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The Impact of Digital Transformation on Corporate Innovation Performance

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ABSTRACT

In the current context of China's economic transition, focusing on the issue of corporate innovation performance can lay a solid foundation for the acceleration of the digital transformation process as well as the improvement of corporate innovation performance. This paper selects the relevant data of a listed enterprise from 2018 to 2023 as a research sample for empirical analysis. Combined with the DIT model to test the role of digital transformation on innovation performance, and on the two perspectives of financing constraints and intellectual property protection, it specifically studies the mediating effect and adjustment mechanism between digital transformation and enterprise innovation performance. Finally, from the perspective of enterprise heterogeneity (whether state-owned or not, enterprise size, geographical policy), the actual impact of digital transformation on performance under different enterprises is specifically analyzed. The results show that digital transformation has a positive effect on enterprise innovation performance, and digital transformation can reduce financing constraints to a certain extent, ensure sufficient financial support for enterprise operations, and contribute to the improvement of enterprise innovation performance. Research on the moderating mechanism shows that intellectual property rights have a positive impact on digital transformation to promote the enhancement of enterprise innovation performance. Further heterogeneity analysis shows that digital transformation has a more prominent effect on innovation performance in large-scale enterprises.

Keywords: DIT model, mediating effect, moderating mechanism, digital transformation, firm innovation performance

1. Introduction

Innovation, as an important engine for high-quality development of enterprises, is a key force to promote the formation of new quality productivity in China [1]. With the rapid change of science and technology and the flourishing rise of the Internet, cloud computing and artificial intelligence,

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enterprises are facing unprecedented opportunities and challenges of change, and many enterprises hope to use digital transformation to innovate and transform their own business models, value systems and product functions, so as to enhance the ability of enterprises to obtain long-term stable and sustainable development [2-6]. Small and medium-sized enterprises (SMEs) are an important part of China's innovation system, and it is of great significance to continuously improve the innovation capability of SMEs to accelerate China's economic development [7]. Therefore, in the context of the rapid development of digitalization, how to seize this opportunity to continuously innovate to enhance the core competitiveness of products has become the most important priority of the current development.

The wide application of digital technology has given rise to new products and new markets, and new organizations represented by the platform economy have been born, and the enterprise's digital transformation has become a general trend [8-9]. Digital transformation not only requires enterprises to have advanced digital technology application capabilities, but also needs to make full use of the information advantages brought by digital technology [10-11]. Through digital transformation, small and medium-sized enterprises can obtain powerful data insight and decision-making support capabilities, optimize resource allocation, improve operational efficiency, and provide solid digital support and technical guarantee for the long-term development of enterprises [12-14]. In the context of intensified global competition and accelerated technological iteration, digital transformation of SMEs is not only a necessary initiative to meet market challenges, but also a key to achieve sustainable development and innovation performance improvement [15-17].

Data-driven decision-making model refers to an approach based on data analysis to guide the decision-making process, which relies on quantitative data rather than on intuition, experience, or unproven assumptions [18]. It has been proven that data as a new factor of production will greatly influence the way companies make innovative decisions and innovate.Kolasani, S. showed that effective data management and data-driven decision making are at the core of an organization's ability to maintain a competitive advantage and create business value in dynamic business environments, and that by establishing a data quality framework based on advanced technologies, companies can harness the power of data as a strategic asset and drive innovation across the enterprise [19]. Zhu, X. et al. explored the impact of enterprise data-driven insights on the development of organizational duality, pointing out that enterprise decision-making based on data analytics will effectively support its efficiency transformation and value transformation, and improve its innovation capability while meeting its own development needs [20]. Bratasanu, V. analyzed the impact of enterprise data-driven decision-making on organizational systems and business goals, the introduction of new technologies significantly improves data transparency and decision making within the organization and will provide valuable recommendations for business decisions [21]. The emergence of this new decision-making model breaks the traditional pattern of enterprise decision-makers relying on experience and intuition to formulate business strategies, and can effectively improve the innovative performance of manufacturing enterprises by analyzing the accompanying data elements of the production process.

