

PROMOTION PATH OF DIGITAL TRANSFORMATION IN CHINA'S MANUFACTURING INDUSTRY BASED ON TECHNOLOGY-ORGANISATION-ENVIRONMENT FRAMEWORK

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Abstract. As the global economy becomes increasingly digitalised, the digital transformation of manufacturing has become an important way to enhance national competitiveness and corporate viability. This study focuses on the digital transformation of the manufacturing industry. First, the digital transformation of listed manufacturing companies is scientifically measured and their current state of transformation analysed. Then, the technology-organisation-environment framework is used to examine the driving factors of digital transformation. Based on this, fuzzy-set qualitative comparative analysis is employed to summarise different digital transformation configurations. The findings show that the digital transformation of China's manufacturing industry is still in its early stages, with significant regional differences. Achieving a high level of digital transformation can be accomplished through four paths: environment- dependent, strategic leadership, internally capability support, and comprehensive-driven approaches. Finally, practical guidance is provided on accelerating the digital transformation process and promoting high-quality development in the manufacturing industry.

Keywords: digital transformation, driving factors, promotion path, TOE framework, fsQCA, manufacturing industry.

JEL Classification: G30, L60, M21, O32, Q57.

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1. Introduction

In the context of globalisation, enterprises have gained a profound recognition of the strategic value of digital transformation as they leverage digital technologies and data resources to innovate and optimise operations management, manufacturing, product services, and business models (Vial, 2019). Digital transformation is considered a key pathway for enterprises to enhance their competitiveness, leading to increased efficiency, cost reduction, and the creation of new business models (Matt et al., 2016).

China places significant emphasis on the development of its digital economy. With strong promotion and support from national policies, China's digital economy has shown robust growth. According to data from the China Academy of Information and Communications Technology, the scale of China's digital economy reached 53.9 trillion yuan in 2023, accounting for 42.8% of the country's GDP. As advanced digital technologies such as big data, the Internet of Things, cloud computing, and artificial intelligence have become increasingly mature and

widely applied, digital upgrading has become the only way enterprises can maintain and enhance their competitiveness (Verhoef et al., 2021).

However, despite the widespread recognition of its importance, digital transformation remains challenging. The PWC's Digital Factory Transformation Survey (2022) shows that only 10% of enterprises have fully implemented digital factory solutions, while nearly two-thirds are still at partial or exploratory stages. This highlights the complexity of digital transformation and has spurred extensive research worldwide.

Therefore, based on the technology-organisation-environment (TOE) framework, this study explores the driving factors and enhancement pathways of digital transformation in China's manufacturing industry, providing theoretical support and references for business practices. This study makes two important contributions to the literature. First, integrating the TOE framework with fuzzy-set qualitative comparative analysis (fsQCA) allows for a nuanced examination of how technological, organisational, and environmental factors can be combined to facilitate successful digital transformation. This methodological innovation offers a more comprehensive understanding of the multifaceted nature of the transformation processes. Second, summarising the different paths through which high levels of digital transformation can be achieved and analysing applicability based on typical cases can provide a reference to help companies choose the right path according to their own characteristics and promote increased digitalisation.

The remainder of the paper is organised as follows. Section 2 provides a review of the existing research. Section 3 explores the TOE framework. Section 4 outlines this study's research methods. Section 5 presents the empirical analysis, and Section 6 discusses the results. Finally, Section 7 summarises the findings, managerial implications, limitations and avenues for future research.

2. Literature review

2.1. Definition of enterprise digital transformation

The definition of enterprise digital transformation can be explained from multiple perspectives, with academia having undergone four processes: technology portfolio → improvement of entities → corporate restructuring → cross-system transformation (Zhao & Fan, 2023). Digital transformation is the process by which an entity's attributes are significantly changed and improved through a combination of information, technology, communication, and connectivity technologies (Vial, 2019). However, it involves not only the simple application of technology but also a business transformation driven by information provision (Fitagerald et al., 2014), involving structural and organisational transformation, information technology use, and value creation for products and services, thereby triggering adjustments to or complete replacements of business models (Chanias et al., 2019). This includes fundamental changes to business processes, operational processes, and organisational capabilities, as well as entering new markets or exiting existing ones (Li et al., 2018). Digital transformation is a continuous process of strategic renewal (Warner & Wäger, 2019), and enterprises must reshape their vision, strategy, organisational structure, processes, capabilities, and culture to adapt to the constantly changing digital environment (Gurbaxani & Dunkle, 2019; Zhang et al., 2025b). The core of digital transformation in manufacturing is leveraging data to integrate information and manufacturing technologies, drive organisational change, and enhance market responsiveness (Chen & Xu, 2020). Its internal manifestations include four aspects: modernisation of manage-

ment models, digitisation of the full product lifecycle process, diversification of digital products, and flattening of corporate organisational structures (Zhang et al., 2022a). The digital transformation of manufacturing is a strategy-driven business change, marked by data and intelligence enabled improvements in R&D, production, operations, and services, advancing profit models and user experience (Liu, 2023). Centered on digitalization and networking, this transformation enables intelligent empowerment, optimizes product development and manufacturing, ensures efficient delivery, and ultimately strengthens core competitiveness.

2.2. Measurement of enterprise digital transformation

With growing awareness, more enterprises are implementing digital transformation, while scholars focus on scientifically evaluating its processes and outcomes using four common approaches.

First, maturity models provide systematic frameworks to help enterprises assess their current stage of digital transformation and identify future directions. These models typically outline the progression from the initial stages to full digital integration. Westerman et al. (2014) evaluated enterprises based on technology application, business process optimisation, and organisational change to reflect their comprehensive digital maturity. Kane et al. (2015) proposed a five-stage model ranging from a “passive” digital strategy to a “fully integrated” one, offering enterprises detailed guidance for their transformation journey.

