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Exploring the Impacts of Digital Technology on Small and Medium-Sized Corporate Competitive Advantage: Evidence from the Chinese A-Share Manufacturing Industry

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Abstract

Against the profound backdrop of digital technology reshaping industrial competition, examining how it enables resource-constrained small and medium-sized manufacturing enterprises (SMMEs) to cultivate a sustained competitive advantage is of considerable practical significance. Grounded in dynamic capability theory, this study conducts an empirical analysis using panel data from 153 SMMEs listed on China's A-share market between 2013 and 2022. The baseline regression results indicate that digital technology significantly enhances firms' competitive advantage, a finding that remains robust across multiple robustness checks involving alternative variable measurements and sample adjustments. Further heterogeneity analyses reveal that this facilitating effect is more pronounced in state-owned enterprises, non-high-tech sectors, and firms located in eastern, northeastern, and northwestern regions, as well as in environments characterized by more developed digital finance or intensified market competition. Moreover, the mechanism analysis identifies a sequential mediating pathway, specifically that digital process innovation enables digital business model innovation, which is validated through structural equation modeling. Digital product innovation does not exhibit a statistically significant mediating effect. These findings extend the applicability of dynamic capability theory to digital contexts and provide actionable insights for SMMEs seeking to design context-specific digital transformation strategies.

Keywords: digital technology; firm competitive advantage; digital innovation; small and medium-sized manufacturing enterprises



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1. Introduction

Against the backdrop of escalating global competition and rapid technological advancement, establishing and maintaining a robust firm competitive advantage (FCA) has emerged as a central strategic objective, essential for enterprise survival and growth [1]. This imperative is especially critical for small and medium-sized manufacturing firms facing resource limitations. In China, these enterprises represent an integral part of the national economy. According to the National Bureau of Statistics of China, by the end of 2023, small and medium-sized manufacturing enterprises (SMMEs), which constitute the backbone of the manufacturing sector, comprised over 97% of all scaled industrial enterprises and generated more than half of the total operating revenue and profits. Consequently, their operational vigor profoundly influences the overall vitality and resilience of the manufacturing ecosystem.

However, these entities confront considerable challenges in attaining and preserving deeply rooted competitive strengths. Most remain clustered in conventional manufacturing fields where mid- to low-level technologies prevail, rendering industrial upgrading a pressing imperative. While smart and digital transformation has achieved broad consensus in both policy and industrial spheres, investigations by the Ministry of Industry and Information Technology indicate that the depth and breadth of digital transformation within China's manufacturing sector remain insufficient. Many SMMEs, in particular, face the dual challenge of "reluctance to transform" and "limited capability to implement transformation," which constrains their upward mobility in the global value chain due to inadequate internal resources, talent, and innovation capacity [2]. Encumbered by resource scarcity, these firms consistently face difficulties in building and sustaining meaningful competitive differentiation, often culminating in product commoditization and weak market entry barriers [3]. Against this backdrop, cultivating a solid and hard-to-replicate FCA is essential for SMMEs to secure market presence, achieve sustained profitability, and ensure long-term development [1,4]. Consequently, examining how SMMEs can effectively cultivate and reinforce their competitiveness has become a research issue of considerable theoretical importance and immediate practical relevance.

Digital technologies (DT), encompassing innovations such as the Internet of Things, cloud computing, artificial intelligence, and big data, are profoundly transforming industrial ecosystems and rearticulating the foundational determinants of corporate competitiveness. They achieve this by effectively amplifying organizational capabilities in information processing, connectivity, and data analytics [5,6]. Functioning as pivotal enablers of organizational change, these technologies empower firms to reconfigure their value creation processes and improve operational efficiency. Within this paradigm, SMMEs are increasingly intensifying their digitalization initiatives [7], perceiving these technological tools as essential mechanisms to reduce inherent resource limitations. However, the adoption of digital solutions remains complex and highly context-dependent, with pronounced heterogeneity across firms in terms of implementation maturity and strategic orientation [8]. This context raises a critical unresolved inquiry: through what precise mechanisms does DT fortify the FCA of SMMEs? Although prior research has established connections between DT and corporate innovation, systematic investigations into its facilitative role on competitive advantage, specifically within the SMME context, remain scarce. Existing literature frequently concentrates on overarching narratives of "digital transformation" [9], leaving the multifaceted pathways, particularly the concurrent and sequential effects of distinct forms of digital innovation, which remain insufficiently examined. Moreover, the contingent effects stemming from organizational and regional heterogeneities are not yet fully elucidated [10]. To address these identified gaps, the present study is designed to investigate three central research questions.

- (1) Does DT significantly enhance the FCA of SMMEs?
- (2) Through what mechanisms, specifically via digital product, process, and business model innovation, does DT affect FCA?
- (3) How does the enabling effect differ under various firm- and region-specific conditions?

To uncover the mechanisms outlined above, this study adopts dynamic capability theory as its underlying theoretical lens. This framework posits that sustainable competitive advantages arise from firms' ongoing capabilities to sense, seize, and reconfigure internal and external resources [11]. DT can substantially augment these dynamic capabilities [5], refining innovation activities and ultimately fortifying the firm's competitive advantage. Therefore, this research empirically investigates the facilitative role of DT in shaping the FCA of Chinese SMMEs, paying particular attention to the mediating functions of digital product, process, and business model innovation. Through this empirical inquiry,

the study contributes to the field in several key ways. First, it positions FCA as the dependent variable within a dynamic “DT → digital innovation → competitive advantage” framework, generating evidence on how DT strengthens the core competitiveness of small and medium-sized manufacturers. Second, grounded in dynamic capability theory, it systematically examines the parallel and sequential mediating effects of three distinct types of digital innovation: digital product innovation (DPDI), digital process innovation (DPCI), and digital business model innovation (DBMI). This framework sheds light on the “black box” connecting DT and competitive advantage, addressing a significant gap in our understanding of the intermediary mechanisms involved. Third, by exploring the heterogeneous effects stemming from regional disparities, ownership structures, and technological intensity in the digital enablement process, this study provides foundational insights for firms to design context-specific digital strategies, filling a crucial gap in the existing literature.

This paper is organized as follows. Section 2 presents a review of relevant literature. Section 3 formulates the research hypotheses. Section 4 details the research design, including sample selection, variable definitions, and the econometric models employed. Section 5 presents the empirical findings, including the baseline regression analysis, a series of robustness and endogeneity checks, heterogeneity tests, and investigations of underlying mechanisms. Section 6 offers a comprehensive discussion of the results and concludes the study by summarizing its key implications, acknowledging its limitations, and proposing directions for future research.

2. Literature Review

This section systematically reviews three streams of literature foundational to our study. Section 2.1 examines DT and its role in reshaping organizational capabilities and innovation processes. Section 2.2 discusses FCA, its theoretical underpinnings, and measurement approaches. Section 2.3 elaborates on dynamic capability theory, which serves as the overarching theoretical lens for understanding how DT enables FCA through digital innovation. By integrating these literature streams, we identify research gaps and establish the theoretical foundation for our conceptual framework.

2.1. DT

DT comprising core components like blockchain, big data analytics, artificial intelligence, machine learning, cloud computing, and the Internet of Things, form an essential infrastructure for collecting, using, and managing data. They serve as key mechanisms for reducing costs, eliminating redundancies, and improving the productivity of businesses [12–15]. By transforming business strategies and organizational capabilities, these technologies significantly improve operational efficiency and redefine the logic, models, and processes of innovation across organizations [16].

At the micro-organizational level, DT reshapes strategic cognition through its inherent openness and generativity [17], prompting executives to rethink established decision-making frameworks [9]. This technological empowerment accelerates the formation of dynamic capabilities: organizations first identify latent value through environmental scanning and data analytics [18]. Next, they develop collaborative networks that enable decentralization and platform-based operations, streamlining resource acquisition [19]. Finally, they achieve real-time adaptability and reconfigure operational structures [20], creating a continuous cycle of “sensing–seizing–transforming.”

At the macro-institutional level, DT exemplified by social media, cloud computing, and the IoT [17], drive business model innovation through three primary pathways: enhancing existing models via automation, expanding operational scope through digitization, and

creating entirely new models through digital transformation [21]. These developments facilitate an in-depth integration of manufacturing and service sectors [14]. In the context of the manufacturing sector's pursuit of high-quality development, leveraging DT to establish a lasting FCA for SMMEs has become a critical task.

DT represents a new category of innovation resource, defined by its powerful information processing and analytical capabilities [5]. It enhances firms' dynamic capabilities across opportunity recognition and capture, resource integration and allocation, and innovation-driven learning [22]. The main attributes of DT—openness, affordances, and generativity—have fundamentally transformed the underlying principles governing value creation and capture [6]. A substantial body of research highlights how integrating DT reshapes strategic cognition, innovation processes, and organizational structures [23,24]. It has increased the permeability of organizational boundaries, facilitated cross-border resource flow and sharing [24], and the proliferation of platform-centric business models and distributed innovation networks [14,17]. These developments establish a critical basis for investigating how dynamic capabilities, facilitated by DT, function as enablers and the mechanisms through which they strengthen competitive advantage in SMMEs. Thus, scholarly work has converged on a shared understanding of DT and its function in reshaping corporate strategies and capabilities. Past research has analyzed its impact from multiple perspectives, including micro-level organizational thinking, dynamic capabilities, and macro-level business model innovation, ultimately connecting these dimensions to broader enterprise competitive advantage. The insights provide a solid foundation for understanding digital transformation. However, several limitations persist. First, while most studies focus on the broad notion of digital transformation or its macro-level performance outcomes, relatively less attention has been given to how DT, and the specific forms of innovation it enables, differentially impact firm competitiveness, particularly in SMMEs with distinct resource constraints. Second, empirical investigation into how DT drives product-level competitive advantage remains scarce, especially within the context of SMMEs. Third, this study directly addresses DT as the central enabler while examining the specific pathways through which it enhances FCA by promoting three types of digital innovation. By pursuing this objective, the study provides a more nuanced understanding of the micro-level mechanisms through which DT enables FCA in SMMEs, addressing the current lack of detailed, context-sensitive analytical frameworks.

2.2. FCA

Grounded in monopolistic competition theory and strategic management theory [25], FCA denotes a company's sustained edge against its competitors, manifested through either cost efficiency or distinctive attributes [1]. It focuses on establishing a value path that competitors cannot easily replicate [26]. Distanont and Khongmalai (2020) [4] argue that firms must establish a distinct market position through cost leadership, differentiation, or entry into new markets, delivering superior value propositions and customer satisfaction to achieve and maintain a competitive advantage. They emphasize integrating three dimensions: product, internal organization, and market environment, forming a holistic view of competitiveness. Consequently, FCA encompasses not only observable outcomes such as market share (MS), pricing power, and iteration speed [27], but also a firm's systemic capability to transform internal competencies into perceived customer value.

