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Original Paper

Research on the Impact of Digital Transformation on Enterprise Innovation - Evidence Based on Patent Quality

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Abstract

In the era of digital economy, digital transformation is becoming a key force driving enterprise innovation and upgrading. This paper selects China's A-share listed companies from 2010 to 2024 as research samples, and uses the breadth of patent knowledge as a proxy variable for innovation quality to systematically examine the actual impact of digital transformation on enterprise innovation, and further explore its transmission mechanism. The data tells us that digital transformation has really broadened the breadth of patent knowledge of enterprises and effectively improved the quality of innovation. In this process, the compensation incentive for management is a non-negligible intermediate link - digitization encourages enterprises to tilt the incentive focus to long-term innovation, managers are more willing to invest in interdisciplinary technology exploration, and the knowledge map covered by patents is expanded. A noteworthy finding is that the impact of digital transformation on patent quality is not balanced. In manufacturing, large companies and more competitive industries, this positive effect is much more obvious; in non-high-tech industries, the effect of digital empowerment is even more prominent than that of high-tech industries. This is probably because the technical field of high-tech enterprises is broad enough, and the incremental space that digital technology can do is not so large. In general, the value of this study is to shift the focus of observation from "how much innovation has been done by enterprises "to "what is the quality of innovation", and try to clarify a conduction path-first use technology to empower, then rely on governance optimization, and finally fall on innovation breakthroughs. These conclusions suggest that enterprises cannot simply copy the experience of others in digital transformation, and tailored strategic design is more desirable, and the supporting reform of internal incentive system cannot be ignored. For regulatory authorities, the formulation of digital economic policies should also be focused on, tilted to areas where the digital dividend is more pronounced, such as manufacturing and competitive industries. In general, this study focuses on the quality of innovation, which adds new evidence to the question of whether digitization can truly transform *into the core competitiveness of enterprises.*

Keywords

Digital Transformation, Corporate Innovation, Patent Knowledge Breadth, Managerial Compensation Incentive

1. Introduction

The report of the 20th National Congress of the Communist Party of China clearly defined the positioning of "innovation is the first driving force," and outlined the implementation path of innovation and development with the framework of " three firsts " and " four new, " highlighting the strategic height of innovation in modernization. As China's economy shifts from high-speed growth to high-quality development, technological innovation has become a basic force driving social progress and improving people's livelihood. The significance of technological innovation is not only to make better use of factor resources and increase the value of products, but also to enable enterprises to form competitive barriers that others cannot take away in the market. In the end, high-quality development is inseparable from these micro-level accumulations.

At the stage of new industrialization, digital transformation is more and more like the 'master switch' of enterprise innovation. The significance of digitization is not only the improvement of governance and financing within the organization, but also the re-linking of the entire production and operation chain. The traditional department wall and information island have been gradually removed. After the threshold of resource acquisition has been reduced, the organizational cost of R & D activities has decreased, and the operational efficiency of the workflow has come up[1]. The improvement of digitalization can reduce the cost of internal control and improve the efficiency of organizational operation[2].

However, the expansion and contraction of enterprise boundaries ultimately depends on the relative changes in external transaction costs and internal control costs[3][4]. Digital transformation may affect both of them at the same time, thus affecting the direction of enterprise boundaries. The " Key Points for the Development of the Digital Economy in 2025 " also emphasizes the direction of integration of digitization and the real economy and enabling innovation. The intelligent factory built by Haier Intelligent Building based on AI is an example. Its design cycle is compressed by 62 %, and it is not accidental to be included in the pilot list. Regarding the relationship between digital transformation and innovation, the existing literature has indeed done a lot of work - someone has verified the role of management efficiency as a bridge[5], and someone has specifically explored how digitization can enhance the innovation resilience of enterprises[6]. But if this piece of research has been done thoroughly, I 'm afraid not to talk about it. First, most of the analysis focuses on the financing constraints of this pipeline in and out, other possible transmission paths have not been given equal attention, and the boundary conditions are also ambiguous. Second, everyone seems to be more concerned about the question of "whether it has any effect," but rarely asks "who has the effect" -the intermediary role of management compensation incentive has not been seriously verified. However, the problem is that the digital transformation first changes the internal governance structure, and the salary incentive is precisely the line that can most affect the behavior of managers in the governance mechanism. It is not complete to talk about the change of innovation decision-making around it. Furthermore, the mechanisms of management efficiency, asset operation and financing tightness are fragmented, and there is a lack of a unified framework to string them together. The differentiation of effects in different situations also lacks in-depth analysis.

China’s economy has entered a phase of high-quality development, with innovation standing at the heart of the country’s modernization drive. As digital technologies integrate deeply with the real economy, digital transformation not only reshapes corporate production and operation modes but also fundamentally restructures the resource allocation, organizational patterns and value creation logic of innovation activities. Most existing studies evaluate the innovation effects of digitalization based on patent counts and R&D investment, yet they pay insufficient attention to its profound influences on patent quality, technological breadth and knowledge integration capacity. However, the question that is most worth asking seems to have not been seriously answered-digitalization has transformed the internal governance of enterprises, but how does this change in governance transmit to the quality of innovation? The middle causal chain is still a dark box to be opened.

In view of the above research gaps, this paper will focus on answering a question: does digital transformation promote high-quality innovation of enterprises through the transmission of management compensation incentives? To this end, we use patent knowledge breadth to measure the quality of innovation, and further reveal the mediating effect of compensation incentives on the basis of testing the direct impact of digitization on innovation. Considering that the effect of digital transformation cannot be generalized, this paper further conducts a grouping test from the perspectives of industry type, enterprise scale, market competition intensity and technical attributes to see which types of enterprises are more likely to benefit from digitization.

When it comes to research contributions, it is roughly concentrated on two points. One is the change of perspective - not to see how many patents the enterprise has made, but to see the knowledge content and quality level behind the patent. This perspective may be more meaningful for the current context of emphasizing core technology research. The other is the excavation of the mechanism - the line of management compensation incentive is brought out to do the intermediary verification, which provides a specific and traceable explanation path for the problem of "how digital transformation affects innovation." Third, this paper identifies heterogeneous boundaries from multiple dimensions. The results show that the innovation effect of digitalization is differentiated by industry type, enterprise size, competition intensity and technical attributes. In other words, digitalization is not a universal solution. This finding helps enterprises and policy makers to form more pragmatic expectations and more targeted strategies according to their own positioning and environment.

2. Theoretical Analysis and Research Hypotheses

It should be noted that innovation itself has two sides. It may not only win market opportunities and expand market share for enterprises[7], but also push up business risks due to high investment and high uncertainty[8]. Since the risk of innovation can not be ignored, enterprises should not only focus on the number of R&D investment, but also make great efforts in resource guarantee and management follow-up. Looking back at the existing literature, the relationship between digital transformation and innovation has been repeatedly tested, and most of the evidence supports its positive effect. Scholars have also contributed a variety of mechanism explanations - such as financing, governance, and organizational synergy. As for what digital transformation itself is, it is usually defined as the systematic adoption and application of digital technology and information software by enterprises[9].

By applying Enterprise Resource Planning (ERP) systems, process automation, smart supply chains, intelligent manufacturing, online platforms, online customer service and automated workflows, enterprises can optimize business processes, build new collaborative relationships[10], strengthen the capability of risk response and management in innovation activities, and ultimately boost enterprise innovation. Furthermore, digital transformation helps enterprises acquire external innovation resources, facilitate open and network-based innovation, and improve overall innovation capabilities.

In addition to the optimization of internal governance, digital transformation also plays a role at another level. It opens a window for enterprises to connect with external innovation resources, making open innovation and network collaboration possible, and the overall innovation ability is supported. Existing research has accumulated considerable evidence in this area, and the direct impact of digitization on new product development, process design and solution innovation has been repeatedly verified[11]. And this effect is not a single point, but systematic[12]. Scholars usually elaborate from the following three transmission channels: The improvement of resource allocation efficiency, the iteration of management mode and the release of economies of scale are several specific points in which digitization plays a role at this level. If the perspective is shifted to the capital and information dimensions, the contribution of digital transformation is equally clear - on the one hand, it relieves the financing constraints of enterprises, on the other hand, it compresses the space of information asymmetry. Under the superposition of the two, the external conditions of technological innovation have been substantially improved[13]. Further, the reduction of financing pressure and the improvement of production efficiency constitute the two main paths of digitalization to improve innovation performance, but the effectiveness of these two paths is not uniform, and will show different performance due to the different nature of enterprise property rights and factor intensity[14].

In terms of digital orientation, it can directly drive corporate digital innovation by fostering digital organizational capabilities and improving information quality[15]. In addition, digital transformation provides all-round support for enterprise innovation through activating human resources and optimizing resource allocation[16], which has been partially verified by existing research. Accordingly, this paper proposes the baseline hypothesis:

H1: Corporate digital transformation has a significant positive impact on enterprise innovation, that is, the higher the degree of corporate digital transformation, the higher the level of enterprise innovation.