Enterprise digital transformation plays an important role in enhancing its resource allocation capacity. Liu, Y. et al. explored the effective path to improve resource allocation efficiency in the process of enterprise digital transformation.Enterprises accelerating digital transformation can effectively attract external financing, and realize enterprise cost reduction and efficiency increase by improving resource allocation efficiency[22]. Liu, Y. et al. investigated the impact of digital transformation of enterprises on their financial asset allocation, and in the context of digital transformation, the change of business risk of enterprises affects defensive financial asset allocation and promotes profit-seeking financial asset allocation through financing arbitrage path analysis [23]. Wang, Y. et al. establish an enterprise human resource management framework based on decision tree technology, which greatly reduces the efficiency of human resource management by data mining the information of the enterprise's recruiting employees, and has practical significance in personnel recruitment with practical significance [24]. The process of enterprise digital transformation through technological innovation helps to improve the structure of the enterprise labor force, improve the efficiency of the use of input capital, and then promote the growth of enterprise total factor productivity.

In addition, digital transformation can significantly improve the operational efficiency of enterprises.Yu, J. et al. revealed the relationship between the strategic positioning of enterprises, digital transformation capabilities and operational performance.Enterprises update their business models and value creation with the help of digital transformation capabilities in order to develop adaptive strategies and business processes in highly changing market environments [25]. Wang, D. et al. found that digital transformation improves operational efficiency and reduces production costs by improving operational efficiency and reducing production costs, thus positively affecting the performance of manufacturing firms, providing some insights into the construction of digital transformation metrics for enterprises [26]. Wang, Y. et al. investigated the impact of digital transformation on enterprise performance, and the introduction of digital technology can effectively reduce the cost of business operations and improve scientific and technological research and development, in order to promote the improvement of enterprise performance [27]. The above studies show that digital innovation can help enterprises improve their performance by creating new value for customers, improving their dynamic adaptability, and changing the way of value acquisition and creation. However, the research on digital transformation for enterprise innovation performance improvement is still in its infancy.

The study hypothesizes the correlation between digital transformation and corporate innovation performance after a theoretical analysis of the relationship between the two. In order to further explore the impact of digital transformation on enterprise innovation performance and its mechanism, this paper selects the 6-year data of a listed enterprise from 2018 to 2023 as the research sample for empirical analysis. First, the impact of digital transformation on enterprise innovation performance is examined in combination with the DIT model; second, the mechanism of the role between digital transformation and enterprise innovation performance is analyzed through the perspectives of financing constraints and intellectual property protection. In further analysis, the differences between enterprises of different natures in terms of the impact of digital transformation on enterprise innovation performance are compared from three aspects, namely, enterprise size and geographical policy.

2. Theoretical analysis and research hypotheses

2.1. Digital Transformation and Business Performance

First, digital transformation can significantly improve the operational efficiency of enterprises, and through the use of cutting-edge digital technologies such as "artificial intelligence" and "Internet of Things", enterprises can hand over simple and tedious repetitive tasks to human-machine collaboration, reduce human dependence, optimize human resource allocation, and reduce labor costs [28]. More importantly, digital technology breaks the information barriers between enterprises, promotes the barrier-free sharing of information between enterprises, optimizes the enterprise transaction process, reduces intermediary links, and then realizes the deep cut of transaction costs. Secondly, digital transformation can help enterprises to strengthen the connection with customers, so that enterprises can more quickly capture the changes in market demand and respond to them, and then realize the rapid iteration and optimization of products, and take the initiative in the market competition. Finally, digital transformation can also strengthen the internal control of enterprises, enterprises through the digital transformation of the introduction of advanced information systems and digital technology tools, so that they can real-time access, processing and analysis of business data, thereby improving the accuracy and timeliness of internal control. These digital systems can automate a series of control activities such as authority management, data validation and anomaly detection, reducing the possibility of human error and fraud and strengthening the effectiveness of internal control.

Based on the above analysis, hypothesis H1 is proposed:

H1: Digital transformation has a facilitating effect on business performance

2.2. Mediating effects of financial constraints

Enterprises carry out financing activities mainly through indirect financing. Considering the risk factor, financial institutions within the traditional system tend to be more hesitant and cautious in carrying out credit operations for enterprises in order to minimize credit risks, and some SMEs therefore find it difficult to achieve the set financing targets and are caught in financing difficulties. In addition, affected by the asymmetry of information in the financial industry, enterprises are unable to be fully informed of financing information, and do not know much about effective financing channels, encountering difficulties in financing. However, enterprise innovation activities require R&D investment and employment of R&D personnel, which need a large amount of funds as support. Insufficient financing will make it difficult for enterprises to formulate measures in line with the science and technology-driven strategy and improve the efficiency of scientific research resource allocation, and the enterprise's innovation performance will be reduced as a result.

