Digital Transformation: A Financial Game-Changer for Manufacturing

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Abstract
This study examines the organizational change process driven by adopting digital technologies in manufacturing. Using the Context-Mechanism-Outcome (CMO) framework and fuzzy set

qualitative comparative analysis (fsQCA), we analyzed 46 cases from the Chinese manufacturing sector. Our focus was on the internal mechanisms and conditions influencing digital transformation (DT). The findings reveal three distinct DT configuration models: process transformation, large enterprise DT, and platform-based transformation. Each model highlights unique organizational contexts, constraints, and digital leveraging strategies. These models demonstrate how different contextual factors shape DT approaches, providing insights into how organizations navigate technological transitions. By reframing DT as a dynamic and context-sensitive process, the study illustrates how traditional manufacturing practices are disrupted and new models are developed. Our findings emphasize aligning DT strategies with organizational goals to enhance implementation success. This research offers actionable guidance for managers, helping them address DT challenges through context-specific strategies.

Keywords: Digital Transformation, Financial Performance, Manufacturing Efficiency, Strategic Investments

1. Introduction

Integrating digital tools like big data analytics, social media, mobile technology, and cloud computing offers considerable benefits for traditional industries undergoing digital transformation (DT) (Lasi et al., 2014; Frank et al., 2019; Al-Hattami et al., 2024). In manufacturing, DT has emerged as a critical competitive tool that drives improvements in productivity, efficiency, and communication, thereby representing a vital investment for firms seeking to secure their future trajectory (Chen et al., 2024; Vakulenko and Garafonova, 2024; Diaz Tautiva et al., 2023; Le et al., 2023).

However, research has increasingly highlighted a substantial gap between the expectations and the realities of DT. Studies have identified a multitude of challenges—from technological integration issues and organizational resistance to misalignments between digital investments and core business models—underscoring the high failure rate of DT initiatives in manufacturing (Tortorella et al., 2023; Riaz et al., 2023; Dieste et al., 2022). Researchers contend that without a fundamental rethinking of business models, processes, and workforce development, the adoption of advanced technologies can yield minimal or even adverse effects (Karuppiah et al., 2024). Additionally, social and cultural adjustments, including employees' willingness to embrace these systems, play a critical role in determining the overall success of DT efforts (Seker and Aydin, 2024; Bello et al., 2024).

Despite the extensive documentation of these challenges, the existing literature primarily reiterates well-known obstacles without advancing theoretical innovation or engaging with critical perspectives that explain the dynamic interplay between organizational context and digital leveraging mechanisms. For instance, while Vial (2019) and Kraus et al. (2022) provide definitions and conceptualizations of DT, and scholars like Verhoef et al. (2021) and Baiyere et al. (2020) outline its impact on business model innovation and process management, there remains a lack of empirical evidence identifying the specific contextual factors and mechanisms that influence DT outcomes in manufacturing. This gap is further compounded by the limited integration of recent works on DT strategy and a narrow focus on individual technological drivers rather than the broader transformation process (Hanelt et al., 2021; Paiola and Gebauer, 2020; Wessel et al., 2021).

To address these shortcomings, this study investigates the organizational change process driven by emerging digital technologies in manufacturing. It seeks to answer how specific contextual factors influence DT strategies, what internal mechanisms and constraints are critical to the success or failure of DT initiatives, and how technology managers can align digital transformation efforts with overarching business objectives. By focusing on these questions, the study aims to provide a more nuanced understanding of DT that transcends the conventional "one-size-fits-all" approach and offers a framework that captures the complexity of transformational change.

Employing the Context-Mechanism-Outcome (CMO) framework and utilizing fuzzy set qualitative comparative analysis (fsQCA) across 46 cases from Chinese manufacturing, this research distinguishes three distinct DT configuration models: process transformation, DT in large enterprises, and platform-based transformation. This methodological approach not only refines existing DT models by elucidating the interplay between organizational constraints, digital leveraging mechanisms, and contextual factors but also provides actionable insights for managers navigating the complexities of DT. The study's findings offer both theoretical advancement and practical guidance, contributing to a deeper understanding of how digital transformation can be successfully implemented in diverse organizational settings.

The remainder of the paper is structured as follows: the next section introduces the research framework, followed by a detailed description of the research methodology, an analysis of the findings and discussion of their implications, and finally, the conclusion, contributions, and directions for future research.

2. Research Framework

2.1 A Research Pattern of DT

Integrating insights from realistic evaluation, Pawson and Tilley (2009) introduced the Context-Mechanism-Outcome (CMO) framework to explain how complex projects unfold across diverse contexts, with each context activating unique mechanisms that disrupt established patterns and create new outcomes. In the realm of digital transformation (DT), the CMO framework has become an influential lens through which researchers analyze how contextual conditions shape the efficacy of digital interventions (Henfridsson and Yoo, 2014; Hanelt et al., 2020; Tamvada et al., 2022). Hanelt et al. (2021) expanded on this framework by conceptualizing DT as a process of innovation and resource integration that is collectively driven by participants and heavily influenced by both organizational and environmental determinants. This perspective emphasizes that DT outcomes—manifesting as adaptable organizational structures and significant economic spillovers—are not merely the sum of technological adoption but the result of dynamic interactions between digital technology, organizational readiness, and external pressures.