A firm's competitive advantage arises from the interplay of internal capabilities and external value creation. Internally, his advantage depends on a firm's resources satisfying the VRIN criteria, being valuable, rare, difficult to imitate, and lacking substitutes [26]. The capacity for dynamic organizational adaptation is equally crucial, allowing firms to reconfigure resources in response to evolving market demands [28]. Empirical evidence

shows that DT fosters firm-level innovation [29], helping firms build diverse competitive barriers through enhanced functionality, service value, and operational models [30]. Externally, firms must translate internal strengths into customer-perceived value; enhancing service experiences directly improves customer satisfaction, which, in turn, facilitates price premiums and encourages repeat purchases [31]. Within the digital economy, firms must strengthen technological application and integrate social responsibility simultaneously to ensure the long-term sustainability of their competitiveness [32].

Existing studies typically assess FCA in two ways: (1) using structured questionnaires to collect subjective evaluations from managers, customers, or experts regarding differentiation, customer satisfaction, and brand premium [33,34]; (2) constructing composite indices from secondary data, incorporating metrics such as MS growth, profit margin [35], and portfolio values derived from IPO prospectuses.

Thus, while past research has examined the antecedents of competitive advantage from resource-based, dynamic capability, and stakeholder perspectives, few studies have systematically explored the formation mechanisms of FCA, particularly the influence of DT within resource-constrained SMMEs. The present study addresses these gaps by: (1) rigorously evaluating the net impact of DT on SMMEs' competitive advantage; (2) elucidating the chain-mediated pathway of "DT → digital innovation → competitive advantage"; and (3) positioning FCA as a core outcome variable within the digital transformation framework, providing theoretical and empirical guidance for SMMEs developing firm-centered competitive strategies.

2.3. Dynamic Capability Theory

Dynamic capability theory emerged from scholarly discourse contrasting the resource-based view (RBV) with the competence-based approach in explaining the fundamental sources of competitive advantage [26,36,37]. It integrates elements of both resources and capabilities, stressing that sustained advantage derives not just from static resource possession but also from an enterprise's capacity to continually absorb, develop, and rearrange both internal and external assets to navigate rapidly changing environments. Teece (2007) [20] later articulated this dynamic process as comprising three linked dimensions: detecting opportunities and threats, capitalizing on identified opportunities, and overhauling the organization's asset base, structural configuration, and operational routines.

In today's highly digitalized world, rapid technological advancement has profoundly reshaped industrial landscapes and competitive dynamics, creating unprecedented environmental turbulence [19]. Dynamic capability theory argues that firms must leverage dynamic capabilities to adapt and compete effectively, a challenge that becomes particularly critical in the digital era [38,39]. DT is a strategic resource [6], with potent information processing, connectivity, and analytical capacities that offer new pathways to enable and enhance dynamic capabilities [38]. In particular, DT strengthens the sensing capability by enabling the extraction of market and customer insights through big data analytics [40]. Digital tools enhance seizing by facilitating agile development and enabling rapid resource allocation and accelerated product introduction through digital platforms [17,41]. They also facilitate transformation by supporting organizational agility and resource reconfiguration via digital tools and process redesign [19,42]. Strong dynamic capabilities help firms mitigate uncertainties and risks associated with digital transformation [43]. Consequently, researchers are actively exploring new digitally enabled forms of dynamic capabilities, such as data-driven dynamic capabilities [44], predictive analytics capabilities [45], and AI-enabled adaptive capabilities [46]. Dynamic capability theory, thus, provides a powerful lens for elucidating the mechanisms by which SMMEs can cultivate and maintain FCA in digital environments.

Building upon the above, dynamic capability theory provides a strong conceptual foundation for analyzing how firms cultivate and maintain their competitive advantage during digital transformation. It underscores that companies continuously amalgamate and restructure their internal and external resources through the fundamental processes of sensing, seizing, and transforming to adapt to environmental changes. DT, endowed with sophisticated capabilities in information processing, connectivity, and data analytics, significantly improves firms' perceptual acuity, resource integration efficiency, and the rapidity of organizational adaptation in volatile settings [19,38], laying the foundation for a competitive edge. Moreover, dynamic capability theory indicates that digitally enabled organizational enhancements must be translated into concrete competitive outcomes through specific innovation activities. In this process, digital innovation acts as the vital mediating mechanism. DPDI demonstrates the firm's capacity to capitalize on market opportunities and promptly iterate product features using digital tools [17]. DPCI exhibits the ability to overhaul internal operations through digital means, accomplishing cost reduction, efficiency improvements, and resource reallocation [47]. DBMI signifies a comprehensive manifestation of sensing-seizing-transforming capabilities, allowing adaptation by restructuring value creation and delivery systems [48]. Furthermore, the focus of dynamic capability theory on contextual factors offers a theoretical foundation for examining heterogeneity among firms, such as differences in organizational structure, resource allocation practices, and external institutional environments, which may lead to varying outcomes in capability development and competitive advantage during digitalization.

As the principal analytical lens employed in this investigation, dynamic capability theory directly informs our focus on the specific pathways through which DT shapes competitive advantage. In the digital context, DT emerges as a pivotal strategic asset that enhances dynamic capabilities, offering resource-constrained SMMEs a critical foundation for navigating digital transformation. This theoretical perspective highlights that digitally enabled capabilities must be translated into tangible market outcomes through concrete innovation activities—specifically, innovations in digital products, processes, and business models.

Despite these theoretical insights, the literature remains limited in several respects. Most studies examine digital transformation at a macro level [9], offering little clarity on how DT enables competitive advantage through distinct innovation pathways—particularly their parallel and sequential effects [6,10]. The boundary conditions of this process are also underexplored, with limited attention to how organizational and regional contexts shape DT effectiveness [8,10]. These gaps constrain theoretical understanding and risk yielding strategic guidance that overlooks firm- and context-specific contingencies. Building on this logic, the following section introduces the integrated conceptual model and develops the corresponding research hypotheses.

3. Hypothesis Development

3.1. *Impact of DT on FCA in SMMEs*

DT is transforming industry landscapes and redefining the foundations of enterprise competitiveness. According to dynamic capability theory, a firm's sustained advantage originates not in static resources but rather in its ongoing capacity to adapt and innovate via three core micro-foundations: sensing market opportunities, seizing them through strategic investment, and transforming resources and processes [11]. As a pivotal strategic resource, DT significantly enhances these dynamic capabilities by providing superior information processing, connectivity, and analytical power [5,37].

DT enhances the sensing capability by enabling the application of big data analytics and artificial intelligence, which empower firms to systematically monitor market trends and anticipate shifts in consumer demand, uncovering new opportunities for value creation [49]. It strengthens the seizing capability by facilitating resource integration and reconfiguration. Digital platforms and cloud-based systems improve operational efficiency and reduce costs through optimized asset allocation and collaboration [50], allowing firms to transcend traditional boundaries and strategically leverage complementary assets. Furthermore, DT underpins the transforming capability. By eliminating information silos and enabling real-time data flows, it accelerates organizational learning, stimulates innovation, and supports the agile reconfiguration of operational structures necessary to respond to environmental changes [19].

For resource-constrained SMMEs, these enhanced dynamic capabilities are particularly critical. Digital tools lower the cost of real-time production monitoring, process optimization, and supply chain coordination [51,52], helping firms overcome traditional constraints. By systematically strengthening the organizational capacity to sense, seize, and transform, DT aligns firms' internal capabilities with evolving market demands, establishing a robust foundation for superior market performance and organizational resilience. Accordingly, drawing on the dynamic capability perspective, we argue that DT empowers SMMEs by enhancing the core capabilities that underpin competitive adaptation and renewal. Building on this theoretical logic, the following hypothesis is proposed:

Hypothesis 1 (H1): *DT has a significant positive impact on the FCA of SMMEs.*

3.2. Mediating Role of DPDI

Grounded in dynamic capability theory, DT can promote DPDI by augmenting a firm's abilities to sense emerging market opportunities and to seize them through agile, data-informed development cycles [6]. The deployment of core DT, including big data analytics, cloud computing, and artificial intelligence, substantially strengthens an organization's capacity to perceive evolving market trends and user preferences, enabling evidence-based product design and development. For instance, cloud computing enables rapid prototyping and the real-time incorporation of user feedback [6], reflecting an enhanced seizing capability, whereas IoT and AI technologies equip products with novel features like intelligent connectivity and functional expandability [52]. These developments not only accelerate the assimilation and reconfiguration of innovation resources but also reduce cognitive load and collaboration costs during product development [24], strengthening the firm's dynamic capability for DPDI.

DPDI directly reinforces a firm's competitive advantage in the marketplace through functional improvements and distinct design. Innovative products not only achieve closer alignment with customer needs and enhance the user experience but also create competitive barriers through distinctive digital attributes, such as remote monitoring and intelligent interaction [24,48]. Empirical research demonstrates that DPDI considerably increases market adaptability and iteration speed, which subsequently leads to greater MS and profitability [53]. Thus, DPDI can serve as a conduit through which technological advantages are transformed into sustainable competitive advantages at the firm level.

However, the efficacy of this mediating pathway may be subject to important temporal and contextual contingencies. The development and commercialization of DPDI often involve extended research and development cycles, and their market success is highly contingent on the timing of market entry [24,54]. This intrinsic feature introduces a temporal misalignment, whereby the competitive returns of DPDI may emerge only after a substantial delay, potentially diverging from the pace of technological advancement and shifts in the competitive environment. As a result, although a theoretical relationship is present, the

strength of the direct mediating effect may be attenuated in rapidly evolving digital contexts. In light of this reasoning, we propose the following hypothesis:

Hypothesis 2 (H2): *DPDI mediates the positive relationship between DT and FCA.*

3.3. Mediating Role of DPCI

DPCI represents an essential pathway through which firms internalize DT, converting them into dynamic operational capabilities [47]. Within the dynamic capability framework, this represents a core manifestation of the transforming capability, whereby firms reconfigure internal routines and resources to attain higher levels of efficiency and adaptability. By leveraging advanced information processing and connectivity, DT significantly enables organizations to achieve process-level digital reconfiguration, enhancing their dynamic operational capacities [47].

This enhancement of the transforming capability is operationalized through specific technologies. Firms implementing technologies like big data analytics, cloud computing, and artificial intelligence can embed intelligent monitoring and optimization into their production systems. This leads to a considerable decrease in operational expenses and repetitive tasks, accompanied by improvements in operational accuracy and the speed of decision-making [55]. Integrating blockchain technology further strengthens process traceability and information transparency, effectively mitigating operational risks [56]. Moreover, DT elevates overall productivity by optimizing supply chain logistics, inventory management, and process automation, reducing human error [57]. These changes collectively exemplify the reorganization of firm assets and the generation of knowledge spillover effects [58], demonstrating how DT builds a foundation for process innovation by enabling substantive operational transformation.