Against the background of reduced financing constraints, the innovation performance of enterprises can be improved. First of all, enterprises can obtain more financing funds, thus forming a stronger attraction to high-quality talents, improving the talent structure as soon as possible, expanding the scale of talents, promoting the innovation of enterprise technology, and accelerating the pace of enterprise innovation performance improvement. Secondly, in order to improve the innovation performance of enterprises, it is necessary to promote the development of enterprise R & D work, which needs to protect the enterprise R & D work of the capital investment, by reducing the obstacles and difficulties in obtaining funds from the outside of the enterprise, the enterprise R & D investment in innovation and R & D talent introduction is more adequate, and the innovation performance of the enterprise has been improved accordingly.

Based on the above analysis, the second hypothesis is made:

H2: Enterprise digital transformation can improve innovation performance by alleviating financing constraints

2.3. The Moderating Role of Intellectual Property Protection

According to the institutional base view, enterprise performance is the result of the interaction between the internal and external systems of the organization, the system of external rules and regulations will have an impact on enterprise behavioural decisions, and the system of the formal innovation environment, such as intellectual property protection, helps to guide and regulate enterprise behaviour.

A high level of intellectual property protection can effectively restrain unethical behavior of enterprises, significantly reduce infringement between enterprises and R&D partners in the process of collaborative innovation, ensure the innovation benefits of enterprises in the context of cooperation, and make enterprises more willing to carry out collaborative R&D activities with other organizations to form knowledge alliances, so as to join hands to carry out joint R&D and innovation activities. Finally, intellectual property protection can effectively solve the enterprise innovation information dilemma. Due to the high risk and uncertainty of innovation activities, enterprises often face the dilemma of information asymmetry, making it difficult for them to fully demonstrate their innovation potential and value to external investors and other stakeholders. And the high level of intellectual property protection effectively guarantees the enterprise's innovation revenue and encourages enterprises to disclose necessary R&D information to relevant subjects, which not only includes key information such as technological innovation results and R&D progress, but also involves the enterprise's innovation strategy, market prospects and other in-depth contents. Therefore, research hypothesis H3 is proposed:

H3: Intellectual property protection positively moderates the relationship of digital transformation.

3. Study design

3.1. Sample Selection and Data Sources

This paper focuses on the impact of digital transformation on innovation performance in order to consider a sample selection where the differences in policy preferences are not too large. In this paper, a listed company from 2018-2023 is selected as a sample.

In order to ensure the accuracy of data and model simulation and results, this paper does the following to obtain the original data:

1) Exclusion of financial companies. Listed companies in the financial industry are excluded due to the specificity of their service industry, which is different from manufacturing technology-based companies in the general sense of innovation investment.

2) Exclusion for firms with serious missing key financial data. As the company's business level reacts to the financial data, the financial level can affect the company's access to resources and thus innovation activities, while this paper considers the financing constraints, government subsidies perspective, all of which require certain financial data.

3) Excluding enterprises belonging to ST and *ST during the sample period. Enterprises that are ST usually have financial status or other abnormal problems, and such enterprises are excluded as samples.

4) Winsorize shrinking tail treatment of continuous variables. In order to avoid the abnormal impact of outliers on the model estimation, all variables are adjusted by tail reduction, and the main object is the upper and lower 1% of observations. Finally, 25703 observations are obtained.

This paper uses digital transformation data based on wind search for listed companies annual report corporate annual report data, keyword search collection, text analysis. CNRDS was used to obtain patent application data and patent grant data to measure innovation, and other control variables were obtained through the Cathay Pacific CSMAR database. After the above methods, this paper utilizes the data processing software Stata16 to conduct descriptive statistics, correlation analysis, regression analysis and robustness test on the samples.

3.2. Definition of variables

3.2.1. Measurement of core variables:

1) Measurement of enterprise innovation performance. This study takes innovation input-output efficiency as a perspective and draws on the research methods of many scholars. Based on this, the innovation performance evaluation index system of digital transformation enterprises is established and combined with the DEA model for measurement. Including innovation input, innovation output and innovation efficiency, the DEA method is a method without assignment, parameter estimation and function representation [29]. Especially for the innovation performance of enterprises, it is a comprehensive indicator with multiple inputs, multiple outputs and multiple dimensions. Therefore, in this paper, the data envelopment analysis (DEA) method is selected to assess the innovation performance of enterprises. According to the change of return to scale, the DEA model can be subdivided into CCR model and BCC model, the CCR model is constructed when the return to scale is constant, and the BCC model is constructed when the return to scale is variable, and the innovation of the enterprise examined in this paper has uncertainty in the scale benefit it generates, so the BCC model is selected.