Second, index evaluation models use various indicators to measure digital transformation. Financial indicators such as return on investment and cost savings reflect the effects on financial performance (Mithas et al., 2011). Operational indicators such as production efficiency and supply chain flexibility assess process optimisation (Bharadwaj et al., 2013). Innovation indicators, including new product development speed and market responsiveness, measure enhancements in innovation capabilities (Yoo et al., 2010). These indicators collectively provide a comprehensive evaluation framework. In China, scholars have developed tailored systems to measure enterprise digital transformation more accurately. Wu et al. (2021) used word-frequency analysis of annual reports, a method subsequently widely adopted (Shi et al., 2025; Chen & Sun, 2025). Others have constructed indicator systems and assigned weights using methods such as the entropy method (Lv & Zhang, 2022; Li, 2024), analytic hierarchy process (Chen & Xu, 2020; Wan et al., 2020; Fu et al., 2024), coefficient of variation method (Wang & Liu, 2023), principal component analysis, and expert scoring method (Zhao & Fan, 2023), and intuitionistic fuzzy entropy and fuzzy set pair analysis (Jing et al., 2021). Zou et al. (2024) further summarized industry-specific methods covering infrastructure, digital capabilities, and organisational change.

Third, questionnaire surveys can be used to gather subjective evaluations from management, employees, and customers. Matt et al. (2016) developed an evaluation system to evaluate transformation progress and anticipate future trends. Similarly, Fang and Zhang (2022) interviewed with manufacturing managers to explore key factors – willingness, obstacles, and benefits – and summarized best practices.

Finally, data-driven approaches employ in-depth analyses of actual operational data to accurately assess digital transformation. Fitzgerald et al. (2014) advocated data analytics to evaluate application levels, including data processing efficiency and automation degree. Building on this, Song et al. (2022), Zhang and Wang (2022) adopted input-output models to quantify industries' dependence on digital economy elements, providing a macro-level indicator of digital input intensity in manufacturing.

2.3. Factors affecting enterprise digital transformation

Digital transformation is a multifaceted process influenced by various factors. Robust technological infrastructure and strong IT capabilities are foundational for building a solid digital framework. Organisational culture also plays a critical role, as a culture open to change, coupled with management support, creates a conducive environment for transformation (Kane et al., 2018). Leadership commitment is essential for aligning strategic objectives and motivating employees.

Employee competencies are equally vital in the transformation process. Employees equipped with digital skills are better positioned to adapt to new technologies and processes that will effectively drive transformation (Vial, 2019). Continuous training and development programs enhance these skills, thereby contributing to the success of digital initiatives (Cascio & Montealegre, 2016).

External environmental factors, such as market competition and changing customer needs, significantly influence digital transformation initiatives. External pressures compel enterprises to adopt digital technologies to stay competitive (Fitzgerald et al., 2014). Regulatory changes and technological advancements also require agility in transformation efforts (Matt et al., 2015).

Several studies have identified the specific factors that influence digital transformation in Chinese enterprises. External drivers include macro environment, industry characteristics, infrastructure, and government policy support, while internal drivers involve enterprise size, informatisation level, resources, capabilities, and organisational culture (Yang & Ye, 2021; Zhang et al., 2022a; Xu et al., 2023). In the context of manufacturing enterprises, entrepreneurial innovation, environmental sensitivity, and transformation stages are also critical (Wei et al., 2021; Lin & Zhang, 2022). Some studies have employed the TOE framework (Zhang et al., 2022b; Tong, 2022), with the “Technologies” and “Organizational capacity” particularly notable for encompassing the largest number of factors (Jara et al., 2023). Ren et al. (2023) identified digital transformation capability as digital technology, digital operation, digital organization and digital strategic capability. Additionally, transformation outcomes are also shaped by organisational inertia, human capital, past performance, and external shocks such as COVID-19, with small and medium-sized enterprises particularly affected (Li et al., 2023a). In response, scholars have proposed targeted strategies at the government, industry, and enterprise levels to strengthen support systems and promote sustainable upgrading (Song et al., 2021).

In summary, existing literature on enterprise digital transformation has explored various methods to measure digital transformation, and identified diverse influencing factors, including technological infrastructure, organisational culture, management support, employee skills, and external pressures. However, despite this extensive research, several gaps remain. First, several studies provide a general perspective on digital transformation without conducting more in-depth explorations into specific industries such as manufacturing, particularly within the Chinese context. The unique characteristics of China’s manufacturing sector, such as its scale, government policies, and market dynamics, have not yet been fully explored. Second, previous studies have often focused on individual factors or dimensions in isolation, without taking a holistic approach that considers the interplay among technological, organisational, and environmental factors. Third, although the TOE framework is widely recognised, few studies have combined it with empirical methods such as fsQCA to identify the configurations of factors driving successful transformation.

Thus, this study focuses on the digital transformation of China's manufacturing industry. First, digital transformation is measured scientifically and the current state of transformation is analysed in depth. Then, the TOE analysis framework is applied to analyse the factors driving digital transformation. Based on this, the fsQCA method is used to summarise different configurations of digital transformation and explore feasible paths for increasing digital transformation levels. This provides practical guidance for enhancing digital transformation and offers intellectual support for accelerating the digital transformation process and promoting high-quality development in manufacturing.

3. TOE theoretical analysis framework

3.1. TOE framework

The TOE framework, developed by Tornatzky et al. (1990), is a widely recognised model for studying the adoption and implementation of technological innovations within organisations. It posits that three contextual factors influence a firm's technology adoption decisions.

First, the technological dimension refers to both the internal and external technologies relevant to a firm. This includes existing technologies within an organisation and new technologies available in the market. Second, the organisational dimension encompasses a firm's characteristics and resources, including size, managerial structure, financial resources, and human resources. Third, the environmental dimension involves the external environment in which a firm operates, including industry characteristics, market structure, regulatory environment, and relationships with competitors and suppliers. The TOE framework provides a comprehensive approach that allows a holistic understanding of the determinants of technological innovation and adoption.