DPCI directly promotes a firm's competitive advantage by holistically boosting operational efficiency, reducing costs, and enhancing product quality. Process digitization enables enterprises to accelerate their response to shifts in market demand and to deliver products and services characterized by superior consistency and reliability [47]. These outcomes are direct consequences of an enhanced transforming capability. Furthermore, highly automated and intelligent processes curtail resource waste and production variability, increasing overall resource utilization and performance stability [59]. These improvements not only help firms establish competition barriers rooted in efficiency and quality but also reinforce their market position by strengthening customer trust and satisfaction. Hence, DPCI serves as a critical and direct mechanism through which technological empowerment is translated, via the transformation of operations, into substantive competitive advantage. In this context, the following hypothesis is proposed:

Hypothesis 3 (H3): *DPCI mediates the positive relationship between DT and FCA.*

3.4. Mediating Role of DBMI

DBMI serves as a critical mechanism enabling firms to transform DT into dynamic capabilities for value creation [48]. It represents the most comprehensive level of transformation within the dynamic capability framework, involving a fundamental reconfiguration of how a firm creates, delivers, and captures value [48,60]. The rise of the internet, mobile technologies, and blockchain has facilitated new and improved organizational forms like platform-based and decentralized business models, laying the groundwork for this holistic renewal [61,62].

DT enhances the firm's capacity for such transformative renewal by augmenting both sensing and seizing capabilities. It reshapes corporate–customer interactions, supporting precision marketing and personalized services through big data analytics [63], which

enhances customer retention and loyalty [64], an outcome of improved market sensing. Furthermore, digital tools can improve operational efficiency by enhancing resource allocation efficiency and reducing hierarchical complexity [65], while expanded online channels broaden market reach [66], reflecting enhanced capabilities to seize opportunities.

However, the direct and near-term influence of investing in DT on the measurable performance linked to business model innovation is theoretically intricate and may not be consistently positive initially. The pursuit of DBMI often entails substantial transition costs, including upfront investments in new digital infrastructure, organizational restructuring, and the temporary disruption of existing operations and revenue streams [67]. This can result in a temporary efficiency decline (or short-term productivity paradox), wherein initial DT investments may strain traditional financial and operational performance metrics, precisely the measures frequently employed to approximate the status of business model innovation. Consequently, the direct path from DT to DBMI could be negative or nonsignificant during the transitional phase.

Despite the potential for short-term suppression, once successfully implemented, DBMI is expected to significantly and directly enhance a firm's competitive advantage. Innovative business models bolster organizational responsiveness, accelerate profit cycles, and cultivate resilient ecosystems through superior value propositions and more efficient resource utilization [68]. Thus, while DT may initially suppress the proximate indicators of DBMI due to transformation costs, DBMI itself remains a potent driver of FCA. These findings imply that DBMI could act as a mediating mechanism in scenarios where effects are complex or temporarily suppressed. Thus, the following hypothesis is proposed.

Hypothesis 4 (H4): *DBMI mediates the positive relationship between DT and FCA.*

3.5. Chain Mediation Effects

Building on the dynamic capability logic outlined in the preceding hypotheses, an integrated sequential pathway is proposed through which a firm's competitive advantage is ultimately enhanced by DT. As a key enabler, DT first empowers firms to reconfigure their internal operational processes [6,69]. This constitutes the foundational transformation of capabilities at the operational level, materializing as DPCI.

DPCI, expressed through automation and intelligent transformation, utilizes technological capabilities to redesign business processes [6,69]. This enhances operational efficiency, reduces costs [70], and establishes a robust data foundation. This enhanced operational foundation serves a dual role. First, it directly contributes to FCA through tangible gains in efficiency, quality, and responsiveness (as posited in H3). Second, it generates the necessary conditions, such as free resources, integrated data assets, and optimized customer interaction points, that enable and support the subsequent evolution of the firm's business model [63,71].

This process-driven transformation thus paves the way for higher-order strategic renewal. The analysis of real-time operational data enables more accurate and timely decision-making [71], while insights derived from process optimization support the re-configuration of firms' fundamental value-creation logic. In this way, DPCI functions as a pivotal enabler for DBMI. However, as noted in H4, the direct translation of these enablers into measured DBMI performance may be complex or suppressed in the short term due to concomitant transformation costs.

Thus, a sequential chain is posited in which the primary and most immediate impact of DT is exerted on DPCI. Process innovation is, in turn, positioned as the central mechanism through which competitive advantage is driven both directly and indirectly by facilitating the development of DBMI, which is recognized as a critical determinant of long-term competitive success. Based on this rationale, the following hypothesis is proposed.

Hypothesis 5 (H5): *DT enhances the FCA of SMMEs through a chain-mediated process: it first drives DPCI, then enables DBMI, and finally achieves higher FCA.*

In summary, integrating the theoretical perspectives discussed above, this study constructs a conceptual framework to illuminate the process by which DT strengthens the competitive advantage of SMMEs. As illustrated in Figure 1, the model proposes that DT, by enhancing firms' dynamic capabilities—namely, sensing, seizing, and transforming—drives three distinct forms of digital innovation: the development of novel products with embedded digital functionalities (DPDI), the optimization of internal operations through digital tools (DPCI), and the reconfiguration of value creation and delivery mechanisms (DBMI). These innovations, in turn, serve as critical mediating pathways that collectively and sequentially translate technological empowerment into sustained market competitiveness.

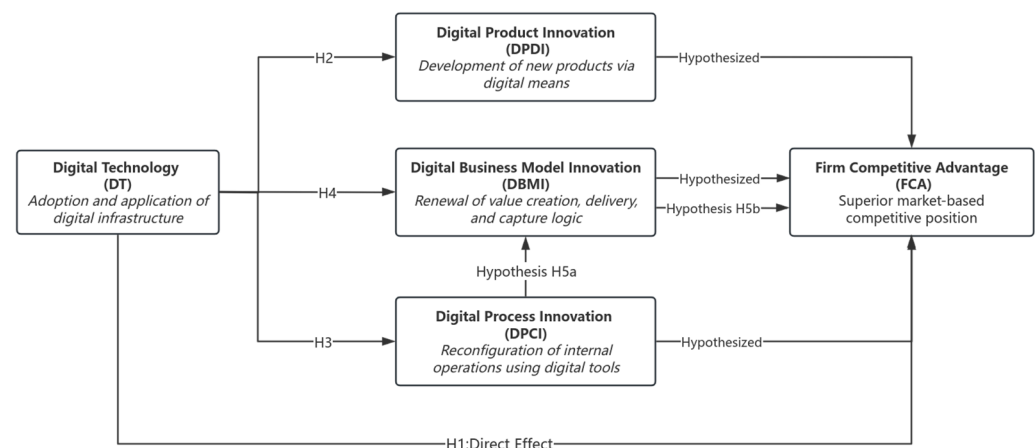


Figure 1. Theoretical Analysis Framework Diagram.

4. Research Design

4.1. Sample Selection and Data Sources

Aligning with the statutory provisions outlined in China's Law on the Promotion of Small and Medium-sized Enterprises, this study defines SMEs as firms employing 20–1000 individuals. The initial sample comprised all manufacturing firms listed on the Shanghai and Shenzhen A-share exchanges from 2013 to 2022. To construct a sample relevant to studying the impact of DT, a three-step refinement was applied. First, to ensure that the sample consisted of firms engaged in digital transformation, enterprises whose annual reports contained no DT-related keywords in the 'Management Discussion and Analysis (MD&A)' section throughout the entire sample period were excluded, as identified through textual analysis. Second, to preserve the integrity of the panel dataset, delisted firms were excluded. Finally, firms lacking complete data for the research period, specifically those with more than five consecutive years of missing values for any core variable, were removed.

The resulting sample consists of 153 listed SMMEs, yielding 1530 firm-year observations across 13 manufacturing subsectors. This sample represents a unique set of A-share listed SMMEs that engaged in digital initiatives and provided sufficient continuous data for longitudinal analysis. Empirical analysis utilizes a two-way fixed effects model for parameter estimation. All data processing and statistical analyses were conducted using Stata 17.0.

4.2. Variable Definition

4.2.1. Explained Variable

FCA has been typically measured in past studies either through survey-based methods or by return on assets. For manufacturing firms, whose central activity and main source of competitiveness reside in product output, this study follows the approach of Hu (2022) [72] by employing market-based competitive performance as a proxy for FCA. It is measured using three complementary aspects that reflect a firm's market position and profit-generating ability: profit conversion rate (PCR), market share (MS), and the intensity of competition within its product market.

FCA is constructed from three components: PCR, MS, and product market competition degree (PMCD). To ensure robustness, gross profit on sales (SGP) serves as the proxy indicator for PCR. The PMCD is measured using the Herfindahl-Hirschman Index (HHI) index. This index is computed by summing the squared proportions of each firm's sales revenue (SR) relative to the total sales revenue of the industry. The formulas are defined as follows:

$$SGP_{i,t} = OR_i - OC_i \quad (1)$$

$$MS_{i,t} = OR_i / \sum_{i=1}^n OR \quad (2)$$

$$HHI_{i,t} = SR_i / \sum_1^n SR \quad (3)$$

In Formulas (1)–(4), subscript *i* denotes a specific firm, while subscript *t* indicates the time period.

To integrate these three dimensions into a composite index objectively, the entropy method was employed to determine their respective weights. This method assigns weights according to the informational content of each indicator, minimizing subjective bias. Subsequently, a weighted linear aggregation approach is employed to compute the annual FCA value for each enterprise. The calculation formula is as follows:

$$FCA_{i,t} = \alpha_{1i,t}SGP_{i,t} + \alpha_{2i,t}MS_{i,t} + \alpha_{3i,t}HHI_{i,t} \quad (4)$$

4.2.2. Core Explanatory Variables

Measuring DT constitutes a key empirical challenge. Unlike traditional methods relying on single objective indicators, textual analysis of corporate annual reports offers a nuanced measure of firms' strategic emphasis and commitment toward digital transformation, guided by the perspective of firm attention. As a legally mandated disclosure, the annual report, particularly the MD&A section, functions as a key medium through which management communicates strategic orientations and future intentions to investors.

The prevalence of DT-related terminology in these documents provides a well-established indicator of strategic intent and resource allocation priorities, providing insight into a firm's transformation initiatives [73–75]. Furthermore, the regulated nature of annual reporting imposes a dual governance effect: it holds management accountable for translating strategies into actions, while public disclosure enables stakeholder monitoring, improving the alignment between stated commitments and subsequent operational activities.

Drawing on Yu et al. (2020) [73], this study measures DT adoption by assessing the prevalence of pertinent terms within the MD&A segments of corporate annual reports. The analysis uses keyword libraries developed by Wu et al. (2021) and Zhao et al. (2021) [74,75], encompassing two dimensions: technology application (TA, 43 keywords) and technical practice application (TP, 99 keywords). Our core explanatory variable, *lnDT*, is constructed as the natural logarithm of one plus the annual total count of identified digital-related keywords in SMME reports.

It is acknowledged that keyword frequency captures strategic emphasis, which constitutes a necessary antecedent to and correlate of substantive capability building. To address concerns regarding the measurement of underlying technological capability and to enhance the robustness of the findings, an alternative outcome-based measure was constructed, namely the number of DT-related invention patents filed by each firm. The development of this measure and its application in extensive robustness checks are described in Section 5.3.

