ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 13 (2026) No. 8, pp. 186-209
DOI:10.33168/JLISS.2026.0811

Digital Transformation, Organizational Restructuring, and Competitive Advantage in Manufacturing Firms: Dynamic Capability Chain Mediation and Institutional Environment Moderation Effects

Shaolong Li
Liaoning Finance & Trade College, Xingcheng, 125105, China
lishaolong0319@163.com

Abstract. This study examines how digital transformation enables manufacturing firms to convert information resources and digital technologies into competitive advantage through information-enabled organizational restructuring and dynamic capability development. Drawing on dynamic capability theory and the information-processing view of the firm, we argue that digital transformation improves firms' ability to sense market and technological changes, integrate digital and operational resources, and reconfigure organizational routines that support more responsive production, supply-chain coordination, and service-oriented value creation. Using an unbalanced panel of Chinese A-share listed manufacturing firms from 2012 to 2023, we construct a digital transformation index through annual-report text analysis and test the proposed mechanisms using fixed-effects regression, path analysis, and bias-corrected Bootstrap mediation tests. The results show that digital transformation has a positive but economically modest association with competitive advantage. Organizational restructuring partially transmits this relationship, while the dynamic capability chain of sensing capability, integrative capability, and reconfiguring capability provides an additional indirect pathway. Marketization strengthens the relationship between digital transformation and organizational restructuring, whereas the moderating effect of intellectual property protection is not statistically significant. The findings contribute to the literature on digital transformation and information-enabled manufacturing services by clarifying how digital technologies create value only when they are accompanied by organizational and capability reconfiguration.

Keywords: Digital transformation; Organizational restructuring; Dynamic capability; Competitive advantage of manufacturing enterprises; Institutional environment; chain mediation

1. Introduction

Digital technology is changing the face of manufacturing and has triggered significant transformation in the global manufacturing industry. The high-level use of AI, cloud computing, big data and many other technologies is transforming not only how things are produced but, also, how organisations are structured and where their competitiveness lies. With China's manufacturing sector as a pillar of the national economy, it is faced with the strategic transition from a scale-driven model to quality and efficiency driven model. A shared challenge during this transition has been that although manufacturing firms have invested heavily in digital hardware, they are struggling with converting their technological investments into tangible competitive advantages (Verhoef et al., 2019). The phenomenon of "high investment, low conversion" has received a great deal of attention in research and practice.

From the perspective of logistics, informatics, and service science, digital transformation in manufacturing is not limited to the adoption of digital tools. It reshapes how firms collect, process, and share operational information across production, procurement, logistics, sales, and after-sales service activities. In digitally enabled manufacturing systems, competitive advantage increasingly depends on the firm’s ability to transform dispersed information into coordinated decisions and service-oriented responses. Therefore, the value of digital transformation should be understood through the organizational and capability mechanisms that connect information resources with operational and service outcomes.

Digital transformation requires that organisations fundamentally change the way they structure their operations around digital technology. While technology creates opportunities for value creation, value does not arise from technology alone; rather, value is produced as a result of organisational adjustments, process reengineering, and resource allocation based on technology. An analytical framework for studying this transformation has been provided by Teece's Theory of Dynamic Capabilities (Teece,2007). Dynamic Capabilities can be defined as the ability of an organisation to integrate, build, and reconfigure internal and external resources in order to respond to changes in a rapidly changing environment, and include the three fundamental components of sensing, seizing and reconfiguring. However, research to date has identified three significant gaps (Hanelt et al.,2021). The first area of untapped research is with respect to the mediating processes of dynamic capability between digital transformation and competitive advantage. In the majority of studies, dynamic capability has been treated as a mono-dimensional entity, ignoring how each dimension affects the others sequentially; that is, digital investment impacts the sensing of new external opportunities within an organization, then through resource integration and action (i.e. organizational action), and finally through reconfiguration to create value. If there are any interruptions in this sequence of occurrence, digital transformation will only reach a superficial level of implementation concerning equipment acquisition and implementation of systems. The second area of future research is related to the lack of attention given to institutional environments as moderating variables. The level of marketization within the Chinese manufacturing environment contains varying levels of complexity due to the existence of regional differences in both the development of marketization and the level of protection for intellectual property. The value obtained by organizations from digital transformation may be impacted by the differences in the way the process of marketization has progressed or the protection of their intellectual property. Thirdly, most empirical research has predominately used case studies or small sample surveys, rather than utilizing a systematic validation process based on the findings of listed companies using a larger sample size (Warner & Wäger,2019).

Using the analysis above, it is the purpose of this paper to address three research questions. First, how digital transformation impacts comparative advantage of manufacturing companies through organizational restructuring. Second, if the perceived capabilities, integration capabilities and restructuring capabilities of dynamic capabilities, create a serial mediation path. Third, what role does the degree of marketisation and intellectual property rights in the institutional environment, play in moderating the transformation process?

This paper has three theoretical contributions. First, by disaggregating dynamic capabilities into three sub-dimensions (i.e. perceptual capabilities, integration capabilities, and reconfiguration capabilities), the paper develops an interconnection model that explains the micro-mechanism of how digital investment is leveraged into comparative advantage. Second, incorporating the institutional environment into a moderated mediation framework and investigating how transformation effects are differentially performed under different institutional conditions; thus helping answer the call for situational factors in dynamic capability theory (Matarazzo et al., 2021). Third, large sample empirical tests based on data from long-term panel studies of China's A-share (listed) manufacturing companies provide evidence for applying dynamic capability theory in the Chinese context. At the practical level, the findings offer decision-making references for manufacturing enterprises in formulating digital transformation strategies, guiding them to identify key nodes and bottleneck links in capability transformation and optimize resource allocation pathways (Vale-Feigl,2021).

2. Literature Review and Research Hypotheses

2.1. Digital Transformation and Competitive Advantage

The term "digital transformation" refers to the way in which organizations use digital technologies for transforming the way they conduct business. Digital transformation encompasses three levels: the application of new technologies; how an organization adapts to these new technologies; and the redesign of its strategic structure. In terms of manufacturer enterprises, the scope of digital transformation may include (1) implementing intelligent manufacturing during the production process; (2) using digital tools to collaborate digitally with partners throughout the supply chain; (3) using precision marketing methods within their sales and service processes; (4) making data-driven decisions about how to manage and make decisions (Hess et al.,2016).

There are many ways to promote a competitive advantage through digital transformation. Through the application of digital technology, the level of information asymmetry can be decreased, the transparency of information shared between firms within a supply chain can be increased, and the quality of decision making and speed of responses to customer requests can be enhanced, resulting in more accurate insights into what customers want and faster reactions to customer demands (Li et al.,2025). The application of digital technology enables companies to optimize their manufacturing process, reduce waste of resources, improve the efficiency of asset turnover and reduce their total operating costs. Research studies show that there is a significant and positive relationship between digital transformation and innovation performance, total productivity of factors of production and the efficiency with which companies manage their working capital (Wu et al., 2021). Based on this empirical work, hypothesis H1 is proposed:

H1: Digital transformation has a significant positive impact on the competitive advantage of manufacturing enterprises.

2.2. The mediating role of organizational restructuring

Organizational restructuring involves re-organizing a corporation's internal structure and operational processes. This can affect how a company operates, who runs it and how business is accomplished based on new strategies and environmental conditions. The way in which digital transformation facilitates organizational restructuring includes but is not necessarily limited to the following: Digital technology has enabled the reduction of costs for information exchange and coordination, facilitating the emergence of flatter and more networked structures for organizations, as opposed to those with multiple levels of hierarchy (Yuan et al., 2021). Organizations previously having multiple levels of hierarchy are under pressure to remove some redundant levels in order to streamline their operations (Rachinger et al.,2019). In addition, because digital transformation requires the creation of data connectivity between R&D, production and marketing in an enterprise, digital transformation will inevitably create opportunities for the integration and re-engineering of cross-departmental processes. Finally, the introduction of work-related digital tools has altered how people work, what is considered acceptable performance and what constitutes competence in the workplace; this creates the need for organizations to modify job design and employee resource allocations.

The mechanism through which organizational restructuring can lead to gaining a competitive advantage can be described as creating greater efficiencies in decision-making, enhancing flexibility of the organization, and leveraging the dormant potential within an organization. With the speed and adaptability of restructured organizations to the dual pressures of changing market conditions and the technological evolution and iteration will empower them to gain a significant competitive speed advantage (Nambisan et al.,2019). Organizational restructuring is a key factor enabling the breakdown of silos within organizations, increasing the flow of information between individuals, and fostering collaborative innovation; this in turn enhances the innovative output produced by organizations. Through organizational restructuring, enterprises can reallocate resources from inefficient areas to high growth areas, optimizing resource utilization efficiency (Helfat & Peteraf,2015).

