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Digital transformation and customer orientation in manufacturing enterprises: A dynamic capabilities perspective

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A B S T R A C T

Driven by globalization and digitalization, competition in the manufacturing industry has become increasingly intense. Developing a customer orientation (CO) strategy helps enterprises improve market competitiveness, satisfy customer needs, increase profitability, and achieve sustainable development. At the same time, digital transformation (DT) has created major changes in the global economy. The extensive use of digital technologies has reshaped enterprise resources and capabilities, resulting in significant changes in organizational structures, business models, and strategic decision-making processes. However, existing studies mainly focus on the outcomes of CO at the micro level, while limited attention has been given to its antecedents, particularly at the macro and meso levels. Therefore, based on dynamic capability (DC) theory, this study empirically examines the impact of DT on CO and explores its underlying mechanisms in manufacturing firms. The study uses panel data from A-share listed manufacturing companies in Beijing, Shanghai, and Shenzhen during the period 2015–2023. The results show that DT significantly enhances the development and implementation of CO strategies in manufacturing enterprises through innovative capability (IC), absorptive capability (AS), and adaptive capability (AD). Among these dynamic capabilities, IC has the strongest mediating effect, whereas AS has the weakest. In addition, the heterogeneity analysis indicates that the positive effect of DT on CO is significant across manufacturing firms of different sizes, with only minor differences among them. Furthermore, the effect of DT on CO is stronger in skill-intensive enterprises than in capital-intensive and labor-intensive enterprises.

1. Introduction

Emerging information technologies such as Artificial Intelligence, Blockchain, Cloud Computing, Big Data, and the Internet of Things are driving digital economic growth. These technologies unlock data value, accelerate industrial digitalization, and enhance cost reduction, quality, and efficiency for enterprises (Blichfeldt and Faullant, 2021). For China's manufacturing industry, a key pillar of the domestic economy, leveraging digitalization is essential to break from traditional approaches and pursue high-quality economic development.

Against the backdrop of the digital economy characterized by the intertwined evolution of informatization, digitalization, and intelligence, the change of the main consumer groups and the shift of consumption scenarios have transformed the business environment for enterprises. Market demand has trended towards personalization, quality, and diversification (Abrell et al., 2016). Traditional manufacturing firms, which are renowned for their labor-intensive processes and economies of scale, have seen a considerable decline in their market competitive advantages. Traditional manufacturing industries need to leverage digital transformation to shift from the past product - oriented mass production to customer - oriented mass customization (Ghobakhloo and Iranmanesh, 2021; Matarazzo et al., 2021). That is to say, enterprises need to prioritize enhancing customer

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satisfaction when formulating and implementing business goals and strategies, namely, establishing and implementing customer orientation (Chaudhry et al., 2019).

During the digital transformation process, data and innovation have emerged as two key elements in the digital production and marketing strategies of manufacturing enterprises. Creative consumers directly participate in product design, enabling enterprises to collect and analyze data and take corresponding actions for innovation. Meanwhile, enterprises can also utilize digital technologies to track the needs of target customers in specific fields on social networks or platforms and identify additional needs of target customers through big data analysis (Shpak et al., 2020). Consequently, some scholars have begun to focus on how to apply customer orientation in the increasingly digitalized companies (Chakravarty et al., 2014). However, only a limited number of studies have been conducted, highlighting that the significant transformation brought about by digitalization and intelligence is a prerequisite for customer orientation (Abbu and Gopalakrishna, 2021). All these studies suggest that a company requires new capabilities if it aims to understand and act in a customer-oriented manner, due to the essence of intelligence, particularly the complexity of big data.

The digital technologies brought about by enterprises' digital transformation are merely auxiliary means. Dynamic capabilities are a crucial type of capability for enterprises. Dynamic capabilities will enable enterprises to internalize and absorb new knowledge during the digital transformation process, thereby integrating the resource base required for innovation. This will unleash the effectiveness of digital technologies, enabling enterprises to better meet customer needs and create value for them, ultimately achieving customer orientation.

First, digital technologies enable enterprises to encode the heterogeneous data obtained in various links of the operation process to support decision-making (Wu et al., 2021). Meanwhile, the interconnection attribute of digital technologies also helps enterprises to promptly perceive the needs of stakeholders, enabling enterprises to accurately grasp market demand changes and predict technological development trends (Rialti et al., 2019). That is, the adaptive capability of enterprises to perceive complex and dynamic environments will be enhanced.

Second, digitalization entails a comprehensive and multidimensional transformation and upgrading of enterprises. Enterprises need to conduct process development based on native data and carry out digital upgrading of existing processes to innovate the organization. These transformation behaviors will establish a resource base characterized by precision, flexibility, and openness for enterprises (Shan et al., 2019). That is, digitalization will enhance the absorptive capability of enterprises. And then acquiring and integrating both internal and external resources becomes easier for the enterprises.

Finally, digital technologies will assist enterprises in managing, extracting, and transforming various organizational resources, thereby transcending rigid resource constraints through the strategic allocation of tangible and intangible assets, and shaping a resource base that matches the innovation needs. That is, digitalization will enhance the innovative capability of enterprises to create new products and expand into new markets.

All in all, digital transformation can assist enterprises in improving their dynamic capabilities, including sensing changes in the external environment, acquiring and reallocating resources, and developing new goods and services. Enterprises can better handle market opportunities and difficulties by implementing customer-centered strategies thanks to these characteristics. In order to provide new empirical evidence for understanding how digital transformation affects customer orientation, this paper uses Chinese A-share manufacturing listed companies as samples. It then determines and tests the relationship and intermediate mechanism of "digital transformation - customer orientation" through performing text analysis of the annual reports to assess the levels of digital transformation and customer orientation of manufacturing enterprises. The potential contributions of this research are reflected in the following three aspects: 1) this paper provides new empirical evidence to confirm the positive impact of digital transformation on enterprise customer orientation, and supplements the research on the influencing factors of enterprise customer orientation; 2) this study, based on the theory of dynamic capability, delves deeply into the operating path of innovative capability, absorptive capability, and adaptive capability between enterprise digital transformation and customer orientation, and further provides a theoretical framework for subsequent research; 3) this study explores the reasons why different types of enterprises exhibit diverse impacts from digital transformation on customer orientation (in terms of enterprise scale and the composition of production factors).

2. Literature review and hypothesis development

2.1. DT and CO: Direct effects

Scholars in the field of marketing were the first to focus on customer orientation. They defined customer orientation as a corporate strategy centered on customers, emphasizing the satisfaction of both current and potential customer needs. That is, it is necessary to meet the needs of customers not only in the current market environment but also in the dynamic internal and external environments of the enterprise (Narver and Slater, 1990). Scholars in the field of strategy believe that, as a business strategy, customer orientation can leverage digital technologies to meet the ever - changing demands of customers and subsequently implement demand management to create a competitive advantage (Pan et al., 2021). Digital transformation involves leveraging cutting - edge digital technologies to enhance operational efficiency and market satisfaction.

The core objective of digital transformation is to trigger significant changes in the corporate attributes through the reintegration of information, computing, communication, and connectivity technologies, thereby enhancing internal operational efficiency and value creation to address changes in the external environment. The essence of digital transformation lies in leveraging digital technologies to convert internal and external corporate data into usable information, which enables enterprises to formulate strategic plans, generate new business models, reduce resource consumption, enhance corporate innovation efficiency, and create greater value (Verhoef et al., 2021).

During the digital transformation process, enterprises utilize technologies such as big data and cloud computing to adjust the interaction processes between enterprises and between enterprises and consumers, aiming to reduce information asymmetry and improve user satisfaction (Ritter and Pedersen, 2020).

On the one hand, in the ubiquitous digital technology environment, the technological advancements in digital marketing and the dynamic transformation towards digitalization have affected the ability of enterprises to perceive and respond to market changes, promoting the implementation of customer-oriented strategies (Abbu and Gopalakrishna, 2021).

