentration is the ratio of the current sales of the firm’s largest customer or top five customers to the total sales revenue for the period. Additionally, some studies used the Herfindahl-Hirschman Index (HHI) of major customers to measure the risk associated with customer concentration (Patatoukas, 2011). This study adopted the ratio of the sales to the top five customers to the total sales as a proxy for customer concentration. A higher customer concentration implies that a significant portion of a company's revenue comes from a few customers, while a lower concentration indicates a more diversified customer base (Wang et al., 2020a).

Supplier concentration refers to the extent to which a firm relies on a small number of suppliers for its inputs or raw materials (Zou & Zhang, 2023). Its indicators are similar to those of customer concentration. In existing research, the main indicator of supplier concentration is the ratio of current purchases from the firm's largest supplier or top five suppliers to the total procurement expenditure for the period (Zhang et al., 2020). Similarly, some studies measure this using the HHI (Patatoukas, 2011). In this study, the ratio of the purchases from the top five suppliers to the total procurement expenditure was employed as a proxy for supplier concentration.

2.6.2 Research on Customer Concentration and Supplier Concentration

Supplier concentration can have an influence on a firm based on Stakeholder Theory (Hernawati & Surya, 2019). First, from the perspective of business entities, the impact of supplier concentration holds two opposite views. One perspective posits that higher supply chain concentration, encompassing both customer and supplier concentration, is preferable. For instance, Zhou et al. (2019) found that high supplier concentration is conducive to the integration of the supply chain, the release of favorable market signals, and lower audit fees. Yang (2023) also argued for the view that firms can create greater market value through the integration of supply chain resources and cooperation with trading partners. Likewise, Fan et al. (2022) maintained that diversity and low supplier concentration are the key drivers of supply chain coordination expenses, and rising coordination demands are bad for businesses' strategic responsiveness and agility. As such, firms should keep a high supplier chain concentration to save operational costs, especially in uncertain environments. Casalin et al. (2017) further pointed out that companies that operate in environments with a greater concentration of suppliers enjoy improved coordination with them and maintain lower levels of inventory. In such cases, firms can benefit from lower risks and higher profits.

On the other hand, the second viewpoint suggests that lower supply chain concentration is more beneficial for firms. Numerous scholars have arrived at this conclusion. Based on the opposing Normal Accident Theory and Social Systems Theory, Wissuwa et al. (2022) claimed that higher supplier concentration will increase the amount of interruptions the consumer encounters, while lower supplier concentration can help firms build more robust resilience. Ivanov and Dolgui (2020) also supported the view that low supplier concentration is better for resilience. Wu and Pagell (2011) investigated decision-making in sustainable supply chain management and emphasized the need to balance multiple priorities. They suggested that reducing supply chain concentration can be a strategic decision to enhance sustainability and mitigate risks. Suppliers with higher concentration may have greater bargaining power, which can lead to the imposition of unreasonable requirements during business negotiations (Zhang et al., 2020). This can negatively impact the firm's profitability and overall business outcomes.

In addition, customers, as important components of a firm’s supply chain, are important stakeholders of the firm. Therefore, according to Stakeholder Theory, customer concentration significantly impacts a company through its revenue structure and strategic choices. When a company has high customer concentration, it is more susceptible to the behaviors and demands of its main customers, which may limit its flexibility and bargaining power due to the heavy reliance on a few customers (Chakravarty et al., 2014). The greater the bargaining power of core customers, the higher the probability of them squeezing economic profits and taking over business credit (Huang et al., 2016).

In summary, customer concentration and supplier concentration reflect not only a firm’s sales and procurement policy but also the bargaining power of its customers and suppliers (Yang, 2023; Zhang et al., 2020). Therefore, they have a considerable impact on the firm's decisions, performance, risks, market performance, and other outcomes.

2.7 Economic Policy Uncertainty (EPU)

This section introduces the moderating variable used in this study, EPU, along with its definition and relevant research.

2.7.1 The Definition of EPU

EPU pertains to the level of uncertainty that exists with regards to economic policies, including monetary policy, fiscal policy, and regulatory policies (Jin et al., 2019). The presence of uncertainty may arise from a multitude of sources due to the inherent ambiguity around potential future changes to current regulations (Ozili, 2021) and fluctuations in governmental personnel (Guo et al., 2020). EPU may have substantial consequences for several facets of the economy, such as stock prices, innovation, firm investment, and profitability (Bhattacharya et al., 2017).

The current body of research employs indirect methodologies for the estimation of EPU, including evaluating the ambiguity around certain fiscal or monetary measures, scrutinizing variations in pertinent indicators at the organizational level, or investigating shifts in government personnel (Guo et al., 2020). Furthermore, several scholarly investigations have constructed indices to measure EPU, incorporating various factors such as the number of news stories reporting uncertainty regarding the economy or fiscal and monetary policy, the influence of planned federal taxes, and the level of disagreement among economic forecasters (Redl, 2018).

The China Economic Policy Uncertainty Index produced by Baker et al. (2016) served as the proxy for measuring EPU in this study. The data was acquired by downloading a structured form from the index's designated official website. The measure is derived from the ratio of the count of relevant articles in the South China Morning Post that include the four specified keywords, namely "China," "economy," "uncertainty," and "policy," to the overall quantity of articles published within the same month. According to Baker et al. (2016), the South China Morning Post effectively monitors and communicates China's economic trends in a timely manner. Additionally, it has the distinction of being the most circulated and most important English daily in Hong Kong. Consequently, it may be considered a representative platform for retrieving news items. Given that the index relies on yearly data, the method used involves calculating the arithmetic mean of the 12-month index pertaining to the present year, followed by dividing this value by 100. This process enables the derivation of annual data for China's Economic Policy Uncertainty index.

EPU serves as a moderating variable in this study because it represents a layer of external environmental volatility that directly impacts how firms perceive and react to strategic decisions, including digital transformation (Baker et al., 2016). It influences how external factors like analyst coverage, customer concentration, and supplier concentration affect a firm's digital transformation efforts. High levels of EPU can lead firms to hesitate or scale back on digital transformation due to uncertainties in economic policies and market conditions (Francis et al., 2014; Gulen & Ion, 2016). This moderating effect means that the relationship between these external factors and digital transformation can vary significantly depending on the current economic policy climate.

In the context of China's unique political environment, it is crucial to recognize the profound impact economic policies have on the market economy (Li & Huang, 2021). Against this backdrop, the relationship between EPU and external stakeholders (analyst coverage, customer concentration, supplier concentration) becomes particularly significant. This is because the level of EPU directly influences the decision-making processes and confidence levels of these external stakeholders in the Chinese market. When policy uncertainty increases, these external participants may reassess their investments and business strategies in China, which, in turn, can impact the progress of digital transformation in Chinese enterprises.

2.7.2 Research on EPU

The concept of EPU has garnered significant interest in academic circles in recent years due to its deep implications for business decision-making and market dynamics. First and foremost, the stability of stock prices is inherently interconnected with EPU. The study conducted by Jin et al. (2019) revealed a positive association between increased levels of macroeconomic policy uncertainty and a heightened probability of stock market crashes. This phenomenon may be attributed to the tendency of investors to take a more cautious investing approach in response to macroeconomic policies that lack clarity or exhibit ambiguity.

Moreover, EPU has a considerable impact on the formulation and implementation of company strategy choices. According to the findings of Li et al. (2023a), an increase in EPU leads to a heightened exposure of enterprises to external environmental hazards. This may lead firms to consider their strategy transformation and market positioning with more caution. Furthermore, Kang and Ratti (2013) conducted a study that examined macroeconomic data and found evidence indicating that EPU has the potential to influence not only the severity of economic downturns but also the speed and robustness of subsequent economic recoveries. Meanwhile, Li and Huang (2021) observed a nuanced and complex correlation between EPU and the economic growth of China, particularly in the context of its fast development.

According to Bonaime et al. (2018), an increase in policy uncertainty may have a negative impact on the occurrence of corporate M&A from a strategic standpoint. This observed pattern may indicate that firms have a propensity to sustain their existing business model within a context of significant uncertainty, rather than actively pursuing prospects for external expansion. Jin et al. (2018) also reported that an elevated level of EPU potentially leads to higher unpredictability in future cash flows of organizations, which provides firms with additional flexibility to engage in earnings management activities.

Simultaneously, Dhole et al. (2021) discovered that an increased level of earnings per share uncertainty may have a negative impact on the capacity to compare corporate accounting information. Nevertheless, a noteworthy phenomenon explicated by Nagar et al. (2019) study is that in the presence of heightened EPU, organizations may strategically increase the dissemination of volunteer information in order to address information asymmetry and improve transparency.

Moreover, the investment and financing behaviors of corporations are significantly impacted by EPU. The study conducted by Gulen and Ion (2016) highlights the negative impact of EPU on the decision-making process of business investments. Concurrently, Gilchrist et al. (2014) and Nagar et al. (2019) have shown that the escalation of information asymmetry between banks and firms is associated with an increase in EPU. This, in turn, results in higher agency costs and heightened risks of corporate default. Similarly, the studies conducted by Francis et al. (2014) and Waisman et al. (2015) also indicate the increased expenses associated with company financing after a rise in EPU.

In conclusion, the presence of EPU has significant effects on several aspects of corporate governance, investment decisions, financing activities, and the disclosure of information. The aforementioned results provide significant and crucial insights that are applicable to both theoretical research and practical implementation.

2.8 Research Framework

Figure 2.1 illustrates the research framework, focusing on three primary effects and three moderating effects. The framework is rooted in Stakeholder Theory. The left side of the figure lists the independent variables: Analyst Coverage, Customer Concentration, and Supplier Concentration, which represent key external stakeholders influencing Digital Transformation. In the center, EPU is depicted as a moderating variable that influences the strength and direction of these relationships. On the right, Digital Transformation serves as the dependent variable, encapsulated by two proxies that measure its presence within firms.

This arrangement underscores the theoretical linkage, with Stakeholder Theory providing a basis understanding that stakeholders not only influence but are integral to the strategic decisions of a firm, such as digital transformation. By focusing on these external groups, the study acknowledges their potential to drive or hinder digital transformation based on their expectations and the firm's dependency on them. Additionally, EPU is considered within this framework to examine how external economic uncertainties affect these stakeholder-firm dynamics, further complicating the decision-making process. Stakeholder Theory provides a robust lens through which to view these relationships, emphasizing the need for firms to strategically manage stakeholder interactions, particularly in volatile economic climates.

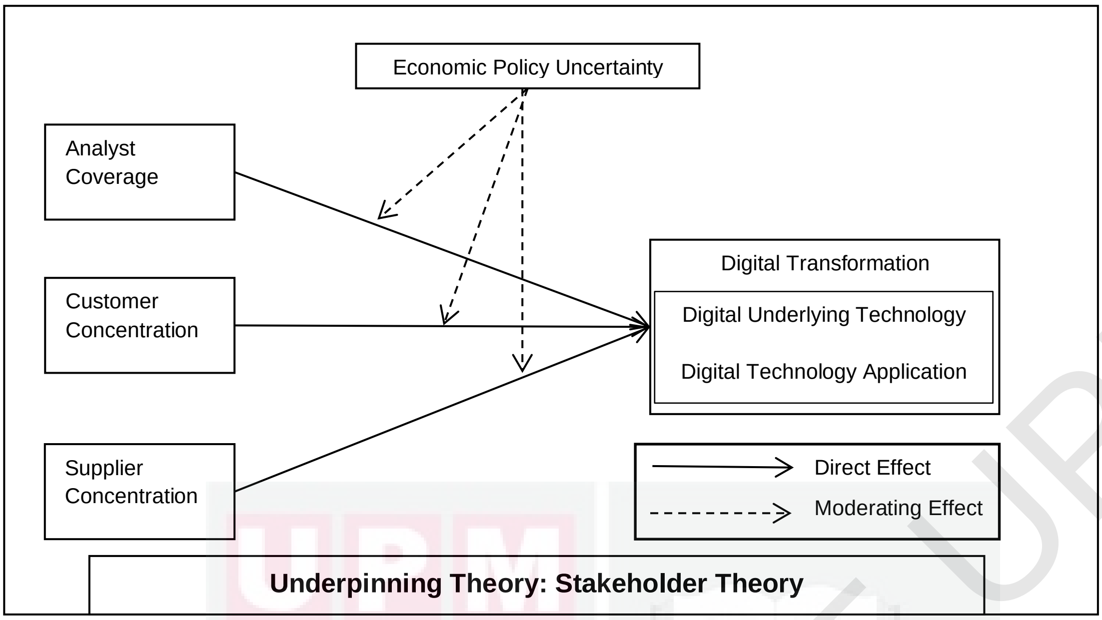

Figure 2.1: Research Framework

2.9 Past Empirical Literature and Hypothesis Development

This section elaborates on the development of the six hypotheses (H1a, H1b, H1c, H2a, H2b, H2c) of this study.

2.9.1 The Effect of Analyst Coverage on Digital Transformation

Analysts, as significant external stakeholders in corporations, play an active role in company management, thereby exerting a tangible influence on corporate digital transformation strategies (Zhou et al., 2023). The attention of analysts, recognized as a crucial component of external corporate governance mechanisms, has increasingly garnered academic interest. Primarily, analysts serve to mitigate information asymmetry among market participants while concurrently overseeing and curtailing opportunistic behaviors by managers (Brauer & Wiersema, 2018; Gentry & Shen, 2013; Jia, 2022; Liu et al., 2020).

Extensive research indicates that heightened analyst attention correlates with increased corporate information transparency and competitive advantage. Consequently, guided by Stakeholder Theory, companies are motivated to cater to the demands of analysts to secure more attention, thereby facilitating greater competitive advantage (Freeman et al., 2010). Analysts, similar to other market participants, have decision-making processes that are subject to various influences. One such is the tendency to chase popular topics, which refers to the inclination of analysts to focus on popular or trendy investment themes (Baker & Wurgler, 2007; Barber & Odean, 2000). Therefore, digital transformation, being among the most prominent contemporary trends (Vial, 2019), compels companies to embark on its strategies to attract analyst coverage and meet their expectations. This step enhances information transparency and competitive advantage (Brauer & Wiersema, 2018; Gentry & Shen, 2013; Jia, 2022; Liu et al., 2020), pushing firms to initiate digital transformation strategies.

