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The Spillover of Digital Transformation in Supply Chain Innovation

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Abstract

Based on a sample of Chinese listed firms from 2010 to 2024, this study employs a complex adaptive systems (CAS) lens to investigate the spillover effects of core-firm digital transformation (CDT) on innovation within supply chain networks. It reveals that CDT fosters supplier innovation while impeding customer innovation. Heterogeneity analysis shows that the spillover effect is more pronounced when suppliers (customers) are non-state-owned, larger, more competitive, and have more able managers. Mechanism analysis suggests that the spillover effect is realized through resource and competition mechanisms. This study contributes to the literature by integrating CAS theory with established supply chain management perspectives to provide a systemic understanding of digital transformation's ripple effects, offering valuable insights for both managers navigating digital ecosystem evolution and policymakers designing industrial innovation strategies.

Keywords: core-firm digital transformation; spillover effect; supplier innovation; customer innovation

1. Introduction

In an era of rapid technological advancement, digital transformation (DT) has become a strategic imperative for firms pursuing a sustainable competitive advantage [1]. However, the true nature of DT extends beyond organizational boundaries. It represents a systemic phenomenon that radiates throughout the interconnected supply chain networks where firms operate [2]. This systemic characteristic presents a challenge to traditional supply chain paradigms. These paradigms often rely on linear relationship models. Such models cannot adequately capture the complex, dynamic interdependencies of modern digital ecosystems [3].

A more accurate conceptualization views supply chains as Complex Adaptive Systems (CAS). This is a dynamic network where suppliers, core firms, and customers continuously interact, adapt, and co-evolve [4]. A core firm is defined as a dominant company occupying a central position in a supply chain network, coordinating flows of goods, information, and finances between numerous upstream suppliers and downstream customers [5]. Within the CAS framework, a core-firm digital transformation (CDT) initiative functions as a significant system perturbation rather than an isolated event. It propagates through network connections. In doing so, it triggers adaptive responses and generates emergent outcomes that may appear asymmetric from conventional perspectives. The existing literature has extensively documented DT's intra-firm effects, including on innovation [6], productivity [7], stock liquidity [8] and financial performance [9]. It has also begun exploring its peer effect within supply chains [10]. However, few studies have adopted a CAS lens to examine the spillover effects of core-firm digital transformation (CDT) on the innovation of

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upstream and downstream partners. The spillover effect refers to the indirect transmission of influence—such as knowledge, practices, or competitive pressures—from the core firm to its partners, extending beyond formal contracts.

This oversight leads to the central research questions: What is the spillover effect of CDT on the innovation behavior of supply chain partners? How does this effect differ between upstream suppliers and downstream customers? What are the underlying mechanisms driving these asymmetric spillover effects? To address these questions, this paper constructs a theoretical framework based on CAS theory to explain the differential impacts of CDT on partner innovation. Furthermore, it empirically validates the influence and distinct mechanisms for suppliers and customers. Finally, it considers the heterogeneous spillover effect of CDT on the innovation for upstream and downstream enterprises in different contexts.

This study provides new knowledge by developing and testing a theoretical model that explains the differential impacts (positive for suppliers, negative for customers) of CDT on partner innovation. It identifies and empirically validates the distinct mechanisms of "collaborative advantage/resource-pull" for suppliers and "competitive pressure/resource crowding-out" for customers. The study's theoretical value lies in integrating insights from Resource Dependence Theory, Knowledge-Based View, and Competitive Dynamics to offer a more nuanced understanding of digital transformation spillovers, moving beyond a simple approach.

2. Literature Review

2.1. Corporate Digital Transformation

This part conducts a literature review on the definition, driving factors, and practices of digital transformation (DT). First, DT is defined from both technological support [11,12] and organizational change perspectives [13,14]. For example, scholars represented by Valdez-De-Leon [15] and Westerman et al. [16] focus on examining the specific roles of new digital technologies within enterprises. Li et al. [17] also argue that this process is a transformation driven by information technology change. While this perspective usefully highlights enablers, it risks presenting an overly techno-centric view, potentially underestimating the profound organizational and strategic reconfigurations required. Meanwhile, researchers represented by Karimi and Walter [13] place greater emphasis on exploring changes in business models, operational processes, and ecosystems. This broader lens more accurately captures the holistic and disruptive nature of DT, though it may lack specificity regarding the technological catalysts that initiate such change. A more integrative definition that bridges technological enablers and organizational outcomes remains an area for further synthesis.

Second, research on the driving factors of digital transformation has focused on two aspects. One stream of research, rooted in the perspectives of enterprise characteristics and internal governance, identifies key drivers of digital transformation in organizational structure, culture, dynamic capabilities, innovation capacity, and executive characteristics [18,19]. This perspective valuably underscores managerial choice and internal preparedness but may understate the coercive or mimetic pressures from the environment. The other stream attributes digital transformation to the external environment, including factors such as fiscal and tax policies [20], shifts in social mechanisms [21], market competition [22], and pressures from external stakeholders [23]. Third, studies have centered on the implementation of digital transformation, identifying the formulation of strategy [24], management adaptability [25], and shifts in business models [15] as critical factors. While this view contextualizes DT within its macro-environment, it can sometimes downplay the variance in how different firms perceive and respond to these external forces.

Finally, research has documented the significant impact of DT at both macroeconomic and micro-level enterprise levels [26]. Studies link it to reduced costs [27] and enhanced operational performance [28]. It is also associated with improved production efficiency [29], greater innovation and R&D efficiency [30], and increased stock liquidity [31]. However, this literature has two limitations. First, it often reports associations rather than established causal relationships, with endogeneity concerns frequently unaddressed. Second, the focus is overwhelmingly on positive performance implications, creating a potential "success bias" in the discourse. While the benefits are well-documented, other dimensions of DT could be further explored. This includes investigating differential impacts on various stakeholders within networks—area our study seeks to explore.

2.2. Supply Chain Relationships and Their Impact

Research on supply chain enterprises, building on upstream–downstream linkages, typically follows two primary perspectives. The first examines the flow of production factors and the emergence of collaborative advantages [32,33]. This perspective highlights how interdependence can translate into mutual value creation beyond simple transactional exchanges. However, it often implies a somewhat stable, cooperative ideal, potentially understating the inherent tensions and power dynamics within these relationships. The second views these relationships as mechanisms for knowledge and information spillover, such as those driven by market competition and supply-demand forces [34,35]. This lens is powerful for explaining efficiency gains and innovation diffusion, yet it can sometimes present a relatively mechanistic view of learning, paying less attention to the social and relational fabric that enables or impedes such spillovers.

Studies have demonstrated that supply chain relationships significantly influence a wide array of corporate outcomes. These outcomes include performance [36–38], capital structure [39], cost of equity capital [40]. Furthermore, they influence access to bank loans [41], trade credit [42], as well as corporate innovation [32] and cash holdings [43]. A specific line of inquiry examines how inter-firm interactions foster knowledge spillovers and information sharing, thereby shaping corporate innovation [34,35]. For instance, Chu et al. [32] found that closer geographical proximity between suppliers and customers boosts supplier innovation. Expanding this view, Haushalter et al. [44] show that secondary social capital from these relationships enhances a firm's green innovation activities. While these studies map that and how spillovers occur in specific contexts, a question remains less explored: how does a core firm digital transformation, reconfigure these knowledge and resource flows differentially across the network, influencing innovation outcomes? The current literature, rich in documenting direct effects, provides a strong foundation but offers fewer answers to this complex, network-wide contingency.

2.3. The Supply Chain Relationships and Corporate Digital Transformation

A growing body of research has productively examined peer effects within supply chains [45,46]. Scholars like Ren et al. [10] have effectively demonstrated how a firm's DT is influenced by the DT status of its suppliers and customers. This line of inquiry has been extended to consider peer influence within broader contexts, such as industry clusters, geographic regions, or shared analyst networks [47,48]. Li et al. [49] further contributed by specifically validating the existence and unpacking the mechanisms—such as competitive pressure and learning—of DT peer effects within supply chain networks. These studies provide a foundation by establishing that DT is contagious along supply chain linkages and that firms' technological choices are interdependent.

However, its focus remains predominantly on the diffusion of the DT behavior itself. It explained why a firm might digitally transform because its partners did. But we know far

less about how a firm's DT then triggers changes in other fundamental strategic behaviors of those supply chain partners. Specifically, the critical leap from studying the contagion of the DT to understanding the contagion of its strategic consequences—such as how a core firm's DT reshapes the innovation activities of its suppliers and customers—remains largely unaddressed. In contrast, our study repositions a DT as a systemic perturbation. This perturbation sets off a new chain of adaptive reactions across the supply network—for instance, in innovation investment. This process requires both a new theoretical perspective and empirical verification—namely, testing whether the impact of DT varies across supply chain partners based on their different positions.