Managerial compensation incentive serves as a core transmission channel for digital transformation to drive enterprise innovation. From the perspective of stripping, the impact of transformation first falls on the link of management compensation incentive. The change brought by digitalization is not simply to pay more or less money, but to make the compensation mechanism more refined and closer to the market logic. The support behind is that technology-big data and AI record every step of managers in innovation, the efficiency of R&D investment, and the actual progress of the project. These ' soft performance ' that used to be judged only by feeling now have quantifiable scales. In this way, the link between compensation and innovation results is no longer an empty word, but a well-founded one[17]. In addition to the technical support, the digital transformation also solves the problem of 'where the money comes from'. With the increase of profitability, enterprises have more room for operation in salary incentives. The practice of commercial banks has shown that digitization can improve profitability by optimizing resource allocation[18]; the data at the enterprise level also supports the decline in operating costs and the improvement of total factor productivity brought about by this logic-digital transformation[19], which provides evidence for the chain of "digital-salary capability." Pay incentives go up, managers are naturally more motivated to do innovation-the willingness and intensity of R&D investment will follow up.

The principal-agent theory tells us that managers are naturally inclined to avoid risks-but if the compensation design can make the innovation results directly related to personal income, this tendency will be hedged. The situation of state-owned enterprises can explain the problem in particular: the innovation effect of digital transformation is more prominent. A reasonable explanation is that digital intervention makes the salary system more ' pure ', the interference of administrative objectives and non-economic factors is compressed, and the direction of incentives is stronger. When managers find that the linkage between compensation and innovation performance is solid, they are naturally more willing to take R&D risks and place their chips on high-return innovation projects. The pressure of short-term statements no longer constitutes an obstacle to innovation[20]. From the previous logic, the digital transformation acts on the salary incentive system and changes the behavior orientation of managers. When the incentive is in place, the innovation motivation comes up and the innovation performance is improved.

H2: Management compensation incentives play an intermediary role between digital transformation and enterprise innovation, that is, digitalization promotes enterprise innovation by enhancing compensation incentives.

The indicator of the proportion of management costs essentially points to the level of internal management of the enterprise-the lower the proportion, the less the administrative consumption, the higher the management efficiency. A direct effect of digitization is to help compress this part of administrative expenses and guide the saved management resources to innovative activities. For those enterprises whose management efficiency is itself online, the engagement between digital technology and innovation tends to be closer, and it is easy to form a self-reinforcing loop of 'innovation output-performance improvement-resource compensation'. The empowerment effect of digitization is also more stable in such organizations[21]. However, if it is an enterprise with a high proportion of management costs, the situation is more complicated. These ' institutional frictions ' of cumbersome approvals, rigid processes, and fragmentation between departments will greatly weaken the efficiency dividends that digital transformation should bring, resulting in technology investment that cannot truly stimulate innovation[22].

H3a: The administrative expense ratio positively strengthens the positive relationship between corporate digital transformation and enterprise innovation.

The total asset growth rate reflects corporate growth potential and resource expansion capacity. High-growth enterprises have stronger demand for innovation and possess sufficient resources such as production capacity expansion space and market channels to commercialize innovation outputs, enabling innovation investment to be more efficiently converted into operational performance[23]. Specifically, enterprises with a high total asset growth rate can better translate the technological advantages and market opportunities brought by digital transformation into revenue growth, allowing more room for designing linkage mechanisms between innovation performance and compensation such as long-term equity incentives. Meanwhile, intense market competition urges managers to sustain corporate growth through innovation, further strengthening the innovation-enabling effect of digital transformation[24]. By contrast, enterprises with a low total asset growth rate have steady development momentum and insufficient resource slack. Even with digital transformation, they cannot support large-scale innovation investment, which weakens the promotional effect of digital transformation on enterprise innovation.

H3b: The total asset growth rate negatively moderates the relationship between corporate digital transformation and enterprise innovation.

Innovation investment is a long-term and sustainable process accompanied by severe information asymmetry and high investment risks, making financing constraints a major obstacle to corporate innovation[25]. Innovation activities and financing constraints are closely correlated and mutually influential. On the one hand, severe financing constraints force enterprises to abandon high-quality innovation projects and hinder innovative development[26]. On the other hand, the long-term nature, high risks, and information asymmetry of R&D activities increase the difficulty of external financing[27]. The innovation-promoting effect of digital transformation depends on the alleviation of financing constraints[28]. Enterprises with weak financing constraints (low SA index) can better implement digital transformation strategies and obtain long-term funds for R&D, enabling digital transformation to give full play to its innovation-enabling effect. In comparison, enterprises with strong financing constraints may delay digital transformation due to capital shortages. Even if digital transformation is implemented, insufficient R&D funds hinder the transformation of digital dividends into innovation outputs, thereby weakening the positive impact of digital transformation on enterprise innovation[29].

H3c: The SA index positively strengthens the positive relationship between corporate digital transformation and enterprise innovation.

3. Research Design

3.1 Data Sources and Variable Definitions

Given the detailed financial disclosure of listed firms and the accessibility of research data, this paper selects Chinese A-share listed companies from 2010 to 2024 as the research sample. To ensure the reliability of empirical results before hypothesis testing, the original sample is processed according to the following criteria: first, ST and *ST listed firms are excluded; second, financial enterprises are eliminated; third, observations with missing core variables are dropped; fourth, to mitigate the interference of outliers, all micro-level continuous variables are winsorized at the 1% and 99% percentiles. The research data are collected from the China Stock Market & Accounting Research Database (CSMAR) and the China National Research Data Service (CNRDS). All empirical analyses are performed using Stata 18.0 software.

1. Dependent Variable

Corporate innovation capability (Patentknowledge). Combining the innovation characteristics of enterprises engaged in core key technology research and development, this paper constructs a multi-dimensional evaluation system for corporate innovation from three perspectives: innovation scale, innovation quality, and independent innovation capability. Corresponding robustness alternative indicators and characteristic indicators are further adopted to ensure the comprehensiveness and reliability of innovation measurement.

In terms of innovation scale, the total number of corporate patent applications (including invention patents, utility model patents, and design patents) is adopted, processed by adding one and taking the natural logarithm, denoted as Patent1. This indicator intuitively reflects the overall scale of corporate innovation outputs. In terms of innovation quality, considering that invention patents contain significantly higher technical content and innovative value than other patent types, the number of corporate invention patent applications is used, processed by adding one and taking the natural logarithm, denoted as Patent2, which accurately characterizes the technical value of corporate innovation achievements. In terms of independent innovation capability, focusing on firms' independent R&D capacity in core technologies, the number of independently applied invention patents is adopted, processed by adding one and taking the natural logarithm, denoted as Patent3, which reflects firms' independent breakthrough capabilities in core technological fields.

In order to ensure that the results stand up to scrutiny, the robustness test part changed a set of "ruler "-run again with the patent authorization data and the same set of models to see whether the conclusions are robust.

A choice on measure needs to be explained. The innovation of core key technologies is often characterized by fundamentality and breakthrough. The value of such innovation is reflected in its radiation range-how many technical fields can be covered and how many knowledge boundaries can be opened up, rather than simple quantity stacking. Therefore, we abandon the single patent quantity index and use the breadth of patent knowledge to measure such innovation.

The more dispersed the technical area covered by a patent, the greater the breadth of its knowledge - which means that companies have the ability to bring together technologies from different sectors, and the quality and technical content of the patent itself is usually higher. Therefore, we use the patent knowledge width to measure the patent quality of the enterprise. The first step is to extract the main classification numbers from the patent application data of listed companies according to the rules of the International Patent Classification (IPC). The IPC system follows a hierarchical structure of "section–class–subclass–main group–subgroup", represented by typical classification codes such as A01B01/00.

The structure of IPC classification number is as follows: the first letters A to H correspond to eight major technical fields-human necessities, transportation, chemistry, machinery, electricity and so on; the numbers and letters followed by are then refined step by step to specific technical branches. This hierarchical system can clearly define the technical attribution of each patent.

However, it should be noted that if the figure is convenient, it is not reliable to directly use the number of patent classification numbers to measure the quality of patents. The technical span of two patents with the same number of classification numbers may be very different - one may only be a few subdivided extensions in a small field, and the other may span several completely different technical sectors. The number of optical numbers, it is easy to push up the valuation of those patents with general technical content. For ease of understanding, a simplified example is used here to illustrate. It is assumed that A company holds three patents, whose main classification numbers are A01B01 / 01, A01B01 / 02 and A01B01 / 03, all of which belong to the same main group A01B01. Enterprise B also holds three patents, the main classification numbers are A01B02 / 00, B02C03 / 00 and C03D04 / 00, which fall under three different main groups. The number of patents and the number of main classification numbers of the two companies are exactly the same, but the patents of Company B are distributed on three technical nodes with greater differences, which means that its knowledge breadth is significantly higher and the patent quality is usually better. Referring to the calculation logic of the Herfindahl–Hirschman Index (HHI)[30], this paper defines corporate patent knowledge breadth at the patent main group level as follows[31][32]:

$$\text{Patentknowledge}_{it}=1-\sum_{m=1}^{M}\left(\frac{Z_{imt}}{Z_{it}}\right)^2$$

where:

$\text{Patentknowledge}_{it}$ denotes the patent knowledge breadth of firm i in year t, ranging from 0 to 1;

Z_{imt} represents the cumulative number of patents (invention patents plus utility model patents) filed by firm i under the m-th technical main group up to year t;

Z_{it} stands for the total cumulative number of patents (invention patents plus utility model patents) of firm i across all technical main groups up to year t;

M refers to the total number of distinct technical main groups covered by firm i up to year t.