For companies that have already initiated digital transformation strategies, digital transformation is an integral part of their innovation activities. Information asymmetry and agency issues are two significant factors affecting corporate innovation (Vial, 2019). Specifically, the inherent expertise, uncertainty, and other characteristics of digital transformation increase the degree of information asymmetry within and outside the enterprise (Vial, 2019). Features such as long investment recovery periods, high risks, and large investment amounts (Guo & Xu, 2021) further make it difficult for investors to accurately judge the future earnings of enterprises undergoing digital transformation. Consequently, they tend to undervalue such enterprises, leading to reduced investments and increased financing constraints for these businesses.

Therefore, enterprises often encounter financing constraints during the initial stages of digital transformation (Du & Wang, 2023). Such constraints can impede their ability to secure essential funding required for establishing a digital transformation strategy. One factor that can intensify these financing constraints is the adverse selection behavior of investors. Adverse selection refers to the situation where investors are unable to accurately assess the quality and potential of investment opportunities, leading to a higher likelihood of selecting suboptimal investments (Balakrishnan & Koza, 1993). This may force companies to reduce or even abandon specialized investments in digital transformation.

In such scenarios, investors require specialized market intermediaries to provide effective information, with an understanding of the impact of digital transformation on a company's growth potential and future value (Zhou et al., 2023). Analysts, as key market intermediaries, are the primary producers of information in the capital market and play a significant role in alleviating information asymmetry (Chang et al., 2006; He & Tian, 2013). Analysts leverage their professional knowledge, industry background, and practical skills, collaborating as teams to collect, process, and analyze a wide range of multi-level financial and non-financial information, and convey it to shareholders and external market participants. As external stakeholders of the company, analysts’ tracking reports on listed companies can increase the supply of information in capital markets, enabling investors to better understand the value of long-term risky investments, and thereby reducing both the company’s information asymmetry and financing costs (Brauer & Wiersema, 2018).

For example, Amazon's aggressive expansion of its logistics infrastructure over the past few decades (initially warehouses and now an aircraft fleet) had an adverse effect on its financial performance. Without analysts' support, this could have led to a loss of investor confidence. However, analysts' positive coverage and disclosure of the strategic long-term significance of these actions have resulted in Amazon trading as one of the companies with the highest price-to-earnings ratio in the Dow Jones Index. Similarly, JD.com, a Chinese self-operating e-commerce company, has kept its earnings relatively low, and even at a loss, due to its active digital transformation and its strategy to build a "JD Intelligent Industrial Supply Chain" - a concept that leverages technology and supply chain capabilities to help partners reduce distribution costs, improve operational efficiency, and lower the application threshold of advanced technologies. This allows small and medium-sized enterprises lacking in technology capabilities to have access to advanced resources and capabilities, while also serving the company’s users more effectively. Despite this, JD.com has attracted substantial investment, thanks to the positive disclosure by analysts who believe the company has a bright future. Therefore, for enterprises that have already begun implementing digital transformation strategies, analysts' reports can still play a role in reducing obstacles to digital transformation.

Moreover, analysts can oversee the process of digital transformation, thereby enhancing the efficiency of funds used for this process and reducing the negative impact of agency conflicts on it. Existing literature suggests that analysts can directly supervise managers through on-site visits, face-to-face communication with management, and teleconferences, reducing the threat of managerial opportunistic behaviors to corporate value (Healy & Palepu, 2001; To et al., 2018). It can thus be inferred that analysts are likely to supervise the behavior of managers during the digital transformation process, reducing the likelihood of managers pursuing personal gains and thereby mitigating the negative impact of agency conflicts on corporate digital transformation.

However, according to He and Tian (2013), there is a contention that analysts exert excessive pressure on managers to meet short-term goals, potentially impeding the organization's capacity to allocate resources for long-term innovative initiatives. Additionally, Gentry and Shen (2013) found a correlation between failing to meet analysts' earnings projections and the reduction of R&D expenditures to enhance short-term performance. Consequently, the pressure to generate profits leads to a trade-off between short-term and long-term investments. Faced with the pressure of meeting analysts' performance expectations, companies might reduce innovative activities and slow down digital transformation processes to align with analysts' forecasts. However, Gentry and Shen (2013) also indicated that for companies failing to meet analysts' expectations, heightened analyst coverage might help to contain agency problems related to R&D investments. Even though analyst coverage can exert short-term performance pressure, potentially discouraging companies from engaging in long-term risky investments like digital transformation, they simultaneously introduce a stricter level of scrutiny for firms under considerable short-term performance stress. This heightened scrutiny can lead managers to act with greater caution and deliberation, which, in turn, can be beneficial for the company's development, including making strategic decisions about digital transformation. Thus, the seemingly negative impact of analyst coverage on digital transformation may be offset by the more vigilant and careful behavior it encourages among managers facing intense short-term performance expectations. This dual effect suggests that while analyst coverage present a challenge by emphasizing short-term gains, they also indirectly foster an environment where careful, strategic planning is rewarded, potentially aligning with the long-term objectives of digital transformation.

Further, in the context of China, firms tend to have highly concentrated equity, with major shareholders often holding corporate stocks for extended periods and demonstrating a higher tolerance to short-term failures. Given that many large-scale Chinese enterprises' managers are appointed by the government (Li et al., 2015; Wang et al., 2012), when faced with the dual pressures of short-term performance expectations and responding to the government's call for a digital economy, they are more likely to opt for the latter. Thus, in the Chinese market, the likelihood of companies abstaining from implementing digital transformation strategies due to analysts' performance pressures is substantially reduced.

Based on the above analysis, this study argues that digital transformation aligns with the needs of both enterprises and analysts. Analyst coverage helps investors fully understand the future value of corporate digital transformation, alleviates adverse selection and consequent financing constraints, and to a certain extent, assists enterprises in attracting investment. This, in turn, enhances the ability and willingness of managers to implement digital transformation strategies. Furthermore, analysts can enhance the efficiency of funds allocated for digital transformation projects by supervising the transformation process, thereby promoting corporate digital transformation. Even in the face of short-term performance pressures from analysts, the negative impact on digital transformation strategies in the Chinese market is significantly reduced due to its unique characteristics. Based on this, the study proposes the following hypothesis:

H1a: There is a positive correlation between analyst coverage and digital transformation in Chinese listed companies.

2.9.2 The Effects of Customer Concentration and Supplier Concentration on Digital Transformation

From the perspective of Stakeholder Theory, existing literature views a company as a collection of social contracts involving various stakeholders. A company must serve not only its shareholders but also protect the interests of other stakeholders like customers and suppliers (Freeman et al., 2010). As such, pressure from these stakeholders push companies to proactively cater to their demands (Phillips, 2003). This theory also posits that business activities should be monitored by stakeholders, as they impact their interests (Jones & Wicks, 1999). Furthermore, external stakeholders such as customers and suppliers need to understand the company's operational status, performance, and management quality. Through comparative analysis, they determine the company's continuous supply ability, product cost and pricing, quality assurance, and after-sales service, making decisions on maintaining current purchasing relationships or seeking alternative supply channels (Kale & Meneghetti, 2014).

Customers and suppliers, as key stakeholders, invest significant resources and bear risks, actively monitoring and influencing the company's operations to protect their interests (Kale & Meneghetti, 2014). Based on this, these stakeholders will pay close attention to the company's operational status and actively involve themselves in management to maximize their own benefits (Freeman, 2001).

Companies have two types of information: public, such as financial reports and audit reports, and private, like product pricing and costs. The former is accessible to all external stakeholders, while the latter is limited to certain stakeholders. Clearly, the more private information suppliers or customers have, the less they rely on public information. In supply chain relationships, there is a critical value for supplier or customer concentration (Kwak & Kim, 2020). Below this threshold, companies can effectively control suppliers or customers. As concentration increases, so does the intimacy of their relationship. To a certain extent, companies provide more private information, reducing their demand for public information like audits. However, as concentration increases further, the power dynamic shifts. Beyond a certain threshold, the bargaining power of suppliers or customers may surpass that of the company, leading to absolute control and coercion to maintain their advantageous position (Dowlatshahi, 1999), or risk losing these major clients and suppliers (Cuñat, 2007).

To illustrate, if a company purchases a large amount of raw materials from a single (or a few) supplier(s), the price and quality changes of the supplier's products are more likely to significantly impact the company's operations. The company's dependency and switching costs are high, giving the supplier strong bargaining power. In other words, when the number of customers or suppliers is too low, and the supply chain is overly concentrated, the bargaining position of major customers or suppliers becomes stronger, possibly forcing the company to make concessions (Piercy & Lane, 2006). Since digital transformation is considered a powerful tool for enhancing competitive capabilities in the digital economy era (Kraus et al., 2021), suppliers in dominant positions may coerce companies dependent on them with high switching costs to make concessions in digital transformation. Even if companies intend to digitally transform, internal and external pressures may impede effective implementation.

Conversely, when a company has many customers and suppliers, with no single customer significantly impacting sales and only a small portion of total purchases from each supplier, the company's dependence and switching costs for individual customers and suppliers are low, and their bargaining power is weakened. They may have to engage in intense market competition, offering better terms to the company, which naturally enhances its competitive capability (Islami et al., 2020). Therefore, to maintain an advantageous position, the company is more motivated to undergo digital transformation. In summary, in the bargaining between companies and their suppliers and customers, the lower the supply chain concentration, the stronger the company's position and motivation for digital transformation. Conversely, if in a disadvantaged position and constrained by dominant suppliers or customers, the motivation for digital transformation weakens. In this scenario, there are not only inherent risks in digital transformation, but also the added risk of losing major customers and suppliers. Hence, after weighing the pros and cons, a company's motivation for digital transformation decreases.

On the other hand, although corporate digital transformation can significantly reduce the degree of information asymmetry and enhance transparency (Cong

& He, 2019; Warren et al., 2015), it somewhat aligns with the expectations of external stakeholders such as customers and suppliers. Nonetheless, there is a significant difference between large and small customers in terms of access to and realization of accounting information. Private information sharing is the primary way for companies to convey accounting information to major customers. A higher concentration in the supply chain leads to the formation of implicit contracts between businesses and their key suppliers and customers (Kale & Meneghetti, 2014). In this situation, major suppliers and customers have higher bargaining power, enabling them to demand the financial information they need through non-public channels (Dyer et al., 2008).

High supply chain concentration implies that a company relies heavily on significant major customers and suppliers (Wang et al., 2020a; Zou & Zhang, 2023). As supply chain concentration increases, major suppliers and customers can more effectively access detailed and tailored accounting and other relevant information through private channels, enhancing their decision-making capabilities based on the quality and quantity of information received (Zhou et al., 2019). In such cases, to maintain their advantageous position, major suppliers and customers might prefer to prevent the company from disclosing too much information publicly to avoid inviting new competitors. This can lead not only to a reduced demand for digital transformation but also to active obstruction of it.

In a supply chain-concentrated scenario, although smaller suppliers and customers still have a high demand for the comparability of publicly disclosed accounting information, their economic significance and influence on the company are much less than that of major suppliers and customers (Islami et al., 2020). If the accounting information needs of the latter are already met through private communication channels and they adopt an obstructive attitude towards digital transformation, then companies with higher customer and supplier concentration are more likely to be impeded in their digital transformation efforts. Assuming other factors remain constant, the motivation for companies to undertake digital transformation to alleviate information asymmetry will weaken due to a cost-benefit trade-off.

From the perspective of the companies themselves, powerful customers and suppliers may compel concessions that worsen financial performance and increase operational risks, resulting in higher costs and diminished cash flow, leaving companies financially strained in adverse external conditions (Liu et al., 2023). This might render them unable or unwilling to undertake digital transformation.

Secondly, from the perspective of financing ability and cost, in practical implementation, regulatory authorities, banks, other financial institutions, and other stakeholders often view a high concentration of and dependence on customers and suppliers as a risk. For example, in debt financing, banks and other financial institutions tend to impose more constraints or demand higher loan interest rates on companies with high customer and supplier concentration (Campello & Gao, 2017). Therefore, companies with strong bargaining power among their customers and suppliers will face higher financing constraints or costs, making it difficult to raise the necessary funds, thereby reducing their capability to undertake digital transformations.

Thirdly, from the perspective of the management's preventative motives, companies face the risk of losing customers and suppliers at any time. Major customers and suppliers might abruptly terminate business relationships or even collaborate with competitors, especially in cases where the supply chain is concentrated. Such companies are likely to suffer significant impacts on their business performance due to the sudden loss of these key customers and suppliers, leading to reduced current and projected cash flows (Hertzel et al., 2008), which in turn affects their financial status (Maksimovic & Titman, 1991). Moreover, if a company is highly dependent on its key customers and suppliers, it will have a higher debt level (Kale & Shahrur, 2007), greater cash flow risks, and a higher probability of financial distress. The more dependent a company is on its main customers and suppliers, the greater these negative effects are.

Lastly, if a major customer declares bankruptcy, a company with a concentrated customer base might face substantial financial losses due to uncollectible accounts receivable and loss of future market share (Dhaliwal et al., 2014). Similarly, if a major supplier goes bankrupt, a company with a concentrated supplier base might face significant disruptions and losses due to unrecoverable advance payments and a lack of alternative suppliers or raw materials.

In summary, customers and suppliers have the motive to actively influence corporate production and operational decisions to safeguard their interests, whereas companies have the motive to cater to customers and suppliers to ensure their competitive advantage in the market. Therefore, in the “customer-company-supplier” relationship, customers and suppliers are in a relatively dominant position, and their influence on companies is often negatively extractive, especially when powerful major customers and suppliers are actively involved (Kale & Meneghetti, 2014; Liu et al., 2023; Zhang et al., 2020). Based on this, this study hypothesizes that customers and suppliers may pose obstacles to corporate digital transformation. The greater the presence of major customers and suppliers, or in other words, the higher the concentration of customers and suppliers, the greater the impediment to digital transformation. Hence, this study proposes the following hypotheses.