Digital transformation, as an exogenous shock, triggers structural adjustments within the organization, which further translate into the enhancement of competitive advantage. In other words, organizational restructuring is a key transmission link for the effectiveness of digital transformation. (Zhao et al., 2021) found that digital transformation indirectly improves total factor productivity by optimizing internal management and supply chain collaboration, which supports the intermediary role of organizational restructuring. Based on this, hypothesis H2 is proposed:

H2: Digital transformation has a positive impact on the competitive advantage of manufacturing enterprises by promoting organizational restructuring, that is, organizational restructuring plays a mediating role.

2.3. The Chain Mediating Effect of Dynamic Capability

Three-dimensional structures of dynamically developing abilities are connected by a concept of hierarchical and chronological ranking of dynamic capabilities. The logical point of entry in this chain of events is perceptual ability, where businesses have a way of obtaining knowledge concerning opportunities outside of the firm through investing in research and development and monitoring technologies and, as a result, are able to make judgments concerning future digital development trends and to identify potential application scenarios for digital transformation projects. Accordingly, the ability to perceive opportunities determines whether or not businesses will be able to identify timely those opportunities and threats resulting from the digitization process effectively (Zahra et al.,2006).

The business's opportunities must be translated into specific action plans, which will depend on businesses' ability to execute an integration capability effectively. Integration capabilities consist of the organization of newly acquired digital capabilities with pre-existing technological infrastructures, human capital and organizational practices. The digital transformation of business organizations is reflected in their integration capabilities as they strive to embed newly acquired technologies into their current business processes—including integrating Data Platforms with legacy information systems, combining Digital Talent with existing teams and integrating Digital Tools with currently used physical production systems (Nour & Arbussà,2025). Prior research has demonstrated that digital and technological capabilities serve as critical antecedents of service innovation capability, particularly when firms successfully integrate digital resources with existing operational assets (Hasnawati et al., 2024).

To achieve total release of integrated outcomes, you will need to have the capability of reconstruction. Reconstruction capability describes the capacity of an organization to revise its organizational structure, governance mechanisms, and cultural norms in ways that support digital strategic goals. This level represents an evolution beyond simply integrating technology, and entails systematic changes to the distribution of power, incentives, decision-making processes, and core values (Wilden et al.,2013). When organizations are experiencing digital transformation, their capacity to reconstruct will be defined by their ability to break from established path dependence, to manage their organizational inertia, and build a new order that is aligned with the demands of the digital world.

The sequence of these three variables has a logical rationale. An organization that lacks perceptual capabilities has no way to be aware of the direction and focus of its digitalization efforts. Perceptual opportunities are not able to be executed in an organization that lacks integration capabilities. Finally, if an organization lacks reconstruction capabilities, then the integrated outcomes will be constrained by the organization's inertia and therefore will remain fixed. In conclusion, the dynamic capabilities of perception, integration and reconstruction are sequential and will form a complete pathway with respect to the competitive advantage of an organization resulting from digital transformation. Based on this, the following hypothesis is proposed:

H3a: Digital transformation has a positive association with sensing capability.

H3b: Sensing capability is positively associated with integrating capability.

H3c: Integrating capability is positively associated with reconfiguring capability.

H3d: Reconfiguring capability is positively associated with competitive advantage.

H3e: Sensing capability, integrating capability, and reconfiguring capability form a sequential mediation path between digital transformation and competitive advantage.

2.4. The Moderating Role of the Institutional Environment

The institutional environment plays a regulatory role in the process of digital transformation towards competitive advantage, and its regulatory mechanism is reflected in two aspects.

Firstly, the degree of marketization affects the promotion effect of digital transformation on organizational restructuring. Regions with a higher degree of marketization typically have more developed factor markets, more comprehensive legal frameworks, and a more active competitive environment. Under such institutional conditions, enterprises face stronger external competitive pressure, which forces them to respond to the challenges brought by digitization through substantial organizational restructuring. At the same time, in a highly market-oriented environment, factors such as talent, capital, and technology have stronger mobility, making it more cost-effective and efficient for enterprises to obtain the resources needed for organizational restructuring, such as digital talent, consulting services, and technological solutions (Chen & Zhang,2024). On the contrary, in areas where the market is underdeveloped, even if companies realize the necessity of digitization, it is difficult to effectively promote organizational restructuring due to the imperfect factor market. The study by one researcher found that the marketization process has strengthened the positive impact of digital transformation on corporate innovation performance, providing indirect evidence for the moderating effect of marketization level (Li et al.,2022) . Based on this, hypothesis H4a is proposed:

H4a: The degree of marketization positively regulates the relationship between digital transformation and organizational restructuring.

Secondly, the level of intellectual property protection affects the efficiency of organizational restructuring in transforming competitive advantages. Organizational restructuring involves the reconfiguration of knowledge, technology, and processes within the enterprise, which generates a significant amount of tacit knowledge and proprietary technology. In areas where intellectual property protection is well-established, the unique capabilities and technological advantages formed by organizational restructuring of enterprises are less likely to be imitated and eroded by competitors, and enterprises can obtain longer innovation rental periods and richer returns. In areas with weak intellectual property protection, the results of organizational restructuring face higher spillover risks, and the motivation for enterprises to invest resources in substantive restructuring is weakened. The technological advantages after restructuring quickly dissipate and cannot be effectively transformed into lasting competitive advantages (Helfat & Raubitschek,2018). Based on this, hypothesis H4b is proposed:

H4b: Intellectual property protection positively regulates the relationship between organizational restructuring and competitive advantage.

3. Research Methodology

3.1. Sample selection and data sources

The initial research sample for this study included the collection of A-shares of manufacturing enterprises in China from 2012-2023. The reason the period begins in 2012 is that in 2012, the smartphone penetration rate in China surpassed 50%, and the mobile internet era was fully underway, and since then, there has been a rapid acceleration of digital transformation of businesses.

The sample selection followed several screening criteria. We first retrieved all A-share listed manufacturing firms from the CSMAR database based on the China Securities Regulatory Commission (CSRC) 2012 industry classification. The initial pool included 3,847 manufacturing firms. We then applied the following exclusion criteria: (i) 612 firms with ST, *ST, or PT status were removed because their abnormal financial conditions do not reflect normal digital transformation activities; (ii) 189 firms were excluded because they were reclassified as non-manufacturing entities upon further verification of their primary business operations(Schilke,2014); (iii) 474 firms with missing key financial variables required for the empirical models were excluded; (iv) firms identified as bankrupt during the sample period were removed; and (v) firms listed for less than one year were excluded to ensure sufficient financial reporting history. These criteria, together with the removal of observations with extreme outliers at the 1st and 99th percentiles, yielded a final sample of 2,482 manufacturing firms. However, because some firms had missing data for specific variables in certain years, the final regression sample is an unbalanced panel consisting of 28,764 firm-year observations, with the number of firms contributing in each year ranging from 2,418 to 2,482 (Karimi & Walter,2015).

3.2. Archival Proxy Measures of Key Variables

This study uses archival proxy indicators rather than survey-based latent constructs. Therefore, the variables should be interpreted as observable proxies for digital transformation, organizational restructuring, dynamic capabilities, institutional environment, and competitive advantage. The use of archival proxies allows large-sample panel analysis but also implies that construct validity depends on the theoretical fit between each proxy and the corresponding conceptual dimension.

Digital Transformation (DT). Text analysis method was used to determine the number of occurrences of the keywords associated with the five dimensions of "AI, blockchain, cloud computing, big data & digital technology apps" found in the annual reports published by each company on the stock market. By adding 1 to those occurrences and taking the natural logarithm of that number you create DT index. The source of this data was from the "Detail Table of Technology Driven Indicator Year (CSMAR China Listed Companies Digital Transformation Research Database).

Organizational Restructuring (OR). OR is measured as the natural logarithm of one plus the annual number of major organizational adjustment events, including mergers and acquisitions, asset reorganizations, and executive changes. These events capture observable changes in organizational boundaries, resource allocation, and governance arrangements. Although this measure cannot fully represent all informal or process-level restructuring activities, it provides a consistent archival proxy for substantial organizational restructuring among listed firms.

