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Construction of Structural Dimensions of Digital Transformation Capability for Manufacturing Enterprises: Empirical Study Based on Grounded Theory and Questionnaire Survey

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Abstract: *In the digital economy era, under the pressure of technological innovation and market competition, most manufacturing enterprises have invested a lot of humans, financial, and material resources to implement a digital transformation. Based on grounded theory and combined with digital transformation practices in manufacturing enterprises, this study selected four manufacturing enterprises that have achieved certain results in digital transformation. We conducted a semi-structured interview of at least one hour with three senior management personnel from each enterprise-a total of 12 interviews. Through open coding and the axis coding process with field interviews, we found that digital transformation capability of manufacturing enterprise consists of three structural dimensions: sensing, organizing, and restructuring. Specifically, the capability of sensing in a digital environment, organizing internal and external available resources, and reworking organizational structures are important dimensions of digital transformation capability. We further analyze the structural framework dimensions of digital transformation capability constructed in this study, and found that the three dimensions of a digital transformation capability are not simple parallel relationships, but have a process sequence relationship from a business perspective. This study makes certain contributions to practical implications for manufacturing enterprises that are preparing for, or are already in, the digital transformation stage.*

Keywords: *Structural dimensions; Digital transformation capability; Grounded theory; Dynamic capability theory; Exploratory research*

1. Introduction

In the digital economy era, the digital transformation has become an important support for enterprises to cope with the risks and challenges, to build the core capabilities, and to enhance competitive advantages. Under the pressure of technological innovation and market competition, most manufacturing enterprises have invested a lot of humans, financial, and material resources to implement a digital transformation [1]. However, most manufacturing enterprises is going through some difficult in the process of transformation, and the failure rate of digital transformation is high. Specifically, on the one hand, enterprises are generally aware of the importance of digital transformation, but lack a systematic capability framework, forcing enterprises to measure their transformation capability at all times, which leads to waste of resources [2,3]. On the other hand, enterprises invested a lot of resources but failed to achieve the expected results. During the transformation process, they focused on the technical dimension and failed to fully consider the impact organizational cultural factors on digital transformation [4,5]. Therefore, it is urgent to explore successful cases of digital transformation in manufacturing enterprises and reveal the transformation laws that can be learned and implemented, providing an advanced roadmap for successful transformation practices.

On the theoretical level, with the development of cloud computing, big data, the Industrial Internet of Things (IIoT), AI and other digital technologies, as well as attention to manufacturing by various countries, research on the digital transformation capabilities of manufacturing enterprises has aroused extensive discussion in the industry and among scholars. Consensus has been formed in three ways. 1) A digital transformation capability reflects deep application of digital technology in various practices of

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enterprises, requiring deep integration of digital technology and business [6]. 2) The digital transformation capability of enterprise is multi-dimensional and hierarchical [7]. 3) The digital transformation capability promotes enterprises to realize digital transformation upgrading [8]. Overall, the existing research has a certain understanding of the importance and effectiveness of enterprise digital transformation capability, which has laid a solid theoretical foundation for this research.

However, the existing research on the construction of digital transformation capability structure dimension is obviously insufficient, which leads to the lack of clear theoretical guidance in the process of digital transformation of enterprises, and it is difficult to build an effective capability framework. First of all, the existing research mostly analyzes transformation capability from a single perspective (technology, organization or strategy), lacking an integrated framework. This makes the understanding of digital transformation capability not comprehensive enough to guide enterprises to develop comprehensive transformation strategies. In the market environment of information explosion, technological shock, and unpredictable user demand, manufacturing enterprises face unprecedented turbulence and change. When the external volatile business environment undergoes rapid changes, enterprises are required to respond and make adjustments [9]. Rapid technological updates have given rise to new business models, and the environmental complexity has sharply increased, forcing traditional manufacturing enterprises to embark on a path of transformation [2]. However, due to the large proportion of fixed assets in manufacturing enterprises, flexibility in a digital transformation is poor, giving manufacturing enterprises different characteristics in digital transformation capabilities compared to other enterprises. Therefore, it is necessary to explore the specific concepts of the digital transformation capability in manufacturing enterprises.

Second, existing research needs to further clarify the structural dimension of manufacturing enterprises' digital transformation capability. For example, it is difficult to capture the hidden capabilities of the organization, and coordinate various departments to resolve conflicts between departments. Digital transformation requires multiple digitally related organizational capabilities to address issues during the transformation [8] (Abou-Foul et al., 2023). Enterprises help achieve a digital transformation by building a dynamic capability that can change their technology, business processes, and business models [9]. Therefore, this study uses grounded theory to mine the hidden dimensions in interviews through open coding, such as the category of coordinating inter departmental conflicts.

Third, in terms of research methods for a digital transformation capability, existing research mainly focuses on quantitative research based on Teece [10] dynamic capability theory, and and analyzes the influencing factors of a digital transformation capability through regression analysis [11,12]. In the digital context, the explanatory power is insufficient, and the dual driving transformation capability of technology and process is ignored. Although a few researchers have applied qualitative methods to summarize the content related to a digital transformation through literature reviews [13,14]. However, due to the high heterogeneity of the industry and the differences in the transformation maturity of enterprises, in order to extract patterns or construct theories, qualitative data such as interviews and observations need to be used for case-level qualitative analysis.

Therefore, on the basis of combing the existing literature in the three fields of digital transformation, manufacturing enterprises and dynamic capabilities, this study clarifies the internal mechanism of the construction of digital transformation capabilities of manufacturing enterprises. The purpose of this study is to build the structural dimensions of a manufacturing enterprise’s digital transformation capability. Specifically, based on grounded theory, this study explores the concept and structural dimensions of manufacturing enterprises' digital transformation capability through semi-structured interviews. This study aims to solve the following core problems: 1) What is the conceptual definition of digital transformation capability in manufacturing enterprises? 2) What are the structural dimensions of digital transformation capability? 3) How do these dimensions interact to enable effective transformation practices?

Based on Teece's [10] dynamic capability model and Warner & W ä ger [15] and other existing research related to digital transformation, this study has certain theoretical and practical significance in the research of digital technology and business process integration innovation. The general dynamic capability model proposed by Teece [10] is suitable for all enterprises to maintain their competitive advantage in a rapidly changing environment, and does not address the complex business process and digital technology integration of the manufacturing industry. This study contextualized the dynamic capability theory to the digital transformation of manufacturing industry, emphasizing that the digital transformation capability built by manufacturing industry focuses on perceiving the data island, equipment heterogeneity, process knowledge gap in the manufacturing scene, the coordination mechanism of cross level organization, and restructuring the production system, supply chain relationship

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and knowledge architecture. Warner & Wäger [15] proposed a digital transformation framework from the perspective of business model innovation at the strategic level to explain how enterprises sense opportunities, seize and transform. This study focuses on manufacturing enterprises, emphasizes the structural dimension of digital transformation capability, and what core capabilities can enterprises have to promote digital transformation, and tries to provide manufacturing enterprises with a feasible ability construction path under the background of situational and structured development in the digital transformation of manufacturing industry.