3. Theoretical Analysis and Research Hypothesis

3.1. Theoretical Framework: A Complex Systems Perspective

Based on CAS theory [50], we conceptualize the supply chain as an interconnected network where firms continuously interact, adapt, and co-evolve. Within this system, CDT acts as a significant perturbation, propagating through network connections and triggering adaptive responses that yield outcomes [51]. The positional context of each firm within the network—whether upstream (supplier) or downstream (customer)—shapes these adaptations [52]. This systemic perspective reveals that the same technological shock can generate opposing effects through distinct feedback mechanisms, leading to asymmetric innovation outcomes across the supply network [53].

We further ground our analysis in Coopetition Theory [54], which provides a framework for understanding how CDT creates simultaneous cooperative and competitive dynamics within the supply chain. The core firm's relationship with upstream suppliers is characterized by predominant cooperation, where digital transformation fosters collaborative advantage through knowledge sharing and joint capability development [55]. The collaborative advantage describes the benefit suppliers gain from being deeply integrated into the core firm's innovation system, leading to enhanced innovation capability through knowledge sharing and joint development. Conversely, the relationship with downstream customers is characterized by predominant competition, where the same digital transformation intensifies competitive pressure through market dominance and resource effects [1].

3.1.1. Impact on Upstream Suppliers: A Collaborative Pull Mechanism

For upstream suppliers, the CDT initiates a self-reinforcing positive feedback loop, positioning the core firm as a collaborative leader. Grounded in Resource Dependence Theory (RDT) [56] and the Knowledge-Based View (KBV) [57], this loop is powered by two primary forces. The first force is resource-pull. The core firm, in order to ensure the advancement and stability of its supply chain, will proactively provide resources to key suppliers, such as sharing digital technology platforms and R&D tools [58,59]. These resources have enhanced the innovation capabilities of the suppliers. The second force is collaborative advantage. The core firm, to ensure the stability and advancement of their own supply chains, will proactively establish a "cooperative R&D" relationship with key suppliers [60]. Through technical assistance and joint development, they deeply integrate suppliers into their innovation ecosystem, providing suppliers with cooperative advantages and thereby promote their innovation [61].

3.1.2. Impact on Downstream Customers: A Competitive Push Mechanism

For downstream customers, the CDT triggers a self-balancing negative feedback loop, wherein the core firm acts as a competitive threat. This loop is explained through the lens of competitive and efficiency theories [62] and driven by two primary forces. The first force

is resource crowding-out. To adapt to the core firm's new digital products [63], customers are often compelled to reallocate scarce resources, which directly diverts funding away from their independent R&D initiatives [64]. Faced with this pressure, downstream firms typically curtail long-term innovation investments to safeguard short-term operational stability [65]. The second force is competitive pressure. The core enterprise leverages its digital capabilities to extend to its downstream market [66]. For instance, it directly develops products or services targeted at end consumers [67]. This transforms it from a "partner" of the customers to a "direct competitor", posing a threat to the core business of the downstream customers, squeezing their profit margins and making it difficult for them to obtain sufficient resources for innovation investment [68].

Figure 1 presents a conceptual framework that captures the above view. It shows how the CDT propagates through distinct mechanisms. These mechanisms, in turn, generate asymmetric outcomes and foster the co-evolution of the entire network.

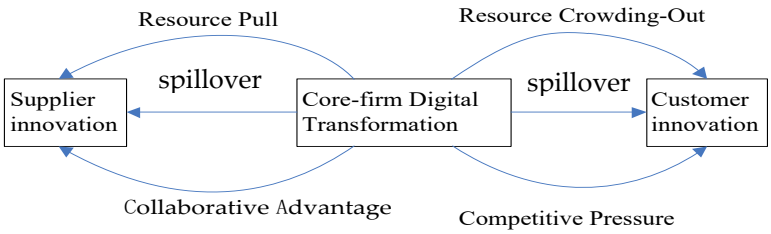

Figure 1. A conceptual framework.

The application of the CAS lens in this supply chain context, however, is subject to important boundary conditions. The responses and outcomes we theorize are not automatic or uniform. Their strength and nature are contingent on several contextual factors. Firstly, the relational embeddedness. The pre-existing depth of trust, information sharing, and mutual commitment between the core firm and its partners influences the quality of knowledge transfer and the potential for collaborative advantage. Secondly, partner absorptive capacity. The ability of suppliers and customers to identify, assimilate, and apply the knowledge and resources stemming from the core firm's DT is a critical factor of the spillover effects. Thirdly, technological characteristics. The modularity, compatibility, and complexity of the digital technologies being adopted affect the ease and cost of their diffusion and integration across the network.

3.2. The Hypothesis of CDT Impact on Suppliers' Innovation

CDT is not an isolated event but generates significant spillover effects through the supply chain network, influencing the innovation of upstream suppliers. Based on Resource Dependence Theory and the Knowledge-Based View, this study argues that this impact is positive, meaning the CDT promotes innovation among upstream suppliers. The reasons are as follows.

Firstly, the core enterprise is often a critical source of resources for suppliers from the perspective of Resource Dependence Theory [69]. When a core enterprise undergoes digital transformation, such as by implementing new digital procurement systems and establishing collaborative digital platforms [70], it sends some resources to its suppliers [71]. The core enterprise shares resources such as technical platforms and R&D tools with suppliers. This enables suppliers to lower the barriers and costs of innovation [17]. At the same time, the core enterprise can also collaborate on R&D projects, combining its own expertise with that of the suppliers, to jointly explore new technological fields [72]. This behavior directly translates into increased R&D investment, upgrades in suppliers' own technological capabilities, thereby stimulating innovation [73].

Secondly, the Knowledge-Based View and Coopetition Theory provides another mechanism for this facilitating effect: collaborative advantage [74]. The knowledge accumulated by the core enterprise during its digital transformation regarding digital technology application, data analytics, smart manufacturing, etc., is not entirely confined within its organizational boundaries [75]. Through close supply chain collaboration, such as co-participation in product design, sharing real-time production data, and communication via unified cloud platforms, knowledge inevitably spills over upstream to suppliers [33]. Consequently, suppliers gain access to advanced technological knowledge and managerial expertise at lower cost and risk, thereby enhancing their own absorptive capacity and innovation efficiency [76]. This implies that the CDT not only "compels" suppliers to innovate but also "empowers" them to do so by reducing the uncertainty associated with innovation [77].

In summary, via resource pull and collaborative advantage mechanisms, the CDT creates incentives and provides knowledge for upstream supplier innovation. Therefore, the study proposes the following research hypothesis:

H1: *The CDT has a significant positive impact on the suppliers' innovation.*

3.3. The Hypothesis of CDT Impact on Customers' Innovation

In contrast to the facilitating effect on upstream suppliers, the CDT is more likely to inhibit the innovation of downstream customers. This study draws primarily on Competitive Theory and Efficiency Theory to argue for this potential negative impact.

Firstly, grounded in Competitive Theory, a CDT can significantly enhance its product competitiveness, operational efficiency, and market power [68]. This strengthens its dominant position within the value chain, potentially squeezing the profit margins of downstream customers [4]. When customers face increased bargaining pressure and competitive threats from the more powerful core enterprise, their operational uncertainty rises. Consequently, the internal cash flow available for long-term investments may diminish [78]. Under such survival pressure, customer firms often adopt more conservative strategies, tending to cut back on long-term and high-uncertainty investments like R&D to maintain short-term financial stability [79]. Therefore, the competitive pressure effect arising from the CDT may directly curb downstream customers' motivation to innovate.

Secondly, from the perspective of Efficiency Theory, the CDT forces downstream customers to invest substantial resources in adaptive adjustments [25]. For instance, customers must allocate funds and personnel to learn new digital systems and reconfigure their business processes to interface with the core enterprise's new digital platform [28]. These relationship-specific investments made for adaptation can crowd out the scarce resources originally earmarked for the customers' own innovation projects, creating a resource crowding-out effect [79]. Thus, customers' innovation activities are constrained as their resources are diverted to adaptive purposes.

In summary, via competitive pressure and resource crowding-out mechanisms, the CDT may deteriorate the innovation environment for downstream customers and limit their investment in innovation resources. Therefore, the study proposes the following research hypothesis:

H2: *The CDT has a significant negative impact on customers' innovation.*

To clearly demonstrate the different impacts of the CDT on upstream and downstream partners, this paper presents Table 1. It compares these varying effects and their driving factors.

Table 1. The Mechanism comparison of the impact of CDT on the SI/CI.

Dimension	Upstream Suppliers	Downstream Customers
Primary logic	Cooperation, Value co-creation	Competitive, value appropriation
Core mechanisms	Resource pull Collaborative advantage	Competitive pressure Resource crowding-Out
Theoretical anchors	Resource Dependence Theory, Knowledge-Base View	Competitive dynamics Theory, Efficiency Theory
The hypothesized net effect on partner innovation	Positive (H1)	Negative (H2)
Systemic feedback loop	Self-reinforcing	Self-balancing

3.4. The Hypothesis on the Moderating Effect of Supply Chain Efficiency

The impact of CDT on innovation in upstream and downstream enterprises may be moderated by supply chain efficiency. The reasons are as follows.