In the digital world, digital technology has significantly influenced communication and interaction based on market intelligence, and has become increasingly important for leveraging such intelligence. Enterprises can utilize the internet to enhance their relationships with customers through specific approaches, such as making it more convenient for customers to access information and enhancing flexibility in responding to customers' information requests (Ulmer et al., 2017). On the other hand, companies need to understand and utilize real-time data and in-use data (Sun and Zhang, 2021).

Particularly, digital customer orientation can only be achieved by generating and applying real-time and in-use customer information. Enterprises can create value for their company by capturing the information that customers use, leveraging their resources to analyze this information, and providing the best digital customer experience based on the generated insights (Sun and Zhang, 2021).

In the process of digital transformation, enterprises are better equipped to perceive and analyze customer needs, enhance the user experience, and thereby establish a customer-centric strategic orientation, ultimately achieving a customer-oriented strategic shift. Therefore, the hypothesis is proposed as follows:

H1: Digital transformation of enterprises has a positive impact on customer orientation.

2.2. DCs: New intermediary mechanism

The theory of dynamic capabilities is a strategic management theory developed from the resource-based view, which explores how enterprises can sustain their competitive advantages over time. Different from the resource-based view that only regards a firm's unique and hard-to-replicate resources as the source of its competitive advantage, the dynamic capabilities view posits that a firm's sustainable competitive advantage stems from its ability to continuously and dynamically transform, upgrade, and protect its unique resource base (Teece, 2007). Specifically, an enterprise absorbs and identifies external information, fully extracts the value of the information to discover new market demands, then allocates and schedules existing resources to establish new resource combinations, and creates and provides high-quality products and services for customers. This process fosters the establishment and implementation of a customer-oriented approach within the enterprise, thereby maintaining its competitive edge.

At the enterprise level, since the resources and capabilities of different enterprises may vary, the paths to achieve dynamic capabilities may also differ across enterprises or industries. The academic community has made detailed classifications of dynamic capabilities (Mota and Castro, 2004). However, at a general level, common characteristics of dynamic capabilities can be identified across different enterprises. Wang and Ahmed (2007) referred to existing empirical research results and identified adaptive capability, absorptive capability, and innovative capability as the three main components of dynamic capabilities. Their classification of dynamic capabilities comprehensively considers the specific manifestations of an organization's dynamic capabilities and fully encompasses the dimensions of dynamic capabilities classified by most scholars currently. It is typical and representative, and thus has been widely applied.

Innovative capability refers to an organization's ability to use knowledge and new - generation digital technologies to conduct research, development, innovation, and transformation of products or services, so that its products or services can meet or even create market demands, thereby enhancing its competitiveness. Absorptive capability refers to an organization's ability to perceive and acquire valuable knowledge and technologies both within and outside the organization, absorb and transform them into internal knowledge or practices, and thereby help the organization achieve its strategic objectives. Adaptive capability refers to an enterprise's ability to coordinate, integrate, and restructure its knowledge, physical, and financial resources to maintain its competitive advantage in a complex and volatile environment.

These three capabilities are interrelated but conceptually distinct. Each capability has its specific focus: Adaptive capability emphasizes an enterprise's ability to adjust itself in a timely manner through the flexibility of resources and by matching resources and capabilities with environmental changes, highlighting the alignment of internal organizational factors with external environmental factors. Absorptive capability emphasizes the importance of absorbing external knowledge, combining it with internal knowledge, and using it for internal purposes. Innovative capability effectively links an enterprise's inherent innovativeness with market - based advantages (such as new products and/or new markets), that is, the connection between an enterprise's resources and capabilities and its product markets.

Therefore, this paper selects three dimensions, namely innovative capability, absorptive capability, and adaptive capability, to elaborate on the impact of digital transformation on dynamic capabilities.

2.2.1. Mediating role of innovative capability

First, digital transformation promotes customer orientation by enhancing innovative capability. Innovative capability enables enterprises to explore uncharted environments and fully utilize their resources and capabilities to develop new products and services. Relying on their own resources and capabilities, enterprises develop and innovate their products and services to align with the product market, thereby safeguarding their market share (Artz et al., 2010). By leveraging advanced digital technologies, enterprises can foster creativity, accelerate product development, and create new solutions to meet market demands. From an internal perspective, digitalization provides employees with more comprehensive and advanced means for learning, communication, discussion, and practice, thereby enhancing the organizational knowledge integration system (Yang et al., 2019). Externally, for enterprises to effectively and rapidly explore market opportunities, they need to identify and evaluate customer information in a timely and accurate manner (Hitt et al., 2001). Technologies such as semantic analysis and search technology in digitalization can assist enterprises in collecting extensive customer information, including product sales volume, service frequency, level of attention, and experience evaluations. Through text analysis and public opinion monitoring, enterprises can quickly determine changes in market demand and adjust their operational strategies to meet customer needs. Enterprises that prioritize digital development often utilize the established Internet business thinking to conduct customer-centric business reconstructions of their value chains and business models. Such enterprises can enhance their innovative capability through digital technologies, which in turn promotes the innovation of business models centered around customer needs. Therefore, the hypothesis is proposed as follows:

H2a: Innovative capability plays a mediating role between enterprise digital transformation and customer orientation.

2.2.2. Mediating role of absorptive capability

Second, digital transformation enhances customer orientation by improving absorptive capability. Absorptive capability enables enterprises to identify and absorb external information, transforming it into their own knowledge and applying it to business practices (Li and Zhu, 2014). The advantages generated by absorptive capability are effectively utilized in the development of new products and services, which can effectively promote the innovation of enterprises' products and services and meet the diverse needs of customers (Vergne and Durand, 2011). In the digital economy era, various information technologies have generated massive amounts of data. Enterprises need to leverage digital technologies such as big data, natural language processing, and machine learning to efficiently analyze the value of information and enhance their ability to identify, digest, and utilize external resources. At the same time, the application of semantic search and artificial intelligence search technologies can help enterprises significantly reduce search costs, transaction costs, operational costs, and even trial-and-error costs in obtaining complementary resources in a digital and intensive innovation environment, thereby promoting the enhancement of enterprises' ability to acquire knowledge and resources. The digitalization of enterprises enables them to continuously transform from basic digital perception capabilities to core digital acquisition capabilities and digital transformation capabilities, thereby obtaining capabilities that other competitors cannot quickly replicate, thereby maintaining their competitive market advantages. By utilizing digital means such as big data resources, enterprises can help themselves obtain customer data from multiple channels, enhance the organizations and their individual members' observational and cognitive abilities regarding customer needs, and thereby create better customer-oriented service performance. Therefore, the hypothesis is proposed as follows:

H2b: Absorptive capability plays a mediating role between enterprise digital transformation and customer orientation.

2.2.3. Mediating role of adaptive capability

Third, digital transformation promotes customer orientation by enhancing adaptive capability. Adaptive capability enables enterprises to accurately grasp market information, customer needs, and competitor information in response to changes in market conditions and evolving customer demands. It allows them to quickly adjust and allocate resources, thereby creating higher customer value. Enterprises with strong adaptive capability can not only embed new knowledge into new business capabilities (Pavlou and El Sawy, 2011) but also effectively reconfigure and reuse existing resources under limited resource conditions. In a dynamic and complex business environment, digital transformation can help enterprises enhance their abilities to identify opportunities, acquire, and reconfigure internal and external resources. The market information and resource conditions obtained by enterprises enable them to implement changes and innovations. Digital transformation can enhance enterprises' abilities to perceive customer needs, acquire and retain customers, and provide products and services to a wide and diverse customer base, thereby expanding the customer base. Enterprises can also use digital technologies to innovate their business models, such as adopting cyber-physical systems, online platforms, VR/AR technologies, and crowdsourcing, to enhance the flexibility and personalization of services, thereby adapting to constantly changing customer needs (Herterich et al., 2015; Li, 2020). Therefore, the hypothesis is proposed as follows:

H2c: Adaptive capability plays a mediating role between enterprise digital transformation and customer orientation.