H1b: There is a negative correlation between customer concentration and digital transformation in Chinese listed companies.
H1c: There is a negative correlation between supplier concentration and digital transformation in Chinese listed companies.

2.9.3 The Moderating Role of EPU in the Effects of Analyst Coverage, Customer Concentration, and Supplier Concentration on Digital Transformation Relationship

Following the global financial crisis, nations intensified market interventions to avoid recession, frequently introducing stimulative economic policies. This trend is especially pronounced in China, where economic growth is slowing, structural transformation is underway, and market reforms are expanding. Such economic intervention policies have introduced greater uncertainty for businesses (Baker et al., 2016), compelling them to closely monitor policy changes to adjust their development strategies and business decisions (Bloom et al., 2018).

Before making behavioral decisions, firms must weigh costs against benefits. Rational enterprises aim to maximize returns with limited resources and minimal costs, considering risk as a critical factor. Increasing EPU implies heightened external environmental risks and uncertainties for businesses (Pástor & Veronesi, 2013). Specifically, rising EPU escalates operational costs and risks, competitively influencing corporate digital transformation. On one hand, heightened EPU exacerbates information friction between enterprises and markets, reducing operational efficiency (Brogaard & Detzel, 2015), affecting relationships between enterprises and analysts. On the other hand, the shock of EPU necessitates frequent adjustments in market demand across the supply chain (Wang et al., 2020b), intensifying performance volatility and operational risks for enterprises, thus impacting relationships with suppliers and customers.

Based on Stakeholder Theory, in response to operational cost and risk impacts, enterprises typically conduct thorough industry research and prospect analysis, which leads them to rebalance stakeholder needs and make decisions about digital transformation. Consequently, with the rise in EPU, enterprises might either intensify or diminish their alignment with external stakeholder demands. Given the significant investment and high cost of digital transformation, businesses might choose to enhance alignment with customers and suppliers and reduce alignment with analyst reporting, delaying digital transformation to avoid the broader uncertainties associated with it during periods of high EPU (Cao, 2023); alternatively, they might opt to cater more to analyst reports, lessening alignment with customers and suppliers and seizing market development opportunities through digital transformation to enhance production capabilities and technological standards, thereby countering the impacts of EPU (Hu & Yu, 2022).

On the contrary, analyst reporting often requires companies to adjust and refine their strategies based on the external information environment. As analysts are significant external stakeholders, their reports can influence investors' perceptions and decisions (Doukas et al., 2005). In an environment of increased EPU, companies may exercise more caution when implementing strategies suggested by analysts, preferring to conserve resources and maintain the status quo rather than embark on transformative actions like digital transformation. Thus, high EPU could weaken the positive relationship between analyst reporting and digital transformation.

As mentioned earlier, a high concentration of customers or suppliers indicates a company's heavy reliance on a few key clients or suppliers (Wang et al., 2020a; Zou & Zhang, 2023). Such concentration grants these external stakeholders substantial bargaining power (Yang, 2023; Zhang et al., 2020). While traditionally dominant customers and suppliers might oppose digital transformation to protect their vested interests or due to concerns over transactional efficiency, the involvement of EPU adds another layer of complexity. Specifically, in high EPU environments, the opposition of these external stakeholders might intensify (Jin et al., 2019). The uncertainty of economic policies heightens the risks associated with digital transformation. Therefore, dominant customers and suppliers might strengthen their opposition to this strategic shift, believing it adds to existing environmental uncertainties.

In summary, EPU can play a moderating role in the relationships of analysts, customers, and suppliers with corporate digital transformation. Essentially, during periods of increased EPU, businesses' positive responses to analyst-recommended digital transformations may decrease. Simultaneously, the resistance of concentrated customers and suppliers to digital transformation might intensify. Based on these considerations, the following hypotheses are proposed:

H2a: EPU weakens the positive relationship between analyst coverage and digital transformation in Chinese listed companies.

H2b: EPU strengthens the negative relationship between customer concentration and digital transformation in Chinese listed companies.

H2c: EPU strengthens the negative relationship between supplier concentration and digital transformation in Chinese listed companies.

2.10 Summary

This chapter delved deep into the multifaceted dimensions and drivers of digital transformation, placing an emphasis on the role of three external stakeholder groups: analysts, customers, and suppliers. By integrating the underpinnings of the Stakeholder Theory, it is evident that these different actors have varying impacts on an organization's digital transformation, which are in turn influenced by the moderating role of EPU.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter details the methodological considerations guiding this study. The objective of this research was to investigate the impacts of analyst coverage, customer concentration, and supplier concentration on firms' digital transformation, and to explore the moderating influence of EPU on these relationships. Within the scope of this study, digital underlying technology and digital technology application served as proxies for the digital transformation of companies. Subsequent sections validate the rationale behind the chosen quantitative methodology and furnish a detailed description of the techniques employed in this research. This chapter also elucidates the epistemological nexus between the theoretical framework, research objectives, and research methods. Furthermore, discussions are presented regarding data sources, variables, measurement explanations, research instrument testing, and estimation methods.

3.2 Research Philosophy

The underpinning epistemology of this study is rooted in a positivist philosophy. This choice stems from the study's primary aim to determine whether a positive or negative influence exists from analyst coverage, customer concentration, and supplier concentration towards firms' digital transformation. Consequently, the study set out to empirically test its hypotheses using parametric statistical tools, drawing from secondary sources aligned with the dependent variables of digital transformation (spanning both digital underlying technology and digital technology application) and the independent variables of analyst coverage, customer concentration, and supplier concentration. The goal was to distill findings into generalizable conclusions. As articulated by Chua (1986), research embodies a positivist stance when it showcases formal propositions, hypothesis testing, quantifiable variable measures, and extrapolates insights about a phenomenon from a sample to a broader population.

The deductive approach, which revolves around "hypothesis generation based on extant theory and the subsequent design of research tactics to test these hypotheses" Wilson (2014), was the chosen methodology for this investigation. It aimed to authenticate and reinforce theoretical tenets posited by prior research (Bernard, 2013). This approach is intrinsically tied to experimental modalities that are subjected to hypothesis validation (Patton, 1990). In essence, the deductive process revolves around inferring outcomes from established premises or claims (Babbie, 2020). Here, the focal point was the empirical verifiability of Stakeholder Theory. The study ventured into examining the relationships of analyst coverage, customer concentration, and supplier concentration with digital transformation, while also probing into the effect of EPU on these interrelations. Thus, the hypotheses, grounded in theoretical assertions, enabled the application of the deductive method.

The architectural design of quantitative research is intrinsically deductive, hinging on hypothesis creation and validation through widely accepted scientific modalities (Nachmias & Nachmias, 1981). Therefore, the adoption of a quantitative methodology for this study was deemed apt due to its inherent efficacy in hypothesis testing and its prowess in dissecting secondary data. Quantitative research designs strive to numerically encapsulate the relevance of a dataset to a posed query, culminating in the quantification of the research outcomes. This methodological route entails the collation and evaluation of numerical data, supplemented by the enactment of statistical evaluations (Collis & Hussey, 2014). It resonates with inquiries into business issues, tethered to theory-driven variable testing.

In the quantitative research spectrum, data predominantly undergoes numeric assessment, refined by verified statistical techniques. This modus operandi frequently finds favor among business and social science scholars aiming to affirm the legitimacy of theoretical conjectures or generalizations (Bazeley, 2004). The potency of the quantitative method lies in its capacity to frame hypotheses in numerical terms, enabling empirical validation and interpretation. The allure of the quantitative approach for most scholars stems from its promise of delivering objective, quantifiable, and generalizable outcomes, often derived from secondary data sources. While its roots are deeply embedded in natural science explorations, social scientists also leverage it for its predictive prowess concerning cause-effect scenarios (Cassell et al., 2006).

3.3 Data and Sources

In this study, the initial research sample of China A-share listed companies from 2011 to 2021 was selected according to the following exclusion criteria: 1. not a ST&PT listed company with abnormal operations; 2. not a company that violates basic accounting principles (asset-liability ratio not in the range of zero to one); and 3. not missing core research variables.

The selection of China's A-share listed companies as a research sample is justified by several reasons that are pertinent to both the rigor and relevance of this academic inquiry. These companies are mandated to comply with stringent disclosure regulations enforced by the China Securities Regulatory Commission and stock exchanges, ensuring high-quality and standardized data for scholarly analysis. The A-share market also encompasses a broad spectrum of industries, from traditional manufacturing to cutting-edge high-tech sectors, providing a representative cross-section of the market for comprehensive research. Additionally, the rapid growth of the Chinese economy and the progressive opening up of the A-share market have garnered increasing attention from global investors. Studying these companies offers valuable insights into both local and international market dynamics, enhancing the research's applicability and strategic significance in the context of corporate governance.

While the use of A-share listed companies as the sample has its rationale, it also comes with limitations. Firstly, there might be survivorship bias, potentially excluding those that exited the market or went bankrupt during the study period, leading to a potential misunderstanding of the market conditions (Gilbert & Strugnell, 2010). Consequently, the research conclusions may lean towards reflecting companies that survived and continued operations in the market, while lacking insights into companies that failed in the market. Secondly, compared to non-listed companies or small enterprises, A-share listed companies may possess different characteristics and operating environments, facing distinct challenges and opportunities (McCahery & Vermeulen, 2010). Focusing the research on A-share listed companies may restrict the understanding of the entire market and potentially limit the conclusions' applicability. Moreover, non-listed companies or small enterprises may be more susceptible to macroeconomic influences, as they may lack the resources and scale of A-share listed companies to cope with external challenges (Cao, 2023). This implies that they may encounter different obstacles and pressures in digital transformation, which, if not fully considered in the research, could limit the applicability of the research conclusions. Therefore, while A-share listed companies provide rich data and opportunities for studying digital transformation, using them as the sole data source may lead to an incomplete understanding of the entire market.

The period of 2011 to 2021 was chosen as the sample duration because of its representativeness. On the one hand, according to the latest China Digital Economy Development Report (2022) released by the China Academy of Information and Communication Technology, the growth rate of China's digital economy was lower than the average growth rate of GDP in the same period before 2011. Since 2011, the scale of China's digital economy has been growing, and the average annual growth rate of the digital economy has been significantly higher than the average growth rate of GDP in the same period, becoming a new driving force for China's high-quality economic development. Therefore, 2011 was chosen as the starting year of the study. On the other hand, based on the availability of data related to the instrumental variables, this study selected 2021 as the end year of the study sample.

To avoid the influence of extreme values, this study Winsorized the continuous variables at the front and back 1% quantile. In the end, a sample dataset of 17,195 observations was obtained for 3545 listed companies. The corporate digital transformation data used in this study was extracted from the annual reports of the chosen listed companies, while the remaining firm-level microdata was obtained from the CSMAR database. The construction of each variable in this study is described in Section 3.4, Description of Variables. The statistical software Stata 16.0 was used to process the data.

3.4 Description of Variables

This section introduces the dependent variables, independent variables, moderating variable, and control variables, elaborating on their sources and measurement methods. A summary of these variables is presented in Table 3.1.

Table 3.1: Summary of Variable Descriptions

Variables	Operational Definition	Sources
Dependent Variables		
Digital Underlying Technology (DUT)	Taking the natural logarithm of the sum of the frequency of occurrence of the segmentation indicators AI Technology, Block Chain Technology, Cloud Computing Technology, Big Data Technology in the report's management discussion and analysis section plus one.	Wu et al. (2021)
Digital Technology Application (DTA)	Taking the natural logarithm of the sum of the frequency of occurrence of the segmentation indicator Digital Technology Application in the report's management discussion and analysis section plus one.	Wu et al. (2021)
Independent Variables		
Analyst coverage (AC)	Number of analysts (teams) who have conducted tracking analysis on the company in a year; one team presented as '1', not counting the number of its members. Then, it is logarithmically processed.	Khatri (2023)

Table 3.1: Continued

Customer Concentration (CC)	Proportion of the amount of sales to five largest customers to total sales amount in the year.	Liu et al. (2023); Patatoukas (2011)
Supplier Concentration (SC)	Proportion of the amount of purchases from five largest suppliers to total purchase amount in the year.	Liu et al. (2022b); Liu et al. (2023)
Moderator		
Economic Policy Uncertainty (EPU)	China Economic Policy Uncertainty Index based on South China Morning Post.	Baker et al. (2016)
Control Variables		
Asset-Liability Ratio (Lev)	The ratio of liabilities at the end of the year to total assets at the end of the year.	O'Brien (2003)
Board Independence (Indep)	The proportion of independent directors to the total number of directors.	Adamas and Ferreira (2007)
Firm Age (FirmAge)	The age of the firm is determined by taking the natural logarithm of the difference between the current year and the year of establishment, then adding one to the result.	BarNir et al. (2003)

Table 3.1: Continued

Number of Employees (Employee)	The logarithmic value of the number of employees is calculated by taking the natural logarithm of the total number of employees plus one.	McKelvie and Davidsson (2009)

3.4.1 Dependent Variable

Digital Transformation: Drawing on studies by Wu et al. (2021), textual analysis was employed to identify and count the word frequency of key terms related to digital transformation in the annual reports of the chosen listed companies. The reliability of this indicator lies in the fact that words and expressions used in companies' annual reports are self-representations of significant strategic orientations for corporate development. If specific keywords appear more frequently in the information disclosed in the annual report, they reflect the business orientations and future development cues that companies are concerned with.

In this study, the digital transformation lexicon was constructed as follows: first, keywords related to digital transformation were identified, based on the structured word frequency mapping of Wu et al. (2021); second, the overall digital transformation indicators for enterprises were decomposed into two major levels, "digital underlying technology" and "digital practical application." In the underlying technology level, this study divided it into four sub-indicators (artificial intelligence, block chain, cloud computing, and big data technology) based on the current authoritative definition of digital transformation.

Meanwhile, at the practical application level, specific digital application keywords in practice were used as the basis (see Table 4.2 for details).