First assume that there are t decision-making units (DMUs), each with m input variables and n output variables, where:

x_{ij} denotes the amount of inputs of the j th DMU to the i th input, $x_{ij} > 0$.

y_{ij} shows the amount of output of the j th DMU for the r th output, $y_{ij} > 0$.

v_i denotes a measure (or "power") of the i th input.

u_i represents a metric (or "power") of the r th output.

where $i = 1, 2, \cdots, m$; $r = 1, 2, \cdots, n$.

x_{ij}, y_{ij} are known data, which can be obtained from historical information, v_i, u_i are variables.

Corresponding to a set of weight coefficients:

$$v = \left(v_1, v_2, \cdots, v_m\right)^T, u = \left(u_1, u_2, \cdots, u_n\right)^T \tag{1}$$

DMU's corresponding efficiency evaluation index:

$$h_j = \frac{u^T y_j}{v^T x_j} = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}, j = 1, 2, \cdots, t \tag{2}$$

Eqs. $x_j = \left(x_{1j}, x_{2j}, \cdots, x_{mj}\right)^T$, $y_j = \left(y_{1j}, y_{2j}, \cdots, y_{nj}\right)^T$.

The weight coefficients and can be appropriately chosen so that they satisfy: $h_j \le 1$, $j = 1, 2, \cdots, t$.

Now the j_0 th DMU is evaluated for efficiency $\left(1 \le j_0 \le t\right)$ and the following optimization model is constructed using the weight coefficients v and u as the variable vectors, the efficiency index of the j_0 th DMU as the objective, and the efficiency indices of all DMUs (also the j_0 th DMU) as the constraints:

$$\max \frac{u^T y_0}{v^T x_0}$$
$$s.t.\begin{cases} \dfrac{u^T y_j}{v^T x_j} \le 1, j = 1, 2, \cdots, t \\ u \ge 0, v \ge 0, u \ne 0, v \ne 0 \qquad (p) \\ x_0 = x_{j0}, y_0 = y_{j0}, 1 \le j_0 \le t \end{cases} \tag{3}$$

Perform the Charnes-Cooper transformation on this fractional plan such that:

$$s = \frac{1}{v^T x_0} > 0, \omega = sv, \mu = su \tag{4}$$

Then there are equivalent linear programming problems: $\max h_{j0} = u^T y_0$:

$$s.t.\begin{cases} \omega^T x_j - \mu^T y_j, j = 1, 2, \cdots, t \\ \omega^T x_0 = 1 \qquad \left(P_{CCR}\right) \\ \omega \ge 0, \mu \ge 0 \end{cases} \tag{5}$$

for which the even plan is $\left(D_{CCR}\right)$: $\min \theta$:

$$s.t.\begin{cases} \sum_{j=1}^{t}\lambda_j x_j \leq \theta x_0 \\ \sum_{j=1}^{t}\lambda_j y_j \geq y_0 \\ \lambda_j \geq 0, j=1,2,\cdots,t \end{cases} \tag{6}$$

2) Measurement of digital transformation. In this, by using Python crawler function, we collect and summarize the annual reports of a listed company from 2018 to 2023, extract the textual information related to digital transformation, screen the vocabulary related to digital transformation, and ultimately form a pool of data, retrieve, match, and statistic them, categorize the vocabulary of each technical field, and summarize them, and then establish a set of indexes capable of reflect the enterprise's digital transformation, and logarithmize the index system.

3.2.2. Selection and description of control variables. In order to exclude the influence of other factors, a series of control variables are set up, including board size (Board), capital intensity (Capint), age of the firm (Age), two positions (Dual), size of the firm (Size), level of informationization in the region (Infor), proportion of independent directors (Indep), nature of ownership of the firm (State), industry (Industry), and year (Year). Industry) and Year. Among them, the age of the enterprise is the natural logarithm of the year of observation minus the year of enterprise registration, the proportion of independent directors is the proportion of the number of independent directors to the total number of board of directors, the capital intensity is the total assets of the enterprise compared to the business revenue, and the two positions are one if the chairman of the board of directors and the general manager are the same person, and zero if they are not.

3.2.3. Intermediate variables. Financing constraints (KZ): If it is more difficult for an enterprise to obtain financing from the outside, its investment expenditure will be greatly affected by its own cash flow, that is to say, the enterprise's investment cash flow shows strong sensitivity due to the existence of financing constraints, so the level of the enterprise's financing constraints can be determined by the sensitivity of its investment cash flow.