The TOE framework is particularly well-suited for analysing digital transformation (Chandra, 2025), as it captures the interplay between internal and external conditions that shape heterogeneous transformation paths (Oliveira & Martins, 2011; Baker, 2012). This framework has been widely adopted in recent digitalisation studies (Tong, 2022; N'Dri & Su, 2024; Toscano-Jara et al., 2024), demonstrating its adaptability and explanatory power in varied contexts.

3.2. Driving factors for digital transformation based on TOE framework

Digital transformation in manufacturing is a complex process shaped by multiple factors, with prior studies supporting the TOE framework as a key analytical lens. Chen et al. (2025) interviewed experts, decision-makers, implementation leaders, and project managers from consulting firms and solution providers. Using grounded theory, they identified critical drivers of enterprise digital engagement, underscoring the multifaceted nature of digital transformation and its dependence on technological, organisational, and environmental factors. Complementarily, systematic literature reviews and meta-analyses further confirm the central role of these three dimensions in shaping digital transformation pathways (Jara et al., 2023; Toscano-Jara et al., 2024). Building on these findings, this study adopts the TOE framework to systematically analyse the antecedent conditions that shape the digital transformation of manufacturing firms.

The technical dimension focuses on enterprises' investments and capabilities in technology, which is the foundation of digital transformation and includes technical funds and talent.

Investments in digital technology and infrastructure are crucial for transformation. Access to advanced machinery, automation tools, and information systems enables manufacturers to upgrade processes and improve efficiency (Zhu et al., 2006). Skilled technical staff is essential for implementing and maintaining new technologies (Froehlich et al., 2025). The availability of employees with expertise in digital tools, data analytics, and IT systems will facilitate successful transformation.

The organisational dimension focuses on the ability of an enterprise's internal resources and strategies to support digital transformation, including strategic guidance and financial assurance. Leadership vision and strategic planning are pivotal in this process. When top management is committed to digital initiatives and integrates them into their corporate strategy, it drives organisational alignment and resource allocation (Bharadwaj et al., 2013). Adequate financial resources ensure that the organisation can invest in necessary technologies and training. Financial stability allows sustained investment in innovation and minimises the risks associated with transformation efforts (Chen et al., 2014).

The environmental dimension captures external influences on enterprise digital transformation, including the business environment, digital finance, and government support. The competitive landscape and market dynamics also influence digital transformation. A supportive business environment with robust demand, supply chain networks, and industry collaboration encourages firms to adopt digital technologies (Bouwman et al., 2019). Access to digital financial services, such as online banking, fintech solutions, and investment platforms will provide manufacturers with the financial tools needed to support transformation initiatives (Yoo et al., 2005). Regulatory policies, subsidies, and government-led programs can significantly influence the pace of digital transformation. In China, initiatives such as "Made in China 2025" and various digital economy policies provide incentives for manufacturers to modernise (Li et al., 2017).

4. Research design

4.1. Data and sample

This study used listed manufacturing enterprises in China as research samples, with 2020 as the starting point for the analysis. To ensure regional comparability across years and sample balance, firms first listed after 2020 or relocated were excluded, along with those with missing or abnormal data. The final sample comprised 2,437 companies across 31 provinces in China, with Guangdong, Zhejiang, Jiangsu, Shandong, Shanghai, and Beijing accounting for 1582 firms (64.86%) of the overall sample.

The data were sourced from authoritative databases such as the CSMAR database and China Statistical Yearbook. Considering the time lag in yearbook publication, the study period was limited to 2020–2022.

4.2. Measurement of enterprise digital transformation

This paper used the index evaluation system developed by CSMAR (Zhen et al., 2023; Ren et al., 2024) to measure enterprise digital transformation. There are several reasons for selecting this system. First, it provides comprehensive coverage of digital transformation dimensions, encompassing strategic leadership, technology adoption, organizational changes, environmental factors, digital outcomes, and practical applications. Second, it has

been validated through extensive empirical testing on Chinese listed companies, ensuring its reliability and applicability to our context. Third, unlike text-mining approaches that may miss nuanced transformation activities, this system captures both disclosed and operational aspects through multiple data sources. Compared with keyword-frequency methods based on annual reports (Wu et al., 2021), it offers broader coverage and more detailed content, enabling more effective and comprehensive measurement of enterprise digitalization levels.

This system comprises 6 primary indicators and 31 specific indicators, to which weights were assigned using the Analytic Hierarchy Process (see Appendix, Table A1). Data were collected based on relevant information disclosed in annual reports, fundraising announcements, qualification certifications, and other announcements.

First, the data were standardised by calculating the mean of each indicator for the current year. Second, the data were further standardised according to the following formula:

$$y_{it} = \frac{x_{it} - \text{med}(x)}{AD}, \quad (1)$$

where x_{it} is the indicator value, $\text{med}(x)$ is the mean value obtained, and AD is the average deviation of the indicator value from the mean.

In the third step, the indicators were mapped to a scale of 0–100.

$$z_{it} = \Phi(y_{it}) \times 100, \quad (2)$$

where $\Phi(y_{it})$ represents the cumulative distribution function of the standard normal distribution.

Weights were assigned based on standardised data to ultimately calculate the digital transformation index of listed companies. The higher the digitalization index, the higher the level of enterprise digital transformation.

4.3. Construction of the fsQCA Model

4.3.1. Introduction of fsQCA

Qualitative comparative analysis (QCA) was initially proposed by Ragin (1987) and then widely promoted in management research by Fiss (2011). Among its variants, fsQCA significantly enhances the ability of QCA to handle interval and ratio variables, allowing analysis of degree variation and partial membership (i.e. permitting cases to have membership scores between 0 and 1).