This study has important theoretical and practical significance. In terms of theoretical significance, 1) this study constructs the structural dimensions of manufacturing enterprises' digital transformation capability, which makes up for the deficiencies of existing research in terms of dimensional; 2) the interview samples covered large, medium and small manufacturing enterprises of different sizes, enriched the research content of digital transformation capability, and provided new research ideas in related fields; 3) using grounded theory to code multiple cases, this study mine the hidden dimension in interviews, and verifies the proposed structural dimension of digital transformation capability through qualitative analysis, which provides a new methodological perspective for the research of digital transformation capability. In terms of practical significance, the structural dimensions of digital transformation capability constructed in this study has certain practical significance for manufacturing enterprises that are preparing for or are already in the digital transformation stage, and can guide manufacturing enterprises to improve transformation capability, formulate scientific transformation strategies, and improve the success rate of digital transformation.

The structure of this study is as follows. First, in a literature review, we searched for relevant content on manufacturing enterprises' digital transformation capability. Second, we describe structural dimensions of digital transformation capability with grounded theory research method. Then, we present the results of empirical research through open coding and the axis coding process. Finally, based on empirical analysis, we suggest academic and practical implications for the structural dimensions of digital transformation capabilities, and we discuss the research findings.

2. Literature Review

2.1. Digital Transformation in Manufacturing Enterprise

With the disruptive social, mobile, analytics, cloud, and Internet of Things impact of digital technologies, enterprises plan digital transformation from a strategic perspective [1]. Digital transformation in manufacturing enterprises requires embedding digital technology into products and innovation processes, restructuring business models, creating networked supply chains, and adopting more intelligent operational processes [2]. Many manufacturing enterprises are using digital technology to empower their business, such as storing data from various nodes in the production chain (including procurement or sales-related data), analyzing customer consumption, and identifying the reasons for inefficiencies to eliminate them [13].

Recently, theoretical research on manufacturing enterprises' digital transformations has mainly focused on the following five aspects.

1) The necessity for digital transformation. Hermann et al. [6] explored the digital transformation of SMEs through externally supported digital innovation project types. Li and Yang [16] believed that based on the current situation of digital transformation in manufacturing enterprises, the process should be accelerated. Manlio et al. [17] analyzed the positive effects of digital transformation on improving quality and efficiency in manufacturing enterprises.

2) Policies and strategies for digital transformation. Hanelt et al. [18] focused on strategic and organizational change and systematically reviewed the literature on digital transformation. Marolt et al. [12] pointed out that enterprises need to formulate digital transformation strategies based on core business data. Curwen [19] sorted out the development status of enterprises under the digital transformation policies of different countries.

3) Digital transformation framework. Kraus et al. [20] proposed research framework by outlining the digital transformation status in business and management. Wan et al. [21] designed a reference framework for digital transformation in manufacturing enterprises from value and element dimensions. Vial [22] constructed a basic digital transformation framework from the organizational structure perspective.

4) Factors influencing digital transformation. Mueller et al. [7] proposed that digital leadership is a

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key capability for enterprise transformation. Yu and Moon [23] emphasized that digital transformation capability is the key capability for manufacturing enterprises to adapt to the requirements of the digital era. Vial [22] (2019) believed that entrepreneurship is the decisive factor for enterprises wanting to carry out digital transformations and upgrading.

5) Digital transformation affects the survival and development of manufacturing enterprises. Ma et al. [13] pointed out that the latecomers in intelligent manufacturing realized digital catch-up through resource orchestration to improve market competitiveness. Li and Yang [16] emphasized the role of digital transformation in promoting the renewal of business models of manufacturing enterprises. Liu [24] empirically revealed the internal mechanism of productivity improvement driven by digital transformation based on the sample of listed manufacturing companies.

Based on the existing research of manufacturing enterprise' digital transformation, this study focuses on the deep integration of business process and digital technology, and defines the concept of digital transformation according to the characteristics of manufacturing enterprises. Specifically, research and design, production and manufacturing, warehousing and logistics, sales and service, and other aspects of manufacturing enterprises are transformed throughout all processes, chains, and elements. While fully leveraging the value creation of data elements, the value model, solutions, and tools of the enterprise also undergo systematic changes.

2.2. Digital Technology and Manufacturing Enterprise

Digital technology is particularly important for traditional manufacturing enterprises. Digital transformation drives manufacturing enterprises to collect product production data from the supply chain to assist decision-making [2]. Manufacturing enterprises integrate vertical and horizontal manufacturing systems to open up internal data chains and value chains [13]. Similar to using small digital equipment such as sensors to improve product safety, manufacturing enterprises gradually promote the digitization of traditional business processes [4].

Paschou et al. [25] identified 9 types of digital technologies in the manufacturing industry, namely: 1) additive manufacturing. Stacked 3D printing, which forms high complexity, small batch customized parts in one go through deposition [26]. 2) Advanced manufacturing. Collaborative robots based on Cyber Physical System work in parallel with humans at shared workstations, relying on environmental perception and AI decision-making to achieve flexible assembly [27]. 3) Artificial intelligence. Using machine learning and data mining to diagnose bottlenecks and optimize parameters in production big data, thereby shortening the cycle time and reducing waste [28]. 4) Big data analysis. Using statistical modeling, neural networks, and Bayesian networks, patterns are extracted from multimodal data such as numbers, text, images, and videos, and predictive models are constructed [29]. 5) Cloud computing. By utilizing a scalable shared resource pool (servers, storage, platforms), on-demand computing services can be achieved anytime, anywhere [30]. 6) Horizontal / vertical integration. Open up information silos within the enterprise and upstream and downstream of the supply chain, reshape organizational processes and physical logistics [31]. 7) Industrial Internet of Things. Connect devices and products to the cloud, collect real-time operating data, support remote operation and maintenance, fleet management, spare parts optimization, and predictive maintenance [32]. 8) Mixed reality. Integrating virtual reality and augmented reality, real-time overlay of digital twin information onto physical objects, achieving immersive operation and training [33]. 9) Machine networking simulation. Prior validation of device layout, process path, and factory design in digital space reduces physical trial and error costs [34].

2.3. Digital Transformation Capability of Manufacturing Enterprise

Although digital transformation has a transformative impact, manufacturing enterprises also face challenges from personnel, management, and the technology in realizing the business value of digital transformation [13]. Manufacturing enterprises need to build an organizational capacity that uses digital technology to create value, improve productivity and competitiveness, and maintain competitive advantage [35].