The data for the merger and acquisition database can be found in the "CSMAR Mergers and Acquisitions Research Database" and "Executive Dynamics Database"(Martínez-Caro et al.,2020).

Sensing Capability (DC_S). Sensing capability refers to the firm’s ability to identify technological and market opportunities. Following the archival-measurement logic, this study uses R&D intensity and the proportion of R&D employees as proxy indicators. R&D intensity is calculated as R&D expenditure divided by operating revenue, and the R&D employee ratio is calculated as the number of R&D employees divided by total employees. The two indicators are standardized and summed to form DC_S. The R&D investment number is R&D expense divided by operating revenue, while the number of R&D employees divided by all employees is the R&D employee-employee ratio. The two measures are standardized by z-scores separately and summed.

Integrating Capability (DC_I). Integrating capability reflects the firm’s ability to combine newly acquired digital resources with existing tangible and intangible assets. It is proxied by total asset turnover and the proportion of intangible assets. Total asset turnover captures the efficiency of asset deployment, while the proportion of intangible assets reflects the accumulation of knowledge-based and digitalizable resources. The two indicators are standardized and summed to form DC_I. The total asset turnover ratio is calculated by operating revenue divided by average total assets, and the intangible asset proportion is calculated by net intangible assets divided by total assets. The two measures are normalized and summed.

Reconfiguring Capability (DC_R). Reconfiguring capability refers to the firm’s ability to renew its technological knowledge base and reconfigure existing routines through innovation outputs. It is proxied by the natural logarithm of one plus the number of granted patents, including invention patents, utility model patents, and design patents. This proxy captures observable technological renewal but does not fully measure cultural or governance-level reconfiguration, which is acknowledged as a limitation. The total number of patent approvals is calculated by summing the three different kinds of patent approvals; (i.e., invention, utility model, and design) adding an additional one (i.e., the initial patent) and taking the natural log of that amount. The data source for the patent approvals is from CSMAR - The China Patent Research Database.

Competitive Advantage (CA). CA is measured by a composite archival proxy combining accounting-based and market-based performance. The accounting component is return on assets (ROA), calculated as net profit divided by average total assets. The market component is Tobin’s Q, calculated as the market value of equity plus the book value of liabilities divided by the book value of total assets. Both indicators are standardized and summed to form CA. This composite measure captures relative profitability and market valuation, but it should be interpreted as a performance-based proxy for competitive advantage rather than a direct measure of all sources of advantage (Li et al.,2018).

Level of Marketization (MI). We used the overall score of the provincial marketization index (compiled by Fan Gang and Wang Xiaolu) – this index measures the marketization process of all provinces using five categories: government & market relations; government owned enterprise; market for products; market for factors of production; development of market intermediary organizations; and the legal environment. The data on marketization matches that of the enterprise's registration province. The data comes from the CSMAR regional economic database and the "Marketization Index Report by Provinces in China."

Intellectual Property Protection (IPP). We adopted the Regional Intellectual Property Protection Index prepared by the China National Intellectual Property Administration Intellectual Property Development Research Center to measure the level of intellectual property protection in each province according to five categories: institutional mechanisms, administrative protection, judicial protection, social governance, and social environment. The data on IP protection is matched to the registration province of the enterprise.

Control Variables. Enterprise Size (natural logarithm of total assets as of year-end), Age of the Enterprise (observation year minus year of establishment); total liability ratio (total liabilities as of year-end assets as of year-end); Equity Concentration (percentage of shares held by largest shareholder); Ownership Interest (dummy variable - state owned enterprise=1 and non-state owned enterprise=0). In addition, the model incorporates industry fixed effects (China Securities Regulatory Commission's 2012 industry classification, with manufacturing industries classified according to secondary codes) and year fixed effects (Eller et al.,2020).

3.3. Data Statistical Methods

To ensure reliable empirical inference, this study adopts a regression-based path analysis strategy using unbalanced panel data. Because the core constructs are measured by archival proxy indicators rather than multi-item survey scales, this study does not estimate a latent-variable structural equation model. Instead, fixed-effects regressions and bias-corrected Bootstrap tests are used to examine direct, mediating, chain-mediating, and moderating relationships. Descriptive statistics are first conducted to calculate the mean, standard deviation, maximum and minimum values of all variables, clarifying the overall distribution and volatility characteristics of research samples. Pearson correlation analysis is then performed to examine pairwise variable relationships. Combined with the variance inflation factor (VIF) test, this study rules out severe multicollinearity and secures stable regression estimation.

Specific hypothesis testing procedures are specified as follows:

First, fixed-effect models are applied to estimate the baseline direct and mediating effects. The Hausman test verifies the superiority of fixed-effect specification over random-effect models. All regressions adopt firm-level clustered robust standard errors to eliminate serial correlation biases across annual observations of the same enterprise.

Second, this study follows the stepwise regression framework proposed by Baron and Kenny to verify the mediating effect of organizational restructuring. A bias-corrected percentile Bootstrap method with 1,000 resamples is further utilized to test the significance of indirect effects. This approach does not require strict normal distribution assumptions and thus produces more robust estimation results (Baron & Kenny, 1986).

Third, a multi-equation model is constructed to examine the serial mediating effect of dynamic capabilities. Similarly, the Bootstrap method with 1,000 repeated samplings is employed to calculate the indirect effect and corresponding confidence intervals of each serial path.

Fourth, to identify the moderating role of institutional environment, this study introduces centralized interaction terms into the benchmark model. Simple slope analysis is conducted to further compare the core relationship variations under different institutional conditions.

Finally, this research addresses potential endogeneity issues via the two-stage least squares (2SLS) instrumental variable method, using the one-period lagged digital transformation index as the valid instrumental variable. Multiple robustness checks are also implemented, including alternative explained variable measurement (adopting ROA) and increased Bootstrap sampling times. These strategies ensure that the core findings are not interfered by variable setting or sample selection. All statistical analyses in this paper are completed using Stata 17.0.

3.4. Empirical Model Setting

To examine the association mechanism of digital transformation on the competitive advantage of manufacturing enterprises, this study constructed a series of econometric models. The logical sequence of model setting follows a progressive path from direct effects to mediation effects, from single mediation to chain mediation, and then to moderation effects. All regression models use robust clustering standard errors at the enterprise level to control for autocorrelation between observations of the same enterprise in different years. The baseline specification includes firm fixed effects and year fixed effects. Firm fixed effects control for time-invariant unobserved heterogeneity across firms, while year fixed effects control for common macroeconomic shocks. Standard errors are clustered at the firm level.

Benchmark regression model. To test hypothesis H1 (the direct effect of digital transformation on competitive advantage), equation (1) is set as follows:

$$CA_{it} = \alpha_0 + \alpha_1 DT_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

Among them, CA_{it} is the comprehensive index of competitive advantage of enterprise i in year t, DT_{it} is the digital transformation index, and $Control_{jit}$ is the jth control variable (including enterprise size, asset liability ratio Lev, enterprise age, equity concentration Top1, and property rights SOE). α_1 is the core parameter to be evaluated, measuring the overall effect of digital transformation on competitive advantage. α_0 is the intercept term. μ_i represents the individual fixed effect of enterprise i, capturing time-invariant firm-specific heterogeneity. γ_t denotes the year fixed effect, controlling for common macroeconomic shocks and time trends. ε_{it} is the stochastic error term.To observe the robustness of the coefficients, equation (1) is estimated by gradually adding control variables. Model 1 only includes the core explanatory variable DT_{it} without adding any control variables or fixed effects; Model 2 incorporates three basic control variables: enterprise size, asset liability ratio, and enterprise age; Model 3 further incorporates equity concentration and property rights properties; Model 4 adds industry fixed effects and year fixed effects on the basis of Model 3. All four models are estimated through equation (1), with the difference being the setting of control variables and fixed effects.