Finally, based on the specific keywords for digital transformation, the keywords with negative words preceding them were eliminated, as well as the keywords for "digital transformation" that were not used by the company (including its shareholders, customers, suppliers, and executive profiles). The keywords in the annual report's management discussion and analysis section were targeted using Python crawler technology, and the frequency of specific keywords was counted. The total frequency of keywords related to digital underlying technology, and the total frequency of keywords related to digital technology application were summed and transformed into logarithms to obtain two proxies, which formed a scale indicator of digital transformation. The following formulae were used in this study:

$$DUT = \ln(1 + \text{Digital Underlying Technology})$$

$$DTA = \ln(1 + \text{Digital Application Technology})$$

Where:

Digital Underlying Technology represents the total frequency of keywords related to digital underlying technology, including Artificial Intelligence Technology, Block Chain Technology, Cloud Computing Technology, and Big Data Technology.

Digital Technology Application refers to the total frequency of keywords related to Digital Technology Application.

Table 3.2: Key Words of Digital Transformation

Digital Transformation			
Digital Underlying Technology (DUT)			
AI Technology	Block Chain Technology	Cloud Computing Technology	Big Data Technology
artificial intelligence, business intelligence, image understanding, investment decision support system, intelligent data analysis, intelligent robot, machine learning, deep learning, semantic search, biometrics, face recognition, speech	digital currency, smart contract, distributed computing, decentralization, bitcoin, alliance chain, differential privacy technology, consensus mechanism	in-memory computing, cloud computing, stream computing, graph computation, internet of things, secure multiparty computation, brain-like computing, green computing, cognitive computing,	big data, data mining, text mining, data visualization, heterogeneous data, credit reporting, augmented reality, mixed reality, virtual reality

Table 3.2: Continued

recognition, identity verification, autonomous driving, natural language processing		converged architecture, billion-level concurrency, EB-level storage, cyber-physical systems	
Digital Technology Application (DTA)			
mobile internet, industrial internet, mobile internet, internet medical service, E-commerce, mobile payment, third party payment, NFC payment, B2B, B2C, C2B, C2C, O2O, network connection, smart wearables, smart agriculture, smart transportation, smart healthcare, smart customer service, smart home, smart investment, smart cultural tourism, smart environmental protection, smart grid, smart energy, smart marketing, digital marketing, unmanned retail, internet finance, digital finance, Fintech, financial technology, quantitative finance, open banking			

Source of Keywords: Wu et al. (2021)

3.4.2 Independent Variables

Analyst coverage (AC): Following Khatri (2023), analyst coverage was used as the proxy because it represents the group of professionals who persistently monitor and produce forecasts about firms, acting as an essential external mechanism that bridges information gaps in the financial market. When exploring the phenomenon of digital transformation, a paradigm shift that reshapes business processes and models, the role of these analysts becomes increasingly crucial. The measure of analyst coverage was calculated as the natural logarithm of the number of analysts tracking a specific listed company in the current year plus one, with larger values indicating higher analyst coverage for the company. The formula was as follows:

$$AC = \ln \left(\begin{array}{c} 1 + \text{Number of analyst teams} \\ \text{tracking the company in the current year} \end{array} \right)$$

Where:

ln represents the natural logarithm.

The "Number of analyst teams tracking the company in the current year" refers to the distinct analyst teams (irrespective of the number of individual members in each team) who have conducted tracking analysis on the company within the year. Each team is represented as one.

The addition of one inside the logarithm ensures that companies with zero analyst teams still have a defined value for analyst coverage.

This formula suggests that as the number of distinct analyst teams tracking a specific listed company increases, the value of AC also rises, denoting a higher analyst coverage for the company.

Supplier concentration (SC) is a measure of the extent to which a firm procures goods and services from its primary suppliers, who account for a significant portion of its overall purchases (Liu et al., 2022b). According to Liu et al. (2022b); Liu et al. (2023), to measure supplier concentration, the proportion of a firm's total purchases that are made from major suppliers is determined. Accordingly, this research defined supplier concentration as the ratio of purchases from the top five suppliers. For example, Beijing Yanjing Brewery Co., Ltd. (a China-based company principally engaged in the brewing and distribution of beer, stock code: 000729; hereinafter referred to as Yanjing Brewery) purchased for 1114.790 million RMB from its top five suppliers in 2021, accounting for 17.78% of its total purchases. Thus, the supplier concentration of Yanjing Brewery in 2021 was 0.1778. The formula is calculated as follows:

$$SC = \frac{Purchase_j}{Purchase}$$

Where:

Purchase and $Purchase_j$ represent a firm’s total purchases and purchases from supplier j (j = 1,2, ..., n), respectively. Here j = 5, which means that it considered the five largest suppliers.

Customer concentration (CC) is the degree to which a supplier sells products or services to its main customers, who account for a significant share of the firm’s total sales (Liu et al., 2023; Patatoukas, 2011). This research defined customer concentration as the ratio of sales from the top five customers. For example, in 2021, sales to Yanjing Brewery’s five largest business customers were 47.103 million RMB, accounting for 3.94% of its total sales, so the customer concentration of Yanjing Brewery in 2021 was 0.0394. The calculation was as follows:

$$CC=\frac{Sales_j}{Sales}$$

Where:

Sales represents the firm's total sales.
$Sales_j$ represents the firm's sales from customer j (j = 1,2, …, n). Here j = 5, meaning that the five largest business customers were considered in this study.

3.4.3 Moderating Variable

The China Economic Policy Uncertainty Index produced by Baker et al. (2016) served as the proxy for measuring EPU in this study. The data was acquired by downloading a structured form from the designated official website. The index is derived from the ratio of the count of relevant articles in the South China Morning Post that include the four specified keywords, namely "China," "economy," "uncertainty," and "policy," to the overall quantity of articles published within the same month. According to Baker et al. (2016), the South China Morning Post effectively monitors and communicates China's economic trends in a timely manner. Additionally, it has the distinction of being the most circulated and most important English daily in Hong Kong. Consequently, it may be considered a representative platform for retrieving news items. Given that this study relied on yearly data, the method used involves calculating the arithmetic mean of the 12-month index pertaining to the present year, followed by dividing this value by 100. This process enabled the derivation of annual data for China's Economic Policy Uncertainty Index. The follow is the calculation process:

Assume:

`N_keywords` as the number of articles in a given month in the South China Morning Post that include the specified keywords ("China," "economy," "uncertainty," "policy").

`N_total` as the total number of articles published in the South China Morning Post in the same month.

`U_month` as the monthly uncertainty index, which is the ratio of `N_keywords` to `N_total`.

The monthly index formula is:

$$U\_month = \frac{N\_keywords}{N\_total}$$

To derive the yearly data:

1. Calculate the arithmetic mean of the monthly uncertainty indices over 12 months:

$$U\_yearly\_mean=\frac{\sum_{i=1}^{12} U\_month_i}{12}$$

2. Normalize the yearly mean by dividing by 100:

$$U\_annual=\frac{U\_yearly\_mean}{100}$$

Thus, `U_annual` represents the annual Economic Policy Uncertainty Index for China, which is the EPU value.

3.4.4 Control Variables

Asset-Liability Ratio (Lev): The asset-liability ratio represents a firm's capital structure and repayment capacity, reflecting its ability to manage debt. When a firm has a lower level of leverage, continuous R&D investment is better ensured, allowing it to expand its knowledge base through methods such as mergers and acquisitions (O'Brien, 2003), resulting in a stronger digital transformation capability. In this study, the ratio of year-end liabilities to year-end total assets was used to measure the asset-liability ratio. The computation of Lev was performed using the following formula:

$$Lev=\frac{\text{Year-end Liabilities}}{\text{Year-end Total Assets}}$$

Where:

"Lev" stands for the asset-liability ratio or leverage.

"Year-end Liabilities" refers to the total liabilities of the firm at the end of the year.

"Year-end Total Assets" signifies the total assets of the firm at the end of the year.

Board Independence (IndepRatio): Independent directors, as an essential supervisory force in corporate governance, are able to make more independent judgments when it comes to significant company decisions, such as whether to pursue digital transformation. By playing a crucial role in internal governance, they can express more neutral opinions that align with the interests of small and medium-sized shareholders (Adamas & Ferreira, 2007). Therefore, the higher the board independence, the stronger the firm's digital transformation capability. In this study, the proportion of independent directors to the total number of board members was used to measure board independence. The computation of Indep was performed using the following formula:

$$\text{IndepRatio}=\frac{\text{Number of Independent Directors}}{\text{Total Number of Board Members}}$$

Where:

"Number of Independent Directors" represents the count of directors on the board who are classified as independent.

"Total Number of Board Members" is the entire count of directors on the board, regardless of their classification.

This formula will yield a value between zero and one, with higher values indicating greater board independence.

Firm Age (LnFirmAge): Firm age plays a pivotal role in influencing digital transformation. Emerging companies are typically more agile, innovation-driven, and adaptable to market changes. Their higher risk tolerance often enables them to more readily embrace digital strategies to respond to market fluctuations and enhance their competitiveness. Conversely, established companies, while possibly requiring more time to overcome technological and cultural barriers, typically possess richer resources and experiences which can be instrumental in their digital transformation journey. BarNir et al. (2003) further highlighted that the correlation between digitalization and strategy is more pronounced in newly founded organizations compared to their well-established counterparts. To quantify the age of a firm, the formula is:

$$\text{LnFirmAge} = \ln(\text{Current Year} - \text{Year of Establishment} + 1)$$

Where:

"Current Year" signifies the present year.
"Year of Establishment" is the year when the firm was initially founded.

The application of the natural logarithm transformation (ln) is prevalent in empirical studies to address potential skewness in data distribution. By adding one to the difference between the current year and the year of establishment, the formula ensures that even for companies established in the current year (which would result in a value of zero), the logarithm remains defined. This transformation effectively caters to both emerging and long-established firms, reflecting their distinct characteristics and adaptability to digital transformation.

Number of Employees (LnEmployee): According to McKelvie and Davidsson (2009), larger firms with more employees may be less adaptable to changes in the business environment. So, the number of employees is an important factor influencing digital transformation, as the size of the employees directly affects internal complexity and external market pressures. Larger companies typically have more business processes and employees, which can lead to more complex organizational structures and technology needs, and therefore require greater digital transformation efforts to optimize and upgrade these processes. In addition, large businesses may need more time to train and adapt employees to ensure they can effectively use new digital tools and systems. On the other hand, smaller companies may be more nimble and able to adopt and adapt digital solutions more quickly but may face challenges with limited resources. The computation of employee number was performed using the following formula:

$$LnEmployee = \ln(\text{the number of employees} + 1)$$

Where:

"LnEmployee" represents the natural logarithm transformation of the company's workforce size.

"The number of employees" refers to the total count of all full-time, part-time, and contract-based staff working for the company.

The addition of one ensures that companies with zero employees do not result in a mathematical error when taking the natural logarithm.

3.5 Preliminary Test

This section presents the results of the descriptive statistics, correlation analysis, and diagnostic tests that were conducted during preliminary testing.

3.5.1 Descriptive Statistics

Using data spanning 2011 to 2021 from Chinese listed companies in the Shanghai and Shenzhen stock exchanges, significant insights were gleaned from 17,195 observations across 3,545 firms. The results shown in Table 3.2 indicate that the two principal indicators of digital transformation, digital underlying technology and digital technology application, possess means of 1.053 and 1.018 respectively, with standard deviations of 1.312 and 1.133. Both indicators have a minimum value of zero but exhibit maximums of 4.984 and 4.159, respectively. This extensive range underscores marked variance, suggesting that a majority of companies are still in the nascent stages of their digital transition, which aligns with earlier research findings.

Analyst coverage demonstrates a mean of 1.997, with a standard deviation of 0.911, a minimum of 0.693, and a maximum of 3.871. These figures intimate that while analyst attention is ubiquitously noted among Chinese listed firms, its magnitude exhibits considerable variability. Considering customer and supplier concentrations, which respectively delineate a firm's revenue from its top five clients as a proportion of annual sales and purchases from its top five suppliers relative to annual procurement, the data is telling. Customer concentration averages at 0.303 with a standard deviation of 0.219, spanning a minimum of 0.009 to a maximum of 0.948. Supplier concentration, meanwhile, averages at 0.328 with a standard deviation of 0.187, ranging between 0.045 and 0.894. This indicates that roughly a third of a listed firm's sales and procurement operations are centralized with a handful of principal clients and suppliers, suggesting significant operational reliance on these key stakeholders.

EPU over the period under scrutiny exhibits pronounced volatility as well. A mean of 4.300 with a substantial standard deviation of 2.226 indicates significant disparity between data points and their mean. EPU values also oscillate between a minimum of 1.139 and a maximum of 7.919. This expansive data range reveals that over the decade, EPU has experienced considerable ebbs and flows, offering a variegated and enriched research milieu. Such conspicuous variation in uncertainty paves the way for further exploration into its relationship with other variables.

The control variables also furnish valuable insights. Lev possesses a mean of 0.399, a standard deviation of 0.194, and a range of 0.052 to 0.840, reflecting firms' capital structural divergences. The proportion of IndepRatio averages at 0.376, with a standard deviation of 0.053, ranging between 0.333 and 0.571, alluding to inter-firm variations in governance structure. The LnFirmAge denotes a mean of 2.866, a standard deviation of 0.329, fluctuating from 1.946 to 3.497. Simultaneously, LnEmployee count averages at 7.866 with a standard deviation of 1.227, encapsulating a spectrum from 5.347 to 11.290, shedding light on firm size and lineage.