Drawing from the aforementioned discourse, the subsequent theoretical framework is developed, as illustrated in Fig. 1.

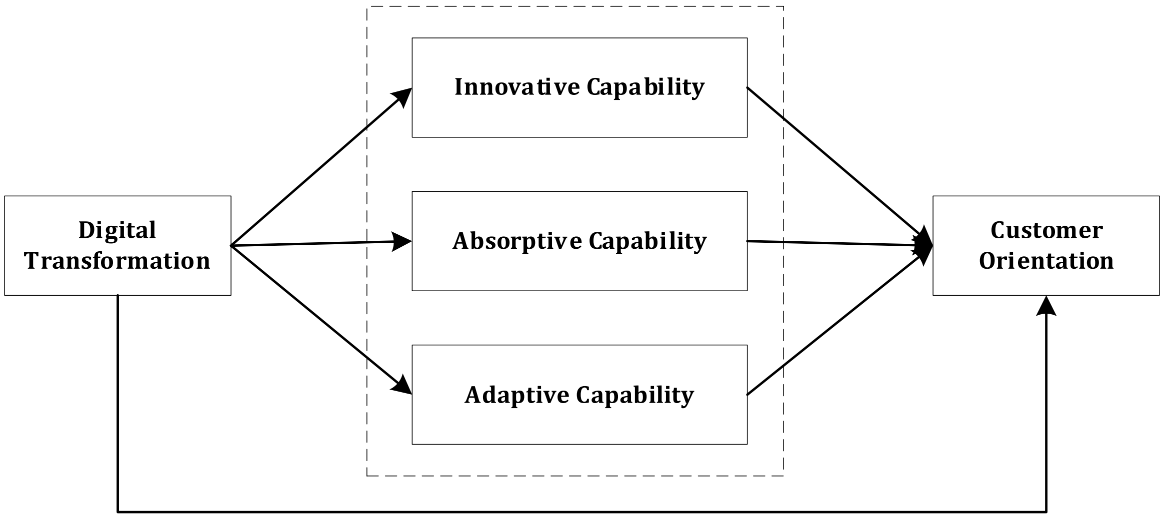

Fig. 1: Conceptual framework

3. Methodology

3.1. Sample and data

Considering that the transformation and upgrading of the manufacturing industry in China which proposed to promote the digitalization and intelligentization of the manufacturing sector began in 2015, we select the manufacturing enterprises listed on the Chinese A-share market from 2015 to 2023 as the research sample and excluded them according to the following criteria: (1) T class (such as ST, *ST) suspended listing, terminated listing firms; (2) firms with abnormal variables; and (3) firms with missing relevant variables. In order to lessen the impact of outliers, 1% and 99% tail reductions are applied to all continuous variables in this study. Finally, 21,469 firm-year observations comprising 3,506 listed manufacturing firms from 29 subsectors of the manufacturing industry are obtained. There are two main data sources: (1) company annual reports obtained from the official websites of the Beijing Stock Exchange, the Shanghai Stock Exchange, and the Shenzhen Stock Exchange, and (2) financial and operational data collected by the CSMAR database.

3.2. Variables measure

3.2.1. Dependent variable

Customer Orientation (CO): Customer orientation is one of the strategic orientations that pertain to an enterprise's future development plans (Gatignon and Xuereb, 1997). Existing studies primarily use questionnaires to collect customer-oriented data; however, the scope of these surveys is relatively limited, which can lead to subjective bias. Corporate annual reports are audited and standardized documents. The numerical data section in the annual report primarily reflects the enterprise’s past performance, while the textual information section can effectively mirror the enterprise's future strategies and development directions. Conducting textual analysis on corporate annual reports can provide a more effective gauge of the enterprise's level of emphasis on a particular strategy. When a particular type of keyword appears more frequently in the annual report, it typically indicates that the business has given this area more focus and funding. The analysis begins with an examination of the text in the annual report, utilizing word frequency analysis to determine the frequency of customer-oriented keywords (see Appendix A, Table A1), which serve as the primary data.

3.2.2. Independent variable

Digital Transformation (DT): Currently, research on digital transformation is gradually shifting from qualitative to quantitative approaches. Extracting the word frequencies of digital transformation-related terms from corporate annual reports can provide a more objective measure of a company's digital transformation, which is scientifically sound and reasonable. Following the methods of Wu et al. (2021), this paper conducts text analysis of the financial annual reports of listed companies to derive digital transformation indicators. Based on the keyword library of digital transformation in four aspects: digital technology application, Internet business models, intelligent manufacturing, and modern information systems, after excluding negative expressions such as "no" and "not" before the keywords, the keywords in the corporate annual report texts are extracted and counted. The word frequencies of the above-mentioned keywords are aggregated to construct digital transformation indicators that reflect the level of digital transformation development among enterprises. After statistical analysis, the data show a right-skewed distribution. Therefore, the natural logarithm of the word frequencies plus one is taken.

3.2.3. Mediating variables

Following the framework of dynamic capabilities (DCs) theory proposed by Wang and Ahmed (2007), we measure the dynamic capabilities of enterprises from three dimensions as follows.

Innovative capability (IC): We quantify the innovative capability of enterprises through the intensity of R&D investment, the proportion of technical staff, and the number of invention patents (Eq. 1). We have three reasons for taking this method.

First, the increase of R&D investment can enable enterprises to fully unleash the value of data elements and significantly improve the utilization of internal and external resources, thereby further enhancing their innovative capability.

Second, Liu et al. (2023) noted that enterprise human capital, especially the skills and quantity of R&D staff, is one of the strongest predictors to explain the heterogeneity of innovation performance.

Third, it has been verified that there is a positive correlation between patents and innovation capacity across enterprises of different industries and sizes, and more than 90% of the studies use the quantity or quality of patents as a key indicator to measure innovative capability of enterprises (Tsakalerou et al., 2025).

$$\mathrm{IC} = \frac{X_{RDI} - min_{RDI}}{max_{RDI} - min_{RDI}} + \frac{X_{RDS} - min_{RDS}}{max_{RDS} - min_{RDS}} + \frac{X_{IPN} - min_{IPN}}{max_{IPN} - min_{IPN}} \quad (1)$$

where, RDI indicates the R&D investment intensity, RDS indicates the proportion of technical staff, and IPN indicates the number of invention patents.

Absorptive capability (AS): In this paper, we adopt the R&D expenditure intensity, which is the ratio of R&D investment to operating income, to measure absorptive capability. Cohen and Levinthal (1990) pioneered the idea that a firm's ability to absorb external knowledge highly depends on its internal R&D foundation. Enterprises with sufficient R&D investment can effectively identify, understand, and transform external technological information. When market and technology information is digested, absorbed, and transformed into useful knowledge, enterprises can achieve organizational strategic goals, including a customer orientation strategy (Qu and Mardani, 2023). Therefore, the R&D activities of enterprises can be regarded as a specific manifestation of absorptive capability in knowledge acquisition and transformation. That is, the firm's ability to acquire and transform external knowledge and information is closely related to R&D expenditure. Generally, the more a firm spends on R&D, the stronger its absorptive capability.