At present, the concept of a digital transformation capability does not have a unified definition or measurement dimensions. Research on the definition and dimensions of a digital transformation capability has mainly focused on computer science and management science, including the three perspectives of technology, management, and resources. First, from the technology perspective of computer science, a digital transformation capability represents how enterprises use digital management and decision-making in IT and OT convergence so that manufacturing enterprises can shorten the time

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to market; improve production flexibility, efficiency, and product quality; and then establish a new business model [36]. Second, from the perspective of management science, a digital transformation capability is one capability of a data-driven organization; that is, each link of the enterprise value chain and different stages of management decision-making can be driven from bottom to top by data, or even directly based on data, for decision-making [37]. Third, from the resource-based view in strategic management, digital resources are the premise of a digital transformation capability. In a broad sense, digital resources include digital infrastructure (cloud hardware, software, and operational platforms), data (traditional enterprise data, machine and sensor data), and a digitalized human resources department. Digital resources are not only a key element in maintaining competitive advantage, but also an essential driving force for enterprises to development digital transformation capability [38].

Based on the perspective of dynamic capabilities, this article defines the digital transformation capability of manufacturing enterprises as a deeply integrated capability in multiple digital technology cluster innovation breakthroughs. That is to say, a manufacturing enterprise uses various digital technologies to mobilize internal and external resources to improving enterprise performance.

3. Methodology

3.1. Research Method

The purpose of this study is to investigate the structural dimensions of a manufacturing enterprise's digital transformation capability construct. Due to the lack of mature theoretical research results that can be directly used for reference in digital transformation, it is difficult to directly conduct quantitative research, and a case study is applicable to these exploratory issues. Therefore, this study refers to an emergent concurrent mixed-methods approach by Marolt et al. [12] for enterprise digital transformation, combined case analysis with empirical investigation, attempting to construct the dimension of digital transformation capability based on case analysis and verify its effectiveness through empirical analysis.

This study combines grounded theory [39] with multiple case studies for qualitative research. They believed that when new data and materials continue to exist, innovative theories can be summarized from these materials. In particular, grounded theory is based on inductive deductive thinking, and through systematic analysis of practical data, it discovers an explanatory framework theory that fits the problem. Therefore, the main purpose of grounded theory is to summarize the original materials, analyze them hierarchically, and finally build a new theory. The core analytical method of grounded theory is to continuously compare past experience data and abstract new theories from them [40]. Based on grounded theory combined with the practice of digital transformation in manufacturing enterprises, this study selected four manufacturing enterprises and conducted a semi-structured interview of at least one hour with each of 12 senior managers either leading their enterprise's digital transformation (e.g., the CEO) or leading all or some of the digital transformation efforts of their respective organizations (e.g., chief information officer, chief digital officer, director of digital transformation). We constructed open coding and theoretical models, and explored the concept and structural dimensions of the digital transformation capability in the manufacturing enterprise.

3.2. Data Collection

The four case enterprises selected for this study are all manufacturing enterprises that have a certain foundation for digital transformation and are committed to exploring the path of digital transformation for a long time, which suited the requirements of the research objective. At the same time, information on the case enterprises is accessible. We established good relationships with the managers in charge of the case enterprises, conducted in-depth interviews, and obtained relevant internal information. In addition, these enterprises had a high level of social attention, and rich second-hand information was available through portal websites.

Before the interviews, we reviewed a large amount of digital transformation material and consulted relevant experts. Based on expert opinion, a semi-structured interview outline was designed that included the process of digital transformation, reviews of key events in the transformation, the characteristics and influencing factors of a digital transformation, experiences and perceptions of a digital transformation, etc. The primary data for this study came from the multiple interviews mentioned above. Basic information on the respondents is in Table 1. Three of the enterprises (A, B, and C) were established before the 1990s, and have more than 20,000 employees and a global business scope. Enterprise D was established later than the others, and its main business scope is concentrated in China. All four enterprises

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achieved industry-leading positions with a high degree of specialization in business services. Combined with their original characteristics, they have successfully expanded or even transformed their business models through digitalization, which is also worth exploring as a case study. The 12 senior managers who participated were responsible for specific business operations during the digital transformation and had a detailed understanding of their enterprise's situation. Through interviews and surveys, we found their education level quite high with most having a master's degree and few with a doctorate. Most of the managers were between the ages of 40 and 50 with rich work experience.

Secondary data came from minutes of meetings, promotional press releases, business research reports provided by the enterprises, as well as information collected from official enterprise websites and from searches with Google, Baidu, and other portals. The primary and secondary materials complemented each other to ensure credibility in the study [41]. At the same time, we sent the raw materials obtained to enterprise management for review and to correct errors based on their opinions. We made further modifications based on expert opinions to ensure the effectiveness of the study.

Table 1: Information on the Interviewees.

Case Enterprise	Founding year	Number of employees	Position	Education	Age
A	1862	42,894	Chief Technology Officer	Master's	42
			Head of Digital & Innovation	Doctorate	45
			R&D Director	Doctorate	50
B	1989	24,600	Head of Digital & IT	Master's	46
			Global E-Commerce Director	Master's	54
			Chief Information Officer	Master's	44
C	1984	55,000	Managing Director	Master's	53
			Head of Analytics	Doctorate	40
			Chief Technology Officer	Master's	41
D	1995	3400	CEO	Master's	37
			Head of Digital Transformation	Master's	43
			Learning & Development Director	Master's	48

3.3. Data Analysis

Based on grounded theory, this study starts with interview data obtained from the semi-structured interviews, and constructs a dimensional framework model of manufacturing enterprises' digital transformation capability structures through open, axial, selective coding, and saturation test. Following the normative coding steps for grounded theory methods outlined by Strauss and Corbin [40], this study divided qualitative data analysis into three steps. The first step is to encode the interview materials in open coding analysis, converting the original data into synonymous encoding so the initial concepts contained in the original data can naturally emerge. The second step is axial coding analysis: identify potential logical relationships between concepts, integrate concepts according to the principle of identity, and identify the aggregate dimension (primary dimension) of digital transformation capability. The third step is selective coding analysis: select core categories, abstract the main categories theoretically, and generate more general secondary dimensions, forming a theoretical concept of digital transformation capability.

3.3.1. Open Coding Analysis

Open coding is the process of decomposing, organizing, and analyzing original interview data, gradually refining and categorizing the data to clarify conceptual attributes and categories [42]. We identified first-order themes using an open coding procedure. After discussing and organizing original interview entries with a frequency greater than six, the preliminary 72 exemplary quotes and 24 conceptual categories were obtained.

According to the requirements of open coding, the initial interview data are encoded sentence by sentence, setting them with corresponding labels, to obtain the initial concepts and conceptual categories. After encoding the original sentences through labeling, exploration of the initial concepts should use the original words of the interviewees as much as possible to avoid being influenced by subjective bias in the researchers.