For upstream enterprises, the level of supply chain efficiency positively moderates the impact of CDT on supplier innovation, as higher efficiency reflects closer collaboration and interdependence with the core enterprise [32]. Within a high-efficiency supply chain system, suppliers can better understand the core enterprise's needs. This enhances them to more precisely position their own markets and products [36]. Digital transformation provides suppliers with data support and management tools via digital technology platforms. This enables them to respond rapidly to market changes and optimize their production and management processes. Consequently, production efficiency and profitability improve, which in turn fosters innovation [80]. For downstream enterprises, however, higher supply chain efficiency tends to amplify the inhibitory effect of CDT on innovation [68]. This occurs because operating within a highly efficient system fosters conservatism. Downstream firms may deem the existing model sufficiently optimal, thereby perceiving scant need for improvement or innovation [81]. Based on the above analysis, the study proposes the following research hypothesis:

H3: *Supply chain efficiency plays a mediating role between the CDT and the innovation of upstream and downstream enterprises.*

4. Data and Methodology

4.1. Sample Source

This study examines the impact of digital transformation in core enterprises on the innovation activities of their upstream and downstream partners. Here, a 'core firm' refers to a focal firm that occupies a central and influential position within its supply chain network. This centrality is derived from its relative size, market power, brand dominance, or control over critical technologies and distribution channels [5]. For our empirical analysis, core firms are identified as the major, publicly listed firms at the center of the supplier-customer relationships in our dataset. The sample of this study consists of Chinese listed companies from 2010 to 2024. Regarding supply chain data, information on the top five suppliers and customers of listed firms was collected from the China Stock Market & Accounting Research (CSMAR) database. The dataset comprised only those cases in which both the suppliers and customers were listed firms. Following the approach of Tao [28] and Li et al. [72], the study constructs a dataset structured by year–core firm–upstream/downstream. For instance, a core firm (X) in a given year (e.g., 2010) might correspond to multiple upstream suppliers (A, B, C) or multiple downstream customers (a, b, c). Accordingly, observations were constructed as X–A–2010, X–B–2010, X–C–2010,

X–a–2010, X–b–2010, X–c–2010. The study excluded samples of ST and PT companies (facing delist or special treatment) and those with missing financial data. Continuous control variables were winsorized at the 1% level. Ultimately, the final datasets comprise 1921 core firm–upstream supplier–year observations and 2920 core firm–downstream customer–year observations for the period 2010 to 2024.

4.2. Variable Measurement

4.2.1. The Innovation in Upstream and Downstream Enterprises (IN)

Following the approach of Custódio et al. [82] and Manso [83], the study measures supplier (customer) innovation using the number of patent applications filed by publicly listed companies. Specifically, innovation is initially calculated as the sum of invention and utility model patent applications. To address the right-skewed distribution, we add one to this count and take its natural logarithm. These data are then matched with the annual records of core enterprises. For robustness tests, the study employs two alternative measures: the number of patent applications (INA) and the ratio of R&D expenditure to total assets (RD).

4.2.2. Core-Firm Digital Transformation (CDT)

This study employs a text analysis method, drawing on the approach of Wu et al., [31] to quantify core-firm digital transformation (DIG1). Using Python 3 crawlers, the study retrieves the full text of annual reports of listed companies and constructed a dictionary of digital transformation keywords. The dictionary is categorized into foundational technologies (e.g., "big data," "cloud computing," "artificial intelligence," "blockchain") and application technologies (e.g., "smart manufacturing," "digital marketing"). The detailed structured feature word map for digital transformation is shown in Appendix A.1. A quantitative indicator of digital transformation was developed by counting and weighting the frequency of these keywords. The validity of this method lies in the fact that annual reports, as formal legal documents, clearly reflect the strategic priorities and future direction of management. A higher frequency of digital transformation-related vocabulary indicates a stronger emphasis and greater strategic commitment by the company to this field. Numerous empirical studies have shown that this indicator is significantly positively correlated with future firm performance metrics such as innovation output and total factor productivity [28,31].

Furthermore, to ensure the robustness of the results, this paper also employs two other methods to measure the core firm digital transformation. One method to measure core firm digital transformation (DIG2) follows the approach of Zhao et al. [84]. This method captures keywords related to digital transformation from management discussions and analysis (MD&A). It counts frequencies of 99 digital-related words across four dimensions: digital technology application, internet business model, intelligent manufacturing, and modern information systems to measure the DT. The detailed dictionary information is shown in Appendix A.2.

The other method is to measure the core firm digital transformation (DIG3) using the proportion of digital intangible assets and intangible assets, which shows the digital investment of the enterprise over time from the asset perspective.

It is important to emphasize that these three indicators capture the characteristics of digital transformation from different yet complementary perspectives. DIG1 reflects the strategic emphasis and discursive commitment of management toward digital transformation, focusing on the digital orientation demonstrated in strategic communication. DIG2 captures concrete digital practices at the operational level, using structured dimensions to identify actual digital initiatives discussed in management discussions. DIG3 mea-

sures substantive investments in digitalization from a resource allocation perspective, providing objective evidence based on financial statements.

These three measurement methods differ in conceptual focus and data sources. DIG1 relies on the full text of annual reports, employs a weighted word frequency approach, and emphasizes comprehensive strategic disclosure. DIG2 is based on Management Discussion & Analysis (MD&A) texts, adopts a structured dictionary method, and focuses on implementation-specific terminology. DIG3 utilizes a financial accounting approach, calculating the proportion of digital intangible assets. Therefore, consistent findings across these three distinct methodologies would significantly enhance the robustness of the conclusions. This demonstrates that the identified relationships are not dependent on any single measurement approach but are robust across different conceptualizations and data sources.

To provide clarity on our measurement strategy, Table 2 offers a systematic comparison of the three digital transformation indicators used in this study. Each indicator captures a distinct yet complementary dimension of the multifaceted digital transformation construct.

Table 2. Comparison of DT measurement approaches.

Dimension	DIG1 (Textual Frequency from Annual Reports)	DIG2 (Structured Dictionary from MD&A)	DIG3 (Digital Intangible Assets Ratio)
Conceptual Purpose	Measures strategic emphasis and discursive commitment to digital transformation at the corporate level	Measures operational focus and implementation specifics discussed in the management's narrative.	Measures tangible resource commitment and capitalization of digital investments.
Theoretical Basis	Upper Echelons Theory, Strategic Communication	Attention-Based View, Managerial Cognition	Resource-Based View, Accounting Representation
Data Source	Full text of annual reports	Management Discussion & Analysis (MD&A) section	Financial statements (Intangible assets disclosures)
Empirical Characteristics	Weighted keyword frequency, reflects breadth of digital awareness	Structured, multi-dimensional keyword count, reflects depth of digital practices	Financial ratio, Objective, monetized measure
Primary Strength	Captures the overall strategic priority and visibility of DT across the entire organization	Provides granularity on the specific domains and applications of DT as prioritized by management	Offers a hard, verifiable measure of financial investment in digital assets
Inherent Limitation	A declarative measure; may not fully reflect the degree of operational implementation.	Limited to the context and style of the MD&A section.	May not capture expensed investments (e.g., salaries, cloud fees) or strategic initiatives not capitalized.

To validate the effectiveness of our measure, we conducted a test using Midea Group (000333) which is a leading home appliance manufacturer. The study analyzed the annual reports of Midea from 2015 to 2024. The analysis shows a dramatic increase in its digital transformation word frequency, aligning with its real-world initiatives. During this period, Midea heavily invested in building intelligent "Lighthouse" factories, implemented a comprehensive industrial internet platform (Midea IoT), and underwent a profound digital shift in its business model.

4.2.3. Control Variables

Additionally, following the studies by Yang [68] and others [10], an array of control variables is incorporated in the dataset. The control variables include Leverage Ratio (Lev), Cash Flow Ratio (cash), Enterprise Profitability (Roa), the Number of Board (Board size) and Enterprise Size (size). Subsequently, these control variables were merged with the data for upstream and downstream enterprises to form the complete dataset.

4.3. Model Setting

Our study investigates how a CDT spills over to the innovation of supply chain partners. This is a longitudinal question as these effects unfold over time. The panel data model is suited for this analysis. Because it allows us to control for unobserved, time-invariant heterogeneity across firms, such as a firm's inherent management culture, long-term strategic positioning. The study incorporates industry, year, and province fixed effects to account for a wide range of potential confounders. For instance, the year fixed effects control for time-varying shocks common to all firms, while province fixed effects control for regional policies such as local digital subsidies. This approach isolates the net effect of the core firm's transformation, which a simple cross-sectional model or a basic panel model could not achieve. Therefore, this paper employs multi-dimensional fixed effect regression method to test the impact of CDT on the innovation of upstream and downstream enterprises, formulating Model (1).

$$IN_{j,t+1}^{s(c)} = \alpha_0 + \alpha_1 DIG_{i,t} + \alpha_2 Controls_{j,t} + \alpha_3 Year_t + \alpha_4 Ind_j + \alpha_5 Prov_j + \varepsilon_{i,t}, \quad (1)$$

where $IN_{j,t+1}^{s(c)}$ is the dependent variable, representing supplier(customer) innovation. SUP_ and CUS_ prefixes are used in the variable definition table (Table 3) to distinguish supplier and customer variables, respectively. During empirical testing, separate regressions are performed for supplier (customer) innovation. $DIG_{i,t}$ is the explanatory variable, representing the degree of core firm digital transformation. $Controls_{j,t}$ denotes the control variables. Additionally, this study controls for year ($Year_t$), industry (Ind_j) and province ($Prov_j$) fixed effects. Detailed definitions of the main variables are shown in Table 3.