Adaptive capability (AD): Adaptive capability refers to strategic flexibility. Moreover, the strategic flexibility is also considered consistent with the flexibility of enterprises in allocating available resources (Rindova and Kotha, 2001). Based on this view, Nadkarni and Narayanan (2007) used the coefficient of variation of R&D expenditure intensity, capital expenditure intensity, and advertising expenditure intensity of sample enterprises to measure their adaptive capability. This measurement method has been adopted by most scholars (Yang et al., 2019). To ensure the indicator aligns with the direction of adaptability, we use the negative value of the calculated coefficient of variation. Therefore, the larger the indicator value, the stronger the adaptive capability. The specific calculation process is shown in Eq. 2.

$$\mathrm{AD} = -\frac{\sigma}{mean} \quad (2)$$

where, σ indicates the standard deviation of R&D expenditure intensity, capital expenditure intensity, and advertising expenditure intensity of the sample enterprises, and mean indicates the average value of these three expenditure intensities.

3.2.4. Control variables

Digital transformation is an activity that requires high resource consumption and high costs, and customer orientation is one of the strategic orientations of enterprises (Gatignon and Xuereb, 1997). The realization of both requires enterprises to have a strong resource foundation and core capabilities. Therefore, to improve the accuracy of the research, the following control variables are incorporated: (1) Firm size (Size), measured by the natural logarithm of the firm's total assets. (2) Firm age (Age), measured as the observed year minus the year of the firm's establishment plus 1. (3) Growth (Grow), measured by the growth rate of operating revenue (%). (4) Leverage ratio (Lev), measured by the debt-to-asset ratio (%). (5) Proportion of independent directors (Indir), measured by the ratio of the total number of independent directors to the total number of the board of directors (%). (6) CEO duality (Dual), where 1 indicates that the chairman of the board and the general manager are the same person, and 0 otherwise. In addition, this paper also controls for the fixed effects of year (Year) and industry (Industry).

3.3. Model

First, to analyze the research hypothesis proposed above, a baseline regression model is constructed to test the impact of digital transformation on enterprise customer orientation, as shown in Eqs. 3 and 4.

Second, in order to examine whether dynamic capabilities play a mediating role in the influence mechanism of digital transformation on customer orientation, the following models (Eqs. 5 and 6) are added based on the baseline regression model (4) by referring to the mediating effect test method that was proposed by Wen et al. (2004). Consequently, Eqs. 4, 5, and 6 collectively form a comprehensive mediation effect test model.

$$CO_{i,t} = a_0 + a_1 DT_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (3)$$

$$CO_{i,t} = b_0 + b_1 DT_{i,t} + \sum b_i Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (4)$$

$$Mediator_{i,t} = c_0 + c_1 DT_{i,t} + \sum c_i Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (5)$$

$$CO_{i,t} = d_0 + d_1 DT_{i,t} + d_2 Mediator_{i,t} + \sum d_i Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (6)$$

where, i indicates the enterprise, t indicates the year; CO indicates enterprise customer orientation; DT indicates digital transformation; $Mediator$ indicates innovative capability (IC), absorptive capability (AS), and adaptive capability (AD); $Control$ indicates the above control variables; a_0, b_0, c_0, d_0 indicate the constant term; a_1, b_1, c_1, d_1 indicate the coefficients of DT; b_i, c_i, d_i indicate the coefficients of control variables; $Year$ indicates dummy variable of year, $Industry$ indicates dummy variable of industry; ε indicates random error term.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 1 presents the descriptive statistics of the main variables in this study. The mean value of Enterprise Customer Orientation (CO) is 2.352, and the median is 2.398, indicating that the level of customer orientation of the sample enterprises is at a moderately low level. The minimum value of Digital Transformation (DT) is 0, the maximum value is 6.742, and the standard deviation is 1.069, indicating a significant difference in digital transformation among the sample enterprises. The mean value of Innovative Capability (IC) is 0.248, and the maximum value is 2.106, indicating that the overall innovative capability of the sample enterprises is relatively low. The mean value of Absorptive Capability (AS) is 5.492, and the maximum value is 95.373, indicating that the average R&D investment intensity of the sample enterprises is 5.492%, and a few enterprises have strong absorptive capability and serve as exemplars. The mean and p50 values of Adaptive Capability (AD) are similar, and manufacturing enterprises have generally established robust, sustainable response mechanisms to market changes.

Table 1: Result of descriptive statistics

Variable	N	Mean	SD	Min	P50	Max
CO	21,469	2.352	0.885	0.000	2.398	5.580
DT	21,469	3.113	1.067	0.000	3.135	6.742
IC	21,469	0.248	0.192	0.000	0.200	2.106
AS	21,469	5.492	5.692	0.000	4.203	95.373
AD	21,469	-0.744	0.360	-1.732	-0.710	-0.004

4.2. Coefficients analysis

Table 2 presents the Pearson correlation coefficients of the main variables in this study. All the correlation coefficients have passed the significance level test at the 1% level. The Pearson correlation coefficient between digital transformation and enterprise customer orientation is 0.497, indicating a statistically significant positive correlation between the two variables. The Pearson correlation coefficients between digital transformation and innovative capability, absorptive capability, and adaptive capability are 0.270, 0.160, and 0.118, respectively, indicating a positive correlation between digital transformation and these three capabilities. The Pearson correlation coefficients between innovative capability, absorptive capability, adaptive capability, and enterprise customer orientation are 0.325, 0.232, and 0.147, respectively, indicating a positive correlation among these variables. This initially supports the research hypotheses of this study. Meanwhile, based on the evaluation results for control variables using Pearson's and Spearman's correlation coefficients (see Appendix A, Table A2 and Table A3), the correlation between the control variables and CO is found to be in line with expectations.

Furthermore, the variance inflation factor is calculated for all explanatory variables and the control variables (see Appendix A, Table A4). The results show that the average VIF across all variables is 1.39. The maximum value is 2.40. They are both less than the threshold of 5, indicating that no obvious multicollinearity problems exist among the variables.

Table 2: Correlation coefficient of main variables

Variables	CO	DT	IC	AS	AD
CO	1				
DT	0.497***	1			
IC	0.325***	0.270***	1		
AS	0.232***	0.160***	0.741***	1	
AD	0.147***	0.118***	0.220***	0.184***	1

***: Indicates that the data is significant at the level of 1%

4.3. Trend analysis

4.3.1. Trend of DT levels

The DT levels of manufacturing listed companies and their trends from 2015 to 2023 are shown in Fig. 2. The DT level of the manufacturing industry is increasing, and the variation range remains relatively consistent. However, they exhibit differences for the varying degrees and investment proportions of different production factors during the manufacturing process (see Appendix A, Table A5). The DT levels of skill-intensive enterprises have consistently led over the years. They usually rely on advanced technologies and professional knowledge, and are more inclined to enhance their competitiveness through digital transformation. They have more technical resources and professional talent, and possess stronger innovative and adaptive capabilities, enabling them to adopt and utilize new technologies more quickly. Thus, it is easier for them to implement and promote digital transformation. The DT level of labor-intensive enterprises is slightly lower than that of skill-intensive enterprises. They mainly rely on a large number of human resources for production and may face difficulties, such as shortages of technical resources and professional talent, during the digital transformation process. Despite such challenges, some labor-intensive enterprises have begun to undertake phased digital transformations through online platforms such as short videos and live streaming to accumulate experience and technical capabilities for a comprehensive digital transformation. Capital-intensive enterprises are significantly lower than the former two. This is because the sub-sector primarily relies on substantial capital investment and advanced production equipment, which may create additional technical and cost challenges during the digital transformation process. Some enterprises, thus, are more likely to lack the motivation for transformation and are more inclined to maintain the status quo, due to factors such as their large scale, high transformation costs, and the risks and uncertainties associated with digital transformation.

Regarding the trend of variation, the DT level of manufacturing enterprises shows a slight decline in some years. This is mainly due to enterprises placing greater emphasis on the stability of their business operations to mitigate risks and slowing the pace of digital transformation to cope with increasingly fierce market competition.