4.2.3. Mediating Variable

(1) DPDI. DPDI denotes the development of novel or substantially enhanced products whose essential functions or user interactions are fundamentally supported by DT. DT empowers this process by enhancing designers' capacity to sense market feedback and seize development opportunities through rapid iteration [17].

Measuring this complex construct with secondary data requires a multi-faceted approach that captures different manifestations of innovative output. In line with the integrative measurement approach advocated by Pesch et al. (2021) and Tang et al. (2023) [76,77], a firm's DPDI output intensity was assessed through a composite index of three complementary indicators: (a) Digital innovation papers (DIPR), reflecting knowledge creation and exploration in digital domains; (b) Digital invention patents (DIPT), representing the formalization and protection of novel technical solutions; and (c) Digital innovation qualifications (DIQC), indicating the attainment of recognized standards or certifications for digital products or processes.

This tripartite measure acknowledges that innovation in SMEs, especially in the digital realm, can manifest not only in formal R&D outputs (patents) but also in knowledge diffusion (papers) and market/regulatory validation (qualifications). Each component contributes to a broader understanding of the firm's engagement in DPDI. The composite measure is calculated as the sum of these three standardized components:

$$\text{DPDI} = \text{DIPR} + \text{DIPT} + \text{DIQC} \quad (5)$$

A higher DPDI score was interpreted as reflecting greater observable output and engagement in the domain of DPDI. While this measure may not capture the entire innovation process or market success, it provides a robust, multi-dimensional proxy for comparing the relative DPDI output across firms in the studied sample.

(2) DPCI. Firms can apply their innovation capabilities directly to production processes and equipment, enhancing competitive advantage. This reflects the impact of technological innovation capacities on products and processes [78].

DPCI involves the use of DT to improve existing processes or create new business processes, enhancing service quality while reducing operational and managerial costs. Given the difficulty of real-time monitoring, this study adopts a text-based approach following Looy (2021) [79] to identify relevant terminology and quantify firm-level DPCI. The variable is constructed as follows:

$$\text{DPCI} = \sum \text{WordFrequency} \quad (6)$$

(3) DBMI. Following Liu et al. (2019) [80] and the 'business model iceberg' framework, DBMI is conceptualized in terms of its observable performance outcomes across three key dimensions: value creation (VC), value delivery (VD), and value realization (VR). This output-oriented approach aligns with the logic that a successfully innovated business model, particularly one driven by DT, should manifest in improved operational and financial results.

VC is measured using the quick ratio (QR), debt coverage ratio (DCR), and equity-to-debt ratio (ELR). VD is assessed using the inventory turnover ratio (ITR), accounts receivable turnover ratio (ART), and total asset turnover ratio (TATO). VR is evaluated through the annual growth rate of operating income (GROI), annual growth rate of net profit (GRNP), and main business profit margin (PMMB).

The entropy method is employed to assign objective weights to the indicators in each dimension, and the overall DBMI index is then constructed via linear weighting of the three dimension scores (Formulas (7)–(10)). This method reduces subjective bias and integrates multi-dimensional performance into a single measure.

$$VC_{i,t} = a_{1i,t}QR_{i,t} + a_{2i,t}DCR_{i,t} + a_{3i,t}ELR_{i,t} \quad (7)$$

$$VD_{i,t} = b_{1i,t}ITR_{i,t} + b_{2i,t}ART_{i,t} + b_{3i,t}TATO_{i,t} \quad (8)$$

$$VR_{i,t} = c_{1i,t}GROI_{i,t} + c_{2i,t}GRNP_{i,t} + c_{3i,t}PMMB_{i,t} \quad (9)$$

$$DBMI_{i,t} = d_{1i,t}VC_{i,t} + d_{2i,t}VD_{i,t} + d_{3i,t}VR_{i,t} \quad (10)$$

Higher DBMI scores are considered to reflect business models that more effectively create, deliver, and capture value, as a result of continuous digital innovation. This measurement strategy also allows for the examination of potential short-term trade-offs: significant investments in digital transformation may initially suppress certain financial metrics, which would be consistent with a complex or non-linear mediation pattern in the empirical analysis. However, it is important to acknowledge that our composite index, based on financial and operational ratios, captures the overall performance outcomes of a business model but may not specifically isolate its digital characteristics. Future research could develop more direct measures of DBMI, such as the proportion of revenue from platform services, digital channel penetration rates, or the density of ecosystem partnerships, to facilitate an in-depth understanding.

4.2.4. Control Variables

The analysis incorporates the following control variables: firm age (Age), firm size (Size), ownership type (Property), regional internet penetration (Internet), and return on assets (ROA), among others. Year and industry fixed effects are included. Table 1 presents detailed definitions and operationalizations for these variables.

Table 1. Variable definitions.

Type	Variable Name	Subdimension (Symbol)	Variable Definition
Explained variable	Firm's competitive advantage (FCA)	Profit Conversion Rate (PCR)	Sales Revenue—Cost of Sales
		Market Share (MS)	Firm's Operating Revenue/Sum of Operating Revenue of All Listed Firms in the Industry
		Product Market Competition Degree (PMCD)	Herfindahl Index
Explanatory Variable	DT-related Keyword Frequency (lnDT)	Technology Application (TA)	Word frequency of terms like AI, Big Data, Cloud Computing, Blockchain, etc.
		Technology Practice (TP)	Word frequency of terms like Industrial Internet, Mobile Internet, B2B, etc.
Mediating Variables	Digital Product Innovation (DPDI)	Digital Innovation Papers	Number of published domestic and international papers
		Digital Invention Patents	Number of newly applied scientific and technological patents per year
	Digital Process Innovation (DPCI)	Digital Innovation Qualifications	Count of innovation qualification certifications
		Digital Process Innovation	Word frequency count of digital process innovation terms in annual reports

Table 1. Cont.

Type	Variable Name	Subdimension (Symbol)	Variable Definition
Mediating Variables	Digital Business Model Innovation (DBMI)	Value Creation	Quick Ratio: Current Assets divided by Current Liabilities Debt Coverage Ratio: Operating Cash Flow divided by Total Liabilities Equity-to-Liabilities Ratio: Owner's Equity divided by Total Liabilities Inventory Turnover Ratio: Cost of Sales divided by Average Inventory
		Value Delivery	Accounts Receivable Turnover Ratio: Sales Revenue divided by Average Accounts Receivable Total Asset Turnover Ratio: Sales Revenue divided by Average Total Assets Year-on-Year Growth Rate of Operating Revenue: (Current Year Operating Revenue/Previous Year Operating Revenue)—1
		Value Realization	Year-on-Year Growth Rate of Net Profit: (Current Year Net Profit/Previous Year Net Profit)—1 Operating Profit Margin: Operating Profit divided by Operating Revenue Current Year—Year of Firm Establishment
Control Variables	Firm Age (Age)		Natural logarithm of total assets
	Firm Size (Size)		Coded as 1 for State-Owned Enterprises, and 0 otherwise
	Ownership Nature (Property)		Number of Internet Broadband Subscribers per 100 People, divided by Resident Population
	Regional Internet Penetration Rate (Internet)		Net Profit/Average Total Assets
	Return on Assets (ROA)		

4.3. Model Construction

To empirically test the research hypotheses, a two-way fixed-effects panel model was utilized to examine the direct influence of DT on the competitive advantage of SMMEs.

$$FCA_{it} = \beta_0 + \beta_1 \ln DT_{it} + \sum_m \beta_m Controls_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (11)$$

In this specification, FCA_{it} measures the firm's competitive advantage of manufacturing enterprise i in year t , while $\ln DT_{it}$ represents the DT level of the same enterprise in that year. The construction of FCA follows Equation (4) as detailed in Section 4.2.1, where it is a composite index derived from three sub-components: profit conversion rate (SGP), market share (MS), and product market competition degree (HHI), with their respective weights objectively determined by the entropy method. Controls encompass the set of control factors detailed above. μ_i and λ_t denote industry and year fixed effects, respectively. ε_{it} is the model's idiosyncratic error term. β_0 is the constant, and β_1 and β_m are the coefficients to be estimated. A positive regression coefficient ($\beta_1 > 0$) implies that DT strengthens SMMEs' competitive advantage, while a negative coefficient ($\beta_1 < 0$) indicates the opposite.

5. Results

5.1. Descriptive Statistics

Table 2 displays the descriptive statistics for the core variables. The average FCA is 0.045, ranging from 0.007 to 0.817, indicating substantial variation in competitive capabilities among the sampled firms. A relatively low average FCA suggests that listed Chinese manufacturing firms exhibit a modest level of FCA.

Table 2. Summary statistics.

	N	Mean	SD	Min	Median	Max
FCA	1530	0.045	0.057	0.007	0.028	0.817
lnDT	1530	3.109	1.092	0	3.135	6.356

Table 2. *Cont.*

	<i>N</i>	Mean	SD	Min	Median	Max
Age	1530	20.703	5.709	3	21	43
Size	1530	5.881	1.403	0	6.108	12.376
Property	1530	0.404	0.491	0	0	1
Internet	1530	32.27	12.247	0	32.598	98.797
ROA	1530	0.049	0.080	−0.495	0.045	0.571

lnDT exhibits a mean of 3.109 and a range from 0 to 6.356, indicating considerable heterogeneity in adoption and untapped potential among SMMEs.

5.2. Baseline Results

Table 3 presents the baseline regression results examining the relationship between DT and FCA. In Column (1), which excludes controls and fixed effects, lnDT exhibits a positive effect. The effect remains significantly positive in Column (2) after including year and industry fixed effects. In Column (3), with the addition of control variables, the coefficient for DT remains positive and is statistically significant at the 1% level ($\beta = 0.003$), indicating a robust positive association between DT adoption and competitive advantage. A one-unit increase in lnDT is associated with a 0.003-unit enhancement in FCA, *ceteris paribus*. The findings indicate that DT substantially enhances the firm's competitive advantage of SMMEs, providing support for Hypothesis H1.

Table 3. Results of the baseline analysis.

Variables	(1) FCA	(2) FCA	(3) FCA
lnDT	0.0013 (0.0012)	0.0022 *** (0.0007)	0.0033 *** (0.0008)
Age			−0.0015 *** (0.0004)
Size			−0.0017 *** (0.0006)
Property			0.0112 *** (0.0026)
Internet			−0.0002 ** (0.0001)
ROA			0.0373 *** (0.0093)
Industry FE	NO	YES	YES
Year FE	NO	YES	YES
Constant	0.0414 *** (0.0041)	0.0385 *** (0.0020)	0.0645 *** (0.0086)
Observations	1530	1529	1529
R-squared	0.0006	0.5199	0.5400

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

5.3. Robustness Tests

While the preliminary regression analysis confirms a significant positive association between lnDT and FCA, robustness tests are performed to address potential concerns stemming from variable and sample selection, evaluating the stability of the model:

(1) To counter potential issues associated with variable selection, the dependent variable was substituted with market share (FCA1) as an alternative measure for FCA, drawing on the methodology of Rego et al. (2013) [81]. Column (1) of Table 4 shows that the lnDT

coefficient remains positive and statistically significant, validating the robustness of the primary findings.

Table 4. Robustness Tests.