2.2 Mechanisms for Complex Organizational Change

Digital transformation offers substantial advantages, such as productivity improvements (Lasi et al., 2014), business innovation (Frank et al., 2019), and enhanced customer experiences (Karre et al., 2017; Liu et al., 2023). Yet these benefits arise from a complex process that introduces substantial challenges. Scholars have described these challenges using varied terminologies—"obstacles" (Shojaei and Burgess, 2022), "inhibitors" (Horváth and Szabó, 2019), "tensions" (Dieste et al., 2022), and "resistances" (Chatterjee et al., 2022)—highlighting the multifaceted nature of DT. The internal mechanisms that drive successful transformation are equally complex. Digital leveraging, as defined by Thomas et al. (2014), captures how digital technologies reconfigure resource availability and value creation by linking machines, people, and business processes (Cennamo, 2020). This concept, underpinned by re-programmability and integration (Yoo et al., 2012; Laleci et al., 2005), provides a critical mechanism through which firms overcome traditional value-creation approaches and build new digital ecosystems.

2.3 Constraints on Organizational Change and Critical Perspectives

The process of digital transformation is not without its constraints. Organizational change in DT involves significant restructuring as firms must integrate digital technologies into every facet of their operations—a challenge that affects internal processes, communication flows, and even the underlying organizational culture (Matt et al., 2015). In manufacturing, the demands for digitalization disrupt established business processes, requiring companies to overhaul both their physical and information infrastructures (Cennamo et al., 2020; Sisinni et al., 2018; Bai et al., 2023). Technological challenges, such as data collection and service delivery conflicts (Chatterjee et al., 2022; Dieste et al., 2022), merge with organizational challenges, including the need for new roles and the restructuring of hierarchies (Gfrerer et al., 2021; Baiyere et al., 2020). Critically, while earlier studies have mapped these constraints, they often neglect to engage deeply with the emergent critical literature that interrogates power dynamics, cognitive limitations, and resistance mechanisms within digital business models (Baiyere et al., 2020; Thelisson, 2024).

2.4 Engaging with Critical Literature to Establish Novelty

A notable limitation in existing DT research is the insufficient integration of critical perspectives that challenge the dominant narrative of technology as a panacea for organizational challenges. Researchers such as Vial (2019) and Kutnjak et al. (2021) have pointed to the low success rates of DT initiatives, emphasizing that digital transformation is as much about reconfiguring existing power structures and cognitive frameworks as it is about technology adoption. Moreover, Wessel et al. (2021) highlight that the complexities of DT are not fully captured when analysis is restricted to individual technological drivers. By engaging more deeply with these critical perspectives, our study seeks to offer a novel theoretical contribution that transcends the conventional "one-size-fits-all" approach to DT. It does so by integrating a comprehensive set of organizational constraints and digital leveraging mechanisms into the CMO framework, thereby providing a more nuanced understanding of how digital transformation unfolds in complex manufacturing environments.

2.5 Integrative Framework of Context, Mechanisms, and Constraints

Building on these insights, this research proposes an integrative framework that links contextual factors, digital leveraging mechanisms, and organizational constraints to explain the multifaceted nature of DT in manufacturing. While Cennamo et al. (2020) and Hanelt et al. (2021) have identified various forms of digital leveraging and transformation constraints, the relationship between these elements remains underexplored. Our framework posits that different organizational contexts not only influence the type and intensity of constraints but also determine the effectiveness of digital leveraging mechanisms in mitigating these challenges. This dynamic interplay is essential for understanding why DT initiatives succeed in some manufacturing settings and fail in others. The framework aims to bridge the existing gap by systematically analyzing how environmental, organizational, and technological factors converge to shape digital transformation outcomes.

3. Research Methodology

3.1 Research Design

This study operates on the premise that the diverse efforts in manufacturing transformation can be systematically categorized by examining how digital transformation (DT) introduces conflicts with established organizational models. DT brings about distinct constraints that organizations must navigate, while early digital leveraging can challenge and modify these structures through innovation, integration, and experimentation. The interplay between contextual conditions, internal mechanisms (influenced by digital leveraging and constraints), and the resulting restructuring provides the basis for understanding DT. In this framework, "Context" refers to the conditions that influence the emergence of both constraints and digital leveraging. Following Hanelt et al. (2021), these determinants include factors related to digital technology, organizational structure, and the environmental setting, such as historical, cultural, and supplier–customer dynamics. "Mechanism" encompasses the internal processes that drive organizational change. Drawing on Matt et al. (2015), we identify three categories of constraints—technological application (Tech), organizational (Org), and value creation (Value)—while adopting Thomas et al.'s (2014) concepts of production leveraging (PL), innovation leveraging (IL), and transaction leveraging (TL) to capture how digital technologies are harnessed. "Outcome" denotes the results of the restructuring process, understood through Verhoef et al.'s (2021) three-phase classification of digitization, digitalization, and digital transformation. Guided by the Context-Mechanism-Outcome (CMO) logic, our design seeks to clarify how contextual factors influence the mechanisms (both constraints and digital leveraging) that drive DT outcomes in manufacturing.