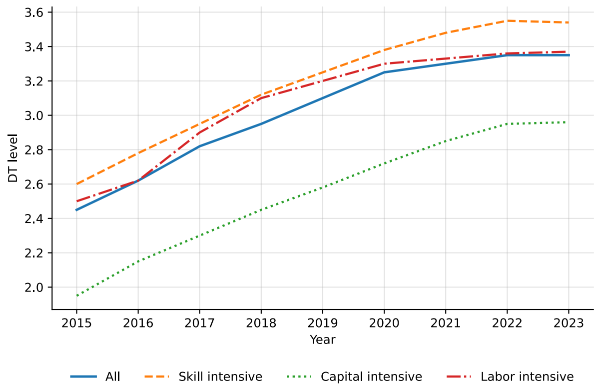

Fig. 2: Digital transformation level trend of manufacturing enterprise (2015-2023)

4.3.2. Trend of CO levels for different DT levels

The average levels of customer orientation (CO) for manufacturing companies from 2015 to 2023 are calculated (see Appendix A, Table A6). The CO level of manufacturing listed companies increased year by year from 1.740 in 2015 to 2.829 in 2023, with a growth rate of 62.59%. It indicates that manufacturing enterprises are increasingly prioritizing customer needs and shifting their business concepts and strategic directions towards a customer-centric approach to enhance customer satisfaction, strengthen market competitiveness, and achieve sustainable development. The entire sample is divided into high digital transformation level (HDT) and low digital transformation level (LDT) based on the median of the DT level. From 2015 to 2023, the CO level of HDT enterprises (HDT_CO) is significantly greater than that of LDT enterprises (LDT_CO) in each year. The average difference in CO level across all years is 0.591. Combining the differences in CO levels of digital enterprises in each year (Fig. 3), it can be seen that the gap in CO levels between HDT enterprises and LDT enterprises has been decreasing year by year. The specific difference decreased from 0.639 in 2015 to 0.464 in 2023. It indicates that digital transformation helps manufacturing enterprises establish and achieve customer orientation.

4.4. Main regression results

4.4.1. Baseline regression results

To examine the impact of digital transformation on the customer orientation of enterprises, a regression is conducted using Eq. 3. The baseline regression results are shown in Table 3. Column 1 only includes the core explanatory variables. From the regression results, it can be observed that digital transformation has a significant positive impact on customer orientation. After adding control variables in Column 2, the significance remains the same; that is, H1 has been empirically supported.

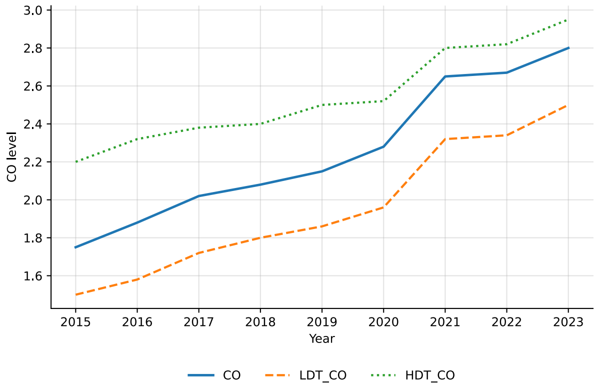

Fig. 3: Difference in customer orientation levels of manufacturing enterprises (2015-2023)

Table 3: Baseline regression results

Variable	(1) CO	(2) CO
DT	0.271*** (53.51)	0.273*** (52.95)
Size		-0.021*** (-4.97)
Age		-0.013*** (-16.08)
Grow		0.055*** (5.07)
Lev		0.002*** (5.26)
Indir		0.004*** (5.36)
Dual		0.130*** (13.04)
Constant	1.509*** (91.82)	1.977*** (22.04)
Year	Yes	YES
Industry	Yes	YES
Observations	21,469	21,469
F	2863.54	513.60
Adjusted R^2	0.403	0.421

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

4.4.2. Endogeneity and robustness analysis

Instrumental variable method: The results of the regression analysis indicate that digital transformation within enterprises can significantly contribute to their customer orientation. However, given endogeneity, the customer orientation of enterprises may also have a reverse impact on the degree of digital transformation, suggesting a causal relationship between the two and potentially leading to biased regression results. Moreover, although the article controlled for factors that might affect the customer orientation of enterprises, there may still be unpredictable factors influencing the empirical results. Therefore, to alleviate endogeneity bias, the instrumental variable method is selected for further testing. Following the method chosen by Li and Zhang (2024), the interaction term "ODT×NDI" between the DT mean of other enterprises in the same sector within the same period (ODT), and the indicators of provincial new-type digital infrastructure (NDI) is used as instrumental variables, which satisfies the relevance and exogeneity of instrumental variables. The two-stage instrumental variable method is employed to address endogeneity. Table 4, Model 1, shows the first-stage estimation results, indicating that the coefficient for ODT×NDI is significantly positive at the 1% statistical level, consistent with the correlation of the instrumental variable. Model 2 is the second-stage regression. The K_P rk LM statistic is significant at the 1% level, rejecting the hypothesis of insufficient identification of instrumental variables. The C_D Wald F and K_P rk Wald F statistics are much larger than the critical value of the Stock-Yogo weak instrumental variable identification F test at the 1% significance level, rejecting the weak instrumental variable hypothesis, indicating the rationality of the instrumental variables. From model 2, the coefficient for the impact of DT on CO is 0.336, supporting the validity of H1.

Table 4: Endogeneity problems (instrument variable method)

Variable	(1) DT	(2) CO
DT		0.325*** (8.58)
ODT×NDI	0.441*** (18.81)	
Controls	YES	Yes
Year	YES	Yes
Industry	YES	Yes
Constant	-236.456*** (-42.01)	-210.499*** (-21.87)
Observations	21,469	21,469
R^2		0.394
F	353.87	1157.44
K_P rk LM		337.476***
C_D Wald F		348.992
K_P rk Wald F		353.867

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

Heckman Two-stage Method: The data used to measure the indicators of digital transformation comes from the annual financial reports of listed enterprises. However, key information such as whether enterprises have achieved transformation through digital technologies is not a mandatory disclosure item in financial reports. It may result in some enterprises having implemented digital transformation strategies, but this information is not clearly reflected in their financial reports. Moreover, because enterprises will face various subjective and objective factors during the digital transformation process, the sample data selected in this study may not fully reflect the true situation of enterprises' digital transformation, potentially leading to deviations in the assessment results. Therefore, the Heckman two-step method is employed to correct for the potential sample selection bias.

In the first stage, a dummy variable DumDT is generated to indicate whether enterprises have undergone digital transformation. If enterprises have undergone digital transformation, DumDT is coded as 1; otherwise, it is coded as 0. It is set as the dependent variable. Secondly, control variables, time dummy variables, and industry dummy variables are added to the first-stage model. Finally, the Probit model is used to estimate the probability of enterprises' digital transformation in the entire sample, and the Inverse Mills Ratio (IMR) is calculated. In the second stage, IMR is used as a control variable to regress into Model 2, and the results are shown in column 2 of Table 5. The regression coefficient for digital transformation is significantly positive (B = 0.300, $p < 0.01$), indicating that H1 remains valid.