Variables	(1) FCA1	(2) FCA	(3) FCA	(4) FCA	(5) FCA	(6) FCA	(7) FCA	(8) LFCA
InDT	0.0023 *** (0.0006)		0.0038 *** (0.0009)	0.0038 *** (0.0009)	0.0034 *** (0.0009)			0.0027 *** (0.0010)
Indigpa		0.0001 ** (0.0001)						
BGDID						0.013 *** (0.003)		
AIDID							0.015*** (0.004)	
Age	−0.0013 *** (0.0004)	−0.0015 *** (0.0004)	−0.0017 *** (0.0005)	−0.0016 *** (0.0005)	−0.0012 *** (0.0004)	−0.002 *** (0.000)	−0.002 *** (0.000)	−0.0015 *** (0.0005)
Property	0.0081 *** (0.0020)	0.0102 *** (0.0025)	0.0104 *** (0.0026)	0.0103 *** (0.0026)	0.0088 *** (0.0025)	0.011 *** (0.003)	0.010 *** (0.003)	0.0110 *** (0.0028)
Internet	−0.0001 (0.0000)	−0.0001 * (0.0001)	−0.0002 ** (0.0001)	−0.0002 ** (0.0001)	−0.0002 ** (0.0001)	−0.000 (0.000)	−0.000 ** (0.000)	−0.0002 ** (0.0001)
Size	0.0008 (0.0006)	−0.0015 ** (0.0006)	−0.0011 * (0.0006)	−0.0004 (0.0006)	−0.0013 * (0.0008)	−0.002 *** (0.001)	−0.002 ** (0.001)	−0.0013 * (0.0007)
ROA	0.0214 *** (0.0053)	0.0388 *** (0.0093)	0.0549 *** (0.0122)	0.0527 *** (0.0119)	0.0256 *** (0.0078)	0.041 *** (0.011)	0.041 *** (0.011)	0.0477 *** (0.0114)
Lev			0.0350 *** (0.0082)	0.0338 *** (0.0080)				
RDfee				0.0000 *** (0.0000)				
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.0237 *** (0.0075)	0.0782 *** (0.0092)	0.0614 *** (0.0072)	0.0306 *** (0.0082)	0.0697 *** (0.0096)	0.081 *** (0.011)	0.085 *** (0.011)	0.0647 *** (0.0099)
Observations	1528	1528	1374	1374	1067	1376	1376	1376
R-squared	0.6714	0.5401	0.5636	0.5731	0.5967	0.495	0.490	0.5643

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2) Alternative measurement of DT. To confirm the robustness of the findings, DT was alternatively proxied by the logarithm of one plus the number of digital patents (Indigpa). This measure captures firms' innovation output specifically in digital domains, providing a complementary perspective to our primary measure of DT adoption. As shown in Column (2) of Table 4, the coefficient for this alternative measure remains positive and statistically significant ($\beta = 0.0002$, $p < 0.05$). These results confirm that the positive effect of DT on FCA is not dependent on a particular operationalization of the key independent variable, improving the reliability and generalizability of the findings.

(3) Other control variables, including the debt-to-asset ratio (Lev) and new product development expenditure (RDfee), were subsequently included. The estimates reported in Columns (3) and (4) of Table 4 indicate that the positive effect of DT persists, consistent with the baseline results, reinforcing the robustness of the main conclusions.

(4) Employing sample adjustment is a conventional robustness check, aimed primarily at verifying the consistency of research conclusions through modifications to sample scope or selection criteria. The year 2017 signifies a pivotal transition in the digital transformation journey of China's manufacturing industry, shifting from a phase of "policy initiation" to one of "deep penetration." During the period, the "Guiding Opinions on Deepening the Development of 'Internet Plus Advanced Manufacturing' and Industrial Internet" officially designated the Industrial Internet as a national strategic focus for the first time. The following years witnessed the swift deployment of multi-level government subsidies, pilot

demonstration projects, and the rollout of 5G infrastructure, coupled with a significant surge in DT investment. From 2018 to 2020, China's Ministry of Industry and Information Technology (MIIT) released the "Enterprise Cloud Adoption Implementation Guidelines" alongside the "Special Action for Digital Empowerment of Small and Medium-sized Enterprises." These initiatives accelerated the adoption of DT—such as cloud computing, big data, and the Internet of Things—among small and medium-sized manufacturers, with adoption rates rising from below 20% in 2016 to 54% by 2020. This created a sufficiently distinct policy shock window for identifying causal effects. Consequently, using a post-2017 sample allows for the capture of policy-driven exogenous variations in DT while reducing measurement error associated with its initially low penetration, providing a more reliable assessment of its impact on FCA. Hence, this study conducts robustness analysis using post-2017 data. The outcomes presented in Column (5) of Table 4 are consistent with earlier results, affirming the robustness of the study's conclusions.

(5) To address potential endogeneity concerns, this study employs a difference-in-differences (DID) design, utilizing the quasi-natural experiments of China's "National Big Data Comprehensive Pilot Zone" and "National AI Innovation and Application Pilot Zone." Firms located in policy-covered cities constitute the treatment group, whereas those never exposed to such policies serve as the control group. As reported in Columns (6) and (7) of Table 4, the DID estimates confirm that both policies exert a statistically significant positive effect on FCA at the 1% level, corroborating the baseline findings. Furthermore, a placebo test based on 500 random treatment assignments confirms that the observed policy effects are not driven by chance (detailed results are provided in the Appendix A), reinforcing the robustness of the causal inference.

(6) Finally, a one-period lag of the product's competitive advantage is incorporated to account for dynamic persistence and mitigate potential bias from omitted variables. The estimated impact of $\ln DT$, as shown in Column (8) of Table 4, persists as positive and statistically significant, offering additional support for the robustness of Hypothesis H1.

(7) Comprehensive validation using Structural Equation Modeling (SEM). SEM was employed to address methodological concerns related to the simultaneous estimation of multiple mediating pathways. This methodology enables the integrated estimation of all direct and indirect effects hypothesized by our theoretical framework, offering a comprehensive assessment of the alternative mediation routes. The results, summarized in Table 5, provide substantial support for the hypothesized mechanisms. The chain-mediating effect of $\ln DT$ on competitive advantage through the sequential path of DPCI and DBMI remains statistically significant (effect = 0.008, $p = 0.003$, 95% CI [0.003, 0.013]). Concurrently, the independent mediating effect of DPDI becomes non-significant (effect = -0.004 , $p = 0.188$). This pattern—wherein the sequential mediation remains robust while the parallel product innovation mediation attenuates under full model estimation—delivers strong empirical validation for the logic underlying Hypotheses 2 and 3. The SEM model demonstrates acceptable fit indices (CFI = 0.910; SRMR = 0.053), offering further corroboration for the robustness of the proposed theoretical model.

5.4. Endogeneity Testing

Considering that endogeneity issues may potentially bias the baseline estimates, the following approaches were employed in this study to address these concerns.

(1) To mitigate potential reverse causality and simultaneity bias, lagged terms of the DT variable were incorporated, following the approach of Ang et al. (2024) [82]. Using the first-, second-, and third-period lags of $\ln DT$ helps account for delayed effects and provides a supplementary check on the robustness of the main relationship. The results presented in Columns (1) through (3) of Table 6 show that the positive relationship between $\ln DT$

and FCA persists in the first lagged period, supporting the short-term impact of digital initiatives. The attenuated or non-significant coefficients observed in the second and third lags may reflect the rapid absorption of technological dividends or the dynamic nature of competition in digital transformation, suggesting that the competitive advantages derived from DT are often most pronounced in the immediate years following adoption. While the lagged analysis provides supplementary evidence on short-term dynamics, it is recognized that it does not represent a fully exogenous identification strategy, and the findings are interpreted cautiously with respect to causal inference.

Table 5. Structural Equation Modeling (SEM) Results for Mediation Analysis.

Path/Effect	Coefficient	S.E.	<i>p</i> -Value	95%CI (Bootstrap)
A. Key Direct Paths (Standardized)				
lnDT → Process Innovation (DPCI)	0.141 ***	0.025	0.000	
lnDT → Business Model Innovation (DBMI)	−0.112 ***	0.026	0.000	
DPCI → Business Model Innovation (DBMI)	0.129 ***	0.026	0.000	
DPCI → Competitive Advantage (FCA)	0.226 ***	0.023	0.000	
DBMI → Competitive Advantage (FCA)	0.420 ***	0.023	0.000	
B. Mediation Effects (Bootstrap, 500 reps)				
via DPCI only (lnDT→DPCI→FCA)	0.032 ***	0.008	0.000	[0.015, 0.048]
via DBMI only (lnDT→DBMI→FCA)	−0.047 ***	0.016	0.003	[−0.078, −0.017]
Chain:via DPCI→DBMI (lnDT→DPCI→DBMI→FCA)	0.008 *	0.003	0.003	[0.003, 0.013]
via DPDI only (lnDT→DPDI→FCA)	−0.004	0.003	0.188	[−0.010, 0.002]
C. Model Fit Indices				
Comparative Fit Index (CFI)	Value			
RMSEA	0.910			
SRMR	0.133			
SRMR	0.053			
Observations	1529			

Notes: *** $p < 0.01$, * $p < 0.10$. Bootstrap confidence intervals are percentile-based. All coefficients are standardized. The SEM analysis follows established recommendations for simultaneous estimation of multiple mediators.

Table 6. Endogeneity test results.

Variables	(1) FCA	(2) FCA	(3) FCA
lnDT1	0.0027 *** (0.0010)		
lnDT2		0.0016 (0.0010)	
lnDT3			0.0012 (0.0010)
Age	−0.0015 *** (0.0005)	−0.0015 *** (0.0005)	−0.0013 *** (0.0005)
Size	−0.0013 * (0.0007)	−0.0006 (0.0008)	−0.0004 (0.0008)
Property	0.0110 *** (0.0028)	0.0108 *** (0.0031)	0.0096 *** (0.0029)
Internet	−0.0002 ** (0.0001)	−0.0002 ** (0.0001)	−0.0002 ** (0.0001)
ROA	0.0477 *** (0.0114)	0.0417 *** (0.0116)	0.0317 *** (0.0098)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.0759 *** (0.0100)	0.0757 *** (0.0112)	0.0732 *** (0.0109)
Observations	1376	1223	1071
R-squared	0.5246	0.5065	0.5407

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2) All empirical models incorporate industry and year fixed effects to account for unobserved time-invariant heterogeneity and economy-wide temporal shocks. This approach helps isolate within-industry, temporal variation in the application of DT, mitigating omitted variable bias to a certain extent. The fixed effects estimation strategy provides additional, albeit not conclusive, evidence that DT is significantly associated with enhanced FCA in SMMEs.

While lagged terms partially address reverse causality, it is recognized that they do not provide a fully exogenous identification strategy. The findings are therefore interpreted as reflective of short-term dynamics, and this consideration is discussed accordingly.