3.2 Research Method

The inherent complexity of DT in manufacturing, characterized by cross-dimensional effects and multifaceted qualitative data, necessitates a research method capable of exploring complex causality. For these reasons, we justify the use of fuzzy set qualitative comparative analysis (fsQCA) over alternative approaches such as regression, structural equation modeling (SEM), or qualitative content analysis. Unlike regression or SEM, which require large samples and assume linear relationships, fsQCA accommodates small-to-medium sample sizes and effectively handles configurational data by focusing on the presence or absence of conditions. This binary comparison approach reduces the need for high precision in numerical measurement, which is particularly beneficial when addressing the inherent challenges in quantifying qualitative phenomena (Ragin, 1987, 2000, 2008; Fiss, 2013; Chen and Tian, 2022; Huarng and Yu, 2022).

The methodological steps in our fsQCA process are clearly delineated to ensure transparency and replicability. First, calibration involves converting qualitative case data into fuzzy set membership scores, establishing anchor points (commonly at 0.33 and 0.67) that reflect non-significant, significant, and substantial impacts on DT outcomes. Second, necessity testing is conducted to determine whether any single condition is indispensable for the observed outcomes, thus informing the subsequent configurational analysis. Third, gradual adjustment analysis is employed to refine the consistency and coverage thresholds, ensuring that our identified configurations are robust. Despite its strengths, fsQCA has limitations, including potential sample size constraints, case selection bias, and a lack of extensive statistical validation. To mitigate these limitations, future research may consider triangulating data sources—such as incorporating expert interviews and surveys—to complement the fsQCA findings. Additionally, while our current analysis provides a detailed descriptive account of DT configurations, further quantitative validation, such as correlation matrices or regression analysis, is warranted to substantiate causal claims and to examine counterfactual cases where companies have succeeded despite the presence of constraints.

3.3 Case Selection

Data were sourced from the China Management Case-sharing Center (CMCC), the largest case library in China, which provides comprehensive accounts of both successful and unsuccessful DT initiatives. A systematic keyword search was conducted using terms such as “digital transformation,” “industrial internet,” “digitalization,” and “strategic transformation.” Initially, 267 cases of manufacturing companies from 2018 to 2022 were collected. After a rigorous screening process to exclude irrelevant and incomplete cases, 46 cases were retained for analysis (see Table 1). This selection process, while thorough, is not without potential bias, and the relatively small sample size is acknowledged as a limitation. Nonetheless, these cases offer a rich, context-specific basis for analyzing the complex interplay between contextual factors, digital leveraging mechanisms, and organizational constraints in manufacturing DT. By integrating fsQCA with the CMO framework, our study not only identifies distinct DT configurations but also critically examines whether the observed constraints truly contribute to DT failure. Although the current findings are largely descriptive, they set the stage for additional robustness checks and quantitative validations in future research. The inclusion of counterfactual cases—where companies have successfully transformed despite apparent constraints—further enhances our understanding of the underlying dynamics and offers practical insights for technology managers.

3.4 Measurements and Data Analysis

The selected cases depict specific transformation processes in diverse scenarios. To enhance comparability, we applied fuzzy measurements to assess digital leveraging, constraints, and transformation outcomes. Fuzzy sets enable us to handle complex qualitative data by employing “membership scores” or “degrees of membership,” where a higher score indicates a stronger connection to a given configuration (Ragin, 2008; Kraus et al., 2018; Chen and Tian, 2022). Our data analysis comprises three key components: converting qualitative case data into numerical form, applying fsQCA to these calibrated scores, and conducting a subsequent case analysis based on the fsQCA results. Variable measurement involves transforming textual data into numerical values between 0 and 1, accomplished through a four-step process detailed in the Appendix.

FsQCA was implemented through three main steps. First, data calibration was performed by mapping variable values using anchor points (0, 0.67, and 1), with an adjustment that aligns the critical constraint decomposition point at 0.5 (Ragin, 2008). Second, a necessity test was conducted to verify whether any single condition was indispensable for the outcome, thereby guiding our configurational analysis. Third, gradual adjustment analysis was carried out by incrementally refining the consistency threshold to enhance robustness, ensuring a constructive dialogue between the data and theoretical expectations.

Configuration analysis produced three distinct configurations and corresponding “good practice cases” that represent the identified logical relationships. In our framework, a consistency level exceeding 0.9 indicates that a specific configuration is necessary for the outcome, supporting the interpretation that particular combinations of constraints lead to distinct DT outcomes.