Table 3. Definition of variables.

Variables	Definition	Measurement
Sup-IN	Supplier innovation	Logarithm of one plus patent number of supplier
Sup-RD	Supplier R&D investment	Supplier R&D expenditure divided by assets
DIG	Core enterprises of digital transformation	Word frequency of "digital transformation" in core firms' annual reports
Sup-Lev	Supplier debt-to-asset ratio	Total liabilities divided by total assets
Sup-cash	Operating cash flow ratio	Operating cash flow divided by current liabilities
Sup-Roa	Supplier profitability	Net income divided by revenue
Sup-size	Supplier size	Logarithm of total assets
Boardsize	Board Size of supplier	the number of directors of supplier board
Cus-IN	Customer innovation	Logarithm of patent count for customer
Cus-RD	Customer R&D investment	Customer R&D expenditure divided by assets
DIG	Core enterprises of digital transformation	Word frequency of "digital transformation" in core firms' annual reports

Table 3. *Cont.*

Variables	Definition	Measurement
Cus-Lev	Customer debt-to-asset ratio	Total liabilities divided by total assets of customer
Cus-cash	Operating cash flow ratio	Operating cash flow divided by current liabilities of customer
Cus-Roa	Customer profitability	Net income divided by revenue of customer
Cus-size	Customer size	Logarithm of total assets for customer
Cus-Boardsize	Board Size of customer	the number of directors of supplier board

The descriptive statistics of the main variables are presented in Table 4. The mean value of supplier innovation (Sup-IN) is 4.520 with a standard deviation of 1.610. The mean value of customer innovation (Cus-IN) is 4.741 with a standard deviation of 1.890. The mean innovation level of downstream firms is slightly higher than that of upstream firms, suggesting that downstream firms are more willing to adopt new technologies or exhibit greater innovation in their products and services. The standard deviation of innovation among downstream firms is also slightly higher, indicating variation in innovation levels across downstream firms.

Table 4. Descriptive statistics of variables.

Variables	Observations	Mean	Standard Deviation	Min	Max
Sup-IN	1921	4.520	1.610	0.690	9.710
Sup-RD	1921	2.365	2.218	0.000	16.947
C-S-DIG	1921	2.758	1.281	0.000	6.631
Sup-Lev	1921	0.504	0.192	0.027	1.050
Sup-cash	1921	0.060	0.074	−0.292	0.437
Sup-Roa	1921	0.046	0.065	−0.276	0.695
Sup-size	1921	23.679	1.979	19.664	30.995
Sup-Boardsize	1921	2.322	0.204	1.609	2.944
Cus-IN	2920	4.741	1.890	0.690	11.28
Cus-RD	2920	2.261	2.552	0.000	73.780
C-C-DIG	2920	2.740	1.356	0.000	6.412
Cus-Lev	2920	0.598	0.198	0.034	1.357
Cus-cash	2920	0.055	0.092	−3.076	0.488
Cus-Roa	2920	0.039	0.053	−0.488	0.655
Cus-size	2920	24.685	2.609	18.671	31.519
Cus-Boardsize	2920	2.374	0.236	0.000	2.996

4.4. Correlation and Multicollinearity Analysis

The correlation analysis is shown in Table 5. Most variables are significantly correlated with each other at the 1% level, which is common in large-scale empirical studies. The strength and sometimes even the direction of these relationships differ notably between upstream and downstream firms, highlighting distinct operational and financial dynamics. Its relationship with the dependent variable IN is positive for upstream firms (0.065 **) but strongly negative for downstream firms (−0.203 ***). This is a critical finding, suggesting the effect of CDT is fundamentally different across these two groups. It reveals a positive association between digital transformation (DIG) and innovation (IN) for upstream firms, but a negative one for downstream firms, justifying our separate analysis.

Table 5. The Correlation Analysis.

Variables	IN	DIG	Lev	Cash	Roa	Size	Boardsize
Panel A: Core—upstream firm							
DIG	0.065 **	1					
Lev	−0.067 ***	0.177 ***	1				
cash	0.014 **	−0.021 **	−0.230 ***	1			
Roa	0.093 ***	−0.065 ***	−0.433 ***	0.355 ***	1		
size	−0.121 ***	0.308 ***	0.568 ***	0.066 ***	−0.131 ***	1	
Boardsize	−0.037 *	0.051 ***	0.347 ***	−0.063 ***	−0.077 ***	0.452 ***	1
Panel B: Core—downstream firm							
DIG	−0.203 ***	1					
Lev	−0.240 ***	−0.130 ***	1				
cash	0.00300	−0.0350	−0.190 ***	1			
Roa	0.135 ***	0.042 *	−0.452 ***	0.511 ***	1		
size	−0.202 ***	−0.069 ***	0.355 ***	0.207 ***	−0.0400	1	
Boardsize	−0.165 ***	−0.205 ***	0.116 ***	0.154 ***	0.058 **	0.363 ***	1

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The multicollinearity diagnosis is as shown in Table 6. The variance inflation factor (VIF) test indicates a low level of multicollinearity, with a mean VIF of 1.35 for the variables in the core-upstream model. A similar pattern was observed for the relationship between the core firm and its downstream customers, indicating a low level of multicollinearity with a mean VIF of 1.32. This falls within an acceptable range, indicating that the regression results are stable and reliable. The vast majority of variables (e.g., Lev, Roa, Boardsize, cash, DIG) have VIF values well below 2, showing no significant correlation with other independent variables, indicating that multicollinearity does not pose a problem for our analysis.

Table 6. Multicollinearity Diagnosis.

Variable	Core—Upstream Firm		Core—Downstream Firm	
	VIF	1/VIF	VIF	1/VIF
Roa	1.640	0.612	1.530	0.654
Lev	1.480	0.678	1.480	0.674
cash	1.450	0.692	1.450	0.691
size	1.350	0.742	1.360	0.734
Boardsize	1.170	0.857	1.060	0.944
DIG	1.060	0.945	1.050	0.954
Mean VIF	1.350		1.320	

5. Empirical Results

5.1. Baseline Results

Table 7 shows the benchmark regression results of the CDT and the innovation of upstream and downstream enterprises. Columns (1)–(3) focus on the core firm and upstream enterprises. All three measures of CDT show a positive and statistically significant

coefficient (0.052, 0.194, 0.059, respectively) at the 1% level. This robust finding across different measures confirms that a CDT is strongly associated with increased innovation from its suppliers. Columns (4)–(6) use the core firm and downstream enterprises as the research sample. The model specifications are consistent with those in columns (1)–(3). The regression results show that the coefficient for CDT is significantly negative at the 1% level. This indicates that CDT significantly inhibits innovation in downstream enterprises. This finding remains stable when using alternative measures such as DIG2 and DIG3. This suggests that CDT stimulates innovation among its suppliers but hinder innovation among its customers. Columns (1)–(6) of Table verify hypothesis H1.

Table 7. Baseline regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	IN	IN	IN	IN	IN
DIG	0.052 ***			−0.009 ***		
	(4.99)			(−3.14)		
DIG1		0.194 ***			−0.005 ***	
		(4.34)			(−5.16)	
DIG2			0.059 ***			−0.016 ***
			(3.37)			(−2.94)
Lev	−1.641 **	−1.232 ***	−1.422 **	−0.760 **	−0.539 ***	−0.502 ***
	(−2.52)	(−2.67)	(−2.52)	(−2.85)	(−14.70)	(−11.84)
cash	0.564 ***	0.767 ***	0.409 ***	0.575 ***	0.538 **	0.265 ***
	(3.45)	(3.82)	(3.35)	(4.53)	(2.74)	(3.31)
Roa	0.115 **	1.147 ***	0.678 ***	3.518 ***	3.869 ***	4.666 ***
	(2.08)	(4.02)	(3.50)	(3.61)	(3.77)	(3.72)
size	−0.059 ***	−0.047 ***	−0.072 ***	−0.020 ***	−0.060 ***	−0.055 ***
	(−2.82)	(−6.90)	(−3.12)	(−4.09)	(−7.06)	(−4.86)
Boardsize	−0.108 **	−0.193 ***	−0.210 **	−0.754 **	−0.508 ***	−0.668 ***
	(−2.27)	(−3.33)	(−2.59)	(−1.98)	(−3.11)	(−3.16)
Obs.	1921	1921	1921	2920	2920	2920
Fixed effect	YES	YES	YES	YES	YES	YES
Adj.R^2	0.373	0.394	0.380	0.373	0.394	0.380

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.2. Robustness Tests

To further ensure the reliability of the regression results, this study adopts the following methods for robustness checks.