5.5. Heterogeneity Tests

While the positive contributions of DT to the competitive advantage of manufacturing SMEs have been established in prior research and corroborated by the robustness checks, it is recognized that these effects may vary according to firm characteristics. Accordingly, regional heterogeneity, differences between high-tech and non-high-tech industries, and variations in ownership structure between state-owned and private enterprises are examined, along with the heterogeneity stemming from digital finance and market competition.

5.5.1. Regional Heterogeneity

Differences in regional resource endowments and uneven development across China have resulted in significant variations in the adoption of DT and firms' innovation capabilities. When segmenting the sample into eastern, central, western, and northeastern regions, the regression results that the coefficient for $\ln DT$ is statistically significant and positive effect on FCA in the eastern, western, and northeastern regions (Table 7, Columns 1 to 4). The coefficient for the central region, while positive, fails to achieve statistical significance. The superior outcomes in the eastern region can likely be attributed to its more advanced economic foundation, including a well-developed innovation ecosystem, stronger appeal for talent, and greater technological resources, all contributing to more effective integration and transformation via digital tools. The significant positive effects identified in China's western and northeastern regions may mirror the policy backing and resource investments associated with national strategies for coordinated regional development, such as the Western Development and Northeast Revitalization campaigns. Such initiatives may have accelerated the deployment of digital infrastructure, enabling local enterprises to utilize DT for innovation while demonstrating a visible "catch-up" effect. Comparatively, the weaker performance observed in the central region may stem from its greater reliance on traditional industries, persistent difficulties in industrial transformation, less widespread adoption of DT, and the outflow of innovative talent and capital to more developed eastern areas. As a result, the mechanism by which DT fosters innovation has not yet been fully realized in the central region. This finding suggests that more tailored policy interventions are required to unlock its potential.

Heterogeneity between central cities (municipalities, provincial capitals, and sub-provincial cities) and peripheral cities is examined, adopting the classification established by Chun-Chung & Vernon (2006) [83]. The regression outcomes show a statistically significant and positive impact of DT on FCA for both city categories (Columns 5 and 6, Table 7). However, the economic magnitude of this effect is considerably stronger in central cities, with the estimated coefficient being roughly three times that observed in peripheral cities. As observed by Forman et al. (2012) and Huang et al. (2025) [84,85], returns on DT are closely related to urban "agglomeration advantages," which are typically concentrated in administrative cores. Central cities enjoy systematic benefits in infrastructure, factor aggregation, and policy responsiveness, amplifying the marginal returns of digital

adoption. Peripheral cities face constraints, e.g., gradient transfer mechanisms and fiscal decentralization, that limit their capacity to keep pace. Thus, although DT confers benefits across all city types, the magnitude and temporal patterns of its effects vary, reflecting underlying structural disparities.

Table 7. Regional heterogeneity analysis.

Variables	(1) East	(2) Middle	(3) West	(4) Northeast	(5) Center	(6) Periphery
lnDT	0.0059 *** (0.0016)	0.0005 (0.0010)	0.0021 ** (0.0010)	0.0038 * (0.0019)	0.0041 *** (0.0015)	0.0015 *** (0.0005)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Constant	0.1099 *** (0.0149)	0.0175 ** (0.0078)	0.0221 *** (0.0063)	0.0596 (0.0671)	0.0915 *** (0.0124)	0.0460 *** (0.0044)
Observations	899	249	309	70	863	664
R-squared	0.5490	0.6084	0.7518	0.7769	0.4988	0.8933

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5.2. Industry and Property Rights Heterogeneity

Heterogeneity in ownership structures significantly shapes resource allocation. Specifically, firms with differing ownership structures operate under distinct business objectives and operational environments. Among these, state-owned enterprises (SOEs) typically benefit from preferential access to resources and policy support, while also bearing greater strategic and social responsibilities. China's manufacturing sector is currently in the midst of a pivotal shift from traditional methods toward intelligent manufacturing. Consequently, examining the impact of DT on FCA in SMMEs highlights the need to consider ownership type. In this study, SOEs are coded as 1, and non-SOEs as 0. The regression outcomes for SOEs and non-SOEs are displayed in Columns (1) and (2) of Table 8, respectively. Both groups exhibit significantly positive coefficients. This finding indicates that lnDT enhances FCA at 1% and 5% for SOEs and non-SOEs, respectively. Moreover, the economic effects are stronger within SOEs. This difference may be explained by the more direct policy support and closer government–enterprise collaboration typically available to SOEs, which helps reduce expenses and risks associated with digital transformation and enables faster technology adoption. SOEs, often occupying pivotal positions within industrial value chains, typically possess greater access to essential industry data and more advanced capabilities for cross-departmental data integration. These advantages create favorable conditions for the effective application of big data and artificial intelligence in areas such as product innovation, quality management, and predictive analytics, translating digital capabilities into enhanced competitive advantage.

Significant differences are observed across industries regarding factor inputs, capital structure, market conditions, technological advancement, and adaptability to digital tools. Given that lnDT is the core explanatory variable in this investigation and that firms exhibit considerable heterogeneity in technological capabilities, varying outcomes are anticipated. Therefore, a further exploration of DT's role in shaping FCA from the perspective of technological intensity is warranted. Per the definitions provided by China's National Bureau of Statistics, high-tech industries are defined as those that utilize advanced, cutting-edge technologies to manufacture sophisticated, technology-intensive products. In this context, the present study designates the following four sectors as high-tech industries (Industry Type = 1): pharmaceutical manufacturing; specialized equipment; computers, communication, and electronic equipment; and instrument and meter manufacturing.

All other sectors are classified as non-high-tech (Industry Type = 0). The findings in Columns (3) and (4) of Table 8 indicate that the coefficient for non-high-tech firms is 0.0059, significant at the 1% level. In comparison, the coefficient for high-tech firms is positive but statistically insignificant.

Table 8. Industry- and ownership-based heterogeneity analysis.

Variables	(1) State-Owned	(2) Non-State-Owned	(3) High-Tech	(4) Non-High-Tech
lnDT	0.0060 *** (0.0022)	0.0014 ** (0.0006)	0.0006 (0.0005)	0.0059 *** (0.0016)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Constant	0.1068 *** (0.0195)	0.0408 *** (0.0045)	0.0280 *** (0.0033)	0.1047 *** (0.0168)
Observations	617	910	699	828
R-squared	0.5239	0.7722	0.4901	0.5456

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

This difference can be attributed to the later adoption of DT by high-tech enterprises, which constrains the potential for further improving the firm's competitive advantage. As a result, these firms may experience decreasing marginal returns and encounter potential technological constraints. As Bohnsack et al. (2021) [86] suggest, high-tech enterprises that have invested heavily in specialized digital assets at an early stage are particularly susceptible to a "capability trap": once a technological path becomes locked in, subsequent digital investments yield only marginal gains. Coreynen and Van (2017) [87] observe that although non-high-tech firms started later, their initially weaker technological foundation enables them to deploy mature, general-purpose digital tools at relatively low cost. Through experiential learning, these enterprises can promptly achieve simultaneous improvements in production efficiency, resource allocation, and risk control.

5.5.3. Competitive Level and Digital Finance Heterogeneity

Significant variation is observed in the development of digital financial ecosystems across regions, as well as in the degree of market competition across industries. Such external contextual conditions are expected to shape the extent to which DT contributes to enhancing a firm's competitive advantage. The advancement of digital finance, exemplified by accessible online financing and digital payment mechanisms, can reduce transaction costs and ease credit limitations, offering vital support for the digital initiatives of SMMEs. Simultaneously, the degree of market competition fundamentally reshapes the strategic motives and external pressures for firms to adopt digital tools aimed at achieving differentiation or efficiency improvements. Accordingly, the role of DT warrants further examination, considering these external factors.

To investigate the contingent effect of digital financial development, this study utilizes the prefectural-level Digital Financial Inclusion Index from Peking University. Firms are classified into high- and low-level groups according to the annual median value of this index in their registered cities. The regression outcomes for these subgroups are shown in Columns (1) and (2) of Table 9. Both subgroups display statistically significant positive coefficients for lnDT. It is noteworthy that the economic magnitude is greater within the high digital financial development group (coefficient = 0.0041) compared to its low-development counterpart (coefficient = 0.0022). The observed divergence likely reflects stronger financial

infrastructure and improved digital credit access in developed regions, easing financing challenges for SMMEs and supporting more substantial and lasting technology adoption.

Table 9. Heterogeneity Analysis: Digital Finance and Market Competition.

Variables	(1) High-Index	(2) Low-Index	(3) High HHI	(4) Low HHI
lnDT	0.0041 *** (0.0012)	0.0022 ** (0.0010)	0.0038 ** (0.0016)	0.0031 *** (0.0009)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Constant	0.1341 *** (0.0209)	0.0420 *** (0.0042)	0.0661 *** (0.0137)	0.0955 *** (0.0152)
Observations	742	736	734	760
R-squared	0.5082	0.7523	0.6857	0.3853

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

To evaluate the impact of market competition, this study employs the industry HHI as a proxy, where a lower HHI value signifies greater competition. The sample is divided into high- and low-competition groups based on the annual median HHI. The estimates in Columns (3) and (4) of Table 9 show that DT positively affects FCA in both competitive contexts (High HHI: $\beta = 0.0038$, $p < 0.05$; Low HHI: $\beta = 0.0031$, $p < 0.01$). These results confirm that digital technology contributes to competitive advantage regardless of market competition intensity.

5.6. Mechanism Testing

To further examine the underlying mechanisms through which a FCA is enhanced, the following econometric model is specified. Building on Model (11), this study applies a stepwise regression approach to examine the mediating effects. Model (12) assesses the impact of the explanatory variable lnDT on the mediating variable (digital innovation), while Model (13) evaluates the joint influence of lnDT and digital innovation on the explained variable, FCA. The specific model specifications are as follows:

$$DPDI_{it} = \gamma_0 + \gamma_1 \ln DT_{it} + \sum_m \gamma_m \text{Controls}_{it} + \lambda_t + \mu_i + \xi_{it} \quad (12)$$

$$FCA_{it} = \alpha_0 + \alpha_1 \ln DT_{it} + \alpha_2 DPDI_{it} + \sum_m \alpha_m \text{Controls}_{it} + \lambda_t + \mu_i + \eta_{it} \quad (13)$$

where $DPDI_{it}$ represents the digital innovation values of enterprises in industry i in year t , including DPDI, DPCI, and DBMI. The definitions for all other variables align with those specified in Model (1).

5.6.1. DPDI

DT enables product designers to gather, analyze, and apply market feedback more swiftly, accelerating and improving product development processes. This study adopts the measurement approach from Pesch et al. (2021) and Tang et al. (2023) [77,78], utilizing indicators such as digital innovation publications, digital invention patents, and DIQC to assess DPDI. Column (1) of Table 10 shows that DPDI exerts a significant positive effect on FCA, with significance at the 1% level. Estimates in Column (2) show that lnDT has a positive and statistically significant effect on DPDI at the 1% level. In Column (3), both lnDT and DPDI exhibit positive and significant coefficients at the 1% level. Consistent with the stepwise regression approach, these findings provide preliminary evidence for a potential mediating role of DPDI. However, to rigorously assess this mediating effect, a

Bootstrap test was performed (Table 11). The results indicate that the confidence interval for the indirect effect contains zero, demonstrating that the mediating effect is not statistically significant. Therefore, Hypothesis H2, which proposed that DPDI serves as a mediator in the relationship linking DT and FCA, is not supported by the data.