Before calculating this indicator, we first made two screenings of patent data. The first is the type - only the invention patents and utility models are left, and the design is removed. The reason is not complicated: the numbering rules used in the design are not a system at all with the other two, and can not be compared with the other two. And the appearance design is more formal innovation, it is difficult to truly reflect the enterprise in the accumulation of technical knowledge and integration capabilities, use it to measure the breadth of knowledge, the amount of information is not enough. The second is quality-to remove those utility model patents that are marked as invalid because of ' circumvention and abandonment ', so that these patents with impure application motives will not lead to biased results.

2. Independent Variable

The independent variable of this study is the digital transformation of enterprises (DCG), which is directly measured by the digital transformation index of listed companies in the CSMAR database. The higher the score, the higher the degree of digitization of enterprises.

This index is not made out of thin air, behind the theory and literature support. Specifically, we refer to the practice of existing research[33][34], and split the digital transformation into two pieces: the underlying digital technology and the practical application scenario. The underlying technology includes artificial intelligence, blockchain, and big data. The construction of the dictionary is not behind closed doors, but combines the keyword table of relevant literature[35][36], and then supplements and adjusts policy documents such as the “14th Five-Year Plan for Digital Economic Development ”.Specific to the data level, this index is not only staring at the annual report 'management discussion and analysis' that small piece of content, but the collection announcement, qualification announcement and other public documents are included, from the strategy, technology, organization, digital results, macro environment six angles comprehensive scoring. Compared with the previous practice of only looking at MD & A texts, the coverage is wider and the quantification is more accurate. Therefore, in the benchmark regression, we directly use this composite index to represent the digital transformation level (DCG) of the enterprise.

3. Mechanism and Moderating Variables

The mediating variable we chose is the management compensation incentive (Magw), which is quantified by the natural logarithm of the total compensation of the top three executives. The position of salary incentive in corporate governance is relatively special-the above is connected with the strategic landing of digital transformation, and the following is the resource investment direction of innovation activities, and the decision-making preference of managers is largely led by it.

The reason why we choose it as an intermediary variable is that it makes sense logically: digital transformation promotes the compensation mechanism to become more refined and more market-oriented, and once the compensation mechanism changes, the innovation motivation of managers will also change. So there is such a chain: digital transformation → salary mechanism optimization to innovation level improvement. Theoretically, compensation incentives pass on the impact of digital transformation at the governance level; In order to investigate whether the innovation effect of digital transformation will be different in different situations, we selected three adjustment variables:

administrative expense ratio (AER), total asset turnover rate and SA index (financing constraints). These three indicators correspond to the internal management efficiency, asset operation ability and financing constraint degree of the enterprise respectively - basically covering several fundamentals of enterprise operation.

The lower the administrative expense rate is, the higher the internal management efficiency is, and the smoother the digital innovation dividend is transformed. The SA index is often used as a proxy variable for financing constraints in the literature. The larger the value, the more intense the external financing environment faced by the company. The reason why this tension is worth paying attention to is that it is directly related to whether the enterprise has enough ammunition to support the investment of digital transformation and the subsequent R & D expenditure. In other words, the degree of financing constraints is different, and the impact and direction of digitalization on innovation may also change.

4. Control Variables

In terms of controlling variables, we refer to the setting of mainstream literature[37][38], and select the variables of corporate profitability (ROE), ownership concentration (Top1, the proportion of the largest shareholder), cash asset ratio (Cash), board size (Bsize), management shareholding ratio, and whether state-owned enterprises (SOE).

In addition, two basic diagnoses are made: one is to see the correlation coefficient between variables, which is below 0.3; the second is to look at the variance inflation factor (VIF), the largest is less than 2, far from the warning line of 10.

Table 1. Variable Definitions

Variable Name	Symbol	Measurement Definition
Patent Application Knowledge Breadth	Patent-s	Constructed and calculated based on the Herfindahl-Hirschman Index (HHI)
Patent Grant Knowledge Breadth	Patent-h	Constructed and calculated based on the Herfindahl-Hirschman Index (HHI)
Corporate Digital Transformation	DCG	Textual analysis based on CN RDS database; take the natural logarithm of the composite index after adding one
Profitability	ROE	Ratio of corporate net profit to net assets
Ownership Concentration	Top1	Sum of shareholding ratios held by the largest tradable shareholder of the firm
Cash Asset Ratio	Cash	Ratio of net cash flow generated from operating activities to total assets
Board Size	Bsize	Natural logarithm of the total number of board directors
Managerial Ownership Ratio	Mag	Ratio of shares held by directors, supervisors and senior management to total outstanding shares

Ownership Nature	SOE	Equals 1 if the firm is state-owned, and 0 otherwise
Managerial Compensation Incentive	Magw	Natural logarithm of the total compensation of the top three executives
Administrative Expense Ratio	AER	Ratio of administrative expenses to operating revenue
Total Asset Turnover	TAT	Ratio of operating revenue to average total assets
Financing Constraint (SA Index)	SA Index	Calculated using two indicators: natural logarithm of corporate total assets and the number of years since the firm's IPO
Year Fixed Effect	Year	Year fixed effect dummy variable
Industry Fixed Effect	Ind	Industry fixed effect dummy variable

3.2 Model Specification

To investigate the impact of corporate digital transformation on corporate innovation capacity, this paper adopts patent application knowledge breadth as the proxy for innovation capacity and constructs a two-way fixed-effects model for empirical testing:

$$Patentknowledge_{i,t}=\beta_0+\beta_1 DCG_{i,t}+\sum Controls+\sum Ind+\sum Year+\varepsilon_{i,t} \quad (1)$$

where subscripts i and t denote firm and year, respectively. The dependent variable is corporate innovation capacity ($Patentknowledge_{it}$); the core independent variable is the level of corporate digital transformation (DCG); *Controls* stands for the set of control variables defined above; $\sum Ind$ represents industry fixed effects; $\sum Year$ denotes year fixed effects; and $\varepsilon_{i,t}$ is the random error term clustered at the firm's industry level. Consistent with the foregoing theoretical analysis and following Jiang Ting (2022), the following mediating effect models are established:

$$Patentknowledge_{i,t}=\beta_0+\beta_1 DCG_{i,t}+\sum Controls+\sum Ind+\sum Year+\varepsilon_{i,t} \quad (2)$$

$$Mit=\alpha_0+\alpha_1 DCG_{i,t}+\sum Controls+\sum Ind+\sum Year+\varepsilon_{i,t} \quad (3)$$

$$Patentknowledge_{i,t}=\beta_0+\beta_1 DCG_{i,t}+\beta_2 Mit+\sum Controls+\sum Ind+\sum Year+\varepsilon_{i,t} \quad (4)$$

In the above equations, M_{it} refers to the mediating variable. Equations (2) and (3) correspond to the two-step mediation method proposed in prior literature[39], while Equations (2) to (4) represent the classic three-step mediation procedure[40]. This study combines both approaches to obtain more robust mediating effect results.

4. Empirical Tests

4.1 Baseline Regression Results

Table 2 presents the baseline regression results regarding the impact of digital transformation on firms' patent knowledge breadth. Columns (1) and (2) report estimation results without control variables. Column (1) does not incorporate industry and year fixed effects, while Column (2) includes two-way fixed effects of year and industry yet excludes control variables. The coefficients of the core explanatory variable DCG are significantly positive in both columns, which preliminarily indicates that corporate digital transformation significantly expands patent knowledge breadth and provides initial evidence supporting the research hypothesis.