The case analysis itself followed three procedures. First, a context analysis was performed on good practice cases—those with outcome scores exceeding 0.5—to consolidate key contextual characteristics, including organizational, environmental, and technical antecedents (Hanelt et al., 2021; Aaldering and Song, 2021; Tortorella et al., 2023; Tamvada et al., 2022). Second, we identified key constraint evidence within each configuration, scrutinizing the underlying logic of each constraint variable. Third, we summarized the main digital leveraging mechanisms for each configuration.

While these measurements and analyses offer a detailed descriptive account of DT configurations, we acknowledge that our findings are largely descriptive. In response to reviewer feedback, we note that additional quantitative validations—such as correlation analyses, regression models, and the examination of counterfactual cases (e.g., companies that succeeded despite constraints)—could further substantiate our empirical claims. These additional robustness checks are suggested for future research to triangulate and validate the observed relationships. Furthermore, potential limitations related to sample size and case selection bias are recognized, and future studies may benefit from incorporating supplementary data sources such as expert interviews and surveys to enrich the analysis.

FsQCA evaluation inherently involves subjective judgment regarding case membership within sets. To enhance the validity and reliability of our analysis, we introduced key reference points and continuously verified the results at each analytical step.

4. Findings and Interpretations

4.1 Case Overview

Table 1 outlines the 46 manufacturing cases drawn from the China Management Case-sharing Center (CMCC), capturing diverse transformation scenarios across sectors including garment production, logistics, electronics, and chemical manufacturing. Each case is labeled with a short name, a brief description, and data sources (a1: case text; a2: firm website/industry data; a3: field investigation and interviews). The range of cases ensures contextual richness and sectoral variation, which is vital for configuration-based analysis using fsQCA.

[INSERT Table 1]

4.2 Necessary Condition Test

The necessary condition test identifies whether any single constraint consistently explains DT outcomes. As shown in Table 2, no individual constraint—whether technological (tech), value-related (value), or organizational (organ)—achieved the required consistency threshold of 0.9. For instance, tech and organ each recorded a consistency of 0.839, while value scored 0.761. These results indicate that no standalone constraint is necessary for digital transformation success in the observed cases, thereby confirming that a configurational approach is appropriate for unpacking the complex interplay between multiple conditions.

[INSERT Table 2]

4.3 Configuration Analysis

Table 3 presents the results of the fsQCA configuration analysis. Three distinct configurations were identified, each surpassing the minimum consistency level of 0.9 and collectively covering 89.1% of cases. These configurations reflect how different combinations of constraints influence the outcome of DT in manufacturing firms:

- ***Configuration 1**:* Technology use and value creation are present, but organizational transformation is not (Tech * Value * ~Org). This combination highlights cases where digital investment and customer-oriented innovation are pursued without fundamental internal restructuring.
- ***Configuration 2**:* Technology use and organizational change are both present, but value creation is not (Tech * ~Value * Org). Here, firms push internal change enabled by technology but struggle to translate those efforts into market-facing value.
- ***Configuration 3**:* Value creation and organizational transformation are evident, despite weak technology use (~Tech * Value * Org). These cases suggest firms can advance transformation through reorganization and new value logics, even without intensive digital infrastructure.

Each configuration is supported by multiple representative cases (e.g., DJFS, ZKXC, ZCQC, STWL, YK, MGJJ), illustrating the diversity of paths toward transformation. The results reaffirm that DT is not a linear or uniform process but one contingent on specific contextual configurations.

[INSERT Table 3]

4.4 Leveraging Mechanism Analysis

To better understand how firms overcome constraints, Table 4 examines the dominant digital leveraging mechanisms in each configuration. The analysis captures the strength and nature of leveraging—categorized into production leveraging (PL), innovation leveraging (IL), and transaction leveraging (TL):

- ***Configuration 1:*** Dominated by production leveraging (PL average: 0.653; consistency: 1.000). Firms focus on efficiency, capacity scaling, and asset recombination to optimize production without deep organizational change.
- ***Configuration 2:*** Shows dual emphasis on production leveraging (PL avg: 0.650; consistency: 0.967) and **innovation leveraging** (IL avg: 0.624; consistency: 0.899), suggesting that both process and product innovations support structural reform in these cases.
- ***Configuration 3:*** Characterized by innovation and transaction leveraging (IL avg: 0.628; TL avg: 0.609), with corresponding high consistencies (IL: 0.904; TL: 0.890). This reflects cases where firms compensate for limited technological infrastructure by rethinking their business models and fostering ecosystem engagement.

These results illustrate that digital leveraging mechanisms operate differently across configurations. The analysis highlights how firms dynamically align leveraging strategies with their contextual constraints to navigate the DT journey.

[INSERT Table 4]

The findings confirm that no single constraint explains transformation outcomes in isolation. Rather, DT unfolds through multiple, configuration-specific pathways. While the consistency and coverage values demonstrate robustness, the results remain descriptive. Causality is not formally tested, and alternative explanations—such as organizational culture, leadership vision, or institutional pressures—are not fully addressed in the current model. To move beyond description and strengthen causal inference, future work should incorporate:

- Triangulated data sources (e.g., expert interviews, employee surveys);
- Counterfactual analysis to explore successful DT under adverse constraints;
- Complementary statistical techniques (e.g., regression, correlation matrices) for quantitative validation.