Building on the TOE framework, this study employs fsQCA for its compatibility with the research objectives. Unlike traditional linear methods that isolate single-factor effects, fsQCA identifies complex causal configurations, revealing how multiple drivers jointly influence digital transformation. Its configurational perspective recognises diverse pathways to transformation, adaptable to different resource endowments and environments. This approach also informs governments in designing differentiated policies to promote digital transformation in manufacturing.

4.3.2. Indicator selection of fsQCA analysis

In selecting condition variables for fsQCA, several principles were followed to ensure the model validity and applicability. First, variables were theoretically grounded in the TOE framework and supported by prior studies (see Table 1). Second, selection was based on observability and data availability at both firm and district level in the Chinese manufacturing

sector. Third, to enhance practical relevance and interpretability, informal consultations were conducted with senior managers and project leaders confirmed that the indicators aligned with managerial concerns and implementation practices. Finally, variables with low variance or high conceptual redundancy were excluded to enhance the discriminatory power of the configurational analysis. Table 1 presents the final indicators.

Table 1. Variables in the fsQCA model

Category	Primary index	Supporting references	Specific index	Description	Symbol
Result variable	Digital Transformation	Zhen et al. (2023); Ren et al. (2024)	Digital Transformation Index	Based on the method described in Section 3.2	TRA
Antecedent variables	Technical dimension	Technical level (Tong, 2022); Absorptive capacity (Wu et al., 2025); Technological innovation capability (Zhang et al., 2025a)	Technical fund	R&D expenditure / operating revenue	RD
		Employee's digital capability (N'Dri & Su, 2024); Human capital level (Zhang et al., 2025a)	Technical talent	Number of personnel with bachelor's degree or above / Total number of employees	HUM
	Organizational dimension	Management support (Chandra, 2025); Digital Strategy Orientation (Chen et al., 2025)	Strategic guidance	The frequency of digital transformation terms in annual reports	STR
		Financial resources (Wei et al., 2021); Level of funding guarantee (Li et al., 2023b)	Financial assurance	Net profit / Total asset	ROA
	Environmental dimension	Market structure (Oliveira & Martins, 2011)	Business environment	Business environment index	MAR
		Financial support (Tong, 2022)	Digital Finance	Digital Inclusive Finance Index	DIG
		Government support (N'Dri & Su, 2024)	Government support	Science and technology expenditure / fiscal expenditure	GOV

Note: MAR data is sourced from the "Evaluation of doing business in Chinese cities 2023" by Zhang and Zhang (2023), DIG data comes from the Peking University Digital Finance Research Centre, GOV data is derived from the China Statistical Yearbook, and other data originates from the CSMAR database.

Technical fund is measured based on research and development (R&D) investment intensity. High R&D investment usually indicates that enterprises attach importance to technological innovation and provide financial support for digital transformation. Technical talent is measured by the proportion of personnel with a college education or above personnel; a higher proportion of technical talent indicates a company's efforts to enhance employee skills to support digitisation. Strategic guidance can be represented by the frequency of digital transformation terms in annual reports, while the application of new technologies such as artificial intelligence, big data, and blockchain reflects the strategic leadership of an

enterprise's top management. Financial assurance is expressed by ROA, with high profitability indicating stronger financial support for digital transformation. The business environment is measured based on indicators from the China Urban Business Environment Research Report (Zhang & Zhang, 2023), covering the market, government, legal, and cultural dimensions. Digital finance development is measured using the Digital Inclusive Finance Index compiled by the Peking University Digital Finance Research Centre. Government support is measured by the proportion of science and technology expenditure to fiscal expenditure, reflecting the government's active promotion of digital development and strong support.

Based on the selected indicators, a conceptual framework for the fsQCA analysis is proposed, as shown in Figure 1.

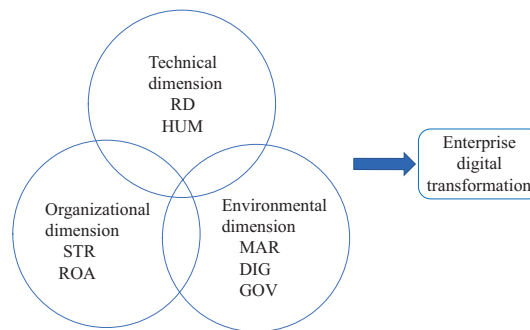


Figure 1. Theoretical framework

5. Empirical analyses

5.1. Analysis of digital transformation

As Figure 2 shows, the strategic leadership subindex gradually increased from 46.65 in 2020 to 50.67 in 2022, reflecting stronger strategic commitment to digital transformation. The technology-driven subindex rose slightly from 34.76 to 35.32, indicating a stable growth in technological development. The organisational empowerment subindex remained at approximately 24 points with minor fluctuations, showing no significant changes in