Table 5: Endogeneity problems (Heckman two-stage method)

Variable	(1) DumDT	(2) CO
DT		0.300*** (62.34)
IMR		1.168*** (3.13)
Controls	YES	Yes
Year	YES	Yes
Industry	YES	Yes
Constant	-281.88*** (-11.48)	-233.698*** (-34.17)
Observations	21,469	21,469
R^2	0.114	0.394
F		1398.04

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

Propensity Score Matching Method (PSM): PSM is employed to address endogeneity arising from sample selection bias. First, drawing on the research by Li and Zhang (2024), enterprises are divided into an experimental and a control group based on the degree of their digital transformation. The enterprises are further divided into a high-degree group and a low-degree group based on the median value of digital transformation. If the digital transformation degree of an enterprise is high, it is coded as 1 and classified as the experimental group; otherwise, it is coded as 0 and classified as the control group. Second, the encoded dummy variables are used as grouping variables, and propensity scores are calculated using Logistic regression. Finally, 1:1 nearest neighbor matching, radius matching, and kernel matching are selected to match the samples. After matching the degree of digital transformation, the standardized deviation of covariates significantly decreased, and the differences between samples with a digitalization degree greater than the median and those with a degree less than the median are significantly reduced, thereby proving the reliability of the PSM matching results. The t-test values corresponding to the ATT effects of 1:1 nearest neighbor matching, radius matching, and kernel matching are much greater than 2.576 ($P < 0.01$), indicating that the average treatment effect in the treatment group is significant. The data after PSM processing are subjected to baseline model regression, and the results are shown in Table 6. From the results, the coefficients for DT are all positive, and all pass the 1% significance level test. Thus, it indicates that digital transformation has promoted the customer-oriented approach of enterprises, and H1 still holds.

Table 6: Endogeneity problems (PSM)

Variable	CO (1) Neighbor Matching	 (2) Radius Matching	 (3) Kernel Matching
DT	0.272*** (51.67)	0.273*** (52.88)	0.273*** (52.88)
Controls	yes	yes	yes
Year	yes	yes	yes
Industry	yes	yes	yes
Constant	2.159*** (20.97)	2.016*** (22.33)	2.016*** (21.24)
Observations	20,175	21,445	21,445
Adjusted R^2	0.421	0.420	0.420
F	476.50	510.08	510.08
ATT	0.688*** (44.66)	0.689*** (60.41)	0.690*** (60.37)

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

Other Robustness Tests: This paper also conducted the following robustness tests. The baseline regression results are presented in Table 7: (1) Replacing the explanatory variables (Table 3, Column 1). Specifically, it reduced digital transformation to two levels: the bottom-level digital technology level and the digital technology application level. The digital transformation is measured by the natural logarithm of the total frequency of keywords in these two levels. (2) Replacing the regression model (Table 7, Column 2). Given that time and industry fixed effects do not adequately control for endogeneity, a method is introduced to incorporate a high-order joint fixed effect for "time × industry" to test the model. (3) Removing special industries such as computer, communication, and other electronic equipment manufacturing (Table 7, Column 3). The results of the baseline regression remained largely consistent, indicating that the conclusions of this paper are robust and reliable.

4.5. Mediating effect test

The research fully demonstrates the impact of digital transformation on customer orientation of manufacturing enterprises. However, the mechanism of action remains unclear. Therefore, this paper will separately test the three channels of action: innovative capability, absorptive capability, and adaptive capability. Drawing on the ideas of Baron and Kenny (1986) and the stepwise regression method proposed by Wen et al. (2004), this paper aims to confirm the existence of a mediating effect.

First, the mediating effect of innovative capability (IC). Columns 1, 2, and 3 in Table 8 correspond to Eqs. 4, 5, and 6, which report the test results of the mediating effect of innovative capability. Column 2 indicates that the regression coefficient of DT on IC is 0.034, which passes the 1% significance level test. It indicates that digital transformation can substantially enhance the innovative capability of manufacturing enterprises.

Table 7: Results of other robustness tests

Variable	CO (1)	(2)	(3)
DT	0.187*** (42.77)	0.273*** (52.66)	0.248*** (42.65)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Constant	2.130*** (23.19)	1.947*** (21.29)	1.880*** (18.82)
Observations	21,469	21,469	18,092
Adjusted R^2	0.397	0.419	0.388
F	369.81	509.13	357.18

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

Column 3 indicates that the regression coefficients for the effects of DT and IC on CO are 0.256 and 0.507, respectively, both of which pass the 1% confidence level test. It indicates that digital transformation and innovative capability have a significant enhancing effect on customer orientation. The regression coefficient of DT diminishes from 0.273 in Eq. 4 to 0.256 in Eq. 6, showing that innovative capability is a partial mediating variable for manufacturing enterprises' digital transformation to achieve customer orientation. H2 is established. The direct effect is 0.256, the mediating effect is 0.034 * 0.507 = 0.017, and the contribution rate of the mediating effect is 0.017/0.273 = 6.23%. Second, the mediating effect of absorptive capability (AS). Columns 1, 4, and 5 in Table 8 correspond to Eqs. 4, 5, and 6, which report the test results for the mediating effect of absorptive capability. Column 4 shows that the coefficient of DT on AS is 0.590, which is significant at the 1% confidence level. It indicates that digital transformation can significantly enhance its absorptive capability. Column 5 shows that the coefficient of AS on CO is 0.010, and the coefficient of DT on CO is 0.267, both of which are significant at the 1% confidence level. It suggests that absorptive capability is a partial mediating variable in manufacturing enterprises' digital transformation in achieving customer orientation. H3 is established. The direct effect is 0.267, the mediating effect is 0.590 * 0.010 = 0.006, and the contribution rate of the mediating effect is 0.006/0.273 = 2.20%.

Third, the mediating effect of adaptive capability (AD). Columns 1, 6, and 7 in Table 8 correspond to Eqs. 4, 5, and 6, and report the test results of the mediating effect of adaptive capability. Column 6 shows that the coefficient of DT on AD is 0.029, which is significant at the 1% confidence level. It indicates that digital transformation can significantly enhance its adaptive capability. Column 7 shows that the coefficient of AD on CO is 0.147, and the coefficient of DT on CO is 0.269, both of which are significant at the 1% confidence level. Adaptive capability is a partial mediating variable in the digital transformation of manufacturing enterprises aimed at achieving customer orientation. H4 is supported. The direct effect is 0.269, the mediating effect is 0.029 * 0.147 = 0.004, and the contribution rate of the mediating effect is 0.004/0.273 = 1.47%.

Table 8: Mediating effect test

Variable	CO (1)	IC (2)	CO (3)	AS (4)	CO (5)	AD (6)	CO (7)
DT	0.273*** (52.95)	0.034*** (27.04)	0.256*** (49.17)	0.590*** (15.62)	0.267*** (51.61)	0.029*** (11.39)	0.269*** (52.10)
IC			0.507*** (18.18)				
AS					0.010*** (11.22)		
AD							0.147*** (10.75)
Constant	1.977*** (22.04)	0.451*** (20.72)	1.748*** (19.45)	23.604*** (35.99)	1.730*** (18.79)	-0.818*** (-18.27)	2.097*** (23.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,469	21,469	21,469	21,469	21,469	21,469	21,469
F	513.60	208.50	497.63	246.82	467.75	33.13	466.24
Adjusted R^2	0.421	0.276	0.430	0.251	0.424	0.131	0.424

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

4.6. Heterogeneity analysis

4.6.1. Heterogeneity analysis of enterprise size

To further analyze the impact of enterprise size on the relationship between digital transformation and customer orientation, based on the classification criteria for industrial enterprises in China, all the samples are divided into large enterprises (LEs) and small and medium-sized enterprises (SMEs). Columns 1 and 2 in Table 9 show that the regression coefficients of DT on CO for LEs and SMEs are 0.285 and 0.263, respectively. It indicates that digital transformation has a significant impact on the realization of customer orientation for both LEs and SMEs. However, the impact of digital transformation on customer orientation of LEs is more significant, indicating that the realization of customer orientation through digital transformation has a greater scale effect on LEs.