5.2.1. Substituting the Dependent Variable

Table A1 in the Appendix B presents the results of a robustness check for a study examining the relationship between a CDT and the innovation of suppliers and customers. The robustness test involves replacing the measure of supplier (customers) innovation with two alternative, widely accepted proxies: patent applications (INA) and the ratio of R&D expenditure to total assets (RD). The coefficient of DIG on INA is 0.211 in column (1), and that on RD is 0.024 in column (2), both are significant at the 1% level. This indicates a strong positive relationship. A CDT is associated with a significant increase in patent filings by its suppliers and their investment in R&D. Conversely, for customers, the coefficient of

DIG1 on INA is −0.144 in column (3), significant at the 5% level. Its coefficient on RD is −0.031 in column (4), significant at the 1% level. This indicates a significant negative relationship between CDT and customer innovation, meaning the CDT is associated with a decrease in patent filings and reduces R&D budgets for customers. This robustness check strongly validates the main study's finding that the impact of digital transformation is not monolithic. It can simultaneously foster innovation in one part of the value chain (upstream) while potentially stifling it in another (downstream).

5.2.2. Adjust the Sample Period

Table A2 in the Appendix B presents the results of a robustness check where the regression analysis was re-run after excluding data from the years 2020–2022. The purpose is to verify if the findings of the study hold outside the period of significant economic and social disruption caused by the COVID-19 pandemic. The coefficients of CDT on supplier innovation are 0.079, 0.147 and 0.025, significant at the 1% level. On the contrary, the coefficients of CDT on customer innovation are −0.033, −0.017 and −0.034, significantly negative at the 1% and 5% levels. The results indicate that CDT fosters supplier innovation while suppressing innovation among downstream partners. These findings are consistent with the baseline regressions, confirming that the core conclusions are robust and not driven by period-specific factors.

5.3. Endogeneity Tests

5.3.1. Controlling for Omitted Variables

Although the regression model includes a comprehensive set of control variables, unobserved factors may still influence the relationship between CDT and innovation in upstream/downstream firms. To address this, the model simultaneously controls for year and province fixed effects(Year#Province), and controls for year and industry fixed effects(Year#Industry). These specifications control for time-varying industry shocks (e.g., tech innovation waves) and region-specific temporal trends (e.g., provincial policy changes). The results are shown in Table A3 in Appendix B; the regression results remain consistent with the baseline findings after incorporating these interaction fixed effects, confirming robustness against omitted variable bias.

5.3.2. Instrumental Variables (IV) Approach

This study acknowledges the potential for endogeneity arising from the mutual influence between CDT and partner innovation. For instance, highly innovative suppliers could incentivize the core firm to accelerate its digital transformation. To address this concern, the study employs an instrumental variable strategy. The construction of the instrumental variable follows the approach of Lewbel [85] and Yang et al. [68]. The instrumental variable (IV) for the CDT is the cube of the deviation between a firm's digitalization level and the average digitalization level of its secondary industry within the same province. This selection satisfies the two key conditions for a valid instrument variable.

First, the relevance condition. A firm's transformation decision is significantly influenced by peer firms within its industry and province. The deviation from the average level creates competitive pressure or a demonstration effect, which substantially impacts the firm's transformation efforts. This is confirmed by the robust results of the first-stage regression in Column (1) and (3) of Table 8. The regression coefficients are 0.751 and 0.814, both significantly positive. It indicates that the instrumental variable is significantly correlated with the independent variable.

Table 8. Instrumental variables approach.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	DIG	IN	DIG	IN
IV	0.052 ***		0.814 ***	
	(24.97)		(56.71)	
DIG		1.278 **		−4.524 ***
		(2.10)		(−6.09)
Obs.	1921	1921	2920	2920
F-statistic	113.20	109.12	185.43	176.46
Fixed effect	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj.R^2	0.274	0.315	0.276	0.327

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Second, the exclusion restriction. After controlling for high-dimensional fixed effects—including industry, province, and year—the instrumental variable captures only the firm's 'idiosyncratic performance' relative to its external environment. This 'relative position' is exogenous. It can only influence downstream innovation by first affecting the CDT behavior and then transmitting this effect through supply chain relationships. Therefore, this instrumental variable is valid. The coefficients of columns (2) and (4) are 1.278 and −4.524, which is consistent with the benchmark regression results, and it is assumed that H1 is further validated

6. Mechanism Analysis

6.1. Resource Mechanism

6.1.1. Resource Pull

Drawing on our theoretical analysis and hypotheses, CDT may exert a resource-pulling effect on upstream enterprises, thereby fostering their innovation. This section empirically tests the hypothesized resource-pull mechanism. To this end, the study uses supplier R&D expenditure (RDs) as the proxy variable and conducts a stepwise regression following the mediation effect method. The results are presented in columns (1)–(3) of Table 9. Specifically, Column (2) reports the effect of the independent variable (DIG) on the mediating variable (RDs). The coefficient of DIG is 0.061, which is significantly positive at the 1% level, indicating that the CDT has driven the supplier's R&D. Column (3) presents the regression results when the mediator is included alongside the independent variable to explain the dependent variable. It can be seen that the coefficient of DIG is 0.131 and RDs is 1.033, both significantly positive at the 1% level. It indicates that the increase in R&D investment further enhances the supplier innovation, and the resource-pull mechanism is established. This represents a reduction in innovation costs and risks for suppliers, as they gain access to shared resources without bearing the full investment burden.

Table 9. Resource mechanism tests.

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	RDs	IN	IN	RDs	IN
DIG	0.194 ***	0.061 ***	0.131 ***	−0.009 ***	−0.023 ***	−0.032
	(4.34)	(2.67)	(3.94)	(−3.14)	(−3.10)	(−1.20)

Table 9. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	RDs	IN	IN	RDs	IN
RDs			1.033 ***			−1.152 ***
			(11.90)			(−6.95)
Cons.	−2.032 *	−8.272 ***	6.514 ***	0.132	−4.535 ***	−5.356 **
	(−1.88)	(−9.54)	(5.59)	(0.04)	(−4.82)	(2.54)
Obs.	1921	1921	1921	2920	2920	2920
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.394	0.773	0.611	0.283	0.830	0.454

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

6.1.2. Resource Crowd-Out

According to theoretical analysis and research hypotheses, the CDT may have a resource extrusion effect on downstream enterprises, thereby inhibiting customer innovation. To verify the resource crowd-out mechanism between CDT and customer innovation, the study employs customer R&D expenditure as the proxy variable and conducts a stepwise mediation analysis. The regression results are presented and analyzed in (4)–(6) of Table 9. The coefficient of DIG is −0.023 from the Column (5), it can be seen that the CDT has reduced the R&D investment of customers. In Column (6), it can be observed that the reduction in customer R&D investment further inhibited their innovation. That is, the resource crowd-out mechanism has been established. It indicates that finite resources are diverted from potentially high-return innovation projects to adaptive expenditures.

6.2. Competition Mechanism

6.2.1. Collaborative Advantage

In order to verify whether the CDT can promote suppliers' innovation by enhancing their collaborative advantages, this paper measures the level of collaboration using the inventory turnover rate (ITR) of suppliers. The inventory turnover ratio (ITR) is equal to the operating cost divided by the average inventory. The regression results are presented in columns (1)–(3) of Table 10. Column (2) indicates that a higher level of CDT is associated with a more pronounced supplier collaboration advantage (ITR), as shown by the significantly positive coefficient for DIG (0.031, $p < 0.01$). Furthermore, this collaboration advantage itself significantly promotes supplier innovation, with a coefficient of 2.932 ($p < 0.01$). These findings collectively verify our hypothesis. They indicate that CDT enhances innovation efficiency by reducing coordination costs and information asymmetries, allowing suppliers to convert inputs into innovative outputs more effectively.