Table 2. Baseline Regression Results

Variables	(1) Patent-s	(2) Patent-s	(3) Patent-s	(4) Patent-s	(5) Patent-s	(6) Patent-s
DCG	0.010***	0.007***	0.014***	-0.008***	0.032***	0.007***
	(4.37)	(2.93)	(5.86)	(0.002)	(0.002)	(2.79)
ROE			0.319***	0.426***	0.243***	0.352***
			(6.07)	(0.050)	(0.047)	(7.59)
Top1			0.001***	0.001***	0.002***	0.002***
			(4.91)	(0.000)	(0.000)	(11.08)
Cash			-0.201***	-0.138***	-0.174***	-0.133***
			(-7.91)	(0.026)	(0.022)	(-5.98)
Bsize			0.056***	0.082***	0.051***	0.080***
			(3.74)	(0.014)	(0.012)	(6.78)
Mag			0.002***	0.003***	0.001***	0.002***
			(7.99)	(0.000)	(0.000)	(9.41)
SOE			0.026***	0.025***	0.048***	0.049***
			(4.06)	(0.006)	(0.006)	(8.89)
Constant	0.368***	0.371***	0.204***	0.143***	0.168***	0.102***
	(103.04)	(111.74)	(6.18)	(0.032)	(0.028)	(3.77)
Industry FE	NO	YES	NO	NO	YES	YES
Year FE	NO	YES	NO	YES	NO	YES
Observations	10118	10118	10118	10118	10118	10118
Adj. R^2	0.002	0.345	0.020	0.076	0.328	0.371

Note. t statistics in parentheses 467

* $p < 0.1$, 468

** $p < 0.05$, 469

*** $p < 0.01$

Columns (3) to (6) further incorporate control variables including profitability, ownership concentration, cash holdings, board size, managerial shareholding and ownership nature. The results show that the coefficients of ROE, Top1, Bsize, Mag and SOE are all significantly positive, implying that higher profitability, more concentrated ownership, larger board size, greater managerial incentives and state-owned ownership all contribute to corporate innovation output. In contrast, the coefficient of Cash is significantly negative, which indicates that excessive cash holdings may crowd out R&D resources and generate a crowding-out effect on innovation.

In terms of fixed-effect arrangements, Column (3) omits both industry and year fixed effects; Columns (4) and (5) only include either year or industry fixed effect separately; Column (6) simultaneously controls for two-way fixed effects of industry and year. Across all specifications, the coefficient of DCG remains significantly positive at the 1% statistical level with stable magnitude and significance. This evidence confirms that the promoting effect of digital transformation on firms' patent knowledge breadth still holds after eliminating the interference of industry characteristics, macroeconomic yearly shocks and firm-level micro attributes. The adjusted R-squared rises markedly as control variables and fixed effects are added step by step, demonstrating that the model specification becomes increasingly reasonable. Overall, the empirical outcomes verify that digital transformation significantly expands corporate patent knowledge breadth, with highly reliable and stable conclusions, which supports the core Hypothesis H1 of this paper.

Table 3. Multicollinearity Test

Variable	VIF	1/VIF
Ownership Nature	1.36	0.734315
Managerial Shareholding Ratio	1.26	0.791829
Ownership Concentration	1.10	0.907748
Profitability	1.10	0.909899
Cash Asset Ratio	1.08	0.922304
Board Size	1.06	0.947716
Digital Transformation	1.04	0.964720
Mean VIF	1.14	

4.2 Robustness Tests

In order to ensure the robustness of the benchmark regression conclusions, this paper further conducts robustness tests from multiple dimensions such as variable measure substitution, extreme value processing, and lag effect test. The results are reported in columns (1) to (7) of Table 4.

1. Adding Additional Control Variables

Although the benchmark regression has put a lot of control variables, the innovation decision-making is more complex, and there are some unseen governance factors that play a role behind it. So we add a variable in the model-the proportion of independent directors (Indep), which is the natural logarithm of the number of independent directors. It is generally believed that the higher the proportion of independent directors, the more in place corporate governance will have a positive impact on innovation. After adding this variable, we run again. Column (1) of Table 4 shows that the coefficient of DCG is still positive, 0.006, which is significant at the level of 1 %, which is similar to the benchmark result. It shows that even considering the factors at the governance level, the conclusion that digital transformation promotes innovation is still tenable.

2. Replacing the Dependent Variable

The innovation indicators (Patent-s) used in the benchmark model are constructed based on patent application data. However, there are often time differences and approval filtering between patent applications and final rights. In order to confirm that the results are not ' biased ' by this link, we have replaced the dependent variable with the patent grant knowledge breadth (Patent-h) -measurement method or based on the HHI, but the data has changed from ' application ' to ' authorization '. The estimation results of column (2) in Table 4 show that the coefficient of DCG is still significantly positive (0.005) at the level of 1 %. The information conveyed by this result is very direct: whether it is based on application or authorization, the effect of digital transformation on the improvement of innovation quality is consistent, and the benchmark conclusion is not sensitive to the choice of patent measurement method.

3. Subsample Regression

A possible question is: will the benchmark results be driven mainly by ' digital native ' industries such as computer, communications and electronic equipment manufacturing? These enterprises naturally have the advantages of digital technology, and the level of digital transformation is generally higher. If they are too large in the sample, the overall effect may be amplified[41][42].Therefore, this paper excludes firms in this specific industry and re-estimates the baseline model based on the modified subsample. The results in Column (3) of Table 4 show that the DCG coefficient is still significantly positive at the 1% level (coefficient = 0.010). After eliminating the interference of digitally advantaged industries, digital transformation still significantly expands firms' patent knowledge breadth, which strongly supports the robustness of the core research conclusion.

4. Re-estimation with Quantile-standardized Independent Variable

To avoid estimation bias caused by a single indicator construction method, this paper standardizes the core independent variable by quantile processing and adopts the quantile-adjusted digital transformation index (DCG_quantile) for re-regression. As reported in Column (4) of Table 4, the coefficient of the standardized digital transformation index is significantly positive at the 1% level (coefficient = 0.029). The result indicates that the innovation-enhancing effect of digital transformation remains stable after changing variable measurement methods, proving that the core finding is not driven by specific index construction rules.

5. Alternative Outlier Treatment (5%–95% Winsorization)

The baseline model adopts 1%–99% winsorization. To further eliminate the disturbance of extreme outliers, this paper reprocesses all continuous variables with 5%–95% winsorization and re-estimates the model. Column (5) of Table 4 shows that the coefficient of DCG is significantly positive at the 1% level (coefficient = 0.035). The conclusion remains unchanged under stricter outlier processing, which excludes the possibility that the baseline results are driven by extreme observations.

6. Lagged Effect Regression

Benchmark regression may face a common question: is digitization driving innovation, or is innovative enterprises more qualified to digitalize? In order to make this causal direction clearer, we have lagged the digital transformation variables-lagged one period and two periods respectively, and re-estimated the model. The regression results in Column (6) (7) of Table 4 provide two interesting information:First, the coefficients of L_DCG and L2_DCG are significantly positive at the 1 % level, indicating that even if the time window is staggered, the early level of digital transformation can still predict the later innovation performance. Secondly, the coefficient of the lag two periods (0.010) is slightly larger than the lag one period (0.009), suggesting that the innovation effect of digitization is not attenuated, but the dividend may still accumulate gradually with the system running-in and deep application. Lag design itself is a common strategy to deal with reverse causality. Combining these two results, the concern of reverse causality is further dispelled.

Table 4. Robustness Test Results

Variables	**(1)** **Patent-s**	**(2)** **Patent-h**	**(3)** **Patent-s**	**(4)** **Patent-s**	**(5)** **Patent-s**	**(6)** **Patent-s**	**(7)** **Patent-s**
DCG	0.006*** (2.61)	0.005** (2.19)	0.010*** (3.79)				
Indep	0.003*** (5.51)						
ROE	0.345*** (7.47)	0.340*** (7.04)	0.388*** (7.98)	0.352*** (7.594)	0.399*** (6.657)	0.342*** (7.173)	0.347*** (7.040)
Top1	0.002*** (10.88)	0.002*** (10.81)	0.002*** (12.13)	0.002*** (11.083)	0.002*** (10.245)	0.002*** (11.417)	0.002*** (11.311)
Cash	-0.130*** (-5.84)	-0.149*** (-6.72)	-0.118*** (-5.01)	-0.133*** (-5.976)	-0.122*** (-4.840)	-0.143*** (-6.089)	-0.158*** (-6.433)
Bsize	0.115*** (8.71)	0.078*** (6.32)	0.087*** (7.03)	0.080*** (6.775)	0.069*** (5.316)	0.082*** (6.727)	0.086*** (6.897)
Mag	0.002*** (9.25)	0.002*** (10.37)	0.002*** (9.10)	0.002*** (9.412)	0.003*** (9.472)	0.002*** (9.514)	0.002*** (9.075)
SOE	0.047*** (8.60)	0.056*** (9.96)	0.048*** (8.35)	0.049*** (8.885)	0.045*** (8.009)	0.050*** (8.762)	0.050*** (8.664)
DCG_quantile				0.029*** (2.787)			
DCG_5%					0.035*** (4.291)		

L_DCG						0.009***	
						(3.611)	
L2_DCG							0.010***
							(3.974)
Constant	-0.063	0.097***	0.066**	0.102***	0.103***	0.106***	0.104***
	(-1.58)	(3.45)	(2.33)	(3.771)	(3.463)	(3.824)	(3.620)
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	10118	10118	9280	10118	9612	9441	8768
Adj. R^2	0.373	0.368	0.387	0.371	0.381	0.369	0.370

4.3 Endogeneity Test

1. Instrumental Variable Approach

This study may suffer from endogeneity problems caused by omitted variables and reverse causality, among which reverse causality is a critical factor interfering with the baseline research conclusions. Therefore, the instrumental variable (IV) method is adopted to mitigate potential endogenous biases.