Table 9: Heterogeneity analysis

Variable	(1) LEs	(2) SMEs	(3) Skill-intensive	(4) Capital-intensive	(5) Labor-intensive
	CO	CO	CO	CO	CO
DT	0.285***	0.263***	0.323***	0.189***	0.199***
	(43.21)	(31.68)	(52.04)	(17.90)	(11.03)
Constant	1.982***	1.302***	1.714***	2.366***	1.521***
	(16.51)	(5.63)	(15.35)	(12.99)	(5.67)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Observations	14,975	6,494	12,942	6,148	2,195
F	342.76	182.26	468.76	73.92	33.26
Adjusted R^2	0.415	0.451	0.452	0.258	0.399

t-statistics are reported in parentheses; ***: Denotes significance at the 1% level

4.6.2. Heterogeneity analysis of sub-sectors

The entire sample is divided into skill-intensive, capital-intensive, and labor-intensive enterprises. Columns 3, 4, and 5 in Table 9 show that digital transformation has a significant impact on customer orientation in different sub-sectors of enterprises. In contrast, the impact of digital transformation on the customer orientation of skill-intensive enterprises is relatively greater than that of others. Further analysis is carried out to test the mediating effect across the three sub-sectors of enterprises. It reveals significant differences in the paths and intensities by which their digital transformation influences customer orientation through three dynamic capabilities (see Appendix A, Table A7).

For skill-intensive enterprises, digital transformation significantly enhances their innovative and absorptive capabilities. It is because skill-intensive enterprises have a large number of highly skilled employees who can fully utilize digital tools and data to acquire and transform external knowledge, and to innovate in products, services, and processes, thereby meeting or even creating customer needs more effectively. Meanwhile, digitalization also positively affects their ability to adapt to market dynamics.

For capital-intensive enterprises, although digital transformation has a significant impact on their innovative, absorptive, and adaptive capabilities, the stimulating effect is far weaker than that of skill-intensive enterprises. Capital-intensive enterprises adhere to an operational paradigm centered around material and capital and oriented towards efficiency and stability. Even when the same digital technologies are introduced, capital-intensive enterprises mainly use them to maintain the stability and efficiency of existing systems, resulting in only a weak improvement in their innovative, absorptive, and adaptive capabilities.

The core advantage of labor-intensive enterprises lies in their low-cost, large-scale production. Their profitability depends on strict control of the process and reduction of labor costs. However, in order to achieve cost reduction and efficiency improvements, the primary goal of digital transformation in these enterprises is usually process automation and labor substitution. It brings about a fundamental conflict between the advantages of enterprises and the goals of digital transformation. The above-mentioned conflict prevents digital transformation from enhancing organizational capabilities. Therefore, the impact on customer orientation mainly relies on digital transformation itself, which lacks the amplification effect of upgrading organizational capabilities.

As mentioned above, digital transformation has the greatest impact on customer orientation in skill-intensive enterprises. Essentially, this is because the foundation of "high-skilled talents" enables digitalization to most effectively activate and strengthen the customer value creation system centered on "innovation capabilities." In contrast, for other types of enterprises, due to their production factors and organizational inertia, digital transformation is difficult to drive innovative behaviors to achieve customer orientation.

5. Conclusions

Based on the dynamic capability theory, this paper uses data from A-share listed manufacturing enterprises in Beijing, Shanghai, and Shenzhen from 2015 to 2023 to empirically test the impact of digital transformation on enterprises' customer orientation and its underlying mechanism. The following research conclusions are obtained:

First, digital transformation significantly promotes the establishment and realization of customer orientation for manufacturing enterprises. On the one hand, this research conclusion strongly supports the theoretical judgment that digital transformation has a positive impact on the establishment and realization of enterprise customer orientation (Ulmer et al., 2017; Ritter and Pedersen, 2020; Pan et al., 2021; Sun and Zhang, 2021). On the other hand, this research conclusion is consistent with that of Abbu and Gopalakrishna (2021). Moreover, this paper uses panel data, which compensates for the common-method bias inherent in cross-sectional questionnaire data and effectively identifies the causal relationship between the two.

Second, digital transformation significantly enhances the innovative, absorptive, and adaptive capabilities of manufacturing enterprises. Warner and Wäger (2019) pointed out from a theoretical perspective that digital transformation is a crucial antecedent for the evolution of dynamic capabilities in enterprises during the digital era. This research conclusion provides empirical evidence for this view.

There is a significant mediating effect of innovative, absorptive, and adaptive capabilities on the relationship between digital transformation and customer orientation. Among them, the mediating effect of innovative capability is the greatest, followed by absorptive capability, and that of adaptive capability is the smallest. This conclusion further clarifies the magnitude of the mediating effect of different dimensions of dynamic capabilities on the relationship between digital transformation and customer orientation. This finding aligns with the research of Matarazzo et al. (2021), who found that different types of dynamic capabilities play distinct roles in promoting customer value creation and enabling enterprises to achieve customer orientation.

Third, the above conclusions remain valid after a series of robustness tests, and there are no significant differences between enterprises of different sizes or sub-sectors. It further indicates that the path through which digital transformation enhances dynamic capabilities and drives the establishment and realization of customer orientation by enterprises has certain representativeness and universality. However, the combined effect of various factors, such as technology, talent, assets, management structure, and market environment, will lead to differences in the impact of digital transformation on the establishment and realization of customer orientation for different types of enterprises. Skill-intensive enterprises can more effectively leverage the impact of digital transformation due to their own technological and innovative advantages. Capital-intensive enterprises are limited by asset characteristics and management structure, and the impact of digital transformation is relatively small. Labor-intensive enterprises have a significant impact on digital transformation driven by human costs and market competition, but are constrained by the technical level of their employees. Therefore, in promoting customer orientation through digital transformation, enterprises should fully consider their types and characteristics and formulate targeted customer orientation strategies.

6. Discussion

This study incorporates dynamic capability as a mediating variable into the analytical framework and explores the heterogeneity impact of enterprises by dividing the sample by sub-sector. In the current complex and volatile market environment, enterprise behavior and performance are influenced by multiple intertwined factors, and focusing on a single factor or a simple causal relationship cannot fully reveal the essence of the problem. Dynamic capabilities, as a key factor for enterprises to adapt to environmental changes and adjust their resources and capabilities to achieve sustainable development, are introduced into the research on digital transformation and customer orientation. It can provide a deeper analysis of the internal mechanism between the two. Dividing the samples by sub-sector fully accounts for differences in resources, technology, capabilities, and management across enterprise types, making the research conclusions more targeted and practical. The in-depth discussion of the research conclusions is as follows.

First, the study indicates that current enterprises generally exhibit an upward trend in digital transformation and customer orientation. However, some enterprises are at a lower level, with significant differences in the magnitude and speed of improvement. This conclusion reflects the overall development trend of the manufacturing industry amid the digital transformation wave and also reveals the imbalance in the development of enterprises within the industry. This imbalance may stem from various factors, such as enterprise scale, ownership nature, and market positioning. For enterprises at a lower level or with slow improvement, it is necessary to deeply analyze the obstacles they face, whether it is a lack of funds, technical bottlenecks, or outdated management concepts, to formulate targeted support policies or improvement measures. Meanwhile, leading enterprises can share their successful experiences to drive the overall improvement of the industry.

Second, different dimensions of dynamic capabilities exhibit measurement overlap because the intensity of R&D investment is used as an indicator for them. The intensity of R&D investment is a core indicator of an enterprise's ability to create new technologies, products, or business models. Meanwhile, only enterprises with a certain level of R&D investment can effectively understand and transform external technological knowledge. That is, the intensity of R&D investment is often used as an indirect proxy variable for absorptive capability. Therefore, the intensity of R&D investment is one of the few quantitative indicators that are authoritative, internationally comparable, and temporally continuous. Building upon theoretical principles and empirical data, it is appropriate to measure different dimensions of dynamic capabilities using R&D investment intensity as an indicator.