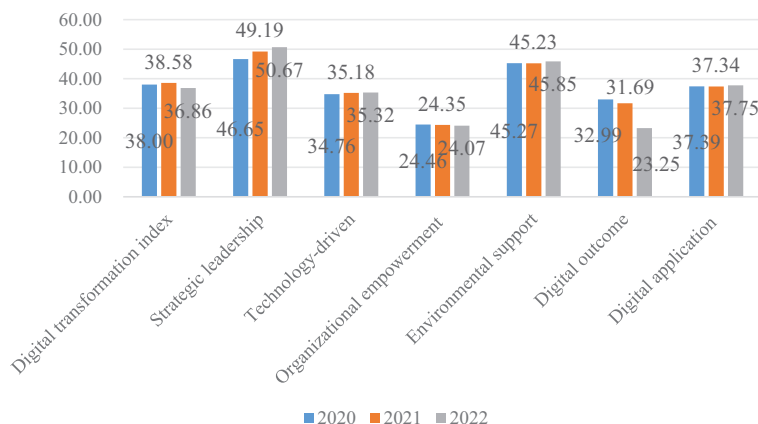


Figure 2. Annual scores for overall and sub-indicators of digital transformation

organisational empowerment. The environmental support subindex dipped in 2021 but recovered slightly in 2022. In contrast, the digital outcome subindex dropped significantly from 32.99 in 2020 to 23.25 in 2022, leading to a decrease in the overall digital transformation index. The digital application subindex remained stable at approximately 37. The overall digital transformation index showed volatility, increasing from 38.00 in 2020 to 38.58 in 2021, before falling to 36.86 in 2022. This decline can be attributed to three factors. First, increased uncertainty in the global and domestic economies in 2022 led to enterprises reducing their investment in digital transformation. Second, severe supply chain disruptions related to the pandemic squeezed manufacturing enterprises' budgets and resources for digital transformation. Third, a significant drop in the digital achievement subindex indicates that enterprises have faced considerable difficulties in implementing new technologies, possibly because of the complexity of the technology and internal coordination issues.

The average digital transformation level over the three years for the 2,437 sample enterprises was 37.81. A total of 1,507 enterprises (61.84%) scored below 40, suggesting most enterprises remain in the early stages of transformation, with only basic digital initiatives undertaken. Another 892 enterprises (36.60%) scored between 40 and 60, concentrated mainly in Guangdong, Beijing, Jiangsu, and Zhejiang. Only 38 enterprises scored above 60, distributed across 13 regions.

From a regional perspective, Guangdong has the largest sample and the highest digital transformation level, followed closely by Beijing; both average above 40. Tianjin, Hubei, Henan, and Fujian ranked third to sixth despite smaller samples. Shanghai, Zhejiang, and Jiangsu, which have more developed manufacturing industries, have average digital transformation levels ranking 7th, 10th, and 14th, respectively, all above average. In contrast, 15 regions (i.e. Liaoning, Chongqing, Shaanxi, Shandong, Hebei, Guangxi, Qinghai, Sichuan, Guizhou, Shanxi, Jilin, Hainan, Ningxia, Yunnan, and Tibet) were below average, with Tibet lowest at 29.68. These findings indicate significant regional differences.

5.2. Configuration analysis

5.2.1. Data calibration

Due to the lack of universally accepted standards for classifying digital transformation among manufacturing listed companies, the direct calibration method was employed. This approach is particularly suitable when external benchmarks are unavailable (Greckhamer et al., 2018). In this study, calibration was based on quartile anchor points: the 75th percentile as full membership ("high"), the 25th percentile as full non-membership ("low"), and the median as the crossover point. The median, rather than the mean, was selected due to its insensitivity to extreme values, thereby mitigating biases caused by outliers (Greckhamer & Gur, 2021). Since indicators of enterprise digital transformation may be susceptible to extreme values, the median was considered more appropriate for reflecting the typical conditions of the majority of firms and reducing distortion introduced by data skewness (Wang et al., 2023).

After calibration, cases with a membership score of 0.5 were excluded by default, which may introduce bias into the analysis results. To address this issue, a constant of 0.001 was added – following Fiss (2011) – to ensure the inclusion of boundary conditions in the analysis, thereby enhancing the comprehensiveness and accuracy of the results. Table 2 presents the calibration anchors and descriptive statistics for the results and condition variables.

Table 2. Data calibration and descriptive statistics

Variable		Fuzzy set calibration			Descriptive statistics			
		Full membership	Cross-over Point	Full- Non-membership	Min	Max	Mean	Standard Deviation
Result variable	TRA	44.407	36.583	30.247	22.850	75.418	37.815	9.537
Antecedent variables	RD	6.560	4.470	3.210	0.027	348.570	6.064	9.798
	HUM	19.610	13.913	10.123	0.163	89.990	16.369	10.855
	STR	2.497	1.504	0.693	0.000	6.008	1.656	1.219
	ROA	0.082	0.048	0.017	-0.310	0.618	0.050	0.070
	MAR	40.425	36.440	34.500	25.820	57.090	41.442	6.317
	DIG	379.576	356.681	336.592	319.290	450.530	395.676	32.403
	GOV	0.032	0.019	0.011	0.004	0.062	0.040	0.016

5.2.2. Necessary condition analysis

Necessary conditions were analysed using fsQCA 4.1 software, with the results reported in Table 3. None of the antecedent variables reached the 0.9 consistency threshold, indicating that no single condition is sufficient and necessary for high digital transformation. Instead, its realisation depends on the interplay and combined effects of multiple factors.

Table 3. Analysis of the necessity of a single conditional variable

Conditional variable	High digital transformation		Non-high digital transformation		Conditional variable	High digital transformation		Non-high digital transformation	
	Con	Cov	Con	Cov		Con	Cov	Con	Cov
RD	0.605	0.619	0.459	0.469	~RD	0.481	0.471	0.627	0.613
HUM	0.603	0.611	0.476	0.482	~HUM	0.488	0.483	0.615	0.607
STR	0.788	0.794	0.315	0.317	~STR	0.323	0.321	0.795	0.789
ROA	0.488	0.491	0.594	0.596	~ROA	0.599	0.596	0.493	0.490
MAR	0.873	0.540	0.820	0.506	~MAR	0.202	0.529	0.255	0.667
DIG	0.895	0.531	0.841	0.498	~DIG	0.155	0.495	0.209	0.664
GOV	0.898	0.528	0.841	0.493	~GOV	0.139	0.466	0.196	0.656

Note: "~" represents "not" in logical operations. "Con" is the abbreviation of Consistency, "Cov" is the abbreviation of Coverage.

5.2.3. Configuration results

The threshold for full condition consistency was set at 0.7, and the frequency threshold at 10, with the screen based on PRI consistency being greater than 0.5. The results of the standard analysis are shown in Table 4.