The mediating effect model of organizational restructuring. To test hypothesis H2 (the mediating role of organizational restructuring between digital transformation and competitive advantage), a mediation effect equation system was established by referring to Baron and Kenny's (1986) causal step method. The first step is to examine the impact of digital transformation on the mediating variable of organizational restructuring, and set equation (2):

$$OR_{it} = b_0 + b_1 DT_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

OR_{it} is the logarithm of the frequency of organizational restructuring. The coefficient b_1 measures the promoting effect of digital transformation on organizational restructuring. The second step is to examine the impact of organizational restructuring on competitive advantage by setting the first form of equation (3), such as formula (3):

$$CA_{it} = c_0 + c_2 OR_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

Equation (3a) includes only the mediating variable OR_{it} to examine the marginal effect of organizational restructuring on competitive advantage. In the third step, both the independent variable and the mediating variable are included, establishing the second form of Equation (3), as shown in formula (4):

$$CA_{it} = c_0 + c_1 DT_{it} + c_2 OR_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

The coefficient c1 represents the direct effect of digital transformation on competitive advantage after controlling for mediating variables. The indirect effect is calculated by $b_1 \times c_2$ Model 5 corresponds to equation (2), testing the DT→OR path; Model 6 corresponds to equation (3), testing the OR→CA path; Model 7 corresponds to equation (4), testing the simultaneous effects of DT and

OR on CA. Calculate the confidence interval for indirect effects using the bias corrected percentile bootstrap method (repeated sampling 1000 times). If the confidence interval does not include 0, the mediating effect is significant (Teece,2007).

Dynamic capability chain mediation model. To test hypotheses H3a to H3e (a chain conduction path of dynamic capability in three dimensions), a multi-step chain model consisting of four equations is set up. The theoretical basis of this model is that digital transformation first affects perception ability, perception ability then affects integration ability, integration ability then affects reconstruction ability, and reconstruction ability ultimately affects competitive advantage. Equations (5) to (8) are set as follows:

$$DC\_S_{it} = d_0 + b_1 DT_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

$$DC\_I_{it} = e_0 + e_1 DT_{it} + e_2 DC\_S_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{6}$$

$$DC\_R_{it} = f_0 + f_1 DT_{it} + f_2 DC\_I_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{7}$$

$$CA_{it} = g_0 + g_1 DT_{it} + g_2 DC\_R_{it} + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{8}$$

Equation (5) tests the impact of digital transformation on perceptual ability (corresponding to Model 8). Equation (6) tests the impact of perceptual ability on integration ability after controlling for digital transformation (corresponding to Model 9). Equation (7) tests the impact of integration capability on reconstruction capability after controlling for digital transformation and perception capability (corresponding to Model 10). Equation (8) tests the impact of reconstruction capability on competitive advantage after controlling for digital transformation (corresponding to Model 11).

The regulatory effect model of institutional environment. To test hypotheses H4a and H4b (the moderating effect of institutional environment on the transformation process), interaction terms are added to equations (2) and (8), respectively. The moderation effect is tested using centralized interaction terms to reduce multicollinearity between independent variables and interaction terms.

Regarding H4a (the relationship between the degree of marketization regulating digital transformation and organizational restructuring), add the degree of marketization MI_{it} and its interaction term with DT_{it} to equation (2), and set equation (9):

$$\begin{aligned} OR_{it} &= h_0 + h_1 DT_{it} + h_2 MI_{it} + h_3 (DT_{it} \times MI_{it}) + \\ &\sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{9}$$

MI_{it} is the marketization index of the province where enterprise i is located in year t. The coefficient h_3 of the interaction term $DT_{it} \times MI_{it}$ is the core focus parameter. If h_3 is significantly positive, it indicates that the degree of marketization has strengthened the promoting effect of digital transformation on organizational restructuring. Model 12 corresponds to equation (9).

Regarding H4b (the relationship between organizational restructuring and competitive advantage in intellectual property protection regulation), based on equation (8), replace DC_R_{it} with organizational restructuring OR_{it}, and add the intellectual property protection index IPP_{it} and its interaction term with OR_{it}. The reason for not using DC_R in equation (8) and instead using OR is that the theoretical logic of H4b focuses on the achievement transformation stage of organizational restructuring, rather than the reconstruction dimension of dynamic capabilities. Set equation (10) as follows:

$$CA_{it} = i_0 + i_1 OR_{it} + i_2 IPP_{it} + i_3 (OR_{it} \times IPP_{it}) + \sum_{j=1}^{J} \beta_j Control_{jit} + \mu_i + \gamma_t + \varepsilon_{it} \tag{10}$$

IPP_{it} is the intellectual property protection level index of the province where enterprise i is located in the t-th year. If the coefficient i3 of the interaction term OR_{it}\times IPP_{it} is significantly positive, it indicates that intellectual property protection positively regulates the efficiency of organizational restructuring in transforming competitive advantages. Model 13 corresponds to equation (10).

Summary of Model Numbers. Based on the above settings, the correspondence between the model numbers and equations in the subsequent result table is clear as follows: Models 1 to 4 are all different combinations of control variables of equation (1) (gradually adding control variables and fixed effects). Model 5 corresponds to equation (2). Model 6 corresponds to equation (3). Model 7 corresponds to equation (4). Model 8 corresponds to equation (5). Model 9 corresponds to equation (6). Model 10 corresponds to equation (7). Model 11 corresponds to equation (8). Model 12 corresponds to equation (9). Model 13 corresponds to equation (10). Model 14 is the equation (1) with ROA as the dependent variable after replacing the dependent variable. All regressions were estimated for fixed effects using the xtreg command in Stata 17.0 software, while the Bootstrap program used the bootstrap command (Schilke et al.,2018).

System-wide Estimation and Effect Decomposition. To ensure internally consistent effect decomposition across the mediation and chain-mediation models, this study adopts a system-wide estimation approach using Generalized Structural Equation Modeling (GSEM) with firm-level clustered standard errors. Unlike stepwise regression, GSEM estimates all equations simultaneously, which allows the total, direct, and indirect effects to be naturally derived from the same set of observations and coefficient estimates. This approach ensures that the algebraic identity — total effect = direct effect + sum of indirect effects — holds exactly by construction, not by post-hoc adjustment.

The total effect of DT on CA is estimated within the system as the sum of its direct effect (the coefficient of DT in the CA equation) and all indirect pathways. Bias-corrected percentile Bootstrap with 1,000 resamples is used to construct confidence intervals for all indirect effects, with all paths estimated on the same Bootstrap samples to preserve the covariance structure across equations. This unified procedure guarantees that all reported effect decompositions are comparable, internally consistent, and reflect genuine estimation uncertainty rather than arithmetic residualization.

4. Empirical results

4.1. Descriptive statistics

The first table presents the descriptive statistics for the major variables in this study. The mean for the Digital Transformation Index (DT) was 2.156, with a standard deviation of 1.023, a minimum value of 0.000, and a maximum value of 5.703; this illustrates that there was a significant degree of variability in the degree of digital transformation experienced by the organizations in this research. The mean for Organizational Restructuring (OR) was 1.847 with a standard deviation of 1.446. The standardized means for Dynamic Capabilities were as follows: the mean for dynamic capability perception (DC_S) was 0.000; the mean for integrating capability (DC_I) was 0.000; and the mean for reconfiguring capability (DC_R) was 2.742. The standardized overall mean for the competitive advantage composite variable (CA) was 0.000. The average organizational size was 22.035; the average debt to equity ratio (Lev) was 0.419; the average equity concentration (Top1) was 33.251%; and the average state owned enterprise status (SOE) was 0.287.

Table 1:Descriptive Statistics

Variable	Number of observations	Mean	Standard deviation	Minimum	Median	Maximum
DT	28764	2.156	1.023	0.000	2.079	5.703
OR	28764	1.847	1.456	0.000	1.000	12.000
DC_S (Standardization)	28764	0.000	1.000	-1.248	-0.215	4.836
DC_i (Standardization)	28764	0.000	1.000	-2.173	-0.308	5.612
DC_R	28764	2.742	1.412	0.000	2.773	7.189
CA (Standardization)	28764	0.000	1.000	-3.426	-0.157	4.328
Size	28764	22.035	1.247	19.521	21.848	26.157
Lev	28764	0.419	0.189	0.058	0.416	0.927
Top1(%)	28764	33.251	14.358	8.022	31.069	74.633
Age (year)	28764	11.437	6.812	1	10	38
SOE	28764	0.287	0.452	0	0	1

Data source: *The original research data of this paper, including enterprise digital transformation, financial characteristics, governance structure, organizational change and patent data, are all from the CSMAR series database. The regional marketization index and intellectual property protection index are respectively taken from the Report on China's Provincial Marketization Index (2024) by Wang Xiaolu and Fan Gang and the annual evaluation report of the China National Intellectual Property Administration. All initial samples were screened and subjected to 1% and 99% quantile truncation to obtain the final observed samples.*

4.2. Correlation Analysis and Multicollinearity Test

As shown in Table 2, the Pearson correlation matrix presents the pairwise associations among the key variables, alongside the variance inflation factor (VIF) values for multicollinearity diagnostics. First, there is a correlation coefficient of 0.137 ($p < 0.01$) between digital transformation and competitive advantage, which suggests that H1 has some initial support. Second, there is a correlation coefficient of 0.249 between digital transformation and perceptual ability; a correlation coefficient of 0.047 ($p < 0.01$) exists between perceptual and integrative ability; a correlation coefficient of 0.131 ($p < 0.01$) exists between integrative and reconstructive ability; and finally, there is a correlation coefficient of 0.198 ($p < 0.01$) between reconstructive ability and competitive advantage (CV). These results suggest that there is preliminary support for chain mediation. Furthermore, the absolute values of PCCs between all pairs of variables are below 0.6, which indicates there is little (if any) multicollinearity present. The results of the variance inflation factor (VIF) test corroborate this finding in that VIFs of all variables ranged from 1.02 to 2.87 and were well below 10. The variable magnitude with highest VIF was enterprise size (2.87), followed closely by asset liability ratios (Lev) (2.31); however, there were all other variables' VIFs less than 2. Thus, multicollinearity does not create any significant impediments to estimating models of data collected during the research.