Table 3.3: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
DUT	17195	1.053	1.312	0.000	4.984
DTA	17195	1.018	1.133	0.000	4.159
AC	17195	1.997	0.911	0.693	3.871
CC	17195	0.303	0.219	0.009	0.948
SC	17195	0.328	0.187	0.045	0.894
EPU	17195	4.300	2.226	1.139	7.919
Lev	17195	0.399	0.194	0.052	0.840
IndepRatio	17195	0.376	0.053	0.333	0.571
LnFirmAge	17195	2.866	0.329	1.946	3.497
LnEmployee	17195	7.866	1.227	5.347	11.290

Note: Company level data related to Chinese Shanghai and Shenzhen Stock Exchanges

3.5.2 Correlation Analysis

The correlation coefficients shown in Table 3.3 reveal significant relationships between the variables. The data reveals a strong positive association, significant at the 1% level, between analyst coverage and the two indicators of digital transformation, namely digital underlying technology and digital technology application. In contrast, it is shown that both customer and supplier concentrations exhibit a substantial negative association, significant at the 1% level, with the digital transformation metrics under investigation. This finding is consistent with the initial hypothesis posited in this research. Moreover, there is a constant and significant positive correlation between EPU and both digital underlying technology and digital technology application. The strong associations shown between the control factors and the key dependent variables highlight the meticulous choice of these variables, which enhances the methodological soundness of the study design.

Table 3.4: Pearson Correlation

	DUT	DTA	AC	CC	SC	EPU	Lev	Indep	FirmAge	Employee
DUT	1.000									
DTA	0.563***	1.000								
AC	0.062***	0.082***	1.000							
CC	-0.016**	-0.110***	-0.119***	1.000						
SC	-0.049***	-0.091***	-0.137***	0.276***	1.000					
EPU	0.249***	0.134***	-0.015*	0.046***	-0.026***	1.000				
Lev	-0.042***	-0.008	0.037***	-0.096***	-0.178***	0.027***	1.000			
IndepRatio	0.059***	0.052***	0.026***	-0.008	-0.017**	0.043***	-0.006	1.000		
LnFirmAge	0.039***	0.023***	-0.056***	-0.092***	-0.079***	0.303***	0.189***	-0.002	1.000	
LnEmployee	0.035***	0.106***	0.351***	-0.246***	-0.347***	0.084***	0.453***	-0.004	0.178***	1.000

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

3.5.3 Diagnostic Tests

In this research, three diagnostic tests were performed to validate the data for subsequent econometric analysis. Initially, the Modified Wald test was conducted to assess heteroscedasticity within the variables, followed by a multicollinearity test using the Variance Inflation Factor (VIF) to evaluate correlations among independent variables. Furthermore, the Wooldridge-Drukker test was applied to detect autocorrelation in the dataset. To determine the appropriate model for regression analysis, the F test and LM test were executed, assessing the need for fixed effects over mixed regression and individual effects, respectively. An overidentification test was also used to decide between fixed and random effects models under conditions of heteroscedasticity. These diagnostics guided the choice of employing a fixed effects model with cluster-robust standard errors. It also took into consideration the extensive number of firms in the dataset by controlling for industry effects, which prevented over-controlling and the loss of degrees of freedom while controlling for time effects to avoid time errors.

3.6 Estimation Method

This section discusses the method used in this study to estimate the empirical models outlined for the two objectives of the study. A panel dataset was utilized, comprised of a number of firms for the specified number of years, leading to a total number of observations. Then, the justification of the chosen method, the fixed effects model, is presented.

3.6.1 Panel Data

This research leveraged a panel dataset encompassing firm-year observations. Panel data, by definition, pertains to data that tracks the same set of entities over a specified period. This type of data encompasses both a cross-sectional dimension (capturing n entities) and a time-series dimension (spanning T periods) (Hsiao, 2022). Panel data offers several advantages, such as addressing omitted variable bias and providing more insightful information on individual dynamic behaviors. Furthermore, the relatively large sample size typically associated with panel data augments the precision of estimations.

Nonetheless, there are challenges inherent to panel data (Hsiao, 2022). For instance, sample data might not always meet the assumption of independent and identically distributed observations, primarily because the disturbance term for the same entity across different periods often exhibits autocorrelation. However, this concern can be mitigated in regression equations by employing clustered robust standard errors (Hoechle, 2007). Bearing these considerations in mind, this study meticulously integrated both the time-series and cross-sectional facets of data spanning from 2011 to 2021. The accumulated data for the variables were chronologically sourced from consistent firms, forming the basis for subsequent regression analyses.

3.6.2 Fixed Effects Model

One extreme strategy in estimating panel data is to treat it as cross-sectional data and conduct a pooled regression, which presupposes that every individual in the sample possesses an identical regression equation. A drawback of this pooled approach is that it overlooks the unobservable heterogeneity among entities. Such heterogeneity might correlate with the explanatory variables, leading to inconsistent estimates. Conversely, the other extreme strategy is to estimate a separate regression equation for each entity. The downside of this individual regression is that it might neglect commonalities among entities; furthermore, there might not be a sufficiently large sample size for each entity (Baltagi & Baltagi, 2008).

In practice, a middle-ground approach is often adopted, which assumes that the regression equation for each entity shares a common slope but may have different intercepts. This model captures the heterogeneity among entities and is referred to as an "individual-specific effects model." From an economic theory perspective, general unobservable heterogeneity often has implications for the explanatory variables. In such scenarios, ordinary least squares (OLS) estimation can lead to inconsistent results. A solution to this is to transform the model, removing the unobservable heterogeneity to achieve consistent estimates. This method is known as the fixed effects model (Bell & Jones, 2015).

To enhance the reliability of the regression outcomes, this study employed the fixed effects model. In all the regression equations, the use of t-statistics adjusted for clustered robust standard errors (Cluster) was assumed to mitigate the impacts of heteroscedasticity and autocorrelation. Additionally, the study controlled for time (Year) and industry (Ind) dummy variables to absorb as much of the fixed effects as possible (Breuer & deHaan, 2023).

3.7 Empirical Models

This section discusses the estimation method used in this study to assess the effects of analyst coverage, customer concentration, and supplier concentration on digital transformation, as well as the impact of the moderator EPU on these relationships. This study estimated the panel data regression models of digital transformation as a function of the three independent variables, while also including various controls.

3.7.1 Direct Effect Models

In this study, two proxies of digital transformation were used: (1) Digital underlying technology and (2) Digital technology application. They were measured using textual analysis. Therefore, the general regression equation was extended as follows:

$$(3.1)\ DUT_{i,t}=\beta_0+\beta_1 AC_{i,t}+\beta_2 CC_{i,t}+\beta_3 SC_{i,t}+\beta_4 Lev_{i,t}+\beta_5 IndepRatio_{i,t}$$

$$+\beta_6 LnFirmAge_{i,t}+\beta_7 LnEmployee_{i,t}+\sum Year_t+\sum Industry_j+\varepsilon_{i,t}$$

$$(3.2)\ DTA_{i,t}=\beta_0+\beta_1 AC_{i,t}+\beta_2 CC_{i,t}+\beta_3 SC_{i,t}+\beta_4 Lev_{i,t}$$

$$+\beta_5 IndepRatio_{i,t}+\beta_6 LnFirmAge_{i,t}+\beta_7 LnEmployee_{i,t}+\sum Year_t+\sum Industry_j+\varepsilon_{i,t}$$

In this formula, the dependent variables are DUT and DTA; β_0 is the intercept term; the core independent variables are AC, CC and SC; Lev, IndepRatio, LnFirmAge, and LnEmployee are the control variables; and ε is the random error term. At the same time, to avoid the regression results being affected by unobservable macro factors and industry characteristics, this study also controlled the fixed effect of year (Year) and industry (Industry).

3.7.2 Moderating Effect Models

The moderating impact of EPU was also examined based on its interactions with analyst coverage, customer concentration, and supplier concentration in influencing digital transformation. To do so, Equation (3.1) became Equation (3.3), and Equation (3.2) became Equation (3.4). It should be noted that Equations (3.3) and (3.4) do not control for time-fixed effects because EPU data is on an annual level. Including time-fixed effects would result in multicollinearity issues, which would impact the estimation results of this study. Therefore, only industry-fixed effects were considered in the baseline regression equation.

$$(3.3)\ \mathrm{DUT}_{i,t} = \beta_0 + \beta_1\mathrm{AC}_{i,t} + \beta_2\mathrm{CC}_{i,t} + \beta_3\mathrm{SC}_{i,t} + \beta_4\mathrm{AC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_5\mathrm{CC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_6\mathrm{SC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_7\mathrm{EPU}_{i,t} + \beta_8\mathrm{Lev}_{i,t} + \beta_9\mathrm{IndepRatio}_{i,t} + \beta_{10}\mathrm{LnFirmAge}_{i,t} + \beta_{11}\mathrm{LnEmployee}_{i,t} + \sum\mathrm{Industry}_j + \varepsilon_{i,t}$$

$$(3.4)\ \mathrm{DTA}_{i,t} = \beta_0 + \beta_1\mathrm{AC}_{i,t} + \beta_2\mathrm{CC}_{i,t} + \beta_3\mathrm{SC}_{i,t} + \beta_4\mathrm{AC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_5\mathrm{CC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_6\mathrm{SC}_{i,t} * \mathrm{EPU}_{i,t} + \beta_7\mathrm{EPU}_{i,t} + \beta_8\mathrm{Lev}_{i,t} + \beta_9\mathrm{IndepRatio}_{i,t} + \beta_{10}\mathrm{LnFirmAge}_{i,t} + \beta_{11}\mathrm{LnEmployee}_{i,t} + \sum\mathrm{Industry}_j + \varepsilon_{i,t}$$

3.8 Robustness Analysis

After selecting the fixed effects model as the basis for our analysis in this study, further verification of the precision in model selection becomes particularly crucial. In the process of empirical analysis, the choices we face are not limited to the fixed effects model but also include two important alternative options: the random effects model and the mixed regression model. To ensure the reliability of the research conclusions, this study employed F-tests, LM tests, and overidentification tests to conduct a detailed comparison and evaluation of these different models.

Furthermore, to provide a comprehensive analytical perspective, this study will also report the analysis results of the mixed regression and random effects models. By comparing the results obtained from the fixed effects model with those from alternative models, we conduct a robustness check. In summary, we can not only validate the rationality of the choice of research method but also further solidify the solid foundation of our research findings through robustness testing.

3.9 Summary

This chapter has provided an examination of the underlying philosophy and methodologies used in testing the research hypotheses. The present study has conducted a thorough examination of the existing scholarly literature pertaining to the variables indicated, in order to have a comprehensive understanding of the research design. The justification for using the quantitative technique is presented, with the use of several causal econometric models for the purpose of evaluating the hypotheses. Additionally, the discussion included the numerous data collecting procedures and measurement methodologies used for different variables and constructs.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Introduction

The primary aim of this chapter is to analyze and present the outcomes derived from the fixed effect model to meet the research goals. The first objective of this research was to evaluate the impact of analyst coverage, customer concentration, and supplier concentration on digital transformation. The second objective of this study was to investigate the potential moderating influence of EPU on these links. The investigation included two specific proxies of digital transformation, namely digital underlying technology and digital technology application. The objectives and findings of this study were carefully analyzed using a sample size of 17,195 observations collected from 3,545 Chinese listed companies between the years 2011 and 2021. The following sections provide detailed explanations of the empirical results and discussions pertaining to each objective.

4.2 Diagnostic Test Results

Three diagnostic tests were executed in this research: the heterogeneity test, multicollinearity assessment, and the autocorrelation evaluation. The results of these tests serve as a foundation for the subsequent analysis using the fixed effect model.

The initial diagnostic undertaking was the Modified Wald test, which probed for the presence of heteroscedasticity among variables. The findings from Table 4.1, reject the null hypothesis of homoscedastic error variance at the 99% confidence level, with a p-value of 0.00. This result signifies the presence of heteroscedasticity, as the variance of observed values of the dependent variable around the regression line was non-uniform. To counteract typical errors introduced by the fixed effects estimator, a cluster robust variance predictor was subsequently deployed.

Next, the study employed the multicollinearity test to ascertain the degree of correlation among multiple independent variables. Through the estimation of the VIF post each regression iteration, an auxiliary multicollinearity verification was undertaken. According to seminal work by Fotheringham and Oshan (2016), a VIF value surpassing 10 is indicative of multicollinearity concerns. Elevated correlation levels among variables can give rise to estimator biases. As depicted in Table 4.2, every variable in this dataset exhibited VIF values spanning 1.00 to 1.65, with an average value of 1.22, thereby alleviating concerns of multicollinearity within the dataset.

Lastly, the Wooldridge–Drukker test was incorporated to discern potential autocorrelation, specifically assessing whether residuals displayed significant association at a 1% significance level. Based on Table 4.1, the null hypothesis of an absence of first-order autocorrelation was emphatically negated. This underscores the presence of autocorrelation in the dataset, necessitating the implementation of a cluster robust variance predictor for correction.

Table 4.1: Result for Diagnostic Tests

Test	Test statistic		Criteria
	DUT	DTA	
The Modified Wald test for heteroskedasticity	3.2E+31***	4.2E+32***	rejecting the null hypothesis of homoscedasticity
Mean VIF	1.22		< 10, no multicollinearity
Wooldridge-Drukker test for autocorrelation	423.424***	684.347***	rejecting the null hypothesis of no first-order autocorrelation

Note: *** indicate statistically significant at 1% level

Table 4.2: VIF of Regression

Variable	VIF	Tolerance
LnEmployee	1.65	0.6062
Lev	1.31	0.7659
SC	1.19	0.8394
AC	1.18	0.8446
LnFirmAge	1.17	0.8539
CC	1.13	0.8865
EPU	1.12	0.8949
IndepRatio	1.00	0.9965
Mean	1.22	

Note: *** indicate statistically significant at 1% level

4.3 Model Development

In practical applications, there are three models to consider: the fixed effects model, the random effects model, and the mixed regression model. This study conducted a comparative assessment of these models using the F test, LM test, and overidentification test. As evidenced by the results presented in Table 4.3, the fixed effects model, with cluster-robust standard errors, was the most suitable and well-aligned model with the dataset of this research.