Table 10. Competition mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	ITR	IN	IN	HHI	IN
DIG	0.194 ***	0.031 ***	0.020 ***	−0.009 ***	0.302 ***	−0.014 **
	(4.34)	(2.81)	(4.44)	(−3.14)	(6.19)	(−2.41)
ITR (HHI)			2.932 ***			−1.058 ***
			(2.75)			(−9.43)
Cons.	−2.032 *	0.097 **	−2.537 **	0.132	−0.121 **	−1.161
	(−1.88)	(2.52)	(−2.35)	(0.04)	(−2.36)	(−0.46)

Table 10. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	ITR	IN	IN	HHI	IN
Obs.	1921	1921	1921	2920	2920	2920
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.394	0.669	0.408	0.283	0.591	0.283

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

6.2.2. Competitive Pressure

To verify whether the CDT has increased the competitive pressure on customers and thereby hindered their innovation, this section uses the reciprocal of the Herfindahl Index (Inverse HHI) to measure the degree of customer competition. The Inverse Herfindahl-Hirschman Index (1/HHI) is a standard industrial organization metric for market competition intensity. The HHI itself is calculated as the sum of squared market shares of all firms in an industry, measuring concentration. Its inverse thus captures fragmentation: a higher value indicates a less concentrated market with more competitors, and therefore, more intense competition. The regression results are shown in (4)–(6) of Table 10. The coefficient of DIG on HHI is 0.302 in Column (5), which is significantly positive, indicating that the CDT has increased the competitive level of customers. Furthermore, the coefficient of HHI is −1.058 in Column (6), suggesting that customers competition inhabit their innovation. This finding aligns with the economic intuition of "competition crowding out innovation." As the core firm advances digitalization and strengthens supply chain integration, downstream customers are forced into more intense homogeneous competition to maintain their market position. Consequently, their strategic focus shifts from long-term R&D to short-term survival, which diminishes both the resources and motivation for innovation, ultimately leading to a decline in overall innovation levels.

6.3. The Moderating Effect of Supply Chain Efficiency

To examine the moderating role of supply chain efficiency, the study augments the model by adding an interaction term between supply chain efficiency and CDT. Supply chain efficiency is measured by inventory turnover (AD). As shown in Column (1) of Table 11, the interaction term is positive and significant at the 1% level. This indicates that higher supply chain efficiency strengthens the positive effect of CDT on supplier innovation. The finding highlights supply chain efficiency as a key moderator in technology diffusion. By fostering transparency, speed and trust, an efficient supply chain enables suppliers to better assimilate digital knowledge, thereby allowing the CDT to more effectively spur upstream innovation. The regression results in Column (2) show a significantly negative interaction term. This suggests that higher supply chain efficiency amplifies the inhibitory effect of CDT on customer innovation.

Table 11. The moderating effect of supply chain efficiency.

	(1) Core—Upstream Firm	(2) Core—Downstream Firm
DIG	0.029	−0.031
	(0.49)	(−0.83)
AD_SC	−0.003 **	−0.010 ***
	(−2.18)	(−2.70)
DIG×AD_SC	0.001 ***	−0.003 ***
	(2.81)	(−2.93)

Table 11. *Cont.*

	(1) Core—Upstream Firm	(2) Core—Downstream Firm
Obs.	1410	1763
Fixed effect	Yes	Yes
Control Variables	Yes	Yes
Adj.R^2	0.418	0.284

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

7. Heterogeneity Analysis

This section conducts a heterogeneity analysis. Specifically, the study examines whether the impact of the CDT on upstream and downstream innovation varies according to firm-level characteristics, including equity nature and firm size, as well as industry-level conditions such as the intensity of market competition.

7.1. Firm Nature Heterogeneity

According to the nature of supplier (customer) property rights, the sample is divided into state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). The regression results are shown in Table 12. Columns (1) and (2) show that the impact of CDT on innovation is more pronounced for non-state-owned suppliers. This can be attributed to the fact that non-state-owned suppliers typically face fiercer market competition and greater economic pressure. To maintain competitiveness, they are more inclined to establish closer and more efficient collaborative ties with the core firm, which in turn enhances their innovation. Columns (3) and (4) show that the inhibitory effect of CDT on innovation is more pronounced for non-state-owned customers, whereas its effect on state-owned customers is statistically insignificant. Given their typically weaker bargaining position, non-state-owned customers have limited room to negotiate innovation-friendly terms with the digitally dominant core firm. This often leads them to accept standardized solutions rather than collaborative arrangements that foster innovation, thereby suppressing their innovative initiatives.

Table 12. Firm nature heterogeneity.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	SOEs	NSOEs	SOEs	NSOEs
DIG	−0.025	0.205 **	−0.008	−0.124 **
	(−0.52)	(2.54)	(−0.19)	(−2.25)
Cons.	−0.403	−9.930 ***	5.550 ***	−13.841 ***
	(−0.38)	(−4.41)	(2.79)	(−4.53)
Obs.	758	1163	1082	1838
Fixed effect	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj.R^2	0.559	0.555	0.527	0.725

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

7.2. Firm Size Heterogeneity

The impact of CDT on suppliers (customers) innovation may vary depending on their size. To test this, they are split into two groups at the median of total assets. The corresponding regression results are reported in Table 13. Columns (1) and (2) show that the positive effect of CDT on innovation is more pronounced for larger suppliers. This can be attributed to the fact that larger suppliers possess greater capacity to collaborate with

core firms on digital transformation, and in turn promotes their innovation. However, small suppliers, constrained by limited resources, often lack the capacity to pursue innovation after engaging in digital transformation initiatives with core firms. From Columns (3) and (4), it can be seen that when the customer is large, the inhibitory effect of CDT on innovation is more obvious. The primary reason lies in the dual pressure of heightened direct competitive threat and intensified resource crowding-out exerted by the core firm on large customers, which constrains their ability to allocate resources to their own innovation.

Table 13. Firm size heterogeneity.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	Big Firms	Small Firms	Big Firms	Small Firms
DIG	0.223 ***	0.099	−0.024 ***	0.095
	(3.41)	(1.53)	(−5.47)	(1.67)
Cons.	0.032	−0.452	2.518	−1.966
	(0.01)	(−0.24)	(1.06)	(−0.26)
Obs.	1205	716	2104	816
Fixed effect	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj.R^2	0.337	0.512	0.396	0.251

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

7.3. Industry Competition Heterogeneity

The degree of industry competition may also lead to differential effects. To test the heterogeneous role of industry competition, this paper uses the industry Herfindahl-Hirschman Index (HHI) to measure the level of industrial competition. The sample is then split into high- and low-competition groups based on the median HHI. The subgroup regression results are presented in Table 14. Columns (1) and (2) report the regression results of CDT on supplier innovation. It can be seen that the coefficient is significantly positive in the high-competition group. This is because fiercer industry competition fosters tighter supply chain collaboration. This enables the core firm to play a stronger orchestrating role. Through digital transformation, it can integrate resources, deepen cooperation, and precisely address upstream needs, thereby promoting supplier innovation via more efficient collaboration that reduces costs and enhances quality. The results in Columns (3) and (4) indicate that the negative impact of CDT on innovation is more pronounced under conditions of high industrial competition than under low competition. This is due to the fact that increased competition often leads customers to focus more on maintaining the market position of existing and core companies rather than innovating.

Table 14. Industry competition heterogeneity.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	High	Low	High	Low
DIG	0.230 ***	0.221	−0.104 **	0.052
	(2.79)	(1.01)	(−2.44)	(1.08)
Cons.	−2.810 **	−0.411	−0.624	−0.159
	(−2.22)	(−0.26)	(−0.48)	(−0.03)

Table 14. *Cont.*

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	High	Low	High	Low
Obs.	719	1202	1166	1754
Fixed effect	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj.R^2	0.454	0.358	0.549	0.219

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

7.4. Managerial Ability Heterogeneity

The impact of CDT on the innovation of upstream and downstream enterprises may vary with the level of managerial capability. This study employs Data Envelopment Analysis (DEA) to estimate firm efficiency scores. Managerial ability is then derived by isolating the portion of firm efficiency attributable to managers, typically through a second-stage regression that controls for other factors. Columns (1) and (2) of Table 15 show that the positive effect of CDT on supplier innovation is more pronounced when managerial ability is high. This is because when suppliers have strong managerial capability, they possess advantages in areas such as resource integration and market acuity. This enables them to more effectively leverage the experience, resources, and technologies accumulated by the core firm during its digital transformation, thereby enhancing their own technical capabilities and innovation levels. The results in Columns (3) and (4) indicate that the inhibitory effect of CDT on customer innovation increases with the level of managerial ability. This may be because customers with strong managerial capability tend to have clearer strategic autonomy in developing their own business lines. Consequently, their operational relationship with the core firm may be less tight, making them less susceptible to the positive spillovers but more vulnerable to the negative impacts arising from the core firm's digital transformation.

Table 15. Managerial ability heterogeneity.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	Low Managerial Ability	High Managerial Ability	Low Managerial Ability	High Managerial Ability
DIG	0.190	0.200 ***	−0.024 ***	0.099
	(1.61)	(3.09)	(−4.34)	(1.36)
Cons.	−4.648 **	1.118	−7.517	5.461 **
	(−2.31)	(0.84)	(−0.95)	(2.54)
Obs.	861	1060	1360	1560
Fixed effect	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj.R^2	0.386	0.493	0.177	0.562

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

8. Discussion

This study reveals a fundamental asymmetry in the spillover effects of CDT within supply chains. It promotes innovation in upstream enterprises while inhibiting innovation in downstream enterprises. This finding challenges the potentially simplistic view of DT as an uniformly positive force, underscoring the importance of a firm's structural position within the supply network.