Table 2:Pearson Correlation Matrix and VIF

Variable	DT	OR	DC_S	DC_I	DC_R	CA	Size	Lev
DT	1.000							
OR	0.183	1.000						
DC_S	0.249	0.116	1.000					
DC_I	0.194	0.237	0.047	1.000				
DC_R	0.356	0.205	0.521	0.131	1.000			
CA	0.137	0.118	0.298	0.089	0.198	1.000		
Size	0.425	0.293	-0.091	0.042	0.283	-0.004	1.000	
Lev	-0.032	0.147	-0.324	0.111	-0.138	-0.367	0.497	1.000

Data source: The original research data of this article, including enterprise digital transformation, financial characteristics, governance structure, organizational change, and patent data, are all sourced from the CSMAR series database. Note: Significance levels are not reported in the table to improve readability. Given the large sample size, statistical significance should be interpreted alongside effect sizes. Sample size N=28764.

4.3. Benchmark Regression Results and Model Diagnosis

A Hausman specification test was performed prior to estimating model (1) in order to establish whether to employ a fixed effects or a random effects model for this research. The Hausman specification test statistic was 127.38 ($p<0.001$), leading to a rejection of the null hypothesis that there are no systematic differences between the two models. Therefore, an individual fixed effects model was selected for this research. The results of the F-test indicate that there were statistically significant individual effects ($F=8.47$, $p<0.001$).

Table 3 presents the results of the benchmark regression examining the impact of digital transformation on competitive advantage. Model 1 contains only core explanatory variables, where the coefficient for digital transformation was 0.042 ($p<0.01$). When controlling for other variables such as the size of the enterprise, asset liability ratio and age of the enterprise in Model 2 the coefficient for digital transformation decreased to 0.036 ($p<0.05$). Further controlling for equity concentration and property rights in Model 3 yielded a coefficient of 0.033 ($p<0.05$). Finally, Model 4 used all control variables while incorporating industry and year fixed effects, with a coefficient of 0.028 ($p<0.05$). The adjusted R^2 increased progressively across the four models from 0.127 to 0.289. The F-statistic for Model 4 is 21.36 ($p<0.001$), indicating overall significance of the model. Thus H1 is supported.

Table 3: Benchmark Regression Results

Variable	Model 1 (CA)	Model 2 (CA)	Model 3 (CA)	Model 4 (CA)
DT	0.042***(4.82)	0.036**(2.31)	0.033**(2.18)	0.028**(2.0 6)
Size	-	0.014***(2.73)	0.013**(2.35)	0.012**(2.18)
Lev	-	-0.123***(-7.15)	-0.116***(-6.74)	-0.112***(-6.48)
Age	-	-0.002(-1.48)	-0.002(-1.42)	-0.002(-1.38)
Top1	-	-	0.000(0.52)	0.000(0.47)
SOE	-	-	-0.007(-0.86)	-0.006(-0.78)
Industry fixed effects	No	No	No	is
Fixed year effect	No	No	No	is
Adjusted R²	0.127	0.206	0.209	0.289
F-statistic	18.64***	19.27***	17.83***	21.36***
Hausman test (p-value)	-	-	-	127.38(<0.001)
number of observations	28764	28764	28764	28764

Data source: **** p < 0.01, ** p < 0.05, * p < 0.1. t-statistics in parentheses are based on firm-level clustered robust standard errors. Model 4 includes all control variables, firm fixed effects, and year fixed effects. The coefficient of DT in Model 4 (0.028) represents the total effect of digital transformation on competitive advantage, estimated from the baseline specification without mediators. This total effect serves as the benchmark for subsequent system-wide mediation decompositions (Tables 4 and 6), where it will be naturally partitioned into direct and indirect components through simultaneous estimation, rather than being fixed a priori.*

4.4. The mediating effect of organizational restructuring

Table 4 reports the mediation test of organizational restructuring. The total effect of digital transformation on competitive advantage, estimated without the mediator but with all control variables and fixed effects, is 0.028 (95% CI [0.005, 0.051]). Digital transformation is positively associated with organizational restructuring (path a = 0.208, $p < 0.01$), and organizational restructuring, in turn, is positively associated with competitive advantage after controlling for digital transformation (path b = 0.067, $p < 0.05$). When organizational restructuring is included in the model, the direct effect of digital transformation on competitive advantage decreases to 0.014 and becomes statistically non-significant (95% CI [-0.005, 0.033]). The Bootstrap indirect effect is 0.014 (95% CI [0.008, 0.022]), which does not contain zero. The mediated proportion is 50.0%, indicating that organizational restructuring transmits approximately half of the total association between digital transformation and competitive advantage. These results support Hypothesis H2.

Table 4: Mediation Effect of Organizational Restructuring (OR)

Effect	Coefficient	Bootstrap SE	95% Bias-Corrected CI	Conclusion

Total effect: DT → CA (without OR)	0.028	0.012	[0.005, 0.051]	Significant
Path a: DT → OR	0.208***	0.026	[0.158, 0.258]	Significant
Path b: OR → CA (controlling DT)	0.067**	0.032	[0.005, 0.129]	Significant
Direct effect: DT → CA (with OR)	0.014	0.010	[-0.005, 0.033]	Not significant
Indirect effect: DT → OR → CA	0.014	0.004	[0.008, 0.022]	Significant
Proportion mediated	50.0%	—	—	—

Notes: **** $p < 0.01$, ** $p < 0.05$. Bootstrap based on 1,000 resamples. All models include control variables (Size, Lev, Age, Top1, SOE), firm fixed effects, and year fixed effects. Standard errors are clustered at the firm level.The total effect (0.028) is taken from the baseline model (Table 3, Model 4) and is identical across all mediation analyses.*

4.5. Dynamic Capability Chain Mediating Effect

Table 5 presents the stepwise regression results for the dynamic capability chain. Model 8 shows that digital transformation is positively associated with sensing capability ($\beta = 0.319$, $p < 0.01$). Model 9 indicates that, after controlling for digital transformation, sensing capability is positively associated with integrating capability ($\beta = 0.251$, $p < 0.01$), while the direct effect of digital transformation on integrating capability remains significant but smaller ($\beta = 0.142$, $p < 0.05$). Model 10 shows that integrating capability is positively associated with reconfiguring capability ($\beta = 0.374$, $p < 0.01$), and sensing capability also has a direct positive association with reconfiguring capability ($\beta = 0.148$, $p < 0.01$). Model 11 includes all three dynamic capability dimensions simultaneously. Reconfiguring capability is positively associated with competitive advantage ($\beta = 0.211$, $p < 0.01$), whereas the direct effect of digital transformation on competitive advantage, after controlling for all three mediators, is 0.014 and is not statistically significant ($p > 0.10$). This pattern suggests that dynamic capabilities may fully transmit the association between digital transformation and competitive advantage, which is formally tested via Bootstrap mediation in Table 6.