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Based on the research method proposed by Glaser and Strauss [39], this study used a double-blinded method to encode the 473 original sentences. Assuming that the same content shares an elementary code, 210 elementary codes were formed, then further organized and classified into codes according to the principle of similarity (if the meaning is similar, one code is retained), leaving 149 codes. Among them, the number of codes with consistent encoding was 131, so the consistency test result was 131/149=0.8792. This is higher than the 0.8 cut-off level for category validity. Afterwards, the 131 codes were further summarized and refined, and individual conflicting codes were eliminated, resulting in the 72 initial concepts (exemplary quotes).

At the same time, during the coding process, we analyzed the directionality among codes in the raw materials and the impact on enterprise digital transformation capabilities. We established logical relationships between codes with clear directionality, and labeled them. Subsequently, a large number of initial concepts with certain intersections were classified and combined, and their respective categories were divided, ultimately obtaining the 24 conceptual categories. The classification of interview materials is shown in Table 2.

Table 2: Classification of the Interview Materials.

Conceptual category	Exemplary quotes
Monitor changes and trends in the marketplace. (A1)	Changes in consumer demand; Competitor actions; Market orientation
Continuously scanning the external environment, timely capturing technological opportunities and potential threats. (A2)	Track technological development; Discovering technological updates; Technical impact
Investigate inefficiencies in existing business processes. (A3)	Production process issues; Low productivity; Disadvantages of business model
Identify opportunities for organizational transformation based on market conditions. (A4)	Identify opportunities; Identification ability; Identify resources
Based on the actual situation, foresee multiple feasible options for implementation. (A5)	Predicting the future development of technological opportunities; Progressiveness technology; Technical scalability
Seek new opportunities for strategic use of IT. (A6)	Combining technological opportunities with the market; Analyze the potential for technological development; Technical and economic benefits
Determine the needs for a digital transformation strategy. (A7)	Carrying out digital transformation; Strategic deployment; Need strategic support
Formulate the digital transformation strategy. (A8)	Building a digital vision; Customized digital strategy; Embrace digital transformation
Align the overall strategic goals of the enterprise with the digital transformation strategy. (A9)	Respond to business objectives; Strategic reshaping; Consistency of business objectives
Try to allocate management resources for digital transformation. (A10)	Assess one's own resource base; Resource compensation; Resource allocation
Implement efficient collaboration and positive interaction among various functional departments. (A11)	Increase communication between departments; Active interaction; Business communication
Integrate internal resources and competency for digital transformation. (A12)	Configure resource combinations; Adjusting one's own resources; Resource sharing
Integrate external resources for digital transformation. (A13)	Technical training; Technical exchange; Technology sharing
Emphasize the strategic position of the procurement functional department in the enterprise. (A14)	Organizational support; Applying new technologies; Technology acquisition methods
Combine internal and external resources for digital transformation. (A15)	Internal and external technological leapfrogging; Search and transmission of internal and external information; Synergistic effect
Prioritize digital transformation investments by the expected impact on business performance. (A16)	Centralized decision-making; Respond to changes; Adjusting decisions
Seek new ways to do something. (A17)	Institutional innovation; New department; Operating efficiency
Continuously try to trial and iterate new products or services. (A18)	Be brave in innovation; Corporate atmosphere; Corporate culture
Continually develop and produce new products or services. (A19)	Product innovation; Service innovation; Product iteration
Shorten the launch cycle of new products or services to seize market opportunities. (A20)	Innovation speed; Agility; Differentiation pursuit
Reconfigure the resources for new products or services. (A21)	Coordination mechanism; Resource integration; Synergistic effect
Apply knowledge resources to products or services. (A22)	Knowledge management; Knowledge application; Technology transformation
Coordinate with each other to solve conflicts. (A23)	Breaking through departmental barriers; Conflict management; Fully express opinions
Facilitate efforts for digital transformation strategy. (A24)	Cross boundary flow; Digital ecology; Continuously improving

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3.3.2. Axial Coding Analysis

After open coding, research has entered the axial coding stage, aiming to clarify the paradigms that affect business digital transformation. At this stage, the fragmented concepts are reassembled by sorting out the attributes and dimensions of each category, connecting them with subcategories, and forming a systematic explanatory framework. The core task of axial encoding is to compare the structure, types, and logical context between categories, merge similar items, and extract dominant main categories [41]. On the basis of axial encoding, nine categories were ultimately classified into three main aggregate dimensions: sensing, organizing, and restructuring. Sensing (B1) consists of monitor changes and trends in the marketplace (A1), investigate inefficiencies in existing business processes (A3), identify opportunities for organizational transformation based on market conditions (A4) and formulate the digital transformation strategy (A8) into four conceptual categories. Organizing (B2) means align the overall strategic goals of the enterprise with the digital transformation strategy (A9), try to allocate management resources for digital transformation (A10), integrate internal resources and competency for digital transformation (A12), and integrate external resources for digital transformation (A13) into the four conceptual categories. Restructuring (B3) consists of seek new ways to do something (A17), continuously try to trial and iterate new products or services (A18), coordinate with each other to solve conflicts (A23) and facilitate efforts for digital transformation strategy (A24) into the four conceptual categories. Axial coding of a digital transformation capability is shown in Table 3.

Table 3: Axial Coding of a Digital Transformation Capability.

Aggregate dimension	Conceptual category	Connotation
Sensing (B1)	Monitor changes and trends in the marketplace. (A1)	The organizational capability to monitor changes, identify opportunities and formulate a digital strategy.
	Investigate inefficiencies in existing business processes. (A3)	
	Identify opportunities for organizational transformation based on market conditions. (A4)	
	Formulate the digital transformation strategy. (A8)	
Organizing (B2)	Align the overall strategic goals of the enterprise with the digital transformation strategy. (A9)	The organizational capability to align digital resources with business needs, source digital resources, then fully combine available digital resources.
	Try to allocate management resources for digital transformation. (A10)	
	Integrate internal resources and competency for digital transformation. (A12)	
	Integrate external resources for digital transformation. (A13)	
Restructuring (B3)	Seek new ways to do something. (A17)	The organizational capability to innovate digital resources, coordinate organizational structures, and facilitate sustainable development of a digital transformation.
	Continuously try to trial and iterate new products or services. (A18)	
	Coordinate with each other to solve conflicts. (A23)	
	Facilitate efforts for digital transformation strategy. (A24)	

3.3.3. Selective Coding Analysis

The final stage is selective coding, which selects the core category from all categories and connects the main category and sub category with it as the axis to abstractly and conceptually interpret the behavior of the sample enterprises, and then construct the theory. Selective encoding aims to cluster and summarize the main categories that have been developed, thus forming a core category and further constructing a systematic explanatory framework [43]. The structural dimension framework of a digital transformation capability is shown in Figure 1.