Table 10. Digital product innovation mechanism testing.

Variables	(1) FCA	(2) DPDI	(3) FCA
DPDI	0.0004 *** (0.0001)		0.0004 *** (0.0001)
LnDT		1.0082 *** (0.3117)	0.0030 *** (0.0008)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.0834 *** (0.0103)	−5.5757 *** (1.9665)	0.0764 *** (0.0095)
Observations	1529	1529	1529
R-squared	0.5433	0.1378	0.5456

Notes: Robust standard errors in parentheses. *** $p < 0.01$.

Table 11. Bootstrap test for digital product innovation bootstrapping.

Variable		(1) Effect	(2) Std. Error	(3) 95% CI	
				Lower	Upper
DPDI	_bs_1(Indirect Effect)	0.0005	0.0002	−0.0000	0.0010
	_bs_2(Direct Effect)	0.0024	0.0017	−0.0003	0.0050

Bootstrapping = 1000

This finding suggests that although DPDI is significantly promoted by DT and itself significantly boosts FCA, it fails to function as a significant mediator connecting DT and FCA in the studied context. A possible explanation for this outcome may reside in the inherent nature of the DPDI process.

Building upon the conceptual framework introduced by Nambisan et al. (2017) [6] regarding the core attributes of digital innovation, the development of DPDI generally entails extended innovation cycles (R&D), and their commercial success is primarily contingent on the ability to capitalize on market opportunities. These characteristics may create a temporal misalignment. While DT can drive product innovation and strengthen competitive positions, the conversion of these initiatives into measurable competitive advantage may not keep pace with fast-evolving technologies and shifting market conditions. This asynchrony implies that the window for realizing competitive benefits may be constrained; the very technologies underpinning the innovation could become obsolete, or market conditions might evolve before the full exploitation of the innovation's value proposition. As a result, the anticipated competitive gains from DPDI are often tempered by the rapid pace of technological advancement and competitive dynamics. (1) R&D Cycle: Transforming DT into market-ready product innovations often requires considerable time. During this extended development phase, the initially implemented technology may become obsolete or superseded, while market conditions or consumer preferences may also evolve. As such, by the time an innovative product is launched, the underlying technology may no longer be advanced, diminishing its potential competitive edge or rendering it misaligned with contemporary technological trends [24,88]. (2) Market Timing: The commercial suc-

cess of DPDI is largely determined by the timing of market entry. In the fast-evolving digital landscape, favorable market windows are often brief. Protracted development can lead to missed optimal launch opportunities [55]. Despite the intrinsic strengths of DT, delays in market entry may restrict the prompt conversion of technological capabilities into observable competitive gains. As a result, although DPDI reflects the outcomes of DT and supports competitive advantage, its protracted development and sensitivity to timing reduce its effectiveness as a mediating pathway.

5.6.2. DPCI

Enterprises can directly apply their innovation capabilities to production processes and equipment, directly impacting their competitive advantage. These findings demonstrate how technological innovation capacities operate across both product and process domains [78]. The adoption of cloud computing, collaborative platforms, and digital process management systems facilitates the breakdown of traditional organizational barriers, promotes information sharing within and beyond the enterprise, and accelerates the pace of decision-making and problem resolution [89]. The present study employs textual analysis following Looy (2021) [79] to identify relevant terminology and quantitatively assess the extent of DPCI.

Column (1) of Table 12 shows that DPCI exerts a significant positive effect on FCA at 1%. The regression outcomes in Column (2) reveal that LnDT significantly facilitates DPCI at 1%. In Column (3), the coefficient for DPCI continues to be statistically significant and positive at the 1% level, while the coefficient for LnDT becomes statistically insignificant. These findings offer preliminary evidence that DPCI fully mediates the relationship between DT and FCA. To rigorously examine this mediating mechanism, a Bootstrap test was conducted (Table 13). The findings demonstrate that the bootstrap confidence interval for the indirect effect excluded zero, whereas that for the direct impact did, confirming that DPCI acts as a full mediator.

Table 12. Mechanism verification of digital process innovation.

Variables	(1) FCA	(2) DPCI	(3) FCA
DPCI	0.0049 *** (0.0015)		0.0048 *** (0.0015)
LnDT		0.3825 *** (0.0661)	0.0014 (0.0009)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.0764 *** (0.0097)	0.2837 (0.6047)	0.0729 *** (0.0089)
Observations	1529	1529	1529
R-squared	0.5820	0.0951	0.5826

Notes: Robust standard errors in parentheses. *** $p < 0.01$.

Table 13. Bootstrap test for digital process innovation.

Variable		(1) Effect	(2) Std. Error	(3) 95% CI	
				Lower	Upper
DPCI	_bs_1(Indirect Effect)	0.0023	0.0007	0.0009	0.0039
	_bs_2(Direct Effect)	0.0005	0.0014	−0.0022	0.0032

Bootstrapping = 1000

For SMMEs, DT alone is not the core driver of directly enhancing competitive advantage. The key to unlocking its value lies in transforming it into innovations within the enterprise's internal operational processes. DT—such as the Internet of Things, cloud computing, and big data analytics, enhance operational efficiency, reduce costs, and improve responsiveness by enabling innovation across production processes, supply chain coordination, quality management, and decision-making. These significant improvements at the process level translate into stronger competitive advantages [90]. This finding underscores that, for resource-constrained small and medium-sized manufacturers, prioritizing digital process overhaul offers a more viable and critical pathway to convert technological investments into tangible competitive outcomes. Without being channeled into process innovations, the potential value of DT remains difficult to fully realize in a highly competitive market environment.

5.6.3. DBMI

DT has reshaped how enterprises engage with customers, significantly enhancing user experience and satisfaction. Through big data analytics, companies can implement personalized marketing and customer service systems that allow them to gain enhanced insight into customer needs and the delivery of tailored services [63]. The capability facilitates the development of business models that closely match customer requirements, strengthening both satisfaction and loyalty. Drawing on the business model iceberg theory proposed by Liu et al. (2019) [81], business models comprise three components: value creation, value delivery, and value realization. Following this classification, the entropy method is employed to integrate the relevant variables.

As presented in Column (1) of Table 14, DBMI exhibits a statistically significant positive effect on FCA at the 1% level. The estimates in Column (2) show that the coefficient for $\ln DT$ on DBMI is negative and significant at 10%. Column (3) reveals positive and significant coefficients for both $\ln DT$ and DBMI at the 1% level. However, the significant negative direct effect of DT on DBMI fundamentally contradicts the premise of a positive mediating relationship. Therefore, Hypothesis H4 is not supported by the data. The observed pattern, where DT exerts a negative direct effect on DBMI but a positive total effect on FCA, with DBMI itself positively influencing FCA, aligns statistically with a suppression model, suggesting a more complex, non-linear relationship. To rigorously assess the mediating mechanism, a Bootstrap test was conducted (Table 15). The results reveal that the confidence intervals for both the indirect and direct effects exclude 0.

Table 14. Mechanism testing of digital business model innovation.

Variables	(1) FCA	(2) DBMI	(3) FCA
DBMI	0.6058 *** (0.2301)		0.6231 *** (0.2295)
$\ln DT$		−0.0019 * (0.0010)	0.0046 *** (0.0010)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.0691 *** (0.0080)	0.0257 *** (0.0050)	0.0583 *** (0.0072)
Observations	1529	1529	1529
R-squared	0.5846	0.3069	0.5900

Notes: Robust standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

Table 15. Bootstrap test for digital business model innovation.

Variable		(1)	(2)	(3)	
		Effect	Std. Error	95% CI	
				Lower	Upper
DBMI	_bs_1(Indirect Effect)	−0.0020	0.0007	−0.0035	−0.0006
	_bs_2(Direct Effect)	0.0047	0.0014	0.0018	0.0075
Bootstrapping = 1000					

For SMMEs, these findings highlight a complex dynamic: while DT exerts a direct positive effect on competitive advantage, its negative relationship with short-term indicators of DBMI may reflect the considerable transition costs, organizational disruptions, and upfront investments associated with a fundamental business model transformation [67]. This phenomenon, often referred to as an ‘efficiency paradox,’ suggests that operational and financial performance metrics, captured in our DBMI measure, may temporarily decline even as the firm establishes the foundation for long-term competitive gains. Accordingly, it is crucial for these firms to strategically navigate the transformation process, proactively managing short-term challenges while harnessing the direct benefits of DT to strengthen competitive advantage [91].

5.6.4. Chain Mediation Test

Building upon the dynamic capability framework and integrating the outcomes from the individual mediation tests, this research further investigates the sequential linkage between DPCI and DBMI, exploring their potential function as chain mediators. The outcomes of the chain regression and Bootstrap analyses are displayed in Tables 16 and 17.

Table 16. Chain mediation mechanism test results.

Variables	(1) FCA	(2) DPCI	(3) DBMI	(4) FCA	(5) FCA
lnDT	0.0034 *** (0.0008)	0.3825 *** (0.0661)	−0.0023 ** (0.0010)		0.0028 *** (0.0011)
DPCI			0.0011 *** (0.0002)	0.0044 *** (0.0014)	0.0042 *** (0.0014)
DBMI				0.5458 ** (0.2198)	0.5587 ** (0.2212)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Constant	0.0743 *** (0.0094)	0.2837 (0.6047)	0.0254 *** (0.0050)	0.0653 *** (0.0076)	0.0587 *** (0.0069)
Observations	1529	1529	1529	1529	1529
R-squared	0.5410	0.0951	0.3183	0.6193	0.6213

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Table 17. Chained mediation bootstrap test.

Variable		(1)	(2)	(3)	
		Effect	Std. Error	95% CI	
				Lower	Upper
DPCI-DBMI-FCA	_bs_1(Indirect Effect)	0.0010	0.0005	0.0001	0.0019
	_bs_2(Direct Effect)	0.0051	0.0016	0.0020	0.0081
Bootstrapping = 1000					

Column (1) of Table 16 reveals a significant positive total effect of lnDT on FCA. Column (2) confirms that lnDT significantly promotes DPCI. Column (3) reveals a nuanced relationship: DPCI exerts a significant positive influence on DBMI, while the direct effect of lnDT on DBMI remains negative and significant. This pattern reinforces the finding from the standalone mediation test, indicating that the pathway from DT to DBMI is not straightforwardly positive but is positively facilitated through the advancement of internal processes. Column (4) shows that DBMI significantly enhances FCA, and DPCI also maintains a significant direct positive effect on FCA. The results in Column (5) reveal that, within the complete mediation framework, lnDT maintains a positive and significant direct impact on FCA, while DPCI and DBMI also show significant effects.