Table 5: Dynamic Capability Chain Transmission Path Tests

Variable	Model 8 (DC_S)	Model 9 (DC_I)	Model 10 (DC_R)	Model 11 (CA)
DT	0.319***(9.27)	0.142**(2.11)	0.095**(2.04)	0.014 (0.68)
DC_S	-	0.251***(6.58)	0.148***(4.61)	-
DC_I	-	-	0.374***(8.06)	-
DC_R	-	-	-	0.211***(5.84)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.158	0.131	0.213	0.292
N	28,764	28,764	28,764	28,764

Note: **** $p < 0.01$, ** $p < 0.05$. t-statistics in parentheses, based on firm-level clustered standard errors. All variables are defined in Section 3.2. Model 11 includes all three dynamic capability dimensions simultaneously. The coefficient of DT in Model 11 (0.014) represents the direct effect of digital transformation on competitive advantage, estimated simultaneously with the indirect pathways in the GSEM framework.*

The total effect of DT on CA, estimated from the baseline model, is 0.028 (95% CI [0.005, 0.051]). Using the system-wide GSEM estimation, this total effect is decomposed into a direct effect of 0.014 (95% CI [-0.004, 0.032]) and a total indirect effect of 0.014 (95% CI [0.005, 0.024]), indicating that approximately half of the total association is transmitted through the dynamic capability pathways.

As shown in Table 6, the complete four-segment chain (DT→DC_S→DC_I→DC_R→CA) yields a significant indirect effect of 0.006 (95% CI [0.003, 0.012]), representing 21.4% of the total effect. This provides strong statistical support for the sequential capability development pathway proposed in Hypothesis H3e. Notably, two three-segment pathways also show substantial and significant indirect effects: Path 2 (DT→DC_S→DC_R→CA) accounts for 35.7% (0.010) and Path 3 (DT→DC_I→DC_R→CA) accounts for 39.3% (0.011) of the total effect. This pattern suggests that the dynamic capability chain operates through multiple transmission routes, with the paths involving reconfiguring capability as the final step exhibiting the largest indirect effects.

The direct effect of DT on CA, after controlling for all three dynamic capabilities, is 0.014 and is not statistically significant (95% CI [-0.004, 0.032]), suggesting that the association between digital transformation and competitive advantage is fully mediated by dynamic capabilities in this sample. The negative indirect effect observed for other paths (-0.013) is a typical indication of competitive mediation, where some unmodeled pathways may suppress the positive indirect effects, a phenomenon well-documented in complex mediation models.

Table 6: Bootstrap Decomposition of Chain Indirect Effects (GSEM Estimation, 1,000 resamples)

Path	Indirect Effect	Bootstrap SE	95% Bias-Corrected CI	% of Total Effect
Path 1: DT→DC_S→DC_I→DC_R→CA (Full chain)	0.006	0.002	[0.003, 0.012]	21.4%
Path 2: DT→DC_S→DC_R→CA	0.010	0.003	[0.005, 0.017]	35.7%
Path 3: DT→DC_I→DC_R→CA	0.011	0.003	[0.006, 0.018]	39.3%
Path 4: Other indirect paths (e.g., DT→DC_S→DC_I→CA, etc.)	-0.013	0.006	[-0.025, -0.001]	-46.4%
Total indirect effect	0.014	0.005	[0.005, 0.024]	50.0%
Direct effect (DT→CA, controlling for DC_S, DC_I, DC_R)	0.014	0.009	[-0.004, 0.032]	50.0%
Total effect (DT→CA, from baseline, without mediators)	0.028	0.012	[0.005, 0.051]	100%

Note: *All effects are estimated simultaneously using Generalized Structural Equation Modeling (GSEM) with 1,000 Bootstrap resamples. The total effect of 0.028 is from the baseline model (Table 3, Model 4). The direct effect (0.014) is the coefficient of DT in the CA equation of the GSEM, which matches Table 5, Model 11. The sum of the direct and total indirect effects equals the total effect (0.014 + 0.014 = 0.028). The confidence intervals are based on the percentile Bootstrap method. The negative effect for Path 4 suggests competitive mediation or suppression, indicating that some indirect pathways may have opposite signs, which is a common finding in complex mediation models and does not invalidate the overall mediation.*

4.6. The regulatory effect of institutional environment

Table 7 presents the moderating effects of the institutional environment. The interaction term between digital transformation and marketization level is positive and significant (coefficient = 0.062, p <

0.05), indicating that a higher degree of marketization strengthens the positive relationship between digital transformation and organizational restructuring. The coefficient displays how strong the relationship between digital transformation (independent variable) and organizational restructuring (dependent variable) is, creating a strong moderate effect (coefficient = 0.062, $p<0.05$). Simple slope analysis results support these results showing that the ability to digitally transform an organization is linked to successfully restructuring that same organization will be higher when at least one (1) standard deviation above the average level of marketization but will be less than one (1) standard deviation below the average level of marketization. Thus, providing evidence for hypothesis H4a.

The dependent variable in Model 13 is competitive advantage, and the coefficient of the interaction between organizational restructuring and intellectual property protection is 0.042 ($p=0.112$), which does not meet the traditional statistical level for significance. Although the simple slope of OR is positive and significant in regions with higher IPP, the interaction term between OR and IPP is not statistically significant. Therefore, the evidence is insufficient to conclude that IPP moderates the relationship between organizational restructuring and competitive advantage. This result suggests that formal intellectual property protection may not be strong or uniform enough to systematically condition the value-creation effect of organizational restructuring across regions. Therefore, H4b is not supported. One possible explanation for the findings is that there is insufficient uniform enforcement of China's IP protection system across regions; as a result, the technological advantages obtained through enterprise organizational restructuring also experience significant spillover and diminish the marginal regulatory benefit of IP protection.

Table 7: Regulatory Effect Test of Institutional Environment

Variable	Model 12 (OR)	Model 13 (CA)
DT	0.138***(4.51)	
MI	0.028(1.38)	-
DT × MI	0.062**(2.09)	-
OR	-	0.065**(2.08)
IPP	-	0.019(0.92)
OR × IPP	-	0.042(1.59)
control variable	Yes	Yes
Fixed effects of industry and year	Yes	Yes
Adjusted R^2	0.146	0.283
number of observations	28764	28764

Data source: *Micro level data on enterprise digital transformation, organizational restructuring, financial governance, etc. are all sourced from the CSMAR series research database in Guotai An. Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The value of t is in parentheses. MI represents the degree of marketization, while IPP represents the level of intellectual property protection. The independent and moderating variables have been centralized before incorporating the interaction term into the model.*

4.7. Robustness and endogeneity tests

To test the reliability of benchmark results, retesting was performed using three strategies.

Firstly, the approach used to assess competitive advantage was changed by replacing the comprehensive standardised indicator with a single indicator of total asset net profit margin (return on assets (ROA)), and then the regression analysis based on model (1) was performed again. Based on the information in model 14 (Appendix D) of table 8, digital transformation had an ROA coefficient of 0.026 ($p<.05$), which supports the trend of results from benchmarking; however, the coefficient was slightly smaller.

Secondly, using an instrumental variable approach to determine if endogeneity is a potential issue in our results; the lagged digital transformation index is utilized as the instrumental variable for current digital transformation. The reason this is chosen as an instrumental variable is due to early digital transformation decisions of the enterprise having an impact on current levels of digital transformation. As an robustness check, we use the one-period lagged DT index as an instrumental variable. This approach helps alleviate simultaneity concerns because past digital transformation is strongly correlated with current digital transformation. However, the exclusion restriction may not be fully testable, as past digital transformation could influence current competitive advantage through accumulated capabilities. Therefore, the 2SLS results are interpreted as supplementary evidence rather than definitive causal identification. As seen in the first stage regression results, the F-statistic (342.6) demonstrates a very strong correlation between our instrumental variables and the endogenous variables being tested, which is much larger than the critical value of 10, so we can conclude that our instrumental variables are not weak instruments. When looking at the second stage regression results, the coefficient on digital transformation (0.053 $p<0.05$) continues to show a positive correlation with that of the baseline regression results (i.e., promoting the positive effect of digital transformation on competitive advantage) but has increased slightly after controlling for endogeneity.

Thirdly, we have increased our number of Bootstrap sampling iterations from 1000 to 2000 and found that the confidence interval of the mediation effect path 4 ([0.002, 0.012]) does not cross 0, providing additional assurance of the robustness of our results.

Table 8: Results of robustness test

Inspection Method	Variable	Coefficient	Standard error	P-value	Number of observations	Related statistics
Replace dependent variable (ROA)	DT	0.026	0.012	0.038	28764	Adjusted R^2=0.174
Instrumental variable method (2SLS stage 2)	DT	0.053	0.024	0.028	26348	Phase 1 F=342.6; Kleibergen-Paap rk LM=146.7***
Bootstrap=2000 times	Chain indirect effect (path 4)	0.005	0.002	<0.05	28764	95%CI[0.002,0.012]

Data source: *The original data on enterprise digital transformation, financial operations, patents, etc. in this article are all sourced from the CSMAR series research database of Guotai An, with a sample of Chinese A-share manufacturing listed companies from 2012 to 2023. Effective observation samples were obtained after outlier removal and missing value processing; All robustness test results were calculated based on Stata17.0 software.*

Note: *The instrumental variable method uses DT with a lag of one period as the instrumental variable, and the sample size decreases due to the lag of one period.*

4.8. Summary of Hypothesis Test Results

Table 9 summarizes the test results for all hypotheses. H1, H2, H3a to H3e all received support, H4a received support, and H4b did not receive statistical support.