Following prior mainstream studies, this paper adopts urban postal and telecommunication data in 1984 as the instrumental variable for corporate digital transformation. Given that the original 1984 postal and telecommunication data are cross-sectional and cannot be directly applied to panel regression analysis, this paper follows existing academic practices and constructs an interactive term by combining the number of fixed telephones per 10,000 residents in each prefecture-level city in 1984 with the one-period lagged national Internet user number, which serves as the instrumental variable for current digital transformation level[43]. The constructed IV satisfies both the correlation and exogeneity constraints.

In terms of correlation, the historical communication infrastructure of a city affects local technological maturity and social digital preference, thereby influencing firms' acceptance and application of information technology during the sample period and exhibiting a strong correlation with corporate digital transformation. In terms of exogeneity, postal and telecommunication facilities are public infrastructure designed for public information transmission rather than specialized corporate production and division-of-labor activities, which means they have no direct correlation with firm-level behavioral characteristics.

The empirical results show that the Kleibergen-Paap rk LM statistic is 30.876, which exceeds the critical value of 16.38 and significantly rejects the null hypothesis of under-identification at the 1% level. Whether the instrumental variable is effective depends on whether several thresholds have passed. The correlation test shows that the correlation between IV and DCG is significant, and the under-identification test and the weak instrumental variable test have also passed smoothly-at least statistically this set of tools is tenable. The endogenous test rejects the exogenous null hypothesis at the 1 % level, which means that the OLS estimation does have bias, and it is a reasonable choice to use IV to solve it. Looking at the results of IV regression (Table 5), the coefficient of DCG is still significantly positive, and the direction, significance and magnitude are generally consistent with the benchmark conclusion. This is more critical - it shows that the innovation effect of digital transformation can withstand the test of instrumental variable method, not the false positive on causal identification.

Table 5. Instrumental Variable Regression Results

Variables	(1) Patent-s	(2) Patent-s
IV	0.0711***	
	(5.9153)	
DCG		0.1892***
		(3.6276)
ROE	0.4124**	0.2857***
	(2.3623)	(4.8421)
Top1	0.0002	0.0018***
	(0.2530)	(8.4450)
Cash	0.1388	-0.1639***
	(1.5969)	(-5.7282)
Bsize	0.0229	0.0773***
	(0.4599)	(5.2390)
Mag	0.0029***	0.0014***
	(3.0975)	(4.2857)
SOE	-0.0792***	0.0609***
	(-3.5713)	(7.8441)
Constant	0.8166***	
	(7.3804)	
Observations	10,118	10,118
R^2	0.427	-0.470
Industry FE	YES	YES
Year FE	YES	YES
Kleibergen-Paap rk Wald F statistic	30.876 [16.38]	
Kleibergen-Paap rk LM statistic	31.042***	
Hansen J statistic overidentification test (p-value)	0.000	
Endogeneity test (χ^2 statistic)	18.787***	

2. PSM Endogeneity Test

This paper adopts the Propensity Score Matching (PSM) method to conduct endogeneity tests, with all control variables set as covariates.

Table 6. Balance Test of Propensity Score Matching

Covariate	Unmatched U / Matched M	Mean (Treated)	Mean (Control)	%bias	% Reduction in Bias	t-test t-value	P>t
ROE	U	0.0338	0.0355	-3.100	62.80	-1.530	0.126
	M	0.0338	0.0344	-1.200		-0.520	0.603
Top1	U	32.86	35.20	-16.20	86.20	-7.970	0.000
	M	32.87	32.55	2.200		1.040	0.299
Cash	U	0.159	0.146	11.90	79.30	5.850	0.000
	M	0.159	0.162	-2.500		-1.050	0.292
Bsize	U	2.148	2.169	-11.10	87.40	-5.490	0.000
	M	2.148	2.151	-1.400		-0.630	0.530
Mag	U	5.129	4.106	9.300	97.20	4.600	0.000
	M	5.117	5.089	0.300		0.110	0.911
SOE	U	0.522	0.606	-17.00	77.80	-8.380	0.000
	M	0.522	0.541	-3.800		-1.690	0.092

Before estimating the regression model after propensity score matching, a balance test is carried out.

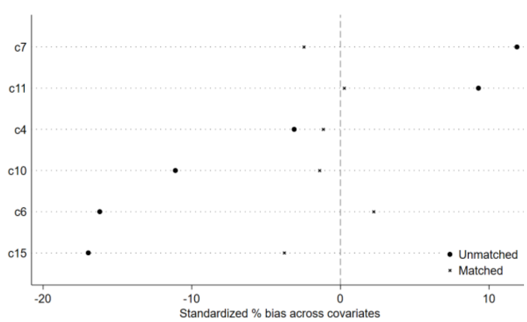

Figure 1. Standardized Bias Plot of All Covariates

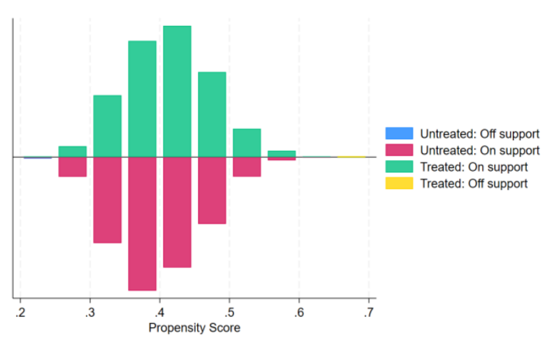

Figure 2. Common Support Range of Propensity Scores

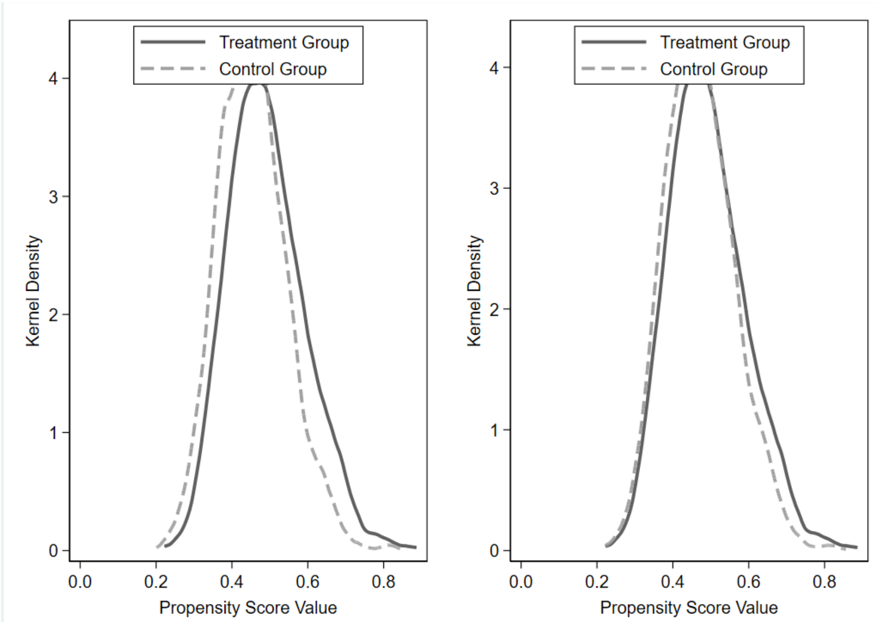

Figure 3. Kernel Density Plot

The test results are presented in Table 6. It can be observed that the standardized bias of all covariates is less than 10% after matching, and there exists no significant difference between the treatment group and the control group for each variable, which indicates that the balance test satisfies the matching requirements well.

Table 7. Regression Results Before and After PSM Matching

Variables	(1) Before MatchingPatent-s	(2) After MatchingPatent-s
DCG	0.0066***	0.0091***
	(2.7869)	(2.8275)
ROE	0.3525***	0.3036***
	(7.5938)	(4.7033)
Top1	0.0019***	0.0021***
	(11.0831)	(8.8568)
Cash	-0.1334***	-0.1284***
	(-5.9756)	(-4.3115)
Bsize	0.0804***	0.0703***
	(6.7751)	(4.4363)
Mag	0.0020***	0.0022***
	(9.4119)	(7.8425)
SOE	0.0491***	0.0554***

	(8.8854)	(7.3767)
Constant	0.1024***	0.1153***
	(3.7715)	(3.1701)
Industry FE	YES	YES
Year FE	YES	YES
Observations	10,118	5,371
Adj. R^2	0.376	0.392

This paper re-estimates the baseline model based on the new matched sample. The regression results after matching are shown in Table 7. The core explanatory variable is significantly positive at the 1% statistical level, which still supports the original hypothesis that digital transformation significantly improves corporate innovation capacity and further verifies the robustness of the baseline regression conclusions.

5. Mechanism Test

5.1 Mediating Effect: Managerial Compensation Incentives

This paper adopts the three-step test method to examine the mediating effect. Table 8 presents the test results of the mediating role of managerial compensation incentives in the relationship between digital transformation and corporate innovation capacity.