Table 4.3: Model Selection Tests

Test	Test statistic		Criteria
	DUT	DPA	
F test	421.58***	210.24***	rejecting the null hypothesis of all individual effects are 0
LM test	21820.30***	22874.59***	rejecting the null hypothesis of all individual variances are 0
Overidentification test	790.969***	367.434***	rejecting the null hypothesis of random effect

Note: *** indicate statistically significant at 1% level

The first test conducted was the F test, designed to discern whether to employ a mixed regression or a fixed effects model. Given prior results indicating the presence of autocorrelation and heteroscedasticity within the dataset, the study employed cluster-robust standard errors for regression analysis. All three regression F-tests yielded a p-value of 0.0000, rejecting the null hypothesis. Hence, in comparison to mixed regression, this research was better suited to utilize the fixed effects model.

The second test was the LM test, which, based on prior outcomes, indicated the existence of individual effects. However, these individual effects might still manifest as random effects. This test is aimed at determining the choice between using random effects or mixed regression. The results showcased a consistent p-value of 0.0000, thereby negating the null hypothesis of “no individual random effects.” This implies that, between random effects and mixed regression, the random effects model should be preferred.

The third diagnostic was the overidentification test. Though prior results have established the presence of both fixed and random effects, the specific model choice remained inconclusive. The traditional Hausman test is apt only when disturbances exhibit homoscedasticity and is inapplicable under heteroscedastic conditions. Given this constraint, the research employed a robust version of the Hausman test, termed the overidentification test. Results consistently indicated a p-value of 0.0000, leading to the robust rejection of the random effects null hypothesis.

To summarize, this research was directed to employ the fixed effects model with cluster-robust standard errors. Additionally, since the study utilized data at the level of publicly listed firms, the sheer number of these companies was vast. Controlling for firm-level individual effects too stringently could lead to an excessive loss in degrees of freedom. To circumvent this potential over-control issue and to preserve analytical integrity, the study opted to control for industry effects.

4.4 Regression Results for the Direct Effects

Regarding the relationships of analyst coverage, customer concentration, and supplier concentration with digital transformation, the regression results provided in Table 4.4 yielded the following insights.

Analyst coverage demonstrated a significant positive influence on digital transformation, as evident by its coefficients in relation to both digital underlying technology ($\beta = 0.0675$) and digital technology application ($\beta = 0.0404$), both of which were statistically significant at the 1% level (p-value < 0.01). This suggests that firms with greater analyst coverage are more inclined or better positioned to undergo digital transformation. Companies extensively covered by analysts are not only under heightened scrutiny but also benefit from the information intermediary role that these analysts play. Analysts, in disseminating their research and insights, significantly reduce information asymmetry, bolstering transparency around a company's operations and prospects. This increased transparency can, in turn, attract a broader set of investors who might have been previously wary due to lack of clear information.

Furthermore, it is worth noting that the desire to align with analysts' expectations or recommendations could also be a motivating factor for companies, which is consistent with Stakeholder Theory. When analysts highlight the benefits or the necessity of digital transformation, companies might perceive this as a cue to prioritize such initiatives, given the potential advantages they can bring. Not only does digital transformation potentially led to operational efficiencies and new revenue streams, but a company's proactive stance on it can also be viewed favorably in the eyes of informed investors and analysts. In essence, by heeding analysts' insights and emphasizing digital transformation, firms are signaling their forward-looking approach and adaptability, aspects that are often rewarded in the capital markets. Thus, H1a was confirmed.

Customer concentration exhibited a negative association with digital transformation. The coefficients for digital underlying technology ($\beta = -0.2164$) and digital technology application ($\beta = -0.2257$) were both significant at the 1% level (p-value < 0.01). A potential interpretation is that in the case of enterprises characterized by high customer concentration, a significant portion of their market share is attributed to a limited number of key clients. In this particular scenario, the corporation may see any strategy alterations that have the potential to adversely affect these primary consumers as carrying a significant level of risk. Although digital transformation has the potential to provide long-term advantages, its implementation may temporarily disrupt company relationships with crucial clients, leading to a perception of it as a potential danger. These primary consumers, owing to their significant negotiating power, could exhibit misgivings or open hostility towards the transition, as they may have a preference for maintaining the current state in order to sustain their prevailing market dominance. Therefore, the confirmation of H1b was established.

Supplier concentration similarly showed a significant negative relationship with digital transformation, as reflected by its coefficients for digital underlying technology (β = -0.2795) and digital technology application (β = -0.2712), which were both significant at the 1% level (p-value < 0.01). This indicates that companies that have a large concentration of suppliers see a similar dynamic as high customer concentration. When a corporation heavily depends on a limited number of suppliers, the suppliers' negotiating power correspondingly increases. Hence, corporations may see digital transformation as a potentially hazardous endeavor due to its potential to alter their business relationships and modes of engagement with crucial suppliers. Suppliers, meanwhile, may see digital transformation as a prospective challenge due to its potential to alter their connection with the organization or disrupt their existing business model. Thus, the verification of H1c was proven.

Among the control variables, asset-liability ratio is negatively related to digital transformation. This hints that firms with more leverage are possibly more conservative and less likely to invest in digital initiatives. Board independence has a positive association with digital transformation, suggesting more autonomous firms might be more agile in their adoption of digital strategies. Older firms, represented by firm age, are less inclined towards digital adoption, perhaps due to entrenched ways or legacy systems. Conversely, the positive coefficient for employee number implies that larger firms with more employees might have the resources or diversified skill sets to drive digital transformation forward.

The adjusted R-squared values for both models (0.4061 for digital underlying technology and 0.2604 for digital technology application) signify that a considerable portion of the variability in the data was explained by the models, underscoring their robustness and the research's credibility.

Table 4.4: Results for Direct Effects

Variable	model 1 DUT	model 2 DTA
AC	0.0675***	0.0404***
	(0.0093)	(0.0090)
CC	-0.2164***	-0.2257***
	(0.0420)	(0.0382)
SC	-0.2795***	-0.2712***
	(0.0474)	(0.0443)
Lev	-0.1135**	-0.1569***
	(0.0505)	(0.0486)
IndepRatio	0.7011***	0.5770***
	(0.1507)	(0.1451)
LnFirmAge	-0.1105***	-0.1211***
	(0.0272)	(0.0264)
LnEmployee	0.0440***	0.0915***
	(0.0107)	(0.0104)

Table 4.4: Continued

_cons	-0.5185***	0.1051
	(0.1669)	(0.1668)
Industry	Yes	Yes
Year	Yes	Yes
N	17195	17195
adj. R2	0.4061	0.2604

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5 The Moderating Role of EPU and Lagged EPU

The second research objective of this study was to investigate the moderating effect of EPU on the direct relationships. The interaction term AC*EPU in models 3 and 4, as shown in Table 4.5, did not exhibit statistically significant results. The lack of significance in this context may be attributed to the fundamental character of analysts' assessments. Analysts mostly direct their attention to the future outlook and financial gains of companies. The evaluations they do, which are usually based on broad market dynamics and industry trends, may not be instantly influenced by temporary factors like EPU. This implies that the concurrent impact of EPU may not have a significant enough influence on the relationship between enterprises' efforts in analyst coverage and digital transformation.

In addition, the current moderating effect examines the impact of EPU at the same time point on the relationship between external stakeholders and corporate digital transformation. It investigates whether EPU directly influences their interaction within the observation period. Conversely, the lagged moderating effect focuses on the time-delayed impact of EPU on this relationship, questioning whether the effects of EPU will manifest at a future time point rather than immediately. The observed lagged effect in the relationship between analyst coverage and digital transformation confirms this, aligning with our theoretical expectations.

Nevertheless, it is crucial to understand the lagged implications of EPU on analyst coverage, considering temporal intricacies. It is evident from Table 4.6 that there is a significant change when EPU is considered with a time delay. The coefficient for the interaction term AC*EPU is statistically significant in both model 5 and model 6. In model 5, the coefficient for digital underlying technology is -0.122 with a p-value of less than 0.01. In model 6, the coefficient for digital technology application is -0.100 with a p-value of less than 0.05. This finding provides evidence that, when considering a delayed timeframe, EPU does indeed act as a moderator in the association between analyst coverage and digital transformation. In summary, H2a has been confirmed. The findings indicate that an increase in EPU diminishes the influence of analysts in driving enterprises towards digital transformation.

In our exploration, the moderating effect of EPU on the relationship between customer concentration and digital transformation lacked statistical significance. Macro-level policy variations have a greater influence on the strategic orientations of enterprises than their core sales activities. Therefore, despite the inclusion of a delayed variable accounting for EPU, its impact remains statistically insignificant.

The aforementioned tendency may be ascribed to the intricate role of consumers as major stakeholders. It is probable that their perspective on digital transformation is characterized by a variety of dimensions. In conventional operational settings, consumers, who are aware of their own positions and interests, may express opposition against enterprises undertaking digital transformation. Nevertheless, in situations characterized by heightened EPU, consumer perspectives tend to bifurcate. On one end of the spectrum, there is an anticipation of enriched digital experiences and services, driven by specific factors or conditions. Contrarily, there is also a prevalent apprehension about the potential upheavals that digital transformation might trigger in their own business operations. Amid heightened EPU, these divergent perspectives have the ability to offset one another, resulting in customer concentration's impact on digital transformation being unaffected by EPU's moderation. Thus, H2b was not supported by the data.

Nonetheless, the moderating effect of EPU on the relationship between supplier concentration and digital transformation was found to be salient. Empirical results indicate a significant amplification of the inhibitory influence of supplier concentration on digital transformation under heightened EPU conditions. Specifically, regression coefficients reveal $\beta = -0.0448$ (p-value < 0.05) for digital underlying technology in model 3 and $\beta = -0.0510$ (p-value < 0.01) for digital technology application in model 4. This observed behavior can be interpreted within the ambit of Stakeholder Theory. When confronted with intensified external uncertainty, firms seem to prioritize core stakeholders' interests. This inclination is especially pronounced amidst escalating environmental uncertainties.

A greater concentration of suppliers could lead to a scenario where enterprises are heavily reliant on a handful of them for resources and raw material procurement, consequently granting these suppliers substantial bargaining power. Within a high-EPU landscape, the inherent uncertainties might induce a conservative disposition among suppliers towards transformative initiatives like digitalization. Their reservations could stem from concerns that such endeavors may jeopardize existing transactional efficiencies and relations. For instance, a pivot towards digital transformation can potentially reconfigure the supply chain, unsettling suppliers about their relative positions therein. Thus, under intensified EPU, the reluctance from suppliers can be expected to surge, further accentuating their suppressive stance on digital transformation.

Meanwhile, the findings in models 5 and 6, showcasing $\beta = -0.0625$ ($p\text{-value} < 0.01$) for digital underlying technology and $\beta = -0.0640$ ($p\text{-value} < 0.01$) for digital technology application respectively, remained consistent with prior result, further reinforcing the validation of H2c.

Table 4.5: Results for Current Moderating Effects

	model 3	model 4
	DUT	DTA
AC	0.0550***	0.0301***
	(0.0093)	(0.0090)
CC	-0.1697***	-0.1969***
	(0.0423)	(0.0384)
SC	-0.2896***	-0.2824***
	(0.0487)	(0.0448)
AC*EPU	-0.0027	-0.0039
	(0.0038)	(0.0037)
CC*EPU	-0.0023	0.0061
	(0.0161)	(0.0150)
SC*EPU	-0.0448**	-0.0510***
	(0.0196)	(0.0185)
EPU	0.1299***	0.0585***
	(0.0037)	(0.0036)
Lev	-0.1206**	-0.1631***
	(0.0515)	(0.0490)
IndepRatio	0.8502***	0.6976***
	(0.1529)	(0.1463)
LnFirmAge	0.0323	-0.0196
	(0.0269)	(0.0260)
LnEmployee	0.0506***	0.0962***
	(0.0088)	(0.0083)

Table 4.5: Continued

_cons	-0.7998***	-0.3296***
	(0.1259)	(0.1266)
N	17195	17195
adj. R2	0.3843	0.2442

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4.6: Results for Lagged Moderating Effects

Variable	model 5 DUT	model 6 DTA
AC	0.0731***	0.0433***
	(0.0113)	(0.0109)
CC	-0.2491***	-0.1762***
	(0.0538)	(0.0483)
SC	-0.2861***	-0.3145***
	(0.0610)	(0.0549)
AC*L.EPU	-0.0122***	-0.0100**
	(0.0045)	(0.0043)
CC*L.EPU	0.0171	0.0190
	(0.0191)	(0.0175)
SC*L.EPU	-0.0625***	-0.0640***
	(0.0237)	(0.0218)
L.EPU	0.0983***	0.0436***
	(0.0043)	(0.0041)
Lev	-0.1824***	-0.1943***
	(0.0640)	(0.0602)

Table 4.6: Continued

IndepRatio	0.9552***	0.6521***
	(0.1828)	(0.1725)
LnFirmAge	0.0096	-0.0648*
	(0.0345)	(0.0332)
LnEmployee	0.0485***	0.0862***
	(0.0107)	(0.0100)
_cons	-0.5420***	-0.0287
	(0.1596)	(0.1557)
N	12241	12241
adj. R2	0.3774	0.2405

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Robustness Analysis Results

To ensure the robustness of our findings, this study conducted an analysis using alternative models, namely the mixed regression model and the random effects model.

The application of the mixed regression model, detailed in Table 4.7, corroborated our primary findings: analyst coverage continues to show a significant positive correlation with digital transformation, whereas customer concentration and supplier concentration remain negatively correlated. These results are consistent with those obtained from the fixed effects model, bolstering the validity of Hypothesis 1a. Regarding EPU's moderating effect, while its significance was not observed in the current or lagged effects on the relationship between supplier concentration and digital transformation, it aligned with our initial findings in affecting the relationship between analyst coverage and digital transformation in the lagged period. Overall, the mixed regression model's results validate the study's hypotheses (H1a, H1b, H1c, H2a), attesting to the robustness of our findings.