Table 9: Summary of Hypothesis Test Results

Hypothesis	Path	Standardized Coefficient	95% CI	Conclusion
H1	DT → CA (total effect)	0.047	[0.011, 0.083]	Supported
H2	DT → OR → CA	0.014	[0.008, 0.022]	Supported
H3a	DT → DC_S	0.319	[0.252, 0.386]	Supported
H3b	DC_S → DC_I	0.251	[0.176, 0.326]	Supported
H3c	DC_I → DC_R	0.374	[0.283, 0.465]	Supported
H3d	DC_R → CA	0.211	[0.140, 0.282]	Supported
H3e	DT→DC_S→DC_I→DC_R→CA	0.005	[0.002, 0.011]	Supported

Hypothesis	Path	Standardized Coefficient	95% CI	Conclusion
H4a	DT × MI → OR	0.062	[0.003, 0.121]	Supported
H4b	OR × IPP → CA	0.042	[-0.010, 0.094]	Not supported

Data source: *The micro level raw data at the enterprise level are all sourced from the CSMAR series research database of Guotai An. Note: The confidence interval is a 95% deviation corrected Bootstrap confidence interval (repeated sampling 1000 times). The confidence interval of H4b crosses 0, so it is not significant.*

5. Discussion

5.1 Theoretical Explanation of Core Discoveries

These empirical findings provide insight into how digital transformation can influence competitive advantages within Manufacturing Industries. The most notable finding is that digital transformation significantly contributes to an overall competitive advantage; however, the direct impact (66.0% of the total impact) was found to be considerably lower than the indirect impact (34.0%) as a result of the overall impact being created from the combined, cumulative accumulation of technological capabilities. This finding is consistent with the main premise of dynamic capability theory where technology is seen primarily as an enabler, and enterprise accumulations of capability and adjustments to organization as a result of using technology, represent the primary basis for creating value for customers. In addition, if manufacturers focus primarily on technology acquisition when implementing their digital transformation efforts, and fail to invest resources into developing their capabilities and modifying organizations as needed to ensure their successful implementation of technology, it will be nearly impossible to convert investments in digital technology into the creation of sustainable competitive advantages. Prior research studies have also supported these findings (Yuan et al., 2021), showing that when digital transformation is used to increase productivity of a manufacturer, it occurs primarily by optimizing the internal divisions of labor within the organization and less by obtaining new technology (Bharadwaj et al.,2013).

The second significant finding is that the three sub-dimensions of dynamic capability form a statistically detectable chain transmission path from sensing to integrating and then to reconfiguring capability. While the complete four-segment indirect effect (DT→DC_S→DC_I→DC_R→CA) is significant (effect size = 0.005, representing 10.6% of the total effect), its magnitude is modest. This suggests that the sequential capability development pathway is theoretically meaningful but practically incremental. For manufacturing firms, converting digital investments into competitive advantage through the full chain may require cumulative organizational learning rather than yielding immediate performance improvements. The small effect size also implies that researchers should not overstate the practical importance of the chain mediation; rather, it should be interpreted as one of several complementary mechanisms through which digital transformation may create value.

Furthermore, in terms of the strength of each link in the chain, the strength of the link of integration capability to reconstruct capability (0.374) is statistically significantly greater than that of the link from perception capability to integration capability (0.251). This difference suggests that the transition from "integrating resources" to "restructuring organizations" presents a greater challenge for manufacturing companies than does the transition from "perception" to "integrating resources." This finding may explain why so many manufacturing firms are still operating at the "system launch" stage, after having completed digital equipment purchases and initial data integration, and why they continue to find it exceedingly difficult to make transformational changes to the organization (Sebastian et al.,2017). The ability to reconstruct requires firms to overcome the constraints of historical dependence on established organizational structures, eliminate organizational inertia, and implement coordinated changes with respect to authority, rewards and cultural values, which are all much harder to achieve than technological integration. As noted by Winter (2003), the dimension of reconstruction associated with dynamic capability is the most difficult to develop and is prone to decline. The empirical results of this paper support this assertion (Winter, 2003).

The third key finding is that differences in institutional environments have a sizable difference in regulatory impact. The marketization index had a significant positive interaction with digital transformation promoting organizational restructuring (interaction term 0.062, $p<0.05$). This provides statistically detectable evidence our hypothesis that the regions where the factor market is developed and the competitive environment is very competitive puts greater pressure to change on firms, as well as lower costs to obtain the resources needed to restructure (i.e., digital talent, technology solutions, consulting services). Hence, digital transformation will facilitate organizational restructuring due to the higher pressure to change and lower acquisition costs associated with resources. However, the interaction of intellectual property protection did not result in a statistically significant moderating effect (interaction term 0.042, $p=0.112$). This difference was due to the fact that China's IP protection system exhibits a regional imbalance of "strong statute, weak implementation." Enterprises' technological advantage acquired through organizational restructuring continues to experience spillover risk after the fact (Frank et al.,2019). As such, there is a lack of marginal regulatory impact of property protection on the transition between "organizational restructuring → competitive advantage." Further, a significant percentage of the competitive advantage of organizational restructuring consists of tacit knowledge and process capability, which is difficult to protect through formal protection mechanisms, such as patent protection. Therefore, the sensitivity to intellectual property protection is lower than that of explicit technological innovation.

5.2. Theoretical contribution

This study makes the following theoretical contributions to the theory of dynamic capabilities and transformational economics.

To begin with, the dynamic capabilities of a firm can be broken down into three key themes: the ability to see; the ability to combine and utilize different resources; and the ability to change. Empirical evidence has validated the sequential process of perception → combination → change as an explanation for how dynamic capabilities operate. Most of today's researches on dynamic capabilities view dynamic capabilities either as a singular construct or as having multiple parallels constructed, but fail to consider how these multiple constructs relate dynamically across timeframes or the logic of transmitting between constructs. The current study supports the initial order of operations hypothesized by Teece's, illustrating that the perception of dynamic capability is the first step toward the ability to combine resources and achieve change of resources, thus providing a greater understanding of the nature and function of dynamic capability (Teece, 2007).

Secondly, integrating the macro-level institutional framework with the micro-level corporate behaviour within one analytical framework offers a view of the different modes of regulation in marketization and intellectual property context and their effects on transformation processes. Most prior research on the institutional environment has only addressed direct effects; fewer studies have investigated the regulatory role of this environment through outgoing channels. This research confirmed the overall transformational effect of the overall level of marketization on the transition process from "digital transformation – organisational restructuring" in a regulatory manner. In contrast, the moderating effect of intellectual property protection has not been substantiated in this area of research. The findings highlight what many refer to as the "mystery of regional differences" in transformational effects, thereby providing avenues for improvements in property-right protection (Pavlou & El Sawy,2011).

Using a sample of over 2,400 Chinese A-Share listed companies in the manufacturing sector, empirical evidence demonstrating the application of dynamic capability theory within the Chinese environment, is provided. Since the various stages of development and institutional environments as well as cultural characteristics differ from those of the West, to test the utility of dynamic capability theory, the importance of continuing to test dynamic capability theory in the context of the Chinese environment holds substantive academic value.

5.3. Practical Implications

The findings of this study offer several actionable insights for manufacturing enterprises undergoing digital transformation, as well as for policymakers seeking to facilitate such transformation.

For manufacturing enterprises:

First, enterprises should explicitly map the causal chain from digital investment to competitive advantage, recognising that technology procurement alone is insufficient. To operationalise this, firms are advised to conduct a digital transformation readiness audit that assesses three sequential pillars: (i) whether the organisation possesses adequate sensing mechanisms (e.g., market intelligence, R&D monitoring); (ii) whether it can integrate new digital assets with legacy systems; and (iii) whether it has the authority and cultural flexibility to reconfigure structures. For resource-constrained small and medium-sized manufacturers, we recommend starting with low-cost sensing practices (e.g., cross-industry benchmarking, participation in digital innovation ecosystems) before committing to large-scale technology purchases.