Through in-depth analysis of cases, and comparisons of all levels of categories with the original data, this study summarizes the three structural dimensions of sensing, organizing, and reconstructing to jointly build the digital transformation capability. Through a theoretical saturation test of the original data, no new concepts or categories were found except for the three main categories of digital transformation capability, which indicates existing theory reached saturation.

Based on grounded theory approach, this study conceptualized digital transformation capability as a multidimensional, second-order construct with three reflective first-order factors, such as sensing, organizing, and restructuring. We need to verify the validity and reliability of the digital transformation capability construct. In order to explore the relationship between digital transformation capability and organizational performance, this study try to conduct survey pilot test. Organization performance is based on the Vial [22] research, which is defined as the overall performance of organizational goal and strategy

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through digital transformation. It is composed of measurement items such as return on investment, market share, customer satisfaction, and competitive advantage [29].

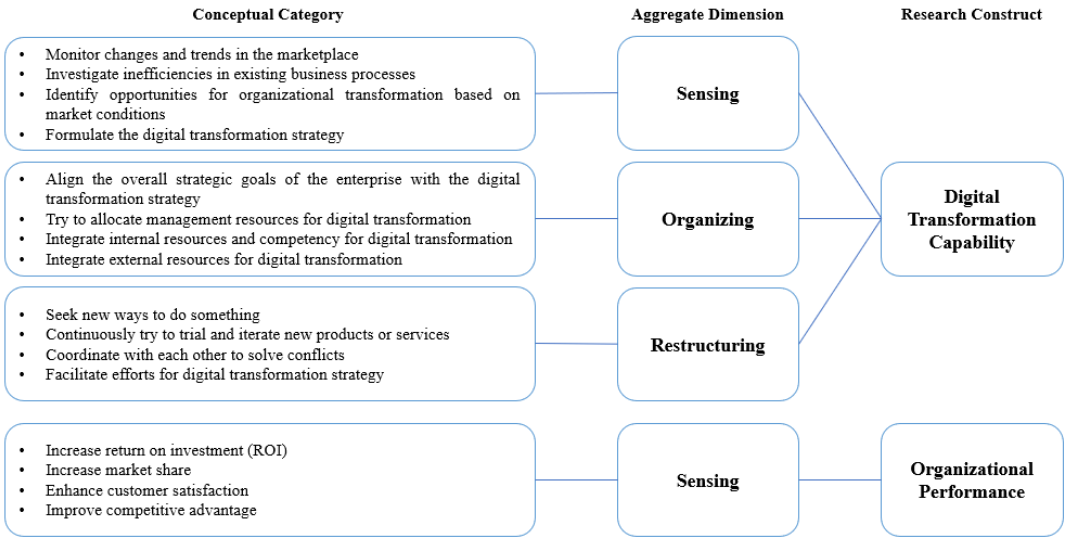

Figure 1: Digital Transformation Capability and Organizational Performance.

3.4. Explanation of the Framework Model

Most of the subsequent research on dynamic capabilities is based on Teece [10], who argued that the dynamic capability dimension focuses on sensing, seizing, and transformation aspects. According to grounded theory, we explain the structural dimension framework of the digital transformation capability constructed, and we found that the digital transformation capability in manufacturing enterprises consists of three structural dimensions: sensing, organizing, and restructuring. Specifically, the capabilities of sensing in the digital environment, organizing internal and external available resources, and reconstructing organizational structures are important dimensions of the digital transformation capability.

Based on the dynamic capability theory, we further analyzed the structural dimension framework of the digital transformation capability constructed, and found that the three dimensions of a digital transformation capability are not simple parallel relationships, but have relationships in the process sequence from a business perspective.

In the digital environment, value networks are becoming increasingly complex, and dynamic monitoring of environmental changes by enterprises has become a key prerequisite for survival and development. By continuously tracking market trends and potential threats, and systematically identifying process inefficiencies and opportunities for change, companies can proactively develop feasible solutions and subsequently formulate digital strategies. This study defines sensing as the comprehensive ability of an organization to monitor environmental changes, diagnose operational inefficiencies, capture transformation opportunities, and build digital strategies.

To cope with the challenges of digital survival and development, enterprises need to have the ability to effectively organize internal and external digital resources. This study will align digital transformation strategies with the business goals of enterprises, acquire and allocate digital resources based on expected business performance, and coordinate internal and external factors to promote the transformation process. This study defines organizing as the comprehensive ability of an enterprise to implement digital transformation by collaborating digital resources with business needs, configuring and managing resources, and systematically integrating internal and external capabilities.

Unlike traditional technology applications and departmental collaboration, digital transformation is a systematic change that involves continuous adjustments to organizational structure, business processes, and employee skills. Therefore, enterprises must establish the ability to promote sustainable digital development. While innovating digital resources, enterprises continuously coordinate internal and external resources to promote the implementation of digital strategies, thereby improving organizational performance. This study defines restructuring as the ability of an organization to explore new methods, innovate digital resources, collaborate organizational structures, and promote sustainable digital evolution.

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4. Pilot Study

4.1. Research Model and Hypothesis generation

The research target of this study is to find out the structural dimensions of a manufacturing enterprise's digital transformation capability and empirically test the relationship between sensing, organizing, restructuring 3 capabilities and organizational performance. Due to the lack of quantitative results, this study tries to investigate the causal relation between digital transformation capability and organizational performance. We made two constructs to investigate the influence of three structural dimensions of digital transformation capability on organizational performance of manufacturing enterprise. This study generated H1 hypothesis on the impact of digital transformation capability on organizational performance, as shown in Figure 2. That is, digital transformation capability does positively influence on organizational performance.

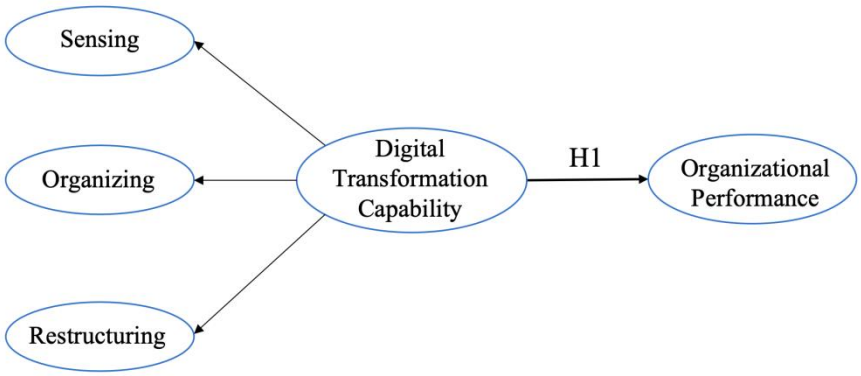

Figure 2: Conceptual Research Model.