Variables appearing in both parsimonious and intermediate solutions are defined as core conditions, whereas those appearing only in the intermediate solution are supplementary conditions. Table 5 presents the results of the analysis.

Table 4. Results of configuration analysis

	Configuration	Raw coverage	Unique coverage	Consistency
Intermediate solution	STR*MAR*DIG*GOV	0.6811	0.6553	0.8110
	~RD*~HUM*STR*~ROA*~MAR*~DIG*~GOV	0.0267	0.0154	0.7574
	RD*HUM*STR*~ROA*~MAR*~DIG*~GOV	0.0235	0.0109	0.8771
	RD*HUM*STR*ROA*~MAR*~DIG*GOV	0.0209	0.0015	0.8993
	Coverage of solutions	0.7111		
	Consistency of solutions	0.8105		
Parsimonious solution	STR*~ROA	0.4772	0.0113	0.8469
	RD*STR	0.5161	0.0019	0.8606
	HUM*STR	0.5060	0.0019	0.8612
	STR*MAR	0.7037	0.0032	0.8085
	STR*DIG	0.7181	0.0054	0.8049
	RD*~DIG*GOV	0.0548	0.0005	0.6830
	RD*~MAR*GOV	0.0920	0.0015	0.7292
	HUM*~DIG*GOV	0.0562	0.0014	0.6874
	HUM*~MAR*GOV	0.0912	0.0020	0.7315
	Coverage of solutions	0.8006		
	Consistency of solutions	0.7753		

Table 5. Configuration high digital transformation

	Configuration			
	1	2	3	4
RD		⊗	●	●
HUM		⊗	●	●
STR	●	●	●	●
ROA		⊗	⊗	•
MAR	●	⊗	⊗	⊗
DIG	●	⊗	⊗	⊗
GOV	•	⊗	⊗	●
Raw coverage	0.6811	0.0267	0.0235	0.0209
Unique coverage	0.6553	0.0154	0.0109	0.0015
Consistency	0.8110	0.7574	0.8771	0.8993
Coverage of solutions	0.7111			
Consistency of solutions	0.8105			

Note: ● Indicates the existence of core conditions. ⊗ Indicates the absence of core conditions. • Indicates the existence of boundary conditions. ⊕ Indicates the absence of boundary conditions. A blank represents that a condition may exist or may not exist.

The consistency of the four configurations and overall solution was greater than 0.7, indicating an acceptable level of consistency, with the overall solution having a consistency of 0.8105 and coverage of 0.7111. The four configurations in Table 5 can be considered sufficient condition combinations for high digital transformation.

Configuration 1 has a consistency of 0.8110 and explains approximately 68.11% of the high digital transformation cases, making it the most widely covered among the four configurations. Notably, 65.53% of such cases can only be reasonably explained through this configuration. In this configuration, STR, MAR, and DIG are the core conditions and GOV is a peripheral condition. No core or peripheral non-existent conditions are included. It emphasises the core roles of corporate strategy, the external business environment, and digital finance development, as well as the auxiliary role of government support. This indicates that a synergistic effect between the internal and external conditions is required for a company to achieve high levels of digital transformation. In practice, companies should focus on strategic leadership, make good use of digital finance, fully utilise a favourable business environment, and actively seek government support.

Configuration 2 has a consistency of 0.7574 and explains approximately 2.67% of the high digital transformation cases, with 1.54% uniquely accounted for by this configuration, indicating some uniqueness. In this configuration, STR is the only core condition present, ROA is the core condition absent, and all others are peripheral conditions absent. This configuration reveals that strong strategic leadership is the key to achieving high digital transformation levels in the context of insufficient financial resources. This underscores the importance of leadership decision-making and strategic capabilities in resource-constrained environments. For enterprises, having a clear strategic direction and firm execution can successfully advance digital transformation, even when facing financial and resource constraints.

Configuration 3 has a consistency of 0.8771 and explains 2.35% of the high digital transformation cases, with 1.09% uniquely explained. In this configuration, RD, HUM, and STR are core conditions for existence, ROA is a core condition for non-existence, and all three environmental dimensions are marginal conditions for non-existence. This reveals the critical roles of technological funding, technical talent, and strategic leadership in the context of insufficient financial security. By effectively integrating their internal resources, companies can overcome financial constraints and achieve high digital transformation.

Configuration 4 has a consistency of 0.8993 and explains 2.09% of the high digital transformation cases, with 0.15% uniquely explained. RD, HUM, STR, and GOV are core conditions for existence, MAR and DIG are core conditions for non-existence, and ROA is a peripheral condition for existence. The configuration reveals that, even with an inadequate business environment and digital financial, companies can successfully achieve digital transformation by combining internal resources (technological capital, technological talent, and strategic leadership) and government support. Financial assurance, as a peripheral condition, provides certain financial support.

It is worth noting that these four configurations do not simultaneously include all three dimensions of the TOE framework, but they encompass at least one of these dimensions, reflecting the comprehensive role of technological, organizational, and environmental factors in digital transformation. Specifically, Configuration 1 emphasizes the combination of environmental factors (MAR, DIG, GOV) and organizational factors (STR). Configuration 2 highlights the core role of organizational factors (STR). Configuration 3 emphasizes the combination of technological factors (RD, HUM) and organizational factors (STR). And Configuration 4 demonstrates the comprehensive effect of technological (RD, HUM), organizational (STR), and environmental (GOV) dimensions. These different configurations reflect the multi-path nature of digital transformation, while also validating the applicability and flexibility of the TOE framework.

To verify the robustness of the configurational results, a robustness check was conducted, referencing the approach proposed by Du et al. (2020). This involved adjusting the case frequency threshold and increasing the consistency threshold. Specifically, the case frequency was adjusted from 10 to 9, and the threshold for full condition consistency was increased from 0.7 to 0.75. The recalculated results remained unchanged in terms of core configurations and outcome interpretations, indicating the stability and reliability of the original findings.