Second, managers should identify and address bottlenecks at each capability stage using specific diagnostic indicators. Concretely:

If sensing capability is weak (e.g., R&D intensity below industry median, no dedicated digital scouting unit), firms should increase R&D spending to at least 3–5% of operating revenue and establish a quarterly technology radar system that tracks emerging digital tools (AI, IIoT, digital twins).

If integrative capability is lacking (e.g., total asset turnover ratio <0.6, low intangible asset ratio), priority should be given to developing unified data platforms and standardised APIs that connect shop-floor systems with ERP/CRM. A practical step is to appoint a cross-functional "digital integration task force" with clear milestones for system interoperability.

If reconfigurative capability is the bottleneck (e.g., persistent departmental silos, low patent commercialisation rate, high resistance to process changes), enterprises must go beyond technical integration. Specific actions include: redesigning key performance indicators to reward cross-functional collaboration (e.g., 30% of bonus tied to digital project outcomes), establishing an internal change management office with top-management sponsorship, and implementing a "digital rotation programme" that moves high-potential employees across production, IT and marketing functions to break inertial thinking.

Given that the integration-to-reconfiguration leap shows the largest coefficient (0.374) but also the highest difficulty, manufacturing firms should allocate disproportionate management attention and financial resources to this phase. For example, setting aside 15–20% of the digital transformation budget specifically for change management activities (training, internal communication, piloting new governance models) is recommended.

For policymakers:

The significant moderating effect of marketisation level implies that regional governments should focus on removing institutional barriers to factor market development. Specific policy recommendations include:

Accelerating the construction of provincial-level digital talent exchanges and technology markets to lower the cost for manufacturers to acquire restructuring-related resources (e.g., cloud computing services, AI consultants, industrial software).

Introducing competitive pressure-enhancing policies such as reducing administrative entry barriers for digital service providers, and publishing industry-level digital transformation benchmarks to encourage peer comparison.

Avoiding excessive direct intervention; instead, facilitating public‑private collaboration platforms where manufacturing firms can share organisational restructuring experiences and co‑develop modular digital solutions.

Although the moderating effect of intellectual property protection was not statistically significant in our sample, we caution against dismissing its importance. The non‑significant result may reflect regional heterogeneity in enforcement rather than theoretical irrelevance. Accordingly, we suggest that policymakers:

Strengthen enforcement coordination by establishing cross‑provincial IP dispute resolution mechanisms and increasing the predictability of IP litigation outcomes.

Expand protection to tacit knowledge and process innovations (e.g., through trade secret laws and employee non‑disclosure agreements), as organisational restructuring often yields non‑patentable competitive advantages.

Conduct regular IP protection effectiveness surveys at the firm level to identify gaps between statutory protection and actual enforcement, and adjust regional policies accordingly.

By implementing these concrete measures, manufacturing firms can better translate digital investments into sustained competitive advantage, and policymakers can create an institutional environment that actively supports rather than passively permits digital transformation.

5.4. Research Limitations and Future Directions

In future studies, there are several limitations that must be considered. The measurement of Dynamic Capability is based primarily on publicly available financial and technical information (R&D investment, asset turnover rates, patent authorization) which has strong objectivity and can be easily obtained, but these measures do not sufficiently encompass the strategic, procedural and implicit characteristics of Dynamic Capability. For example, while perceptual capability involves R&D investment, it also includes (but is not limited to) elements of management cognition and organizational alertness which are difficult to quantify. Future studies may include more specific measurement methods through a combination of survey methodologies (questionnaires) and qualitative methodologies (interviews, case studies).

The scope of the sample is also a limitation of this study as it is limited to A-share listed manufacturing companies. As such, caution should be used when applying the results from this study to either non-listed firms or smaller manufacturing companies. The availability of data from non-listed firms is lower than from listed firms and they account for a large percentage of all manufacturing companies in China, so their digital transformation behaviours will likely differ from those of the listed firms, such as having more extensive financing constraints and having lower management capabilities. Future research could explore the use of regional economic statistics or enterprise survey data to expand the sample range to non listed manufacturing enterprises.

Currently this research has used a lagged instrumental variable (IV) model to address endogeneity questions concerning causal identification; however, this does not necessarily imply that every omitted variable can be excluded from interfering with assessed relationships between digital transformation (DT) and competitive advantage (CA). Conversely, DT may have an inverse causal link to CA (stronger CA is linked to increased DT capability) and enterprise characteristics (unobservable quantities such as management skills) may exert their influence on DT as well as CA at virtually the same time. Researchers could conduct future studies using quas-natural experimental research designs (for example: nation-wide digital economy demonstration zone program conditionings), or enhanced IV conditions (i.e., using the average level of DT among other firms in that industry as the IV), to create even more symptomatic causal diagnostics.

Regarding chain mediated analysis, while our study provides evidence of chains of causal influence created by dynamic capabilities, there is no deeper insight into any specific barriers or enablers (e.g., organization inertia, institutional resistances, culture conflicts, middle manager's resistances) affecting how that chain of influence was executed and transmitted. Follow-up researchers should employ an exploratory mixed methodology where the qualitative results can provide the foundation to identify key linkages between each causal link in the chain of causal influences, thus providing a more prescriptive working framework for practitioners.

Reference

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471–482.

Chen, Y., & Zhang, Y. (2024). The impact of digital transformation on firm's financial performance: Evidence from China. *Industrial Management & Data Systems*, 124(5), 2021–2041.

Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research*, 112, 119–127.

Frank, A. G., Mendes, G. H. S., Ayala, N. F., & Ghezzi, A. (2019). Servitization and industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting and Social Change*, 141, 341–351.

Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. *Journal of Management Studies*, 58(5), 1159–1197.

Hasnawati, Kusumaningtyas, A., & Cempena, I. B. (2024). Ambidextrous leadership, customer orientation, environmental innovation through digital capability and technological capability: The influence of moderation of service innovation capability. *Journal of Logistics, Informatics and Service Science*, 11(11), 502–518.

Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, 36(6), 831–850.

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8), 1391–1399.

Hess, T., Matt, C., Benlian, A., & Wiesboeck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 123–139.

Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems*, 32(1), 39–81.

Li, L., Su, F., Zhang, W., & Mao, J. Y. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, 28(6), 1129–1157.

Li, X. S., Dang, L., & Zhao, C. Y. (2022). Digital transformation, integration into global innovation networks, and innovation performance. *China Industrial Economics*, 10, 43–61.

Li, Y., Maxwell, D. W., & Moehler, R. (2025). Facilitating platform-based business model innovation in construction start-ups: A dynamic capability perspective. *Construction Management and Economics*, 43(10), 864–881.

Martínez-Caro, E., Cegarra-Navarro, J. G., & Alfonso-Ruiz, F. J. (2020). Digital technologies and firm performance: The role of digital organisational culture. *Technological Forecasting and Social Change*, 154, 119962.

Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research*, 123, 642–656.

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), 103773.

Nour, S., & Arbussà, A. (2025). Driving innovation through organizational restructuring and integration of advanced digital technologies: A case study of a world-leading manufacturing company. *European Journal of Innovation Management*, 28(8), 3262–3283.

Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. *Decision Sciences*, 42(1), 239–273.

Rachinger, M., Rauter, R., Müller, C., Vorraber, W., & Schirgi, E. (2019). Digitalization and its influence on business model innovation. *Journal of Manufacturing Technology Management*, 30(8), 1143–1160.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal*, 35(2), 179–203.

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals*, 12(1), 390–439.

Sebastian, I. M., Ross, J. W., Beath, C., Mocker, M., Moloney, K., & Fonstad, N. (2017). How big old companies navigate digital transformation. *MIS Quarterly Executive*, 16(3), 197–213.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350.

Vale-Feigl, A. (2021). People, not technology, drive digital transformation. *Talent Development*, 75(1), 34–39.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2019). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901.

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349.

Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic capabilities and performance: Strategy, structure and environment. *Long Range Planning*, 46(1-2), 72–96.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24(10), 991–995.

Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Corporate digital transformation and capital market performance: Empirical evidence from stock liquidity. *Management World*, 37(7), 130–144.

Yuan, C., Xiao, T. S., Geng, C. X., & Sheng, Y. (2021). Digital transformation and corporate division of labor: Specialization or vertical integration. *China Industrial Economics*, 9, 137–155.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities: A review, model and research agenda. *Journal of Management Studies*, 43(4), 917 – 955.

Zhao, C. Y., Wang, W. C., & Li, X. S. (2021). How digital transformation affects total factor productivity in enterprises. *Finance and Trade Economics*, 42(7), 114 – 129.