4.2. Measurement and Data Collection

This study tried to conduct a pilot study on the relationship between digital transformation capability and organizational performance of an enterprise in the digital environment. To test H1 hypothesis, a questionnaire was made to collect data from Chinese manufacturing enterprises. Based on the original dynamic capability [44-46], the digital transformation capabilities of manufacturing enterprises proposed in this study include three sub capability: sensing, organizing, and restructuring. Moreover, organizational performance (OP) was developed by Vial [22] and Yu and Moon [23]. The operational definitions and measurements are shown in Table 4.

Table 4: Operational Definition and Measurement Model.

Variables	Operational Definition	Measurement Items
Sensing	The comprehensive capability of an organization to monitor environmental changes, diagnose operational inefficiencies, capture transformation opportunities, and build digital strategies	1. Monitor changes and trends in the marketplace
		2. Investigate inefficiencies in existing business processes
		3. Identify opportunities for organizational transformation based on market conditions
		4. Formulate the digital transformation strategy
Organizing	The comprehensive capability of an enterprise to implement digital transformation by collaborating digital resources with business needs, configuring and managing resources, and systematically integrating internal and external capabilities.	1. Align the overall strategic goals of the enterprise with the digital transformation strategy
		2. Try to allocate management resources for digital transformation
		3. Integrate internal resources and competency for digital transformation
		4. Integrate external resources for digital transformation
Restructuring	The comprehensive capability of an organization to explore new methods, innovate digital resources, collaborate organizational structures, and promote sustainable digital evolution.	1. Seek new ways to do something
		2. Continuously try to trial and iterate new products or services
		3. Coordinate with each other to solve conflicts
		4. Facilitate efforts for digital transformation strategy
Organizational Performance	Organizational achievements through the digital transformation.	1. Increase return on investment (ROI)
		2. Increase market share
		3. Enhance customer satisfaction
		4. Improve competitive advantage

To prove the impact of digital transformation capability on organizational performance, this study,

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first of all, searched the Fortune China 500 list of enterprises and selected those enterprises that have already achieved digital transformation project results. This study was conducted from January 2025 to December 2025 distribute data to enterprises. This study collected 98 firms survey data through e-mail survey. The survey results showed that senior management had the highest number of responses, manager 53 (54.1%), senior manager 29 (29.6%), and executives (CIO, COO, CEO) 16 (16.3%). This study used SPSS software to analyze the survey data. Sample statistics on the respondents are shown in Table 5.

Table 5: Sample Statistics.

Item	Category (N = 98)	Frequency	Percentage
Position	Manager	53	54.1
	Senior Manager	29	29.6
	Executive (CEO, CMO, CFO, CIO)	16	16.3
Years Since Established	Less than 5 years	33	33.7
	5-10 years	26	26.5
	10-15 years	23	23.5
	More than 15 years	16	16.3
Main Industry Type	Automobile	18	18.4
	Machine & Equipment	12	12.2
	Electronics	18	18.4
	Textile & Clothing	11	11.2
	Food & Beverage	12	12.2
	Medical & Medicine	10	10.2
	Other	17	17.4
Number of Employees	Less than 100	18	18.4
	100-300	24	24.5
	300-2000	37	37.8
	2000-10,000	11	11.2
	More than 10,000	8	8.1

4.3. Data Analysis

This study used SmartPLS 4.0 software to test the reliability and validity of the measurement model. According to Table 6, the Cronbach's alpha coefficients, factor loadings, and combination reliability of all constructs are greater than 0.7, and the average variance extraction (AVE) is higher than 0.5, indicating that the measurement model has good reliability and convergence validity [47,48].

Table 6: Factor Loadings, AVE, CR, and Cronbach's Alpha Values.

Factor	Items	Loadings	AVE	CR	Cronbach alpha
Sensing Capability	sen1	0.851	0.702	0.904	0.858
	sen2	0.829			
	sen3	0.855			
	sen4	0.815			
Organizing Capability	org1	0.790	0.674	0.892	0.838
	org2	0.874			
	org3	0.813			
	org6	0.806			
Restructuring Capability	res1	0.848	0.727	0.914	0.875
	res2	0.861			
	res3	0.851			
	res4	0.850			
Operational Performance	opp1	0.802	0.645	0.879	0.816
	opp2	0.834			
	opp3	0.769			
	opp4	0.805			

AVE = Average Variance Extracted; CR = Composite Reliability.

To test the applicability of high-order models, this study compared and analyzed first-order and second-order measurement models using Smart PLS 4.0. Based on the criteria proposed by Sarstedt et al. [47], if the second-order factor loading is significantly higher than the first-order factor loading, it indicates that using a second-order model is more appropriate. As shown in Table 7, the factor loadings of the perception, organization, and restructuring dimensions covered by digital transformation capabilities in the second-order model are higher than those in the first-order model. Therefore, this study chose the second-order factor model for subsequent structural model analysis.

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Table 7: Factor Loading Comparison of First-order Factors and Second-order Factors.

Construct	Items	2nd Order Factor Loading	Construct	Items	1st Order Factor Loading
Sensing (xSen)	sen1	0.851	Digital Transformation Capability	sen1	0.748
	sen2	0.829		sen2	0.792
	sen3	0.855		sen3	0.740
	sen4	0.815		sen4	0.656
Organizing (xOrg)	org1	0.790		org1	0.679
	org2	0.874		org2	0.750
	org3	0.813		org3	0.756
	org4	0.806		org4	0.743
Restructuring (xRes)	res1	0.848		res1	0.774
	res2	0.861		res2	0.730
	res3	0.851		res3	0.778
	res4	0.850		res4	0.774

This study used Smart PLS 4.0 for discriminant validity testing. Following the suggestion of Hair et al. [48], the correlation coefficient between variables was evaluated by comparing the square root of the average variance extracted (AVE) of each construct. As shown in Table 8, the square roots of AVE for all constructs are greater than the corresponding correlation coefficients, indicating that the measurement model has good discriminant validity.

Table 8: Discriminant Validity.

	xSEN	xORG	xRES	xOP
xSEN	0.838			
xORG	0.681	0.821		
xRES	0.671	0.712	0.853	
xOP	0.614	0.609	0.610	0.803

SEN = Sensing; ORG = Organizing; RES = Restructuring; OP = Organizational Performance.

To test the research hypothesis of the conceptual research model, path analysis was used to extract the value of path coefficient by using Smart PLS 4.0, and the path coefficient was estimated by using bootstrap resampling method [47]. The result is shown in Table 9 and Figure 3. Digital transformation capability (path coefficient = 0.688, t value = 11.594) had a 99% statistical significance on the organizational performance. Therefore, Digital transformation capability had a positive (+) relationship between organizational performance; hence, H1 is supported. In addition, all variance inflation factors (VIFs) were below 5, which indicated that multicollinearity is not an issue for this study [48].