Table 4.7 Mixed Regression Model Results

	model 7	model 8	model 9	model 10	model 11	model 12
	DUT	DPA	DUT	DPA	DUT	DPA
AC	0.0729***	0.0480***	0.0788***	0.0518***	0.0959***	0.0645***
	(0.0119)	(0.0102)	(0.0113)	(0.0101)	(0.0139)	(0.0122)
CC	0.0379	-0.3945***	-0.1027**	-0.4622***	-0.1921***	-0.5184***
	(0.0454)	(0.0386)	(0.0430)	(0.0379)	(0.0537)	(0.0471)
SC	-0.2945***	-0.2708***	-0.2750***	-0.2609***	-0.2408***	-0.2699***
	(0.0591)	(0.0514)	(0.0571)	(0.0509)	(0.0723)	(0.0629)
Lev	-0.4933***	-0.3831***	-0.3897***	-0.3359***	-0.4129***	-0.3336***
	(0.0575)	(0.0501)	(0.0556)	(0.0497)	(0.0701)	(0.0615)
Indep1	1.3983***	1.0417***	1.1171***	0.9127***	1.1672***	0.8578***
	(0.1867)	(0.1623)	(0.1830)	(0.1617)	(0.2198)	(0.1909)
FirmAge	0.1894***	0.0416	-0.1268***	-0.1057***	-0.1630***	-0.1556***
	(0.0308)	(0.0270)	(0.0315)	(0.0282)	(0.0408)	(0.0360)
Employee	0.0312***	0.0793***	0.0090	0.0693***	-0.0001	0.0539***
	(0.0102)	(0.0088)	(0.0099)	(0.0088)	(0.0122)	(0.0106)
AC*EPU			-0.0008	-0.0046		
			(0.0046)	(0.0041)		
CC*EPU			0.0094	0.0213		
			(0.0191)	(0.0172)		

Table 4.7: Continued

SC*EPU			-0.0190	-0.0236		
			(0.0240)	(0.0219)		
EPU			0.1521***	0.0715***		
			(0.0046)	(0.0040)		
AC*L.EPU					-0.0106*	-0.0111**
					(0.0055)	(0.0048)
CC*L.EPU					0.0329	0.0441**
					(0.0226)	(0.0199)
SC*L.EPU					-0.0316	-0.0367
					(0.0290)	(0.0257)
L.EPU					0.1183***	0.0557***
					(0.0053)	(0.0046)
_cons	-0.1247	0.1495	0.3908***	0.3809***	0.7840***	0.7915***
	(0.1338)	(0.1145)	(0.1322)	(0.1152)	(0.1685)	(0.1439)
N	17195	17195	17195	17195	12241	12241
adj. R^2	0.0140	0.0277	0.0734	0.0453	0.0518	0.0373

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The random effects model results, as presented in Table 4.8, continue to validate the significant positive impact of analyst coverage on digital transformation. Similarly, the significant inhibitory effect of customer concentration on digital transformation is also confirmed. However, the model did not exhibit significant effects for supplier concentration in its relationship with the two proxies of digital transformation, reaffirming H1a and H1b. Regarding the moderating effect of EPU, no significant impact was observed in the current period. Yet, in the lagged period, the interaction term AC*L.EPU showed a significant negative correlation with DUT, aligning with previous reports and confirming H2a. But the remaining results did not support H2c.

Table 4.8 Random Effects Model Results

	model 13	model 14	model 15	model 16	model 17	model 18
	DUT	DPA	DUT	DPA	DUT	DPA
AC	0.0318^{***}	0.0152	0.0382^{***}	0.0182^{*}	0.0547^{***}	0.0350^{***}
	(0.0112)	(0.0100)	(0.0109)	(0.0100)	(0.0136)	(0.0120)
CC	0.1031	-0.2078^{***}	0.0329	-0.2400^{***}	-0.0974	-0.3379^{***}
	(0.0805)	(0.0645)	(0.0776)	(0.0634)	(0.0954)	(0.0758)
SC	-0.0789	-0.1007	-0.0779	-0.0999	0.0016	-0.1111
	(0.0714)	(0.0627)	(0.0704)	(0.0620)	(0.0841)	(0.0731)
Lev	-0.0877	-0.0926	-0.0405	-0.0741	-0.1559	-0.1824^{**}
	(0.0852)	(0.0712)	(0.0825)	(0.0704)	(0.1010)	(0.0847)
Indep1	-0.3097	-0.1836	-0.3715^{*}	-0.2155	-0.3261	-0.2638
	(0.2220)	(0.1890)	(0.2180)	(0.1888)	(0.2566)	(0.2153)
FirmAge	1.5416^{***}	0.7912^{***}	0.8826^{***}	0.5277^{***}	0.8515^{***}	0.3108^{***}
	(0.0526)	(0.0464)	(0.0519)	(0.0472)	(0.0745)	(0.0631)
Employee	0.1368^{***}	0.1320^{***}	0.1161^{***}	0.1232^{***}	0.0915^{***}	0.0975^{***}
	(0.0194)	(0.0158)	(0.0185)	(0.0155)	(0.0229)	(0.0188)
AC*EPU			-0.0110^{***}	-0.0049		
			(0.0036)	(0.0033)		
CC*EPU			-0.0100	0.0085		
			(0.0170)	(0.0146)		
SC*EPU			-0.0288	-0.0196		
			(0.0177)	(0.0171)		

Table 4.8: Continued

EPU			0.0828***	0.0357***		
			(0.0036)	(0.0033)		
AC*L.EPU					-0.0099**	-0.0037
					(0.0042)	(0.0039)
CC*L.EPU					0.0266	0.0291*
					(0.0193)	(0.0174)
SC*L.EPU					-0.0594***	-0.0343*
					(0.0211)	(0.0203)
L.EPU					0.0634***	0.0368***
					(0.0045)	(0.0043)
_cons	-4.2697***	-2.0794***	-2.5886***	-1.4113***	-2.1822***	-0.5006**
	(0.1993)	(0.1736)	(0.1963)	(0.1700)	(0.2686)	(0.2306)
N	17195	17195	17195	17195	12241	12241
adj. R^2	0.0024	0.0080	0.0211	0.0171	0.0120	0.0187

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

By comparing the outcomes derived from these alternative models with our primary fixed effects model, we've reinforced the soundness and reliability of our research approach, highlighting its empirical strength and the validity of our conclusions.

4.7 Summary

This chapter has systematically presented the empirical results pertaining to the two primary objectives set forth in this study. Broadly speaking, the variables analyst coverage, customer concentration, and supplier concentration were found to be pivotal determinants of digital transformation. Furthermore, EPU emerged as a noteworthy moderating variable in these relationships.

Delving into the specifics, the data illuminates that analyst coverage exerts a positive influence on digital transformation. Conversely, both customer concentration and supplier concentration appear to negatively impact digital transformation. As for the moderating dynamics introduced by EPU, it plays a dual role. On one hand, it attenuates the positive relationship between analyst coverage and digital transformation, suggesting a diminished impact of analyst coverage on digital transformation under heightened EPU conditions. On the other, it intensifies the negative association between supplier concentration and digital transformation, implying that the suppressive effect of supplier concentration on digital transformation becomes even more pronounced in an environment characterized by high EPU. Notably, no moderating effect of EPU was observed in the relationship between customer concentration and digital transformation.

This nuanced understanding of the factors in the context of digital transformation sets the stage for further deliberation on the implications and potential strategies that organizations might adopt. For a summarized overview of these findings and their alignment with the study's research problem, questions, objectives, and hypotheses, please see Table 4.9.

Table 4.9: Research Summary

Focused Problems	Research Questions	Research Objectives	Research Hypotheses	Research Findings
1. The struggle to achieve equilibrium in relationships with external stakeholders (analyst coverage, customers concentration, supplier concentration) for achieving digital transformation.	1. What is the relationship between external stakeholders (analyst coverage, customers concentration, supplier concentration) and digital transformation in Chinese listed companies?	1. To examine the relationship between external stakeholders (analyst coverage, customers concentration, supplier concentration) and digital transformation in Chinese listed companies.	H1a: There is a positive correlation between analyst coverage and digital transformation in Chinese listed companies.	Analyst coverage and digital transformation are significantly positively correlated, confirming the hypothesis.
			H1b: There is a negative correlation between customer concentration and digital transformation in Chinese listed companies.	Customer concentration and digital transformation are significantly negatively correlated, confirming the hypothesis.
			H1c: There is a negative correlation between supplier concentration and digital transformation in Chinese listed companies.	Supplier concentration and digital transformation are significantly negatively correlated, confirming the hypothesis.

Table 4.9: Continued

2. External crises like the environmental uncertainty. Especially for economic policy uncertainty.	2. How does EPU moderate the relationship between external stakeholders (analyst coverage, customers concentration, supplier concentration) and digital transformation in Chinese listed companies?”	2. To examine the moderating role of EPU in the relationship between external stakeholders (analyst coverage, customers concentration, supplier concentration) and digital transformation in Chinese listed companies.	H2a: EPU weakens the positive relationship between analyst coverage and digital transformation in Chinese listed companies.	The interaction coefficient between analyst coverage and EPU is significantly negatively correlated, confirming the hypothesis.
			H2b: EPU strengthens the negative relationship between customer concentration and digital transformation in Chinese listed companies.	No significant coefficient was observed for the interaction between customer concentration and EPU. The hypothesis was not confirmed.
			H2c: EPU strengthens the negative relationship between supplier concentration and digital	The interaction coefficient between supplier concentration and EPU is significantly

Table 4.9: Continued

			transformation in Chinese listed companies	negatively correlated, confirming the hypothesis.

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter offers a comprehensive overview of the principal findings in line with the two established research objectives. Subsequent sections delve into the significant contributions this research makes to the existing body of knowledge and as well as its implications for policymakers and industry practitioners. The chapter concludes by addressing the limitations of this study and proposing avenues for future research.

5.2 Summary of Key Findings

The main aims of this study were to investigate the determinants influencing enterprise digital transformation and EPU's moderating effect on these relationships. This section presents a summary of the findings for each research objective.

5.2.1 Research Objective 1

In the age of the digital economy, the digital transformation of businesses has been universally acknowledged as a crucial strategy. Nevertheless, a pronounced gap persists in studies about its influential factors. This study primarily investigated the effects of analyst coverage, customer concentration, and supplier concentration on digital transformation. The focal point was the profound exploration of how external stakeholders, especially analysts, suppliers, and customers, influence decision-making related to digital transformation. This perspective not only broadens the research on driving factors at the enterprise level but also transcends the traditional focus on internal factors alone, emphasizing how external stakeholders and their behavioral demands shape a company's digital transformation strategy.

To examine the proposed framework, a fixed-effects model was adopted, analyzing 17,195 observations from 3,545 listed Chinese companies. Treating analyst coverage, customer concentration, and supplier concentration as proxy variables for the respective external stakeholders, it was found that analysts, customers, and suppliers indeed exert significant influences on the implementation of a company's digital transformation strategy. Specifically, analyst coverage tends to foster digital transformation in enterprises, whereas high customer and supplier concentrations act as constraining forces.

From the perspective of analyst coverage, analysts, as critical external stakeholders, play an indispensable role in promoting corporate digital transformation strategies. Firstly, analysts consistently monitor overall market and industry trends, offering invaluable insights into market demand and expectations for digital transformation. In the current milieu, digital transformation has garnered widespread attention and discourse. Analysts are particularly keen on such trends (Baker & Wurgler, 2007; Barber & Odean, 2000), recognizing their immense appeal to investors. This not only aligns with analysts' expectations but also prompts enterprises to stay ahead of societal focal points, further catering to market demands.

Furthermore, proactive analyst coverage bolsters investor confidence in digital transformation (Brauer & Wiersema, 2018), thereby potentially attracting additional investment, while also serving a supervisory function over management practices (Gentry & Shen, 2013), ensuring that the commitment and implementation of the transformation process are effectively monitored. Analyst coverage may underscore the importance of digital transformation in maintaining competitiveness and enhancing efficiency, thus stimulating the company to initiate or expedite the transformation process (Zhou et al., 2023). Concurrently, by juxtaposing digital transformation efforts with other business operations, analyst evaluations may highlight deficiencies within a company's approach to digital transformation, prompting necessary reforms. As a form of oversight, these assessments enhance the transparency and accountability of management (Gentry & Shen, 2013; Healy & Palepu, 2001). From the perspective of Stakeholder Theory, analysts, as key stakeholders of the corporation, exert significant pressure through their evaluations, compelling management to better adapt to or respond to industry and market fluctuations (Freeman et al., 2010).

Moreover, analyst coverage aids in mitigating information asymmetry and boosting transparency (Chang et al., 2006; He & Tian, 2013). This can help investors gain a deeper understanding of the long-term value of a company's digital transformation strategy, enabling more judicious investment decisions. Hence, in their strategic choices pertaining to digital transformation, enterprises consider not just the strategy's intrinsic value but also the prospect of aligning with analysts to foster and maintain healthy relations with investors, ultimately solidifying their market position.

In sum, analyst coverage significantly facilitates digital transformation for several reasons. Firstly, companies prioritize analyst reports due to their tendency to focus on trending topics, thereby accelerating digital transformation projects (Baker & Wurgler, 2007; Barber & Odean, 2000). Secondly, analyst coverage enhance transparency, enabling companies and investors to appreciate the long-term value of digital transformation (Brauer & Wiersema, 2018; Gentry & Shen, 2013; Jia, 2022; Liu et al., 2020). Furthermore, the supervisory role of analyst coverage not only offsets the reluctance to undertake high-risk, long-term investments like digital transformation due to "short-term performance pressure" (He & Tian, 2013; Healy & Palepu, 2001; To et al., 2018). but also encourages management to implement digital transformation strategies diligently and cautiously, thereby promoting digital transformation efforts (Gentry & Shen, 2013). In the context of China, the challenge of "short-term performance pressure" is even less significant when considering the overarching influence of digital transformation policies (Li et al., 2015; Wang et al., 2012), underscoring the pivotal role of analyst reports in advancing digital initiatives.

This enriches Stakeholder Theory by illustrating that analysts, as external stakeholders, play a critical role in shaping corporate strategies for digital transformation. By providing market insights, influencing investor confidence, and supervising managerial behavior, analysts not only reflect but also drive corporate behavior. This dynamic suggests an expanded role of analysts within the Stakeholder Theory, where external evaluators actively participate in and influence the strategic decisions and transparency of the firms they assess, such as those pertaining to digital transformation strategy, thereby underlining the theory's assertion of the importance of stakeholder engagement in corporate success (Phillips, 2003).