Our results align with but also significantly extend the existing literature. Prior research has established that DT drives intra-firm innovation [6] and spreads through peer effects within supply chains [10]. However, it has largely overlooked the differential impact on other outcomes of supply chain partners, particularly innovation, based on the directional relationship (upstream vs. downstream). The study demonstrates that the nature of the inter-firm relationship, predominantly cooperative with suppliers and competitive with customers, shapes the influence of the DT spillover.

Adopting a Complex Adaptive Systems (CAS) lens provides a powerful framework for interpreting these asymmetric outcomes. The supply chain is not a linear pipeline but a dynamic network where a perturbation like CDT triggers distinct adaptive responses. For upstream suppliers, the CDT initiates a self-reinforcing positive feedback loop. Grounded in Resource Dependence Theory (RDT) and the Knowledge-Based View (KBV), the core firm acts as a "Collaborative Leader," creating pressures for suppliers to innovate while also providing the resources and knowledge, such as through technical assistance and joint R&D, to do so effectively. This "resource-pull" and "collaborative advantage" mechanism, empirically validated in our mediation tests, explains the observed promotion of supplier innovation.

Conversely, for downstream customers, CDT triggers a self-balancing negative feedback loop. Through the lens of Competitive Dynamics and Efficiency Theory, the CDT into a "Competitive Pressure" Its enhanced capabilities and potential market encroachment intensify competitive pressure, while the need for customers to adapt to core firm's digital products or platforms creates a "resource crowding-out" effect, diverting scarce funds from their own R&D. This "competitive pressure" and "resource crowding-out" mechanism, empirically validated in our mediation tests, suppresses customer innovation.

While the findings demonstrate an overall inhibitory effect of CDT on customer innovation, it is acknowledged that this relationship may be contingent upon important boundary conditions. Specifically, when the CDT takes the form of creating open platforms or ecosystems, e.g., application programming interfaces for third-party developers, shared digital infrastructure, it may actually enable complementary innovation among downstream partners. In such contexts, the competitive pressure and resource crowding-out effects the study identifies might be attenuated or even reversed, as downstream firms leverage these platforms to develop complementary products and services. The net effect likely depends on whether the core firm's digital strategy prioritizes control and standardization versus openness and ecosystem co-creation.

Furthermore, our model, which emphasizes the transmission of influence from the core firm, abstracts from the internal systems of the receiving partners. The promotion or inhibition of innovation is unlikely to be deterministic. Rather, the adaptive capacity of upstream and downstream firms, shaped by their internal digital culture, strategic digital drive, and existing digital maturity, mediates the external contagion effect. As recent research employing a systems perspective underscores [3], these internal elements are crucial for translating external digital pressures or opportunities into tangible innovation performance. Thus, the net effect the study observes is the aggregate result of the core firm's influence being filtered and interpreted through the heterogeneous internal systems of its partners.

9. Implications

These findings offer guidance for various stakeholders:

For core firms, beyond internal transformation, core firms must embrace their role as digital orchestrators. This involves proactively designing collaborative platforms and knowledge-sharing initiatives to strengthen positive feedback loops with suppliers. Simul-

taneously, they should develop support mechanisms, such as phased integration plans or co-invention projects, to mitigate the negative impacts on customers and maintain the long-term health of the downstream system.

For suppliers, upstream firms should recognize the digital demands of core firms not merely as compliance costs but as strategic opportunities for capability development. Proactive investment in digital compatibility, employee upskilling, and collaborative R&D can allow them to fully leverage the resource-pull effect and solidify their position within the evolving digital supply chain.

For customers, downstream firms need to develop strategic responses to counterbalance the observed inhibitory effects. This includes diversifying innovation portfolios, negotiating data-sharing and co-innovation agreements with core firms, and creating internal buffer mechanisms (e.g., dedicated innovation funds) to maintain R&D capacity despite short-term adaptive pressures.

For policymakers, industrial and innovation policies should evolve from supporting individual firms to fostering entire ecosystem resilience. This includes promoting data interoperability standards, facilitating the development of shared digital infrastructure, and designing regional innovation policies that consider the network effects and asymmetric impacts within supply chains.

10. Conclusions, Contributions and Future Research

10.1. Conclusions

This study adopts a CAS lens to investigate the spillover effects of CDT on innovation within supply chain partners. The findings reveal an asymmetrical phenomenon: CDT promotes innovation in upstream suppliers while simultaneously inhibiting innovation in downstream customers. This asymmetric pattern persists robustly across various model specifications, alternative variable measurements, and after addressing potential endogeneity concerns.

The mechanisms driving these outcomes align with complex system dynamics. For upstream firms, CDT creates self-reinforcing positive feedback loops through resource-pull and collaborative advantage mechanisms, thereby enhancing suppliers' innovation capabilities. Conversely, for downstream customers, mechanisms generate self-balancing negative feedback loops where resource crowding-out and competitive pressure constrain innovation investments. These findings demonstrate how interactions within the supply chain network produce emergent properties that cannot be predicted through linear models.

Our heterogeneity analysis further enriches this understanding. The innovation-promoting effect on upstream firms is more pronounced among large, non-state-owned enterprises in highly competitive industries with strong management. Meanwhile, the innovation-inhibiting effect on downstream firms is strongest under similar conditions. Notably, higher supply chain efficiency amplifies both effects, revealing how supply efficiency characteristics moderate the propagation of digital transformation impacts.

10.2. Contributions

This paper makes several contributions. First, it advances supply chain literature by integrating Complex Adaptive Systems (CAS) theory with established strategic management perspectives like Resource Dependence Theory (RDT) and the Knowledge-Based View (KBV). This integration provides a more nuanced framework for understanding DT spillovers, moving beyond linear relationship models. Secondly, the study identifies and empirically validates the distinct mechanisms driving these spillovers: "resource-pull" and "collaborative advantage" are the primary mechanisms for suppliers, while "competitive pressure" and "resource crowding-out" are for customers. This resolves the paradox of si-

multaneous positive and negative effects. Thirdly, the study reveals that the spillover effects of CDT on innovation in upstream and downstream enterprises are heterogeneous. This heterogeneity is shaped by firm size, ownership nature, industry competition intensity, and managerial capability. The study provides a more realistic model of digital transformation's spillover effects.

10.3. Limitations and Future Research

The keyword frequency measure (DIG) provides a valuable and established proxy for a firm's strategic focus on digital transformation; it primarily captures discursive commitment and stated strategic intent within annual reports. It may not fully encompass the operational integration or resource allocation underlying a firm's digital capabilities. This is an inherent limitation of text-based measures. To overcome the limitations of the keyword frequency measure (DIG), this study adopts a two-pronged approach. First, it employs the ratio of digital intangible assets to total assets as an alternative measure of digital transformation. Second, it uses a case study of the Midea Group to demonstrate that the keyword-frequency measure aligns well with the firm's actual level of digitalization in practice.

It is important to note that our empirical analysis treats 'core firms' as a homogeneous group. This approach provides a foundational understanding but inevitably overlooks the significant heterogeneity in the nature and strategy of these firms, which likely acts as a critical moderating factor. Acknowledging this limitation opens a compelling avenue for future research to develop a more nuanced, contingency-based model of knowledge spillover, one that classifies core enterprises into typologies to precisely delineate their divergent impacts on downstream innovation.

Our study focuses on inter-organizational contagion dynamics and does not account for the heterogeneity in the internal systems of partner firms. A vital direction for future research is to investigate how the digital maturity, digital culture, and strategic digital drive of upstream and downstream firms moderate the strength and direction of the contagion effects we identify [81]. Integrating firm-level internal system variables with our network-level perspective would provide a more holistic, multi-level understanding of how digital transformation propagates through complex economic systems.

Furthermore, our empirical design, while employing robust methods to address the endogeneity of the digital transformation decision, implicitly treats the formation of supply chain relationships as exogenous. It is plausible that core firms proactively select suppliers based on their innovative capacity or that the dynamics of digital transformation influence the selection and retention of customers. Such endogenous matching could potentially influence the observed spillover effects. While our use of multi-dimensional fixed effects helps control for time-invariant unobserved confounders, future research could more directly address this issue by employing methodologies designed for endogenous network formation, such as two-stage selection models or dynamic network panel models, to perform the even more robust identification of these complex spillover mechanisms.

Future research can investigate the contingency factors that might reverse the inhibitory effect on downstream innovation. It would be particularly valuable to examine how different types of digital transformation—such as platform creation versus process digitization—and varying levels of ecosystem openness moderate these supply chain contagion effects.