Table 9: Hypothesis Testing Results.

Hypothesis	Path	Coefficient	p	T	Result
H1 (+)	Digital Transformation Capability → Organizational Performance	0.688	0.000 ***	11.594	Supported

*** $p < 0.001$.

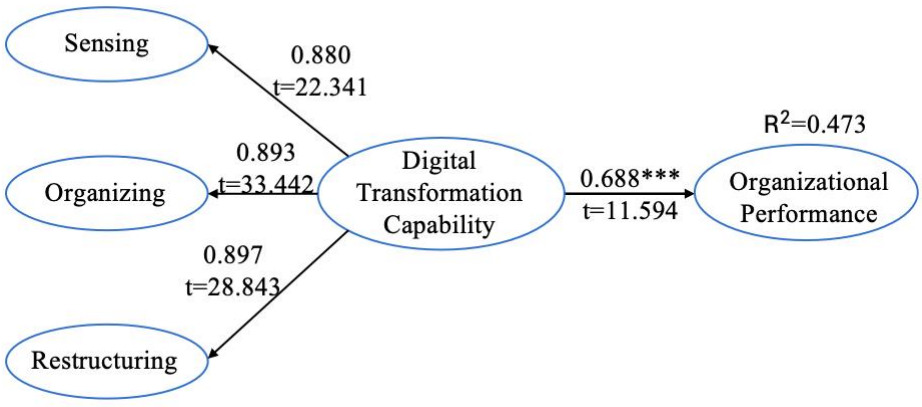

Figure 3: The Result of Path Analysis.

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To explore the relationship between digital transformation capability and organizational performance, this study further incorporates an analysis of the impact relationship between first-order factors. The result of path analysis show that sensing, organizing and restructuring capability all has impact on organizational performance. The path coefficients and t value of impact analysis are: sensing (path coefficient=0.281, t value=2.569), organizing (path coefficient=0.230, t value=2.412) and restructuring (path coefficient=0.268, t value=2.389). Compared with the first-order model, the second-order model of digital transformation composed of sensing, organizing and restructuring capabilities, has a more obvious impact on organizational performance. In other words, the structural dimensions model of digital transformation capability proposed in this study can better reflect how enterprises develop digital transformation capabilities to improve organizational performance. The result is shown in Table 10 and *Figure 4*.

Table 10: Impact Analysis between 1st order Factor Variables Results.

Path	Coefficient	p	T	Result
Sensing Capability → Organizational Performance	0.281	0.010*	2.569	Supported
Organizing Capability → Organizational Performance	0.230	0.016*	2.412	Supported
Restructuring Capability → Organizational Performance	0.268	0.010 *	2.389	Supported

*** p < 0.001, ** p < 0.01, *p < 0.05

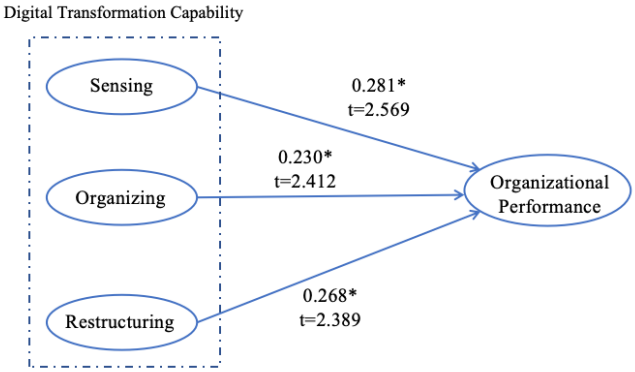

Figure 4: The Result of Impact Analysis.

5. Discussion

In the context of the digital economy, enterprises deeply integrate tangible and intangible resources such as personnel, equipment, and knowledge into business processes through the application of digital technologies such as artificial intelligence and big data, thereby constructing data-driven intelligent business models. Especially for manufacturing enterprises that are not native digital organizations, fixed assets (such as equipment) and raw materials account for the majority of their assets. It is urgent to solve the problem of how to effectively allocate resources and successfully utilize a digital transformation to empower sustainable and high-quality development. This study focuses on manufacturing enterprises and defines their digital transformation capability as a dynamic ability, which refers to the comprehensive ability cultivated by enterprises to adapt to environmental changes and gain competitive advantages through the application of digital technology in response to the development of the digital economy.

5.1. Academic Implications

The theoretical significance of this study is as follows.

First, according to grounded theory, we explain the structural dimension framework of the digital transformation capability constructed, and we found that the digital transformation capability in manufacturing enterprises consists of three structural dimensions: sensing, organizing, and restructuring. Specifically, in order to successfully carry out a digital transformation, an enterprise first senses the digital environment, then organizes the available internal and external resources, and finally, reworks the

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organizational structure. This is similar to the results of Yu et al. [11] and Santa-Maria et al. [45]. The development of an organizational capability can help enterprises obtain good development opportunities, introduce new resources, combine them with existing resources, and promote performance improvement [10]. Enterprises can effectively identify changes in consumer purchasing decisions or shifts in preference values, then combine them with the development and iterative upgrading of new products [11]. Enterprises make precise structural adjustments and reforms to multiple departments for future sustainable development, such as matching sales and functional personnel [45].

Second, based on grounded theory and dynamic capability theory, this study explores the concept and structural dimensions of a manufacturing enterprise's digital transformation capability through semi-structured interviews. Moreover, we further found that the three dimensions of a digital transformation capability are not simple parallel relationships, but have relationships in the process sequence from a business perspective. This is greatly different from previous studies on dynamic capabilities, with the vast majority of studies that elucidate the dimensions of dynamic capabilities only revealing the parallel relationships of each dimension [38,46]. This study regards the digital transformation capability of manufacturing enterprises as the ability to innovate and deeply integrate multiple digital technology clusters. Firstly, it is necessary to cultivate sensing capabilities to monitor environmental changes, diagnose operational inefficiencies, identify opportunities, and develop digital strategies. Subsequently, develop organizing capabilities, achieve effective matching between digital resources and business needs, allocate management resources reasonably, and coordinate internal and external resources to promote transformation. Finally, it is necessary to build a restructuring capability, dedicated to exploring new paths, innovating digital resources, and collaborating organizational structures to promote the sustainable evolution of the digital process.

Thirdly, this study integrates the perspectives of grounded theory and dynamic capability theory, and based on multiple case studies, systematically analyzes the structural dimensions of digital transformation capability. This is consistent with the emphasis placed on the digital transformation capability in qualitative research [22], but is different from the use of regression analysis in quantitative research to reveal the growth of a dynamic capability in promoting organizational performance [11,49]. This study reveals how a dynamic capability in the digital transformation era utilizes multiple dimensions of sub-capabilities to help enterprises converge and aggregate organizational capability, and this high-level capability has a significant positive impact on improving operational efficiency and organizational flexibility. The research conclusions have a stronger explanatory power to suggest the necessity and importance of a digital transformation capability through case studies with the application of grounded theory.