Based on relevant research conclusions, the author determines the KZ index by using the elements of money fund size, cash flow, debt level, cash dividend payout and enterprise growth to characterize and measure the level of financing restrictions on enterprises. The specific process is as follows:

Firstly, the ratio of the company's monetary funds to the total assets of the previous year, the ratio of cash flow to the total assets of the previous year, the ratio of debt, the ratio of cash dividends to the total assets of the previous year, and the median of Tobin's Q value are calculated and expressed in Cash, Cashflow, Leverage, Dividend and TobinsQ respectively, and the size of these factor indicators is determined, if Cash is smaller than the median, kz1 is considered to be equal to 1, and vice versa, it is considered to be equal to 0; If Cashflow is smaller than the median, kz2 is considered equal to 1 and vice versa. If the Leverage is greater than the median, kz3 is considered to be equal to 1, and vice versa. If the Dividend is smaller than the median, kz4 is considered to be equal to 1, and vice versa. If TobinsQ is greater than the median, kz5 is considered to be equal to 1, and vice versa.

Secondly, the kz values of each indicator are summed up and calculated, i.e., KZ=kz1+kz2+kz3+kz4+kz5.

Further, KZ is taken as the dependent variable and Cash, Cashflow, Leverage, Dividend, and Tobinsq are taken as the independent variables, and the regression coefficients corresponding to the different indicators are determined through sequential logistic regression.

Finally, the regression coefficients of each index and the corresponding independent variables are multiplied to determine the KZ index of the enterprise in this year.

3.2.4. Moderating variables. Intellectual property protection (Ipp): Technology market transactions can reflect the development of the local digital economy and the flow of innovation resources between regions. It can also be considered that the technology market turnover contains information on the preferences of both parties in technology transactions, utility evaluation, regional technology transaction market environment and other aspects. Referring to related research results, the regional IPR protection level is measured by the proportion of technology market turnover to local GDP. The specific description of each variable is shown in Table 1.

Table 1. Variable definition

Variable type	Variable name	Variable symbol
Explained variable	Enterprise innovative performance	*IP*
Explanatory variable	Digital transformation	*DT*
Mediation variable	Financing constraints	*KZ*
Regulated variable	Intellectual property protection	*Ipp*
Controlled variable	Enterprise age	*Age*
	Board size	*Board*
	Enterprise size	*Size*
	Ownership property	*State*
	Independent proportion	*Indep*
	Capital intensity	*Capint*
	Regional information level	*Infor*
	Two positions	*Dual*
	Industry	*Industry*
	Year	*Year*

3.3. Modeling

Referring to previous studies, this paper adopts a double difference model [30] to verify the relationship between digital transformation and corporate innovation performance.

Based on the theoretical analysis above and the relevant proposed basic assumptions, the following specific model is constructed:

IP as the explanatory variable, DT as the explanatory variable, KZ as the mediator variable, Ipp as the moderator variable, and Age, Board, Size, State, Indep, Capint, Infor, Dual, Industry, Year as the control variables.

According to hypothesis one, this paper constructs the regression model, i.e., the main model:

$$IP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \sum_k \alpha_k Controls_{k,i,t} + \sum Year + \sum Industry \tag{7}$$

According to hypothesis two, this paper constructs the regression model, i.e., the mediation effect model:

$$IP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \sum_k \alpha_k Controls_{k,i,t} + \sum Year + \sum Industry + \varepsilon \tag{8}$$

$$KZ_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \sum_k \alpha_k Controls_{k,i,t} + \sum Year + \sum Industry + \varepsilon \tag{9}$$

$$IP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 KZ_{i,t} + \sum_k \alpha_k Controls_{k,i,t} + \sum Year + \sum Industry \tag{10}$$

According to hypothesis three, this paper constructs the regression model, i.e., the moderating effect model:

$$IP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Ipp + \alpha_3 Ipp\_DT_{i,t} + \sum_k \alpha_k Controls_{k,i,t} + \sum Year + \sum Industry \quad (11)$$

4. Empirical testing

4.1. Descriptive statistical analysis

Before starting the regression analysis, this paper shows the results of the descriptive statistics of the variables used, as shown in Table 2. These descriptive statistics give a general idea of the data magnitude, distribution, etc. of the variables and ensure that they are within a reasonable range of values. The table shows that each variable is in a more reasonable interval after taking logarithms or shrinking treatment.