6. Discussion

According to the core and edge presence/absence conditions of the four configurations, the model can be summarised based on four paths.

6.1. Environment-dependent oriented

The environment-dependent path reflects the importance of external infrastructure and institutional support, as highlighted by Bouwman et al. (2019). Configuration 1 belongs to this path, in which enterprises mainly rely on a favourable external environment, such as a sound business environment and developed digital financial services, to achieve digital transformation under the guidance of high-level strategies. With limited internal technological resources, these enterprises rely heavily on external resource support.

This path highlights the significant influence of environmental factors in combination with organizational leadership, in line with the TOE framework's emphasis on external context. This path is suitable for enterprises located in economically developed areas that enjoy favourable business environments and abundant digital financial services. These enterprises have relatively insufficient internal technological investment and talent reserves but a strong strategic leadership team. Therefore, enterprises can accelerate digital transformation in three ways. First, enterprises should formulate clear digital strategies, fully utilise favourable external conditions, and achieve strategic goals. Second, they should actively cooperate with financial institutions and use digital financial services to obtain financial support. Third, enterprises could closely monitor market trends, flexibly adjust strategies, and fully leverage the advantages of the business environment.

A total of 847 typical cases (configuration membership degree and reconciliation membership degree greater than 0.5) were selected from this path. The distribution of cases shows a clear regional pattern: most are concentrated in the eastern regions, particularly Guangdong, Zhejiang, Jiangsu, Shanghai, Beijing, Shandong, and Fujian. In contrast, only a smaller number of cases are located in the central regions such as Anhui, Hubei, and Henan, and in the western regions such as Sichuan and Chongqing.

6.2. Strategic leadership oriented

The strategic leadership path aligns with Bharadwaj et al. (2013), who emphasise the critical role of top management commitment in overcoming resource limitations. Configuration 2 belongs to this path, in which companies with limited resources (e.g. funding, technology, and talent) and insufficient external support rely on strong strategic leadership to achieve digital transformation. The determination and vision of the top management are the main forces driving this transformation.

This path specifically emphasizes the organizational dimension of the TOE framework, showcasing the crucial role of internal strategic capabilities. This path is suitable for resource-constrained enterprises, particularly those lacking financial and technological investments. Senior management places high importance on digital transformation, with enterprises possessing strong leadership and execution capabilities. These enterprises hope to overcome resource and environmental constraints through strategic guidance to achieve digital transformation. Therefore, enterprises can accelerate digital transformation in the following ways: (1) cultivating and enhancing senior managers' digital awareness and strategic planning capabilities, (2) focusing on key areas with limited resources and seeking efficient digital solutions, and (3) inspiring creativity and enthusiasm among employees to promote digital transformation.

From this path, 11 typical cases were selected (with both configuration membership and solution membership greater than 0.5). The number of typical cases is limited due to the low coverage of this path. The cases are mainly distributed in Guangxi (002175, 000703, 000528, 002329), Heilongjiang (300040, 603567, 600822), Liaoning (002689), Qinghai (600869, 002646), and Hebei (603385).

6.3. Internally capability support oriented

The internally driven path resonates with Zhu et al. (2006), where firms rely on in-house technical capabilities and skilled personnel to drive change. Configuration 3 belongs to this path in which companies rely on internal investments in technology and talent cultivation to achieve digital transformation under strategic guidance. External support, such as the business environment, digital finance, and government support, is relatively minimal, emphasising the integration and utilisation of internal resources.

This path integrates both technological and organizational dimensions of the TOE framework, underlining the significance of internal technological capabilities combined with strategic leadership. This path is suitable for enterprises that value R&D investment and technological innovation, have a certain financial strength, have a high-quality technical talent team, and focus on talent cultivation and development. Therefore, enterprises can accelerate digital transformation in the following ways: (1) continuously investing in technological R&D to enhance their technological innovation capabilities, (2) cultivating talent and introducing plans to build high-level technical teams, and (3) ensuring that technological development is consistent with the enterprise's digital strategy, thus promoting effective resource allocation.

A total of 13 typical cases were selected from this path, with relatively few cases due to the low coverage of this path. The cases are mainly distributed in Liaoning (300024, 300097, 300210, 603396, 002231, 688529), Heilongjiang (000901, 688011), Jilin (300510), and Hebei (300491, 002691, 601633, 603050).

6.4. Comprehensive drive oriented

The comprehensive-driven configuration mirrors findings from recent literature (Toscano-Jara et al., 2024; Zhang et al., 2025a), which suggest that integrated capabilities across all TOE dimensions are associated with higher transformation performance. Configuration 4 belongs to this path, in which enterprises have abundant internal resources, including sufficient technological funds and high-level technical talent. Guided by strategy and with strong government support, enterprises with this configuration can achieve digital transformation.

Although the business environment and digital financial services may be insufficient, through comprehensive coordination of internal and government resources, an enterprise can overcome the limitations of the external environment.

This configuration demonstrates a comprehensive integration of the TOE framework, illustrating the ideal alignment scenario. This path is suitable for enterprises with abundant internal resources and strong technological and talent advantages. Simultaneously, these enterprises can receive strong government support, providing policy and financial assistance. Therefore, enterprises can accelerate digital transformation in the following ways: (1) effectively integrating internal technology and talent resources to enhance core competitiveness, (2) actively communicating with government departments to obtain policy support and resource assistance, and (3) formulating and implementing comprehensive digital strategies and coordinating internal resources with government support.

Nine typical cases were selected from this path. Due to the low coverage of this path, the number of typical cases is limited. However, it is noteworthy that all these typical cases originated from Hunan Province.

In summary, a detailed analysis of each path demonstrates effective strategies for promoting corporate digital transformation under different conditions, with regional variations. Enterprises can choose a suitable path based on their resources and environmental conditions to increase the success rate of digital transformation.