Additionally, while fsQCA effectively captures complexity, its reliance on calibrated qualitative data introduces potential subjectivity and sensitivity to case selection. These limitations are acknowledged and can be mitigated by extending the dataset and expanding the analytical toolkit.

4.2 Discussions on Configurations

Configuration 1: Business Process Transformation

This configuration includes production- and sales-oriented firms such as TPS, ZKXC, and JYJT. These firms face constraints in *technology use* and *value creation*, primarily due to low digital readiness and resistance from staff used to traditional workflows. The core mechanism is production leveraging, aimed at improving efficiency through targeted digital adoption. Transformation is compartmentalized and focused on operational gains, where success hinges on aligning technologies with direct employee benefits to ease resistance and boost capability.

Configuration 2: Enterprise-Wide Transformation

Firms like ZCQC, KTZN, and BLJT represent larger, more complex organizations facing constraints in *technology use*and *organizational change*. These firms require both production leveraging for immediate performance improvements and innovation leveraging to coordinate transformation across multiple units. Digital heterogeneity and structural inertia intensify the challenge, but competitive pressure supports adaptation. This configuration reflects a hybrid approach—balancing internal restructuring with responsiveness to evolving industry demands.

Configuration 3: Platform-Based Transformation

Digital platform leaders such as ZSZK, QHW, and SYB face *organizational* and *value creation* constraints tied to coordination, trust, and ecosystem dynamics. Equipped with advanced IT infrastructures, these firms rely on innovation leveraging and transaction leveraging to scale digital platforms. Innovation attracts participants through data-driven services and new business models, while transaction mechanisms support trust and integration. As Baiyere et al. (2020) highlight, cognitive and structural tensions remain key challenges, particularly when transitioning from traditional to digital-first logic.

Cross-Configuration Insights

Across all three configurations, DT in manufacturing is shaped by internal processes and sectoral context. Integration across "all facets and operations of an organization" (Kraus et al., 2022, p. 2) is inherently complex, generating distinct constraints and requiring adaptive leveraging strategies. Material determinants (Hanelt et al., 2021) and technological embeddedness (Wessel et al., 2022) influence how firms navigate transformation. The comparison of configurations reveals how contextual conditions—such as industry maturity, external pressure, and internal readiness—mediate the relationship between constraints and mechanisms, reaffirming the need for differentiated, context-sensitive DT strategies.

5. Implications and Future Research

The findings demonstrate how organizations can effectively adopt a tailored approach to navigate their unique digital transformation (DT) challenges. Consequently, this study offers actionable insights for technology managers by illustrating how aligning DT project goals with one of the identified configuration models can improve the likelihood of successful outcomes. First, by framing DT as a context-dependent process with distinct configurations, this research equips decision-makers with specific, evidence-based strategies suited to diverse organizational contexts and constraints. Rather than adopting a uniform strategy, technology managers are encouraged to align their digital transformation efforts with their organization's technological maturity, internal structure, and market position. This tailored approach helps maximize the impact of DT investments by focusing on solutions that leverage contextual strengths and directly address organizational constraints.

Second, the study underscores the importance of organizational readiness as a foundational element of effective transformation. Successful DT requires internal capabilities not only in digital infrastructure, but also in workforce adaptability, data governance, and process flexibility. Technology managers should focus on strengthening digital literacy, cross-functional collaboration, and continuous learning to support and sustain transformation efforts. Our identification of constraint types and readiness factors offers decision-makers a practical framework to assess internal conditions and strategically plan capacity-building initiatives.
Third, the results highlight that DT constraints are both technical and contextual, differing significantly across industries and even within the same sector. This variability implies that rigid, prescriptive solutions are unlikely to succeed. Instead, managers should adopt flexible and adaptive strategies, allowing for real-time responses to emerging challenges. This pragmatic approach supports smoother transitions and increases the likelihood of achieving sustained transformation outcomes across a range of manufacturing scenarios.

Although this study is grounded in cases from the Chinese manufacturing sector, the implications extend well beyond national boundaries. We support this broader applicability from three angles. First, the application of the Context-Mechanism-Outcome (CMO) framework offers a structured, theory-driven approach that is not country-specific. Organizations in different regions can use the CMO logic to identify how their contextual factors interact with internal mechanisms, shaping unique transformation outcomes. Second, the insight that DT is deeply context-dependent has universal relevance. Firms operating in different global markets can adapt the configuration logic by accounting for local conditions, including regulatory landscapes, industry norms, cultural attitudes toward innovation, and economic development levels. Although the specific constraints and leveraging strategies may vary, the framework encourages localized adaptation while maintaining conceptual coherence. Third, the emphasis on organizational readiness and adaptive capability reflects a foundational principle of transformation that transcends geography. While the nature and intensity of readiness factors may vary across regions, the critical importance of internal capability-building remains consistent. Manufacturing firms in both emerging and advanced economies can benefit from the strategies identified in this study by modifying them to fit their own workforce, infrastructure, and governance contexts.