As essential external stakeholders of companies, both customer and supplier concentrations have a pronounced inhibitive effect on corporate digital transformation strategies (Li et al., 2023b; Zhang et al., 2020). Initially, when a company procures substantial raw materials from a single or a few suppliers or relies heavily on a few primary customers, its dependence escalates, elevating switching costs. In such scenarios, suppliers or primary customers wield formidable bargaining power (Huang et al., 2016; Zhang et al., 2020), possibly compelling companies to make concessions in their digital transformation strategies (Islami et al., 2020; Piercy & Lane, 2006). Furthermore, suppliers or customers with a dominant position in the supply chain might dissuade companies from undergoing digital transformation to preserve existing business models and agreements (Kwak & Kim, 2020).

Additionally, high supply chain concentration might enable principal suppliers and customers to acquire a company's accounting and other pertinent information through confidential communication channels (Kwak & Kim, 2020). Such personalized and specialized information exchange might predispose major suppliers and customers to prioritize their close relationship with the company over broader transparency (Dyer et al., 2008; Kale & Meneghetti, 2014). Consequently, such a concentrated supply chain structure might diminish a firm's motivation for digital transformation, as they might be more inclined to nurture relationships with current primary suppliers and customers rather than pursue a holistic digital transformation strategy.

From a financial and operational viewpoint, high customer or supplier concentration could amplify a company's operational risks (Campello & Gao, 2017; Dhaliwal et al., 2016). Any adversities faced by a customer or supplier, such as bankruptcy or mismanagement, could inflict substantial damage on companies heavily reliant on them (Kale & Shahrur, 2007). Moreover, if a company suddenly loses these key customers and suppliers, or if these customers and suppliers begin collaborating with competitors, it could cause significant upheaval in the company's structure, bringing incalculable risks (Cuñat, 2007; Hertzel et al., 2008). Such risks might further stifle a company's adoption of a digital transformation strategy, given the potential hefty investments and structural changes it might entail.

From above mentioned, we can conclude that in addressing the challenges of digital transformation within China's specific context, companies can mitigate the impact of high customer and supplier concentration by diversifying their partnerships, leveraging government support for digital initiatives, and fostering collaboration for technological innovation (Li et al., 2023b). By strategically expanding their digital and operational ecosystems, Chinese firms can reduce dependency, enhance transparency, and align interests with key stakeholders (Wang et al., 2020a). This approach not only spreads operational risks but also capitalizes on China's dynamic digital landscape and policy environment to drive successful digital transformation.

In conclusion, the heightened dependency, formidable bargaining power, and intimate information exchange and collaborations stemming from higher customer and supplier concentrations render them a deterrent to digital transformation strategy (Dowlatshahi, 1999; Kale & Meneghetti, 2014). These findings are consistent with recent research indicating that supplier concentration increases the risk-taking behavior of companies that have already undergone digital transformation, thereby hindering further digital transformation efforts (Yang & Guo, 2022). Similarly, Li et al. (2023b) corroborated from a supply chain management perspective that customer concentration plays a role in inhibiting corporate digital transformation initiatives. This convergence of evidence underscores the complex interplay between supply chain concentration and digital transformation strategies, where significant customer and supplier concentration influence can create barriers to adopting digital transformation within corporate strategies.

Stakeholder Theory suggests that for a company to be successful, it must appropriately manage its relationships with key stakeholders (Freeman, 2001). The present findings reinforce this by showing that concentrated stakeholders can become gatekeepers who must be engaged and managed effectively to facilitate digital transformation. Thus, Stakeholder Theory not only supports the study conclusions but also necessitates that companies recognize the potential for concentrated stakeholders to resist change, suggesting that strategic management involves navigating these relationships to advance innovation and transformation despite potential resistance (Freeman et al., 2010).

5.2.2 Research Objective 2

Under the research context of digital transformation strategies, how the uncertain macroeconomic environment influences the relationships between external stakeholders and companies was the second objective of this study. Given that different macroeconomic environments may have varying impacts on the drivers of digital transformation, it is crucial to further understand these specific mechanisms for corporate decision-making, especially in China's context (Li & Huang, 2021). Particularly, extant research based on EPU is relatively scarce in the academic field, making this exploration particularly valuable.

Using a fixed effects model that combined current and lagged EPU data, this study's in-depth analysis revealed that EPU has a significant moderating effect on the relationship between two external stakeholders—analysts and suppliers—and corporate digital transformation strategy. Specifically, EPU weakens the positive impact of analyst reports on digital transformation but amplifies the inhibitory effect of supplier concentration on it. However, it is noteworthy that customer concentration's influence on digital transformation is not affected by EPU.

First, the moderating effect of EPU on the relationship between analyst coverage and digital transformation is not reflected in the current period but in the lagged period, indicating that analysts typically make assessments and reports based on in-depth studies of the company and industry, focusing on long-term prospects (Brauer & Wiersema, 2018). When new economic uncertainties arise, analysts need time to collect, integrate, and process this information, re-evaluating their previous forecasts (Bonaime et al., 2018). Additionally, they may observe market and competitors' responses to EPU and how these changes affect the company's long-term strategy and performance (Brogaard & Detzel, 2015). Therefore, while short-term economic policy changes may immediately affect a company's decisions, analysts might reflect this change in their assessments only after a lag in EPU.

At the same time, this inhibitory moderation suggests that companies tend to adopt more conservative strategies when facing increased EPU (Bonaime et al., 2018). They consider not only their position but also the responses of their core external stakeholders, such as customers and suppliers (Freeman et al., 2010). To stabilize relationships with these key stakeholders, companies may choose to maintain the status quo, responding to their expectations. This means that although analysts may recommend digital transformation, companies might be more cautious in balancing risks and opportunities under high policy uncertainty, avoiding large-scale changes to secure their future cash flow and profitability. The result is consistent with conclusions that EPU inhibits financial development, corporate progress, and innovation, and that corporate strategy should be informed by a long-term outlook, rather than being solely driven by immediate economic conditions or policy shifts (Baker et al., 2016; Nagar et al., 2019; Waisman et al., 2015).

Second, EPU amplifies supplier concentration's inhibitory effect on corporate digital transformation. In high-EPU environments, companies become more reliant on a few key suppliers, giving these suppliers greater bargaining power (Wang et al., 2020b). Intrinsic uncertainty may make these key suppliers more conservative towards transformations like digitization, fearing potential disruptions to existing relationships or processes. Moreover, high EPU may strengthen dominant suppliers' opposition to digital transformation. They may view it as increasing existing uncertainties, leading them to be more conservative and less willing to support or participate in digital transformation (Cao, 2023). Therefore, in exacerbated EPU situations, the inhibitory impact of these suppliers on digital transformation is expected to increase. Market turbulence impedes the positive effects of supplier concentration on supplier integration, whereby EPU is frequently indicative of such market instability (Pástor & Veronesi, 2013). Meanwhile, the finding reveals a dimension of Stakeholder Theory that considers the economic context as a determinant of stakeholder influence. It suggests that the theory needs to account for the ways in which companies' dependencies on certain stakeholders, such as analysts and suppliers, can be exacerbated by economic instability, which in turn can either constrain or compel changes in corporate strategy.

However, as for customer concentration, its impact on digital transformation is not altered in the EPU environment. This could be because, in high-EPU conditions, digital transformation is influenced by multiple customer factors. For one, compared to suppliers, customers demonstrate different needs and expectations in strategic choices (Huang et al., 2016; Kale & Meneghetti, 2014). Although dominant customers may not be very optimistic about a company's digital reform in general conditions, their aversion does not significantly intensify under rising EPU. They are more focused on the quality, price, and stable supply of products and services, rather than the company's internal strategies and operational models (Li et al., 2023b). Furthermore, customers enjoy greater flexibility of choice in the market. If they are dissatisfied with a company's products or services, they can easily switch to other brands or suppliers. This freedom of choice in the market means that a high-EPU environment may not necessarily strengthen the inhibitory effect of customer concentration on digital transformation.

As important stakeholders, customers have divergent views on digital transformation in high-EPU scenarios; they may desire a better digital experience to some extent but also fear that such transformation could adversely affect their business (Hu & Yu, 2022). This divergence of attitudes in high-EPU environments may neutralize each other, statistically making the moderating effect of EPU on the relationship between customer concentration and digital transformation insignificant. The differential effects observed—where supplier concentration becomes a more significant force under EPU, while customer concentration does not—indicate that Stakeholder Theory could be refined to differentiate between types of stakeholders and the specific conditions under which their influence is magnified or muted (Freeman, 2001).

The Stakeholder Theory traditionally focuses on the importance of managing stakeholder interests within stable environments but does not explicitly address how fluctuating economic policies can alter stakeholder dynamics (Freeman et al., 2010). Therefore, this study's conclusions extend Stakeholder Theory by broadening its application scenarios to include the influence of macroeconomic environments, particularly EPU, on the relationship between companies and their external stakeholders.

5.3 Contributions of the Study

This study originates from the research gap in the factors influencing digital transformation. Much of the current literature is limited to discussing single variables or conventional scenarios, offering scarce attention to the real driving factors of digital transformation in terms of depth and breadth. In contrast, this research demonstrates an important innovation: for the first time, it integrates three major external stakeholders—analysts, customers, and suppliers—and ingeniously introduces EPU, providing a new and comprehensive perspective for interpreting the complex driving mechanisms of digital transformation. This unique research angle not only offers valuable insights for the ongoing advancement of the digital economy but also effectively fills a knowledge gap in academic literature.

5.3.1 Theoretical Contributions

This study delved into the driving factors of corporate digital transformation strategy, grounded in Stakeholder Theory. Not only does it provide a new application domain for this theory, but it also offers fresh research perspectives and theoretical support to the academic field of digital transformation.

Firstly, this research systematically integrates the perspectives of three key external stakeholders: analysts, customers, and suppliers. It provides an exhaustive analysis of their roles in corporate digital transformation strategies. This integrative research approach not only reveals the specific functions and importance of these three external stakeholders but also highlights their interactions and influences during the digital transformation process.

Secondly, by introducing EPU as a significant moderating variable, this study further deepens the understanding of how external stakeholders influence digital transformation against different macroeconomic backgrounds. This approach extends the depth of research on digital transformation’s influencing factors.

Most importantly, this research thoroughly considers the complexity of Stakeholder Theory. It investigates the impact of external stakeholders on digital transformation holistically, while also specifically analyzing the roles and influences of each stakeholder. This comprehensive and in-depth research approach provides new directions and insights for the academic field of digital transformation.

5.3.2 Practical Contributions

The practical significance of this study is particularly pronounced, enriching both corporate and governmental understanding of the multifaceted impacts of digital transformation and offering valuable strategic insights.

From a corporate perspective, this research presents a comprehensive method that integrates the demands of external stakeholders, including analysts, customers, and suppliers. Businesses can now move on from solely relying on experience or intuition for planning their digital transformation strategies. Instead, they can scientifically formulate strategies based on the findings of this research, combined with their actual circumstances and environmental variables. This not only prompts enterprises to view their digital transformation initiatives from a broader perspective but also allows for a more precise identification of their core competencies, positioning them distinctively in a fiercely competitive market. Furthermore, against various macroeconomic backdrops, corporations can draw on this study to tailor their strategies for optimal digital transformation outcomes. Moreover, the in-depth analysis of this research elucidates the bottlenecks and challenges in the digital transformation journey, guiding businesses to adopt pertinent measures for a successful transition.

5.3.3 Policy Contributions

For governments and relevant policymakers, this research offers a more detailed and holistic perspective on the intricate ecosystem of digital transformation. When formulating associated policies, governments can weigh the needs and considerations of all parties more precisely, ensuring policies not only promote technological and economic growth but also maintain a balance of interests among stakeholders, culminating in optimal policy effects. Notably, the study highlights the uncertainties of economic policies and their influence on corporate digital transformation, revealing potential risks arising from policy unpredictability. This compels governments to place greater emphasis on minimizing uncertainty, ensuring that businesses operate within a stable and conducive environment for digital transformation.

In sum, the profound contribution of this research lies in its establishment of a closer collaboration framework between corporations and governments. Within this framework, both parties transcend being mere collaborators to become joint innovators, collectively exploring the best pathways for digital transformation and economic and societal progress.

5.4 Limitations and Suggestions for Future Research

Firstly, a significant limitation of this study is the bounded nature of its sample. While data from the Chinese market holds substantial empirical significance, its generalization to enterprises in other countries and regions may be influenced by cultural, policy, and market structure differences. To ensure the global applicability of the research findings, future researchers should consider collecting and analyzing more extensive cross-national data. Additionally, future studies are encouraged to incorporate data from non-public companies to render the research more comprehensive.

Secondly, this study focused primarily on three types of external stakeholders: analysts, customers, and suppliers. However, the array of external stakeholders businesses encounter is much broader, including government entities, media, competitors, investors, communities, and non-governmental organizations. These groups can have direct or indirect impacts on a company's digital transformation. Future research should incorporate a more diverse range of stakeholders to construct a more complete and integrated impact framework.

Furthermore, the use of EPU as a moderating variable in this study represents just one dimension. Considering the complex interplay between digital transformation and its environment, future studies could introduce additional factors, such as technological advancements, international competition, and social changes, to elucidate their specific impacts on corporate digital transformation strategies.

Additionally, while this study has examined the overall impact of external stakeholders, it did not explore the specific channels or mechanisms through which they affect digital transformation. For instance, the demands of customers and suppliers might influence business operational risks, and analysts' reports could affect digital transformation by influencing corporate transparency. Future research should delve deeper into these specific mechanisms of influence.

Lastly, due to the availability of data, the indicators for digital transformation were based on information from corporate annual reports. This approach may overlook changes and innovations at the micro level. To more accurately reflect the true progress of digital transformation, future research should explore a broader range of data sources, such as internal corporate reports, employee surveys, customer feedback, or even direct data from digital technology applications, to build a more precise and comprehensive assessment system for digital transformation.

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