7. Conclusions and insights

7.1. Conclusions

This study used the TOE framework and fsQCA method to explore the driving factors of digital transformation and their configurational effects. The main conclusions are presented below. (1) Digital transformation levels fluctuated between 2020 and 2022, with most enterprises still in the early stages. Significant regional differences were observed, with better performance in Guangzhou, Beijing, Tianjin, Hubei, Henan, and Fujian. (2) Strategic leadership was a core condition in each configuration, whereas technological funding, technological talent, and government support were also core conditions in some configurations. (3) Four paths are identified that can significantly enhance digital transformation, including environment-dependent, strategy-led, internal capability-supported, and comprehensive-driven types. (4) Enterprises should choose the most suitable path based on their own resources and environmental conditions and make comprehensive use of various resources and strategies to achieve digital transformation.

7.2. Managerial insights

Based on the research conclusions, this study provides some practical insights.

(1) Strategic leadership is the core condition for enterprise digital transformation, requiring manufacturing companies to recognise and leverage its central role. Senior management should enhance digital awareness, formulate clear digital strategies and ensure implementation across all levels. Simultaneously, enterprises need to cultivate a digital mindset among senior team members, establish strategic execution mechanisms, integrate resources, overcome challenges, and succeed in digital transformation. In addition, the participation and execution of all employees are equally important.

(2) Enterprises in the eastern region should fully utilise the favourable business environment and advanced digital financial services, strengthen strategic leadership, actively integrate external resources, and accelerate the digitalisation process. Enterprises in the central and western regions should choose strategic leadership, internal capability support or comprehensive driving paths to promote digital transformation based on the resource endowment of their respective areas and their actual conditions.

(3) Enterprises should attach importance to investments in technological funds and technical talent cultivation. They should continuously increase investment in R&D for new technologies, pay attention to cutting-edge trends in the industry, formulate a clear technology development roadmap, and ensure that technological innovation matches their corporate strategy. Enterprises should also develop effective talent strategies, attract and cultivate high-quality digital talent, and establish comprehensive talent incentive mechanisms to attract and retain outstanding technical talent. Through cooperation with universities and research institutions, technical training and project cooperation should be conducted to enhance employees' professional and innovative capabilities.

(4) Enterprises should proactively understand and fully utilise various support policies and resources provided by the government to accelerate the digital transformation process. This includes policy benefits such as tax incentives, special funding support, and technical training. Enterprises can establish a dedicated policy research department or designate personnel responsible for collecting and interpreting government policy information and actively implement government-led digital transformation projects to secure more funding and technical support.

(5) Enterprises should recognise that digital transformation is the result of multiple factors working together and thus require an ecosystem be constructed that includes both internal and external resources. By establishing strategic partnerships with upstream and downstream enterprises in the supply chain, technology companies, research institutions, and other relevant entities, enterprises can access more innovative resources and support.

7.3. Limitations and avenues for future research

In summary, this paper innovatively integrate the TOE framework and fsQCA into an analysis of the factors driving digital transformation, presenting a novel perspective for enhancing it. Nonetheless, certain constraints of this study warrant attention further research. First, the research sample is limited to listed manufacturing enterprises, which may not fully represent the situation of non-listed enterprises and small and medium-sized enterprises. Second, due to the lag in the disclosure of some data involved in the study, the research time span covers the period from 2020 to 2022. Affected by the COVID-19 pandemic, data from this special period may not fully reflect the patterns of digital transformation under normal economic conditions. Third, although the fsQCA method can reveal the relationship between combinations of factors and outcomes, it still has limitations in providing in-depth explanations of causal mechanisms.

Based on the findings and limitations of this study, future research can be expanded in the following directions. First, broaden the sample scope to include non-listed enterprises and small-to-medium enterprises, in order to obtain a more comprehensive picture of digital transformation in the manufacturing industry. Second, optimize the TOE research framework by incorporating indicators without disclosure lags, enabling the study to cover the most recent years. Third, integrate qualitative research methods to conduct in-depth case analyses

on the specific implementation mechanisms and success factors of various configuration pathways.

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APPENDIX

Table A1. Digital transformation indicators system and weights

Primary indicators and weights	Secondary indicators and weights
Strategic Leadership (34.72%)	Establishment of digital positions at the management level (23.82%)
	Management's digital innovation-oriented forward-looking (27.88%)
	Continuity of Management's digital innovation orientation (18.79%)
	Breadth of digital innovation orientation at the management level (12.83%)
	Strength of digital innovation orientation in management levels (16.68%)
Technology-driven (16.20%)	Artificial Intelligence Technology (55.04%)
	Blockchain technology (12.98%)
	Cloud computing technology (18.32%)
	Big data technology (13.66%)
Empowerment of organizations (9.69%)	Digital Capital Investment Plan (50.22%)
	Digital Manpower Investment Plan (25.53%)
	Digital Infrastructure Construction (12.06%)
	Construction of Science and Technology Innovation Base (12.19%)
Environmental Support (3.42%)	Number of invention patents in the industry (19.23%)
	R&D activities in the industry (17.79%)
	New product development and sales in the industry (14.98%)
	Digital technology intensity in the industry (11.57%)
	Digital Capital Intensity in the Industry (11.4%)
	Intensity of human capital investment in the industry (7.89%)
	Optical fiber cable density in the city (4.77%)
	Capacity of mobile switching center in the city (4.03%)
	Scale of internet broadband access users in the city (4.00%)
	Scale of mobile internet users in the city (4.34%)
Digitalization outcomes (27.13%)	Digital innovation standards (36.68%)
	Digital innovation paper (11.74%)
	Digital invention patent (23.54%)
	Digital innovation qualification (14.73%)
	National-level Digital Awards (13.31%)
Digital applications (8.84%)	Technological innovation (63.42%)
	Process Innovation (23.78%)
	Business Innovation (12.80%)