Third, dynamic capabilities partially mediate between enterprise digital transformation and customer orientation. This conclusion reveals the complex relationship among the three. Enterprise digital transformation not only directly affects customer orientation but can also indirectly influence its realization through its impact on innovative, absorptive, and adaptive capabilities. However, the mediating effect of innovative capability is stronger than that of both absorptive and adaptive capabilities. In particular, the mediating effect of adaptive capability is enormously lower than that of innovative capability. This discrepancy arises because the measurement indicators employed in this study, derived from panel data of listed companies, primarily capture organizational-level adaptive capability. But employees' professional skills, industry-specific knowledge, and ability to learn new competencies constitute fundamental pillars of an enterprise's adaptability to external changes. Consequently, the mediating role of adaptive capability may have been underestimated.

Finally, enterprise digital transformation significantly promotes customer orientation through various means, such as accurately capturing customer needs, shortening the feedback cycle, anticipating demand trends, and optimizing the entire customer experience process. In enterprises of varying scales, the impact of digital transformation on customer orientation is not significantly different. This conclusion aligns with the widespread application and significant role of digital technology in establishing and achieving customer orientation in contemporary manufacturing enterprises. However, the discussion on specific industries reveals that different types of enterprises are affected by digital transformation to varying degrees. Skill-intensive enterprises can efficiently leverage digital technology to meet customer needs, suggesting that they should further invest in digital technology research and innovation to consolidate and expand their advantages. Constrained by their assets and management structures, capital-intensive enterprises' digital transformations inhibit their innovative capability. It may mean that capital-intensive enterprises need to pay more attention to organizational structure adjustments and management model innovations during the digital transformation process to overcome traditional constraints and unleash their innovative vitality. Labor-intensive enterprises are significantly impacted by the technical level of their employees. Therefore, strengthening employee digital skills training and enhancing employee quality is crucial for labor-intensive enterprises to achieve digital transformation and customer orientation.

This study still has certain limitations and needs further improvement and exploration in the future. First, the sample used in this study is from manufacturing enterprises, and the generalizability of the research conclusions needs to be further verified. Future research can further examine the relationship between digital transformation and customer orientation in other industry enterprises, such as agriculture and service industries. Second, from the perspective of dynamic capability theory, this study explores the mechanism by which digital transformation affects enterprise customer orientation. Future research still needs to identify further the moderating variables that shape the relationship between digital transformation and enterprise customer orientation, and to deepen the research into the mechanisms that influence both. Finally, this study mainly examines the forward influence mechanism of enterprise customer orientation. Future research can further construct a comprehensive model to explore the post-effect of enterprise customer orientation on factors such as company performance and competitive advantage, thereby forming a more complete and in-depth understanding of the development driven by digital transformation.

Appendix A. Additional empirical evidence

Supplementary statistical analyses and supporting results used to validate the study findings are shown in Tables A1 to A7 in this appendix. These include additional information related to keyword construction, correlation analysis, multicollinearity testing, trend evaluation, and heterogeneity analysis across different manufacturing sub-sectors, which further strengthen the reliability and robustness of the empirical findings.

Table A1: Customer-oriented keywords

Level	Dimension	Keywords
Strategy	Strategy principle	Customer orientation, customer first, customer relationship management, establish/maintain customer relationship
	Strategy significance	Customer value creation, cooperation with customers, win-win situation with customers, customer stickiness
Implementation	Customer focus	Find/support quality customers, meet customer needs, pay attention to customer needs, obtain customer information, customer feedback
	Customer involvement	Integrate/optimize customer resources, customer participation improvement, customer comments
	Communication with customers	Interaction, customer sharing, solutions (after sales), optimized communication channels

Table A2: Correlation coefficient of control variables (Pearson correlation coefficient)

Variable	CO	DT	IC	AS	AD
Size	-0.020***	0.151***	-0.153***	-0.271***	-0.050***
Age	-0.054***	0.019***	-0.140***	-0.125***	-0.031***
Grow	0.023***	-0.001	0.012*	-0.043***	-0.028***
Lev	0.040***	0.105***	-0.137***	-0.183***	-0.018**
Indir	0.069***	0.040***	0.019***	0.021***	-0.0016**
Dual	0.143***	0.057***	0.096***	0.109***	0.008

***, **, *: Indicate respectively that the data is significant at the level of 1%, 5%, and 10%

Table A3: Correlation coefficient of control variables (Spearman correlation coefficient)

Variable	CO	DT	IC	AS	AD
Size	-0.043***	0.148***	-0.228***	-0.346***	-0.054***
Age	-0.060***	0.020***	-0.128***	-0.147***	-0.039***
Grow	0.049***	0.020***	0.026***	-0.029***	0.009
Lev	0.051***	0.120***	-0.146***	-0.218***	-0.008
Indir	0.072***	0.038***	0.013*	0.037***	-0.0017**
Dual	0.146***	0.057***	0.088***	0.123***	0.005

Table A4: Correlation coefficient of main variables

Variable	VIF	1/VIF
DT	1.14	0.875
IC	2.40	0.416
AS	2.36	0.423
AD	1.06	0.944
Size	1.47	0.679
Age	1.07	0.933
Grow	1.02	0.977
Lev	1.33	0.751
Indir	1.01	0.986
Dual	1.06	0.943
Mean VIF	1.39	-

Table A5: Digital transformation levels of manufacturing enterprise (2015-2023)

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
All	2.440	2.628	2.809	2.944	3.085	3.228	3.336	3.402	3.402
Skill-intensive	2.675	2.858	3.024	3.128	3.281	3.408	3.515	3.583	3.568
Capital-intensive	1.970	2.192	2.353	2.523	2.648	2.823	2.948	3.024	3.026
Labor-intensive	2.521	2.660	2.936	3.118	3.190	3.331	3.355	3.362	3.369

Table A6: Customer orientation levels of manufacturing enterprise (2015-2023)

Year	CO	LDT_CO	HDT_CO	Difference in the value of CO
2015	1.740	1.565	2.204	0.639
2016	1.874	1.660	2.326	0.666
2017	2.019	1.781	2.391	0.61
2018	2.087	1.821	2.421	0.6
2019	2.187	1.869	2.516	0.647
2020	2.288	1.962	2.549	0.587
2021	2.622	2.326	2.813	0.487
2022	2.669	2.359	2.851	0.492
2023	2.829	2.535	2.999	0.464
Average	2.257	1.986	2.563	0.577

Table A7: Mediating effect test in different sub-sectors

Skill-intensive	CO (1)	IC (2)	CO (3)	AS (4)	CO (5)	AD (6)	CO (7)
DT	0.323***	0.050***	0.302***	0.882***	0.316***	0.043***	0.316***
IC			0.424***				
AS					0.008***		
AD							0.170***
Capital-intensive	CO (1)	IC (2)	CO (3)	AS (4)	CO (5)	AD (6)	CO (7)
DT	0.189***	0.009***	0.183***	0.115***	0.184***	0.017***	0.187***
IC			0.743***				
AS					0.043***		
AD							0.114***
Labor-intensive	CO (1)	IC (2)	CO (3)	AS (4)	CO (5)	AD (6)	CO (7)
DT	0.199***	-0.001	0.200***	-0.048	0.202***	-0.030***	0.199***
IC			0.918***				
AS					0.060***		
AD							-0.009

List of abbreviations

AD	Adaptive capability
Age	Firm age
AS	Absorptive capability
ATT	Average treatment effect on the treated
CO	Customer orientation
DT	Digital transformation
Dual	CEO duality
Grow	Growth rate of operating revenue
HDT	High digital transformation level
HDT_CO	Customer orientation level of high digital transformation enterprises
IC	Innovative capability
IMR	Inverse Mills ratio
Indir	Proportion of independent directors
LDT	Low digital transformation level
LDT_CO	Customer orientation level of low digital transformation enterprises
LEs	Large enterprises
Lev	Firm leverage ratio
NDI	Indicators of provincial new-type digital infrastructure
ODT	Digital transformation means for other enterprises in the same sector within the same period
Size	Firm size
SMEs	Small and medium-sized enterprises

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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