To rigorously test the chain-mediated pathway, a Bootstrap test was performed (Table 17). Evidence from the bootstrap analysis indicates a significant specific indirect effect through DPCI and DBMI, alongside a significant total direct effect of lnDT. Therefore, the empirical evidence supports a core chain mechanism in which DT enhances FCA by first driving DPCI, which subsequently catalyzes the development of DBMI (despite the latter's complex short-term relationship with DT itself). The results provide evidence in favor of the revised Hypothesis H5, demonstrating a significant sequential effect centered on DPCI. These findings highlight a sequential mechanism in digital transformation, particularly for SMMEs. Digitization of operational processes not only directly enhances competitive advantage but also generates an indirect effect on market competitiveness by enabling subsequent business model innovation. For resource-constrained small and medium-sized manufacturers, process innovation establishes the foundation for improved operational efficiency and efficiency-based advantages, while business model innovation functions as a critical conduit for converting these efficiency gains into tangible market value [92,93].

5.7. Discussion

Drawing on dynamic capability theory, this study conducts an empirical analysis using data from SMMEs listed on China's stock exchanges to evaluate the impact of DT on FCA. This study corroborates and extends the dynamic capabilities theoretical framework by examining how DT enhances the competitive advantage of SMMEs. The findings demonstrate that DT functions as a strategic resource, enhancing firms' sensing, seizing, and transforming capabilities, which collectively underpin competitive advantage. Empirical results consistently indicate that DT significantly strengthens these firms' competitive advantage. This effect remains robust across multiple sensitivity analyses, including alternative operationalizations of the dependent variable, the inclusion of additional controls, adjustments to the sample timeframe, and strategies to mitigate endogeneity. Unlike prior research, which has largely focused on macro-level effects or isolated aspects of innovation, this study situates the transmission mechanism—'DT → digital innovation → competitive advantage'—within a dynamic capabilities framework. This approach clarifies how DT reshapes firms' micro-level capability foundations, alters the competitive landscape, and substantially advances academic understanding of the economic implications of DT.

Furthermore, the study highlights the underlying processes by which DT impacts a firm's competitive advantage and delineates the critical mediators involved. Interpreted through the dynamic capability lens, the identified mediation pathways represent distinct manifestations of enhanced organizational capabilities. The mechanism analysis shows that the positive effect of DT on competitive advantage is achieved through a chain-mediating effect involving innovation in processes and business models. DPCI is identified as a full mediator (supporting H3), constituting the most direct and effective pathway. This aligns with the 'transforming' capability, where DT enables the reconfiguration of internal routines and assets. DPDI does not show a significant mediating effect (H2 not supported), likely

due to its extended development cycles and sensitivity to market timing. Furthermore, while DBMI itself strengthens FCA, the direct effect of DT on DBMI is negative, leading to a suppression pattern rather than the hypothesized positive mediation (H4 not supported). This suggests that DBMI may involve significant short-term transition costs. This finding furnishes a critical insight into the dynamics of digital transformation for SMEs: substantial investments in business model redesign can initially depress observable financial and operational performance metrics due to upfront costs, organizational restructuring, and the friction of running dual business models. This ‘suppression effect’ provides empirical evidence for the ‘efficiency paradox’ often discussed in the literature on strategic transformation and IT investments, enriching our understanding of the temporal and costly nature of fundamental business model innovation. The Bootstrap test confirms a significant chain mediation path: $DT \rightarrow DPCI \rightarrow DBMI \rightarrow FCA$. This sequential pathway reflects a logical capability-building progression, from operational transformation (process innovation) to strategic renewal (business model innovation). These findings support the central sequential framework of Hypothesis H5, demonstrating that process innovation serves both as a direct driver and a critical facilitator of subsequent business model development.

Finally, the heterogeneity analysis provides robust empirical evidence and actionable insights into the contextual conditions that shape the effectiveness of DT. These contingent effects can be understood through the dynamic capability perspective, which emphasizes the role of context in shaping how resources are converted into competitive outcomes. The analysis indicates that the positive impact of DT on competitive advantage varies across groups, being especially significant for state-owned firms, non-high-tech industries, and SMMEs in key geographic regions, including eastern, northeastern, and northwestern China and central cities.

Furthermore, the positive effect is stronger for firms operating in environments with higher levels of digital financial development, and remains significant across different levels of market competition intensity. This divergence highlights the critical roles of resource endowments, policy environments, market maturity, and digital infrastructure in realizing the dividends of technology. The absence of a significant effect for high-tech firms represents a theoretically meaningful boundary condition. This pattern may reflect diminishing marginal returns on digital investments for firms that are already technologically advanced. These insights highlight that digital competitive advantage is not automatic but depends on a firm’s existing resource endowment and innovation trajectory, extending the application of dynamic capability theory to diverse industry contexts.

6. Conclusions and Implications

6.1. Concluding Remarks

This study provides empirical evidence on how DT enhances the competitive advantage of Chinese manufacturing SMEs through distinct innovation pathways, grounded in dynamic capability theory. The core findings confirm that DT serves as a pivotal strategic resource that significantly strengthens the competitive position of SMMEs. This effect is not uniform but is most effectively channeled through a sequential capability-building process: DT first drives internal operational transformation through process innovation, which in turn lays the necessary foundation for and enables the evolution of the business model, ultimately culminating in superior market competitiveness. The immediate path from DT to product innovation, while present, does not translate into a significant competitive advantage within the observed timeframe, highlighting the differential temporal logic of various innovation types. Furthermore, the enabling power of DT is context-dependent, being amplified in environments characterized by supportive owner-

ship structures and complementary digital finance ecosystems, while remaining robust across different competitive landscapes.

6.2. Managerial Implications

For managers of manufacturing SMEs, the findings offer several actionable insights. First, DT capability must be placed at the heart of competitive strategy. This requires a dedicated investment in digitally skilled talent, alongside the proactive development of strategic partnerships to leverage external resources and expertise beyond the organization's internal capabilities. Second, the digital transformation journey should be strategically sequenced. Prioritizing investments in DPCI, such as automating production lines, implementing IoT for real-time monitoring, or optimizing supply chain logistics, offers the most direct and reliable path to achieving cost efficiency and quality improvements. Subsequently, the data and operational efficiencies gained from process digitization should be leveraged to experiment with and gradually scale new business models, such as offering data-driven after-sales services or transitioning to a platform-based operational model. Managers must exercise strategic patience during this phase, anticipating and managing potential short-term disruptions to financial metrics. Third, a one-size-fits-all approach is inadvisable. Strategies must be tailored to the firm's specific context, considering its industry technological intensity, regional digital infrastructure, and the competitive dynamics of its market.

6.3. Policy Implications

For policymakers aiming to foster a vibrant and competitive manufacturing sector, the results suggest several directions. First, policy support should be differentiated to address regional disparities. While eastern regions and central cities can be encouraged to pioneer advanced digital applications and high-end value chain integration, targeted programs are needed in central, western, and northeastern regions to accelerate digital infrastructure deployment and facilitate knowledge transfer. Second, developing the digital financial ecosystem is crucial. Policies that enhance SMEs' access to digital financing tools can alleviate a critical barrier to their initial technology investments. Third, industry-specific guidance can help channel efforts effectively. For non-high-tech sectors, policy can promote the adoption of mature, productivity-enhancing digital tools. For high-tech sectors, support might focus on integrating DT with core R&D and overcoming potential capability traps from earlier specialization. Finally, ensuring a level playing field between state-owned and private enterprises in accessing digital transformation resources and opportunities is essential for fostering broad-based innovation.

6.4. Limitations and Future Research

This study has certain limitations that highlight avenues for future research. First, although our measures are well-established, there is scope for further refinement. The text-based proxy for DT captures strategic emphasis rather than realized capability, and the DBMI index reflects performance outcomes rather than the structural digital attributes of the business model itself. Future research could develop more direct measures. Second, despite using fixed effects and lagged terms, stronger causal identification through instrumental variables or quasi-natural experiments is needed. Third, the focus on listed Chinese SMEs limits generalizability; furthermore, the keyword-based sample selection implies our findings are most relevant to firms already expressing strategic intent towards digitalization. Future work should examine unlisted firms and cross-country contexts. Finally, future studies should further explore the conditions for effective DPDI and investigate additional mediators (e.g., organizational agility) and moderators to refine the contingency framework.

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Appendix A

To verify that the baseline DID estimates are not driven by random factors, this study conducts a placebo test. The treatment group assignment is randomly generated, and the estimation procedure is repeated 500 times to obtain a distribution of pseudo-treatment effect coefficients based on random grouping. If the true policy effect were attributable to chance, the actual estimated coefficients would be expected to fall near the center of the randomized distribution. The results indicate that the estimated coefficients derived from the actual policy grouping (Big Data Pilot Zone: 0.013; AI Pilot: 0.015) are both situated significantly in the right tail of the distribution of randomized coefficients ($p < 0.01$), suggesting that the observed policy effects are highly unlikely to result from random variation. This test further reinforces the reliability of the baseline DID estimates and supports the validity of the causal interpretation. Detailed results of the placebo test (coefficient distribution plot) are presented in Appendix A Figure A1.

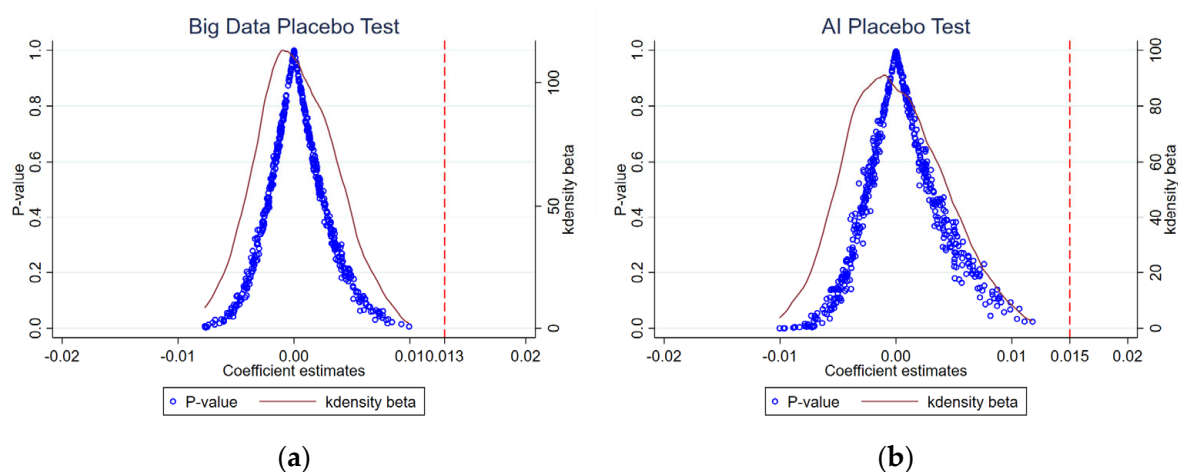


Figure A1. Placebo Test. (a) Big Data Comprehensive Pilot Zone; (b) AI Innovation and Application Pilot Zone. The red dashed line represents the actual estimated coefficient from the policy pilot (0.013 for the Big Data Pilot Zone and 0.015 for the AI Pilot Zone).

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