This study has several limitations that offer opportunities for future research. The primary limitation is the reliance on secondary data. Although the case data sourced from the China

Management Case-sharing Center is extensive and diverse, the absence of primary data (such as in-depth interviews or surveys) limits our ability to probe into unreported dynamics, especially informal or tacit decision-making processes. Future research could address this by integrating firsthand insights from technology managers, operational staff, and external stakeholders through qualitative fieldwork. Second, while the fsQCA method captures complex causality and configuration effects, it does not test causality in the traditional statistical sense. Future research could complement our findings using quantitative methods (e.g., regression analysis, structural equation modeling) to validate the strength and direction of identified relationships. Triangulating data sources would also improve analytical robustness and reduce potential biases arising from case selection. Third, the temporal scope of this study presents a further limitation. DT is a longitudinal and evolving process, and our analysis provides a snapshot of firms at specific moments in their transformation journeys. Future studies should adopt a longitudinal design, tracking how DT configurations evolve over time and identifying transition pathways from early digitization to full transformation. Such a dynamic perspective would capture the sequencing of internal mechanisms, shifts in constraint intensity, and the pacing of organizational change.

6. Conclusion

This study represents a valuable contribution to the literature on digital transformation (DT) in manufacturing by integrating the Context-Mechanism-Outcome (CMO) framework with fuzzy-set qualitative comparative analysis (fsQCA) applied to 46 cases from the Chinese manufacturing sector. Through this approach, we identified three distinct DT configurations—process transformation, large-scale enterprise transformation, and platform-based transformation—each reflecting a typical scenario that manufacturing firms may encounter. These configurations illuminate the interaction between contextual constraints and digital leveraging mechanisms, offering a more nuanced understanding of the DT process.

The results emphasize that the complexity of DT in manufacturing stems from the organization-wide integration of digital technologies across structures, operations, and business models. This pervasive integration generates both challenges and opportunities: constraints such as technological, organizational, or value-related barriers, and internal mechanisms like production leveraging and innovation leveraging that can help firms navigate these challenges. These mechanisms play a pivotal role in enabling firms to restructure their operations, increase efficiency, and align transformation efforts with organizational goals. At the same time, contextual conditions—including industrial environment, technological maturity, and supply chain dynamics—mediate how constraints are experienced and how leveraging efforts are deployed.

Consistent with Baiyere et al. (2020), DT can be viewed as a fundamental shift in organizational logic, requiring firms to transition from legacy systems and processes to digitally enabled, innovation-driven operations. When supported by effective management and enabling incentives, this transition is facilitated, reducing resistance and enhancing adoption. However, in the absence of such internal alignment, transformation efforts are often derailed by structural inertia, cultural resistance, or strategic misalignment. By framing DT as a dynamic, context-sensitive, and multi-mechanism process, our study advances theoretical insights and responds to the call for more structured, empirically grounded analyses of how digital technologies are embedded within real-world manufacturing settings.

We offer two primary contributions. First, this research introduces a robust, context-sensitive approach to studying DT in manufacturing by combining the CMO framework with fsQCA. Rather than treating DT as a standardized, technology-led transition, we emphasize its dependency on organizational context, internal constraints, and adaptive mechanisms. This theoretical advancement highlights the need for tailored transformation strategies based on distinct internal configurations, enriching both academic and managerial understandings of DT. Our framework ease technology managers to reduce implementation risks and craft responsive strategies aligned with organizational readiness, capabilities, and market positioning.
Second, through our identification of three DT models—process-based, enterprise-wide, and platform-driven—we offer a strategic guide for firms seeking to understand and benchmark their transformation journeys. These models illustrate how organizations can mobilize different types of digital leveraging to overcome specific constraints. Drawing on insights from 46 cases, we show how each model features unique pathways, resource allocations, and organizational reconfigurations. This helps managers identify the most appropriate model for their organization's needs, enabling better resource prioritization, realistic expectations, and clear transformation roadmaps (Joussen et al., 2024).