Column (1) reports the total effect of digital transformation on corporate innovation capacity. The regression coefficient of digital transformation is 0.0066 and statistically significant at the 1% level, which indicates that digital transformation significantly improves corporate innovation capacity. Accordingly, we proceed to test the existence of the mediating effect of managerial compensation incentives.

Column (2) estimates the impact of digital transformation on managerial compensation incentives. The regression results show that the coefficient of digital transformation is 0.0646 and statistically significant at the 1% level (note: the original text contains a logical inconsistency: the positive coefficient implies a positive effect rather than a negative one). This result suggests that the advancement of corporate digital transformation significantly raises the level of managerial compensation incentives. Organizational restructuring and efficiency gains brought by digital transformation drive firms to optimize their compensation systems to incentivize managers to advance innovative activities, which verifies the prerequisite for the mediating channel.

Column (3) incorporates both the core independent variable digital transformation and the mediating variable managerial compensation incentives into the regression model simultaneously.

Table 8. Regression Result Table

Variable	(1) Patent-s	(2) Magw	(3) Patent-s
DCG	0.0066***	0.0646***	0.0058**
	(2.6455)	(9.7651)	(2.3276)
Magw			0.0119***
			(3.1591)
ROE	0.3525***	3.1165***	0.3154***
	(8.0589)	(26.9175)	(6.9661)
Top1	0.0019***	0.0005	0.0019***
	(11.3949)	(1.1834)	(11.3619)
Cash	-0.1334***	-0.0361	-0.1330***
	(-6.1279)	(-0.6262)	(-6.1108)
Bsize	0.0804***	0.4757***	0.0747***
	(6.4268)	(14.3670)	(5.9159)
Mag	0.0020***	-0.0011*	0.0020***
	(8.5250)	(-1.8287)	(8.5851)
SOE	0.0491***	-0.0838***	0.0501***
	(8.8755)	(-5.7216)	(9.0452)
Constant	0.0536	12.9787***	-0.1010
	(1.3496)	(123.3640)	(-1.6018)
Industry Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	10,118	10,118	10,118
Adj. R^2	0.376	0.359	0.377
Sobel Test	3.006***		

When the management compensation incentive is added to the regression equation, the coefficient of DCG is still positive at the significance level of 1 % (0.0058), and the coefficient of compensation incentive is also significant. This shows that the role of digital transformation in promoting the breadth of patent knowledge is partly direct, and the other part is the existence of an indirect path achieved by improving salary incentives, which does not weaken the significance of the direct effect.

The further confirmation of the mediating effect comes from the Sobel test. The test statistic is 3.006, which is significant at the level of 1 %, which is consistent with the results of stepwise regression.With the help of Bootstrap repeated sampling (5000 times), we made an additional investigation on the robustness of the mediating effect, and the test results did not change the original judgment.The coefficients, standard errors, Z-statistics, p-values and 95% confidence intervals of the indirect and direct effects are reported. The results fully validate the statistical significance and stability of the mediating effect.

These findings strongly verify the real existence of the indirect channel where digital transformation expands the knowledge breadth of corporate patent applications by boosting managerial compensation incentives, and this indirect effect is highly reliable statistically. It demonstrates that even after controlling for the mediating variable, digital transformation still exerts a positive direct impact on the knowledge breadth of corporate patent applications, which further supports the conclusion of partial mediation. Specifically, the promoting effect of digital transformation on firms' innovative knowledge breadth is partially realized indirectly via the internal compensation incentive mechanism, and partially realized through direct channels such as technology empowerment and improved information efficiency.

Table 9. Bootstrap Test

Mediating Variable	Direct / Indirect Effect	Coefficient	Standard Error	Z-statistic	P-value	95% Confidence Interval
Magw	Indirect effect	0.00077	0.0002568	3.00	0.003	[0.00031, 0.00131]
	Direct effect	0.00584	0.0023209	2.52	0.012	[0.00139, 0.01047]

5.2 Moderating Effect

1. Moderating Effect of Corporate Administrative Expense Ratio

As shown in Column (1) of Table 10, the regression coefficient of digital transformation on corporate innovation capacity is 0.0051 and significant at the 10% level. The interaction term between digital transformation and managerial equity incentives yields a significantly positive coefficient of 0.0574 at the 10% level. This finding indicates that managerial equity incentives exert a positive moderating effect. Specifically, compared with firms with a low administrative expense ratio, enterprises with a high administrative expense ratio can achieve a greater expansion in the knowledge breadth of patent applications when advancing digital transformation.

A plausible explanation is that reasonable investment in administrative expenses helps optimize internal management procedures and improve organizational coordination efficiency, thereby offering sound internal supporting conditions for digital transformation to empower corporate innovation. Hypothesis H3a is verified.

2. Moderating Effect of Total Asset Turnover Ratio

According to the estimation results in Column (2) of Table 10, the coefficient of digital transformation on corporate innovation capacity is 0.0063 and statistically significant at the 5% level. The interaction term between digital transformation and total asset turnover ratio has a coefficient of -0.0099, which is significantly negative at the 5% level. The result reveals that total asset turnover plays a negative moderating role: the higher a firm's total asset turnover, the weaker the positive promotional effect of digital transformation on the knowledge breadth of patent applications.

High-efficiency enterprises invest more in fine operation and capacity expansion of existing businesses, but resources in long-term activities such as digital cross-border innovation and knowledge boundary extension are relatively scarce. This resource mismatch may be an important reason for the above phenomenon, which also confirms the hypothesis H3B.

3. Moderating Effect of Financing Constraints SA Index

Regarding the measurement of financing constraints, we follow the common practice in the academic community, taking the absolute value of the SA index[44][45]. The larger the value, the higher the degree of constraint[46]. Preliminary estimates show that the index is negatively correlated with the breadth of patent knowledge, which reflects that financing constraints lead to limited R&D investment, enterprises are unable to take into account the exploration of multiple technical directions, and patent activities tend to be concentrated. However, after adding the interaction term, we find that digital transformation can reverse this trend: in enterprises with a higher degree of digitization, the negative impact of financing constraints is significantly weakened. This buffering effect may be due to the optimization of the information environment and the allocation of funds by digitization - increased transparency and reduced financing barriers, enabling companies with limited resources to apply for patents on a broader technology spectrum.

The results of column (3) in Table 10 show that the direct effect of digital transformation on innovation capability is 0.0050 (significant at 10 % level), and its interaction coefficient with the absolute value of SA index is 0.0171 (also significant at 10 % level). This shows that digitization not only directly promotes technological innovation of enterprises, but also indirectly releases innovation potential by alleviating financing constraints. In particular, it is worth noting that for enterprises with more serious financing constraints, digital transformation plays a more prominent role in promoting the width of patent knowledge-for every one unit increase in the absolute value of SA index, the marginal driving effect of digitization on knowledge width will increase by 0.0171 units. These results provide empirical support for the regulatory role of digital transformation in improving the financing environment and stimulating innovation vitality.

This mechanism may be understood as follows: digital transformation reduces the information asymmetry inside and outside the enterprise, and reduces the financing cost, thus weakening the suppression of financing constraints on innovation activities. Thanks to this, the expansion of enterprises in the field of knowledge is more smooth, especially for enterprises subject to capital bottlenecks, digitization has instead formed a ' compensatory ' innovation incentive. The above logic is consistent with H4C.

Table 10. Moderating Effect Regression Results

Variable	(1) Patent-s	(2) Patent-s	(3) Patent-s
DCG	0.0051*	0.0063**	0.0050*
	(0.0024)	(0.0024)	(0.0023)
ROE	0.2884***	0.3413***	0.3471***
	(0.0470)	(0.0470)	(0.0461)
Top1	0.0018***	0.0019***	0.0015***
	(0.0002)	(0.0002)	(0.0002)
Cash	-0.1219***	-0.1343***	-0.1403***
	(0.0223)	(0.0223)	(0.0221)
Bsize	0.0732***	0.0807***	0.0803***
	(0.0119)	(0.0118)	(0.0116)
Mag	0.0021***	0.0020***	0.0016***
	(0.0002)	(0.0002)	(0.0002)
SOE	0.0478***	0.0495***	0.0521***
	(0.0055)	(0.0055)	(0.0055)
AER	-0.4028***		
	(0.0505)		
DCG*AER	0.0574*		
	(0.0238)		
TAT		0.0172*	
		(0.0072)	
DCG*TAT		-0.0099**	
		(0.0036)	
SA Index			-0.1587***
			(0.0144)
DCG*SA Index			0.0171*
			(0.0071)
Constant	0.0828*	0.0502	0.0169
	(0.0402)	(0.0401)	(0.0402)
Industry Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	10118	10118	10118

6. Heterogeneity Test

6.1 Industry Heterogeneity

The industry attribution characteristics of environmental performance are obvious, and the focus and difficulty of digital transformation in different industries are also different. Therefore, from the perspective of industry heterogeneity, this part divides the research samples into two categories: manufacturing and non-manufacturing. As an important support of the national economy, manufacturing enterprises usually show higher enthusiasm for technology adoption, but their production activities are subject to tangible factor inputs, so environmental performance shows strong path dependence and rigidity, and it is difficult to rely solely on substantive green innovation to achieve rapid improvement. Based on this difference, we further compare the similarities and differences between the innovation effects of digital transformation on manufacturing and non-manufacturing enterprises.