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Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Appendix A.1. Structured Characteristic Term Map of Enterprise Digital Transformation

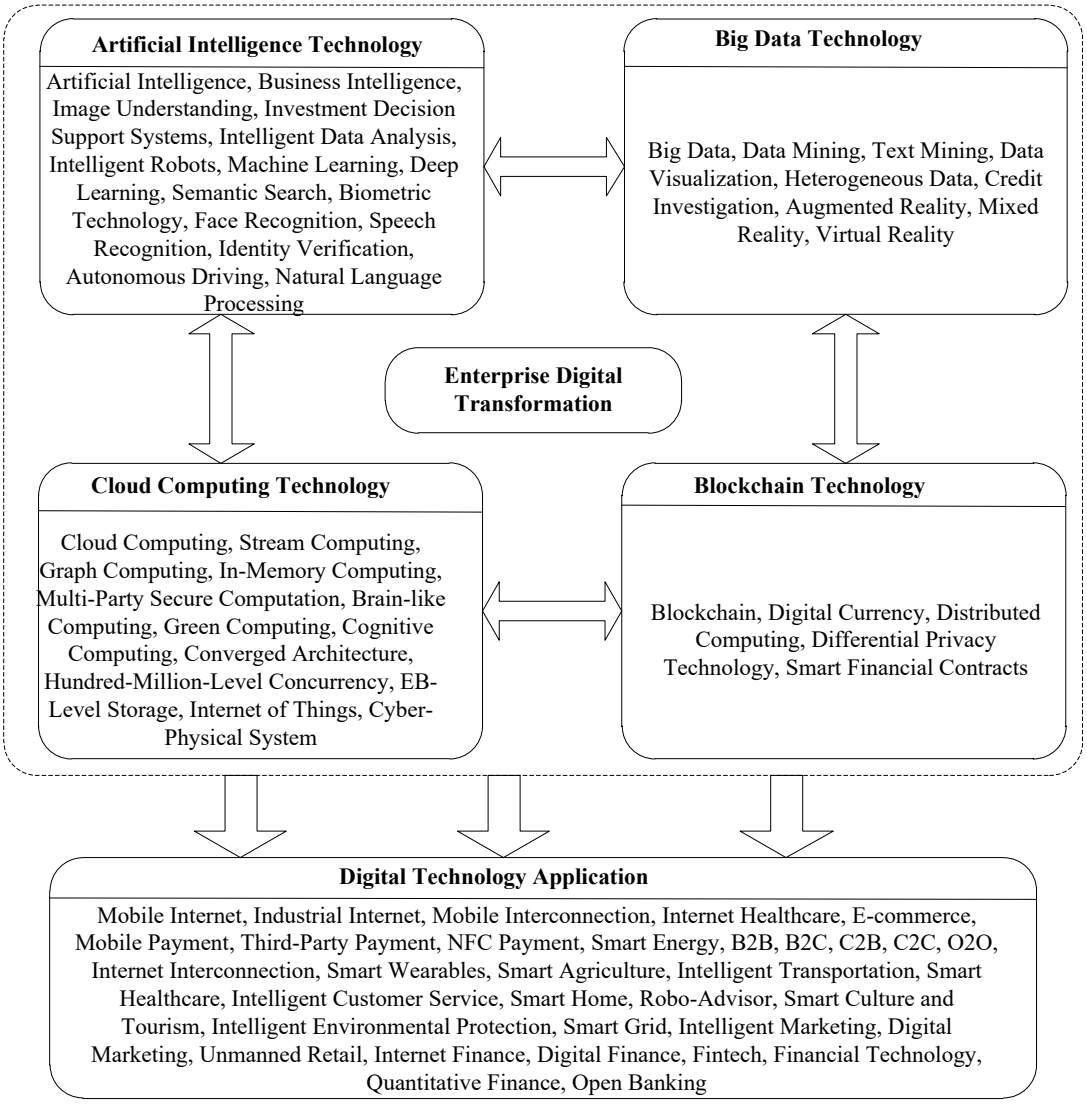

Figure A1. Structured Characteristic Term Map of Enterprise Digital Transformation.

Appendix A.2. Construction of the Enterprise Digital Transformation Index and Keyword Selection

Dimension	Category Terms	High-Frequency Text Combinations	Participle Dictionary
Digital Technology Application	Data, Digital, Digitization	Data Management, Data Mining, Data Network, Data Platform, Data Center, Data Science, Digital Control, Digital Technology, Digital Communication, Digital Network, Digital Intelligence, Digital Terminal, Digital Marketing, Digitization	Data Management, Data Mining, Data Network, Data Platform, Data Center, Data Science, Digital Control, Digital Technology, Digital Communication, Digital Network, Digital Intelligence, Digital Terminal, Digital Marketing, Digitization, Big Data, Cloud Computing, Cloud IT, Cloud Ecosystem, Cloud Service, Cloud Platform, Blockchain, Internet of Things, Machine Learning
Internet Business Model	Internet, E-commerce	Mobile Internet, Industrial Internet, Industrial Internet, Internet Solutions, Internet Technology, Internet Thinking, Internet Initiative, Internet Business, Internet Mobility, Internet Application, Internet Marketing, Internet Strategy, Internet Platform, Internet Model, Internet Business Model, Internet Ecosystem, E-commerce, Electronic Commerce	Mobile Internet, Industrial Internet, Industrial Internet, Internet Solutions, Internet Technology, Internet Thinking, Internet Initiative, Internet Business, Internet Mobility, Internet Application, Internet Marketing, Internet Strategy, Internet Platform, Internet Model, Internet Business Model, Internet Ecosystem, E-commerce, Electronic Commerce, Internet, "Internet+", Online-to-Offline, Online To Offline, Online and Offline, O2O, B2B, C2C, B2C, C2B
Intelligent Manufacturing	Intelligent, Smart, Automation, CNC, Integrated, Integration	Artificial Intelligence, Advanced Intelligence, Industrial Intelligence, Mobile Intelligence, Intelligent Control, Intelligent Terminal, Intelligent Mobility, Intelligent Management, Smart Factory, Intelligent Logistics, Intelligent Manufacturing, Intelligent Warehousing, Intelligent Technology, Intelligent Equipment, Intelligent Production, Intelligent Connected, Intelligent System, Automation, Automatic Control, Automatic Monitoring, Automatic Surveillance, Automatic Detection, Automatic Production, Automation, Integrated Solutions, Integrated Control, Integrated System, Industrial Cloud, Future Factory, Intelligent Fault Diagnosis, Lifecycle Management, Manufacturing Execution System, Virtualization, Virtual Manufacturing	Artificial Intelligence, Advanced Intelligence, Industrial Intelligence, Mobile Intelligence, Intelligent Control, Intelligent Terminal, Intelligent Mobility, Intelligent Management, Smart Factory, Intelligent Logistics, Intelligent Manufacturing, Intelligent Warehousing, Intelligent Technology, Intelligent Equipment, Intelligent Production, Intelligent Connected, Intelligent System, Automation, Automatic Control, Automatic Monitoring, Automatic Surveillance, Automatic Detection, Automatic Production, Automation, Integrated Solutions, Integrated Control, Integrated System, Industrial Cloud, Future Factory, Intelligent Fault Diagnosis, Lifecycle Management, Manufacturing Execution System, Virtualization, Virtual Manufacturing

Dimension	Category Terms	High-Frequency Text Combinations	Participle Dictionary
Modern Information System	Information, Informatization, Networking	Information Sharing, Information Management, Information Integration, Information Software, Information System, Information Network, Information Terminal, Information Center, Informatization, Networking	Information Sharing, Information Management, Information Integration, Information Software, Information System, Information Network, Information Terminal, Information Center, Informatization, Networking, Industrial Information, Industrial Communication

Appendix B

Table A1. Replace the explained variable.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
	INA	RD	INA	RD
DIG	0.211 ***	0.024 ***	−0.144 **	−0.031 ***
	(2.80)	(2.75)	(−2.02)	(−3.03)
N	1921	1921	2920	2920
Control variables	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
Adj.R^2	0.524	0.357	0.697	0.472

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A2. Adjust the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)
	Core—Upstream Firm			Core—Downstream Firm		
	IN	IN	IN	IN	IN	IN
DIG	0.079 ***			−0.033 **		
	(4.29)			(−2.39)		
DIG1		0.147 ***			−0.017 **	
		(3.09)			(−2.44)	
DIG2			0.025 ***			−0.034 ***
			(3.49)			(−3.72)
N	1921	1921	1921	2920	2920	2920
Fixed effect	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
Adj.R2	0.362	0.393	0.377	0.190	0.249	0.226

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A3. Add fixed effect.

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
DIG	0.399 ***	0.238 ***	−0.249 ***	−0.021 ***
	(5.11)	(4.06)	(−4.89)	(−3.46)
Cons.	4.257 ***	−1.705	7.418 ***	−1.116
	(3.38)	(−1.14)	(3.10)	(−0.30)

Table A3. *Cont.*

	(1)	(2)	(3)	(4)
	Core—Upstream Firm		Core—Downstream Firm	
N	1921	1921	2920	2920
Year#Province	Yes	No	Yes	No
Year#Industry	No	Yes	No	Yes
Control variables	Yes	Yes	Yes	Yes
Adj.R^2	0.168	0.372	0.021	0.200

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Year#Province implies that the model simultaneously controls for year and province fixed effects, while Year#Industry implies that the model simultaneously controls for year and industry fixed effects.

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