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Table 1: Case information

Case No.	Chinese name in short	Case introduction	Sources
1	KTZN	Suit customization: intelligent manufacturing for mass customization	a1、a2、a3
2	ZKXC	Yarn manufacturing: intelligent manufacturing of flexible production	a1、a2
3	LBJT	Daily chemical production: internal resource informatization optimizes firm operation	a1、a2
4	MCYP	Department store retail: data driven intelligent supply chain	a1、a2、a3
5	HBJT	Garment Production: Industrial Ecology of Intelligent Garment Manufacturing	a1、a2、a3
6	BLJT	Footwear production: an firm in the value chain of digital empowerment products	a1、a2、a3
7	ZHCG	Feed production: digital procurement platform	a1、a2、a3
8	JYJT	Production and sales of small household appliances: digital procurement platform	a1、a2
9	HMZY	Garment manufacturing: digital flexible manufacturing	a1、a2
10	ZCQC	Transportation manufacturing: collaborative design and lean production firms	a1、a2
11	XGJT	Mechanical equipment manufacturing: vertical e-commerce platform for electromechanical industry	a1、a2、a3
12	HPZN	Equipment manufacturing: organizational structure reengineering	a1、a2
13	ZNZN	Industrial robot production: industrial chain collaborative design and manufacturing	a1、a2
14	YSJJ	Customization of household goods: the industrial ecology of C2F online personalized customization	a1、a2
15	AJSH	Customization of household products: an firm that realizes personalized customization of household products	a1、a2
16	BCJJ	Household goods marketing: personalized marketing platform	a1、a2
17	TPS	Outdoor products production: digital lean manufacturing firm	a1、a2、a3
18	DJFS	Garment manufacturing: an intelligent manufacturing firm with flexible production	a1、a2
19	HFSS	Garment manufacturing: color textile factory with intelligent and flexible production	a1、a2
20	HSB	Garment manufacturing: to realize personalized customized garment production firms	a1、a2
21	LJPZ	Catering retail: promote product development and sales with digital technology	a1、a2、a3
22	TLL	Catering retail: catering chain stores that realize digital operation	a1、a2
23	ZMJT	Department store retail: realizing digital firm operation	a1、a2
24	MGJJ	Furniture customization: a household manufacturing firm with personalized customization	a1、a2
25	LG	Consumer goods manufacturing: a digital firm co created with users	a1、a2、a3
26	ZTJT	Mechanical manufacturing: low-voltage electrical apparatus intelligent manufacturing digital workshop	a1、a2
27	YZZL	Logistics and transportation: an intelligent ship solution to meet customers' personalized needs	a1、a2、a3
28	SYB	Parts processing: collaborative manufacturing crowdsourcing platform	a1、a2
29	QHW	Chemical industry information trading service: chemical industry P2P platform	a1、a2
30	MHS	Chemical industry information trading service: chemical industry B2B platform	a1、a2
31	HCB	Logistics service: vehicle cargo matching, after vehicle service, financial sharing platform	a1、a2
32	XTR	Human resource service: human resource scheduling and settlement platform	a1、a2、a3
33	YY	Software and information technology services: firm cloud service platform based on ERP software	a1、a2
34	THGY	Blockchain service platform: blockchain solution	a1、a2、a3
35	TJ	Manufacturing service: provide target customer portrait for firms with artificial intelligence and big data technology	a1、a2
36	ZXNY	Energy saving service: comprehensive service of gas supply	a1、a2
37	ZSZK	Manufacturing service: an industrial Internet platform based on data services	a1、a2、a3
38	PM	Building supplies management: construction platform based on BIM software and solutions	a1、a2
39	SND	Manufacturing services: provide digital solutions in the field of energy management and automation	a1、a2
40	HEJT	Industrial internet platform: intelligent manufacturing solution	
41	YKKJ	Industrial Internet platform: non-standard spring production	a1、a2
42	STWL	Logistics and transportation: digitalization of transportation, distribution, warehousing and processing	a1、a2
43	YW	Advertising service: marketing platform	a1、a2

44	LQX	Cosmetics production and sales: Internet marketing platform	a1、a2
45	KJ	Electronic weighing instrument production and sales: industrial weighing overall solution provider	a1、a2
46	FSK	Electronic component manufacturing: intelligent manufacturing platform	a1、a2

Note: a1 - Case text; a2 - Firm website and industry research data; a3 - Field investigation and interview.

Table 2: Necessary Condition Test

	Consistency	**Coverage**
tech	0.839	0.839
~tech	0.685	0.957
value	0.761	0.812
~value	0.725	0.932
organ	0.839	0.890
~organ	0.655	0.847

Note: "tech" represents the degree of membership in the constraint related to technology use. "~tech" represents the negation of this constraint, indicating that technology use is not working. Similar principles apply to the other two constraints.

Table 3: Configurations based on Constraints

	Configuration 1	**Configuration 2**	**Configuration 3**
Tech	●	●	○
Value	●	○	●
Org	○	●	●
Configuration consistency	0.922	0.983	0.987
Logic relation	*Tech*Value*~Org*	*Tech*~Value*Org*	*~Tech*Value*Org*
Representative cases	DJFS/ZKXC/ZHCG HMZY/TPS/FSK/ JYJT/ZM/HFSS/ LQX/TLL/MCYP	KTZN/LBJT/ZCQC/ BLJT/ KJ/ ZTJT STWL/GN/ZNZN /MGJJ/LJPZ	HSB/SND/ZSZK/ MHS/HBJT/QHW/ YK/HCB/THGY/TJ/ SYB/YW/YZYL/XTR/Z XNY/YY
Solution consistency	0.929		
Solution coverage	0.891		

Note: "●" signifies that the antecedent is in actualization, "○" indicates a lack of actualization for the antecedent, "*" represents the logical product, and "~" denotes the absence of actualization.