The results of Column (1) of Table 11 show that the coefficient of digital transformation to the patent knowledge width of manufacturing enterprises is 0.0012, and the 1% level is significant, while the coefficient in non-manufacturing samples is −0.002 and not statistically significant. The comparison between the two groups clearly shows that the digital transformation has indeed played a role in promoting the expansion of the knowledge boundary of manufacturing enterprises. The reason is that the manufacturing industry, as a typical scenario of the deep penetration of digital technology, has embedded intelligent manufacturing, industrial Internet and big data analysis in all aspects of production, which has gradually eliminated the traditional technical barriers. This integration not only opens up the information gap between different departments, but also encourages enterprises to cross-explore in the multi-technical directions of materials, machinery, electronics, etc., and ultimately reflects the obvious improvement of the breadth of patent application knowledge.

6.2 Firm Size Heterogeneity

Considering that the scale of enterprises directly affects the basic conditions and innovation performance of digital transformation, and there are systematic differences in capital, talent, financing and innovation paths between large and small enterprises[47],this paper groups the samples by scale. This approach aims to control the potential bias of mixed regression and clarify the specific context in which digitization affects the breadth of knowledge, so that the conclusions have differentiated reference significance for enterprises of different sizes. In data processing, a single observation sample is automatically eliminated.

The data in column (2) of Table 11 reveals a clear scale threshold: digital transformation has significantly expanded the patent knowledge breadth of large enterprises (coefficient 0.009, $p < 0.01$), but has no significant impact on SMEs. The reason is that large enterprises not only have sufficient resources to invest in digital construction and high-precision R&D, but also have the platform advantage of driving collaborative innovation in the industrial chain. Under the superposition of the two, cross-domain knowledge integration is smoother, and the knowledge breadth of patents is naturally improved. Small and medium-sized enterprises are limited by resource endowments, and the effectiveness of digitization is still difficult to be reflected in the breadth of knowledge.

Table 11. Heterogeneity Analysis: Industry and Firm Size

Variables	Column (1)		Column (2)	
	Manufacturing	**Non-manufacturing**	**Large Firms**	**SMEs**
	Patent-s	**Patent-s**	**Patent-s**	**Patent-s**
DCG	0.012***	-0.002	0.009***	0.004
	(4.20)	(-0.56)	(2.67)	(1.31)
ROE	0.268***	0.535***	0.380***	0.233***
	(4.74)	(6.52)	(5.07)	(3.90)
Top1	0.002***	0.003***	0.002***	0.002***
	(6.68)	(9.13)	(7.86)	(5.59)
Cash	-0.118***	-0.165***	-0.036	-0.137***
	(-4.05)	(-4.69)	(-0.98)	(-4.87)
Bsize	0.075***	0.086***	0.099***	0.047***
	(4.75)	(4.87)	(6.17)	(2.71)
Mag	0.002***	0.001***	0.001**	0.002***
	(8.66)	(3.23)	(2.33)	(9.71)
SOE	0.045***	0.060***	0.065***	0.038***
	(6.51)	(6.63)	(8.18)	(4.89)
Constant	0.212***	-0.087**	0.062	0.175***
	(5.86)	(-2.16)	(1.63)	(4.48)
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	6549	3569	5057	5059
Adj. R2	0.148	0.388	0.386	0.387

6.3 Heterogeneity of Economic Development Levels

Considering the imbalance in the distribution of digital infrastructure, marketization and innovation resources among regions, we divide the samples into three sub-samples: eastern, central and western sub-samples according to the place of registration of enterprises, and carry out regression tests respectively. The results are reported in Table 12. Column (1) corresponds to the estimation of the eastern region: the coefficient of DCG is 0.007, which is positive at the 5 % significance level. This result means that in the eastern region where the digital economy environment is more mature and the factor supply is more abundant, the promotion effect of digital transformation on enterprise innovation is still significant, which is consistent with the main conclusion.

In Column (2) for the central region, the coefficient of DCG is significantly negative. This implies that digital transformation has not yet generated positive incentives for corporate innovation in central China, and even exerts a certain inhibitory effect to some extent. A plausible explanation lies in the relatively traditional industrial structure and insufficient depth of digital application in central regions, where short-term investment in digital transformation has not yet been effectively matched by innovative outputs.

Column (3) displays the results for the western region. The coefficient of DCG is 0.030, significantly positive at the 1% level and markedly larger than that of the eastern region. This demonstrates that digital transformation exerts the strongest promotion effect on corporate innovation in western China. This phenomenon may be attributed to the relatively weak traditional innovation foundation in western regions: the access to information, technology spillovers and efficiency gains brought by digitalization yield more pronounced marginal improvements. Meanwhile, vigorous policy support and rapid construction of digital infrastructure further amplify the innovation-enabling effect.

The regression results of each control variable maintain good consistency between regions-ROE, Top1, Bsize and Mag are mostly significantly positive, and Cash is mostly significantly negative, which is consistent with the main regression conclusion. The coefficient of the core variable DCG shows distinct regional characteristics: the western region has the most obvious benefit, followed by the eastern region, and the central region has not reached a significant level. This ' gradient decreasing ' pattern shows that the innovation dividend of digital transformation is unevenly distributed among different regions, and the design of regional differentiation policies should be fully considered.

Table 12. Heterogeneity Analysis: Division by Economic Zones

Variables	**(1) Eastern Region** **Patent-s**	**(2) Central Region** **Patent-s**	**(3) Western Region** **Patent-s**
DCG	0.007**	-0.011**	0.030***
	(2.55)	(-2.03)	(4.32)
ROE	0.356***	0.223**	0.268**
	(6.23)	(2.33)	(2.26)
Top1	0.002***	0.002***	0.003***
	(10.31)	(4.18)	(6.27)
Cash	-0.147***	-0.145***	0.093
	(-5.60)	(-2.86)	(1.29)
Bsize	0.074***	0.146***	0.073**
	(5.03)	(4.95)	(2.57)
Mag	0.001***	0.003***	0.003***
	(6.10)	(4.75)	(3.89)
SOE	0.032***	-0.014	0.150***
	(4.73)	(-1.16)	(8.54)
Constant	0.113***	0.057	-0.026

	(3.41)	(0.86)	(-0.39)
Industry Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	6564	1929	1623
Adj. R2	0.385	0.465	0.475

6.4 Heterogeneity of High-Tech and Non-High-Tech Enterprises

This paper further examines the heterogeneity from the dimension of technical attributes, and divides the sample into two groups: high-tech enterprises and non-high-tech enterprises[48], and introduces the DCG × Tech interaction term to test the moderating effect. The regression results are shown in table 13. It can be seen from Column (1) that the DCG coefficient in the sub-sample of high-tech enterprises is-0.0019 and not significant, indicating that digitization has no significant independent impact on the breadth of patent knowledge of such enterprises. This may be because the original technical ability and innovation investment of high-tech enterprises have been relatively saturated, and the marginal expansion space brought by digitization is limited.

The regression results of non-high-tech enterprises are shown in column (2) of table 13: the DCG coefficient is 0.0122 (1 % significant), indicating that the digital transformation has a more significant innovation promotion effect on traditional industries. This is due to the fact that digital transformation improves the information integration efficiency, process coordination level and knowledge acquisition ability of enterprises, thus systematically enhancing innovation performance. In general, the innovation dividend of digital transformation shows the characteristics of technological heterogeneity - non-high-tech enterprises benefit more obviously, while high-tech enterprises have not yet released significant digital effects.

Table 13. Heterogeneity Analysis: High-tech vs. Non-high-tech Firms

Variables	**(1) High-tech Firms**	**(2) Non-high-tech Firms**	**(3) Model with DCG×tech Interaction**
DCG	-0.0019	0.0122***	0.0124***
	(-0.513)	(3.911)	(4.130)
ROE	0.2066***	0.4823***	0.3507***
	(3.085)	(7.573)	(7.569)
Top1	0.0012***	0.0024***	0.0019***
	(4.128)	(10.655)	(10.989)
Cash	-0.2078***	-0.0853***	-0.1344***
	(-5.828)	(-2.981)	(-6.012)
Bsize	0.0530***	0.1016***	0.0803***

	(2.858)	(6.639)	(6.771)
Mag	0.0028***	0.0014***	0.0020***
	(9.572)	(4.590)	(9.492)
SOE	0.0621***	0.0436***	0.0495***
	(7.012)	(6.175)	(8.970)
DCG×tech			-0.0127***
			(-2.954)
Industry Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	3998	6120	10118
Adj. R2	0.190	0.445	0.371

6.5 Regulated Enterprises and Competitive Enterprises

This paper further examines the heterogeneity from the perspective of market environment, and divides the sample into regulated enterprises and competitive enterprises for group regression. The results are shown in table 14. Column (1) shows that the DCG coefficient in regulated enterprises is 0.0078 but not significant, indicating that the driving effect of digitization on the breadth of patent knowledge has not been effectively played in such enterprises. This may be attributed to the fact that the regulatory industry is subject to more policy constraints, the business objectives are relatively dispersed, and the market competition is not sufficient, so that the innovation expansion effect of digital technology is difficult to be effectively transformed.