Finally, this study empirically proved that digital transformation capability to improve organizational performance is an important research construct affecting the theory building on dynamic capability research area. Under the theoretical approach of dynamic capability [10,16,46]. This study confirmed similar results to compare the previous studies [10] which developing digital transformation capability is the key determinant in affecting to organizational requirements for competitive advantage in the digital business environment.

5.2. Practical Implications

In the era of digital transformations, a dynamic capability remains crucial. For non-digital native manufacturing enterprises, it is even more necessary to effectively allocate resources to develop a digital transformation capability. The structural dimension framework model proposed in this study can comprehensively and accurately reflect the characteristics of a manufacturing enterprise's digital transformation capability, which has practical significance in the following three ways.

First, manufacturing enterprises should develop an organizational capability based on the existing situation and the structural dimension framework model of a digital transformation capability. Enterprises need to develop a sensing ability that includes monitoring changes, investigating inefficiencies, identifying opportunities, and formulating a digital strategy. As the value network on which enterprises rely becomes increasingly complex, their ability to perceive the digital environment becomes particularly critical. Enterprises must adhere to business as the core, continuously promote the synergy between digital resources and business needs, effectively acquire and allocate digital resources, and systematically integrate internal and external factors to achieve digital transformation. Enterprises are driven by digital allocate management resources, strengthen the utilization of the data resource value, and build data-driven, intelligent decision-making management models. It is necessary for enterprises to develop a restructuring capability that includes is seek new ways, innovative digital resources, coordinates

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organizational structures, and facilitates sustainable digital development. Although digital technology is important for product and service innovations, institutional coordination at the organizational level is also indispensable.

Secondly, manufacturing enterprises need to emphasize the importance of digital governance and the feasibility of deploying a digital strategy at all levels of the organization. Corporate governance determines the resource supply and top-level design of a digital transformation, and a lack of digital knowledge can lead to failure in a manufacturing enterprise transformation. Enterprise executives, especially shareholders located at the center, can mobilize and access resources from the shareholder network, shaping an ecological environment of abundant resources, and must trust in cooperation over an enterprise digital transformation, solving the problem of external resource connection and utilization during the transformation. The implementation of digital strategy is a creative reaction process of enterprises to the market and technology. The formulation of a transformation strategy requires the corporate governance system to be able to respond to the opportunities of digital technology and any threats to organizational development. The complexity of digital technology and the uncertainty of innovation increase the risk of transformation failure, and the degree of risk-taking by enterprises to cushion external environmental shocks determines the initiation and deployment of a digital transformation. Enterprises need to excel in developing redundant resources, organizational flexibility, a long-term orientation, a fault-tolerant culture, and their employees' psychological security. Transforming an enterprise also needs to simultaneously carry out exploration and utilization activities to alleviate internal tensions caused by attention allocation and innovation path competition, such as resolving conflicts between traditional manufacturing enterprises' online and offline channels.

Finally, other employees in manufacturing enterprises are mostly at the forefront of the manufacturing process, so enterprises need to pay more attention to developing digital literacy in top managers. A digital transformation spans multiple functional areas, surpassing traditional innovations and changes, bringing a new organizational context to the executive team responsible for strategic execution. It requires them to quickly understand and judge digital characteristics, transform traditional role positioning, and respond to unknown challenges. Highly knowledgeable managers can influence the results of the transformation, and executive teams with digital backgrounds are more digital friendly, and are able to better identify and understand digital innovation opportunities and internal logic. At the same time, a digital background enables the executive team to meet the new role's need to be a digital communicator, motivating other members to participate in digital innovation activities, thereby cultivating digital thinking in the executive team. In addition, executive teams with digital backgrounds can enhance employees' enthusiasm for participating in digital change, and can adopt more effective communication methods to solve problems when employees resist and procrastinate on transformation tasks. Enterprises can cultivate employees' digital awareness, and create a digitally oriented organizational atmosphere by conducting digital knowledge and skills training for employees, promoting their active participation in project discussions and in providing problem-solving solutions. In addition, enterprises should actively promote a culture of challenge, create high-performance teams composed of top digital talents, encourage employees to learn from each other to cope with the challenges in the transformation, and also help companies identify problems in a transformation as early as possible to propose appropriate solutions.

5.3. Limitations and Future Research

This study has certain limitations. First, it is limited to sample enterprises in China. Based on grounded theory, through semi-structured interviews with senior managers either leading their enterprises' transformation (e.g., the CEO) or leading all or some of the digital transformation efforts of their respective organizations (e.g., chief information officer, chief digital officer, director of digital transformation), this study analyzed the digital transformation capability of several manufacturing enterprises that have made certain digital achievements. In the future, the sample range can be expanded to further test the universal applicability of the results. Second, it is limited to defining structural dimensions by time sequence and process approach. This study revealed the structural dimensions of manufacturing enterprises' digital transformation capabilities and the internal relationships between the dimensions. It is necessary to further develop measurement tools to evaluate the digital transformation capability of a manufacturing enterprise. Finally, this is a qualitative study based on grounded theory about the digital transformation capability of manufacturing enterprises without a causal relationship analysis on the effectiveness of the theoretical framework. Specific measurement scales for each factor can be developed based on this research, and quantitative methods such as structural equation modeling can be used to test the relationships between variables in the research model through large-scale questionnaires in order to construct a more solid and universal theory.

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6. Conclusions

Manufacturing enterprises deeply integrate multiple digital technology fuses with their own business models through digital transformation. This study constructs structural dimensions of a manufacturing enterprise's digital transformation capability from a qualitative study with semi-structured interviews. Based on grounded theory combined with the practice of digital transformation in manufacturing enterprises, this study selected four manufacturing enterprises, and conducted semi-structured interviews with 12 senior managers who were either leading their enterprise's transformation (e.g., the CEO) or leading all or some of the digital transformation efforts of their respective organizations (e.g., CIO, CDO, director). We constructed a coding scheme (open coding, axial coding, selective coding, and a saturation test), built theoretical models, and explored the concept and structural dimensions of a digital transformation capability in manufacturing enterprises.

We found that the digital transformation capability of manufacturing enterprises consists of three structural dimensions: sensing, organizing, and restructuring. Based on dynamic capability theory, we further analyzed the structural dimension framework of the digital transformation capability constructed in this study, and found that the three dimensions of a digital transformation capability are not simple parallel relationships, but have relationships in the process sequence from a business perspective. This study contributes a certain theoretical and practical significance for manufacturing enterprises that are preparing for, or are already in, the digital transformation stage.

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