Table 4: Leveraging Effects in DT

	Configuration 1	Configuration 2	Configuration 3
Significant effects	Production leveraging	Production leveraging Innovation leveraging	Innovation leveraging Transaction leveraging
Everage leveraging level	Ave. PL: 0.653>0.5 Ave. IL: 0.254<0.5 Ave. TL:0.310<0.5	Ave. PL: 0.650>0.5 Ave. IL: 0.624>0.5 Ave. TL: 0.385<0.5	Ave. PL: 0.333<0.5 Ave. IL: 0.628>0.5 Ave. TL: 0.609>0.5
Coefficient consistency	Coe (PL, DT): 1.000 Coe (IL, DT): 0.508 Coe (TL, DT): 0.620	Coe (PL, DT): 0.967 Coe (IL, DT): 0.899 Coe (TL, DT): 0.576	Coe (PL, DT): 0.515 Coe (IL, DT): 0.904 Coe (TL, DT): 0.890
Case number	12	11	18
Explanation	Enhancing efficiency not only transforms employees' preconceptions but also eradicates subjective barriers to technology application and value creation. The organization consistently advances DT by fostering the development of digital skills and capabilities in its workforce, thereby expanding its proficiency in digital applications.	The onset of production leveraging marks eliminating subjective and objective constraints in the initial stages. The advent of innovation leveraging, driven by digital technology, has emerged as a pivotal mechanism for overcoming organizational constraints.	Innovation leveraging propels the platform initiator's business endeavors, motivating accessing providers to overcome business constraints and existing operational limitations. This dynamic stimulates transaction leveraging, fostering an environment that encourages the increased participation of additional members.

Note: PL- Production leveraging, IL- Innovation leveraging, TL- Transaction leveraging, DT- Digital transformation.

Appendix

Appendix 1: Example of Fuzzy Measurements

	Step 1	Step 2	Step 3	Step 4
Description	**Information gather.** According to the materials collected from the cases, the statements that can best reflect the characteristics of the case indicators are classified according to variable dimensions.	**Key point determ.** Comprehensively understand the meaning of the expression, rank them in order of the impact of the transformation constraints, and find out whether there is a significant impact and substantial impact on the transformation.	**Dimension assign.** In the three groups determined by division at the two key points, the statements of each case are compared independently, and the corresponding values are assigned according to the strength of the role.	**Index merg.** Determine variable value according to logical "OR" principles.
Example of assignment	**Subjective attitude (of Technology use)** Very interested in new technologies and patterns (YSJJ). **< Dividing point 0.33>** The capital market is generally not optimistic about the "Internet plus Logistics" scenario (HCB). It is difficult for workers to change their thinking (HBJT). Lack of reference, strong resistance of purchasers, and pressure and resistance in decision-making (ZHCG). **< Dividing point, >** Middle-level leaders are sceptical and believe that the convention change has swallowed up the leadership authority, and they cannot reach a consensus and work (ZTJT). Intelligent manufacturing has caused a great stir. The opposition has a strong opinion that it is a weak foundation and a lack of talent (DJFS).	**←Key point 0.33** The boundary between the low segment and the middle segment. i.e. whether there is a realistic and credible significant influence. **←Key point 0.67** The dividing line between the middle section and the high section, i.e. whether it has a substantial impact on the system construction	**< 0-0.33>** **< 0.33-0.67>** **< 0.67-1>**	**Example:** *Tech*=max(*Subjective attitude, Technical ability*) If Subjective attitude=o.67 Technical ability=0.40 Then Tech=0.67
Matters needing attention	Generally, the statements that can best reflect the core business or have a substantial effect on the corresponding materials of this indicator.	The key point is not to divide the material sequence into three equal parts, so you should pay attention to determine the influence degree of the material.	It is not necessary to strive for uniform differences in the assignment within the group, and the order and size should be judged according to the actual content.	The sub-indicators of each dimension are merged into the first-level indicators according to the logical "OR" principle.

The steps of fuzzy measurements are following the following steps:

- *Information gathering*: Summarizing and extracting information from the chosen cases through a thorough analysis that best captures the features of firms related to the pertinent variables.
- *Key point determination*: Key values were established by interpreting the significance of case materials related to variable dimensions and ranking them by their impact strength. We positioned two anchor points at 0.33 and 0.67 to represent *significant (0.33) and substantial (0.67) influences* on DT outcomes. Consequently, we have three groups based on the qualitative data's meaning: 0-0.33, 0.33-0.67, and 0.67-1, denoting non-significant, significant, and substantial impacts on DT outcomes, respectively. This

method minimizes measurement error and ensures that comparisons between groups with indicator values below 0.33 and above 0.67 predominantly impact the research results.

- *Dimension assignment*: We compared each statement individually within the three sub-groups defined by the two anchor points and assigned values based on their impact.
- *Index merging*: We determined the value of the three constraint variables using the logical "OR" principle. This merging operation helps reduce the fragility of configuration analysis arising from too many variables. It aligns with the principle of variable influence significance, which posits that if any dimension of a variable is significant, then the entire variable is deemed significant. Importantly, the traceability of dimensional information is preserved despite the merging of indices.