Column (2) of Table 14 shows the estimated results of the sub-sample of competitive enterprises. The coefficient of DCG is 0.0061, which is significantly positive at the 5 % statistical level. This means that competitive industries provide a suitable soil for digital transformation to play an innovation-driven role. In the fierce market competition, in order to maintain or enhance the market position, enterprises have a stronger incentive to use digital technology to improve internal operational efficiency and optimize the structure of R&D investment, so as to more effectively transform digital investment into the improvement of patent knowledge breadth. Based on the results of the two columns in Table 14, a clear conclusion can be drawn: the innovation promotion effect of digital transformation is dependent on the market competition environment, and its significance mainly exists in competitive industries, but not in regulatory industries. This finding further verifies the important role of competition mechanism in the transformation process of digital technology and innovation performance.

Table 14. Heterogeneity Analysis: Regulated vs. Competitive Enterprises

Variables	(1) Regulated Enterprises	(2) Competitive Enterprises
DCG	0.0078	0.0061**
	(1.330)	(2.351)
ROE	0.3862***	0.3655***
	(3.561)	(7.122)
Top1	0.0037***	0.0012***
	(10.642)	(5.734)
Cash	-0.1270***	-0.1404***
	(-2.622)	(-5.601)
Bsize	0.0336	0.0912***
	(1.266)	(7.112)
Mag	0.0014**	0.0019***
	(2.120)	(8.612)
SOE	0.0760***	0.0412***
	(5.603)	(6.792)
Industry Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	2683	7435
Adj. R2	0.347	0.387

6.6 National Big Data Comprehensive Pilot Zone Policy

In order to identify the impact of external policy factors on the innovation effect of digital transformation, this paper uses the exogenous event of the establishment of the National Big Data Comprehensive Experimental Zone in 2016 to construct a quasi-natural experiment. The test area covers eight key areas: Guizhou, Beijing-Tianjin-Hebei, Pearl River Delta, Shanghai, Henan, Chongqing, Shenyang and Inner Mongolia. In the empirical study, we introduce the policy dummy variable (BigData) and its interaction with DCG (BigData × DCG) to evaluate the policy effectiveness of the national data strategy at the micro-enterprise level.

The reason why policy support can amplify the innovation effect of digital transformation is inseparable from the consolidation of digital infrastructure in the region, the smooth circulation of data elements and the optimization of industrial synergy conditions, which together shape a good external digital ecology. At the level of control variables, the coefficients of ROE, Top1, Bsize, Mag and SOE are significantly positive, while Cash is significantly negative, which is basically consistent with the main regression results. The addition of industry and year fixed effects makes the estimation more credible, and the adjusted R^2 is 0.3768, which further confirms the robustness of the regression results.

The estimation results of the policy effect show that the construction of the pilot area itself does not constitute an independent driving factor for enterprise innovation, but its interaction with digital transformation is significantly positive. This means that the real value of the policy is to build an external platform for digital technology enabling innovation - through multiple improvements in infrastructure, factor circulation and industrial synergy, the knowledge expansion effect of digital transformation can be amplified. Therefore, it can be concluded that there is a complementary relationship between macro policy support and digital technology application, and the coupling of the two is an important prerequisite for releasing the innovation dividend.

Table 15. Heterogeneity Analysis of National Big Data Comprehensive Pilot Zones

Variables	Patent-s
Bigdata	-0.0117436*
	(-1.79)
Bigdata×DCG	0.0085288**
	(2.34)
DCG	0.003001
	(1.07)
ROE	0.3534***
	(7.61)
Top1	0.002***
	(11.12)
Cash	-0.1337***
	(-5.97)
Bsize	0.0805***
	(6.78)
Mag	0.002***
	(9.38)
SOE	0.049***
	(6.51)
Constant	0.212***
	(8.88)
Industry Fixed Effects	YES
Year Fixed Effects	YES
Observations	10118
Adj. R2	0.3768

7. Conclusions and Policy Implications

Taking China's A-share listed companies from 2010 to 2024 as research samples, this paper systematically examines the direction, transmission mechanism and situational conditions of digital transformation affecting enterprise innovation with the help of two-way fixed effect regression model. In the theoretical framework, we incorporate the internal incentive mechanism and the external adaptation situation into a unified analysis perspective to enhance the explanatory power of the empirical results. Benchmark regression shows that digital transformation has a significant driving effect on enterprise innovation. The mechanism test further reveals that digital transformation can optimize the internal governance structure of enterprises and enhance the incentive intensity of management compensation, and through this path, it has a positive spillover on innovation performance, thus verifying the transmission logic of digitization-incentive optimization-innovation improvement.

The results of heterogeneity analysis show that the innovation effect of digital transformation shows obvious differentiation in different types of enterprises. From the perspective of industry attributes, the driving effect of manufacturing enterprises is stronger than that of non-manufacturing enterprises; from the perspective of scale characteristics, the innovation dividend of large-scale enterprises is also significantly higher than that of small and medium-sized enterprises. There are different logics behind this difference: the advantage of manufacturing industry is that it has rich digital application scenarios, digital technology can be deeply coupled with the whole process of manufacturing, and the channel of innovation and transformation is smoother; the disadvantage of small and medium-sized enterprises is that they are subject to capital bottlenecks and talent shortcomings for a long time. The speed and depth of digital advancement are limited, and innovation efficiency is difficult to fully release.

The analysis of the moderating effect shows that the policy of the national big data comprehensive experimental zone has a significant positive adjustment on the innovation effect of digital transformation, indicating that the macro-level institutional support is an important driving force for digital technology to empower innovation. Taking the approval of the pilot area in 2016 as an exogenous policy shock, the quasi-natural experiment results constructed in this paper show that enterprises in the policy coverage area have gained additional gains in innovation output. This result verifies the synergistic effect between digitization and institutional environment from a policy perspective. Based on the above findings, we put forward operational suggestions from the enterprise level, industry level and government level, in order to provide path guidance for different subjects to promote digital-driven innovation growth.

Enterprise-level Implications: Enterprises should formulate refined digital transformation strategies and improve internal governance mechanisms. Manufacturing firms should focus on core fields including intelligent manufacturing, industrial Internet, and big data-driven R&D, strengthen the in-depth integration of digital technologies with production and manufacturing processes, break departmental barriers and knowledge boundaries in traditional R&D activities, and broaden the knowledge breadth of innovation and patent applications. Large enterprises should balance short-term operational efficiency and long-term innovation investment, rationally allocate resources, and avoid over-reliance on existing businesses at the expense of cross-border innovation. Meanwhile, they should establish managerial compensation incentive systems closely linked to innovation performance, incorporating patent applications and technological breakthroughs into performance appraisal to stimulate the innovation initiative of management teams. SMEs can concentrate on digital application scenarios in segmented fields, acquire resources through collaborative cooperation and joint innovation platforms with large enterprises, and gradually break through resource bottlenecks in digital transformation.

Industry-level implications: Industries should strengthen industrial collaborative mechanisms and implement differentiated digital transformation strategies. The manufacturing industry should take the lead in building industry-level digital sharing platforms, integrate data resources of upstream and downstream enterprises, promote cross-firm and cross-field collaborative innovation, and reduce the costs and thresholds of digital transformation for SMEs. Non-manufacturing industries should fully explore digital application scenarios, achieve breakthroughs in service process optimization, precise customer demand identification, and business model innovation, and cultivate new drivers of innovation growth. Technology-intensive industries such as computer and communication industries should give full play to technology spillover and demonstration effects, drive the overall digital upgrading of the industrial chain, and form a development pattern of “benchmark demonstration — radiation driving — comprehensive upgrading”.

Government-level implications: The government should optimize the policy support system and build a high-quality innovation ecosystem. At the government level, efforts can be made from the following aspects: replicating the mature experience of the big data comprehensive pilot area to the whole country, increasing investment in digital infrastructure, and giving preference to the central and western regions and small and medium-sized enterprises. For enterprises with limited financing, it is suggested to build a digital credit evaluation platform, improve the financing service chain, reduce the financing cost caused by information asymmetry, and broaden the innovative financing channels of enterprises. In terms of industrial policies, manufacturing enterprises should be given differentiated support such as tax incentives and R & D subsidies, and encouraged to expand their investment in digital innovation. At the same time, it is necessary to strengthen the protection of intellectual property rights, effectively safeguard the digital innovation achievements of enterprises, and continuously optimize a stable, fair and efficient policy environment.

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