Table 2. Descriptive statistics for the main variables

VarName	Obs	Mean	SD	Min	Max
IP	28143	0.28	0.148	0	0.554
DT	28143	0.166	0.14	0	0.481
FC	28143	3.502	1.721	0	10.914
Ipp	28143	1.49	1.573	0	9.895
Age	28143	17.9	1.577	7.574	24.468
Board	28139	0.138	0.107	0	0.333
Size	20433	5.599	1.294	0	11.449
State	20433	16.994	13.511	0.36	70.378
Indep	28143	1.462	1.484	0	6.359
Capint	28142	0.146	0.139	-0.183	0.413
Infor	28143	0.489	0.344	0.009	31.525
Dual	28142	1.017	0.147	0.14	1.058
Industry	26302	60.244	15.772	3.592	101.218
Year	28143	0.128	0.283	-30.975	7.504

4.2. Benchmark regression analysis

4.2.1. Correlation analysis and multicollinearity analysis. In this paper, before formalizing the regression analysis, variable correlation analysis and multicollinearity tests were also conducted to review the reasonableness of all the variables in the baseline regressions used and the reasonableness of the model settings. In this paper, the correlation matrix between the variables was generated using the external command pwcorr_a from stata15.0, as shown in Table 3.IP (S1), DT (S2), *FC* (S3), Ipp (S4), Age (S5), Board (S6), Size (S7), State (S8), Indep (S9), Capint (S10), Infor (S11), Dual (S12), Industry (S13), Year (S14).

The results of the analysis show that there are more significant correlations between the variables, but the correlation coefficients are generally lower than the threshold value of 0.8. This suggests that there is a better correlation between the variables but there is not a problem of multiple full covariance.

Table 3. Correlation analysis and multicollinearity test

	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*S11*	*S12*	*S13*	*S14*
S1	1													
S2	0.289***	1												
S3	0.139***	0.087***	1											

S4	0.046***	0.043***	0.025***	1										
S5	-0.039***	0.051***	-0.027***	-0.012***	1									
S6	0.038***	-0.007	-0.125***	-0.026***	0.009*	1								
S7	-0.005	0.131***	0.021***	0.134***	-0.022***	0.008*	1							
S8	0.078***	-0.008	-0.006***	0.017***	0.071***	-0.021***	-0.003	1						
S9	0.007	-0.006	0.126***	0.005	-0.004	0.070***	-0.004	0	1					
S10	1	-0.105***	0.152***	0.003	0.001	-0.004	0.023***	-0.002	0.003*	1				
S11	-0.003	0.132***	0.143***	-0.026***	0.031***	0.002	0.24**	-0.041***	0.035***	0.007***	1			
S12	-0.005	0.240***	0.007	0.051***	-0.048*	0.011***	-0.224***	0.005**	0.007***	-0.003***	0.007	1		
S13	-0.225***	-0.004	0.009	0.003***	0.002	0.004	0.002	0.024	0.035***	0.028***	0.009	0.025***	1	
S14	0.135***	-0.045***	0.006	0.004***	0.007	0.031*	0.001**	0.007*	0.008**	0.031*	0.007	-0.227***	0.255***	1

4.2.2. Impact of digital transformation on firms' innovation performance Table 4 shows the results of the baseline empirical regression of this paper, column (1) shows the regression results obtained without the control variables, the degree of digital transformation is 0.148 with a significance level of 1%, which is positive. Column (2) shows the results obtained with the introduction of control variables, with a coefficient on the degree of digital transformation of 0.104 and a significance level of 1%, which is positive. The R-squared values of all regressions fluctuate around 17%, indicating that all the control variables and fixed effects in this paper can explain around 17% of the fluctuations in firms' innovation performance, which suggests that the model is set up more reasonably and that the explanatory validity of the explanatory variables is high enough. The regression results in different columns show that changing the measure of the variables and adding control variables do not affect this result, confirming the robustness of the results.

Important empirical findings are presented through the benchmark regression results, which clearly confirm the first research hypothesis of this paper, namely that digital transformation has a profound positive impact on firms' innovation performance. Regardless of the variables employed and used as a measure of firms' innovation performance, and whether or not other control variables are introduced, the degree of digital transformation indicates a profoundly positive relationship at the 1% level of statistical significance. This finding further reinforces the critical role of digital transformation in energizing firms to innovate. The magnitude of the regression coefficients ranges from around 0.10 to 0.15, with each 100% increase in the degree of digital transformation increasing firms' innovation performance by around 1.0% to 1.5% or so.

Table 4. The benchmark empirical regression results

	1	2
VARIABLES	*IP*	*IP*
DT	0.148***(0.000416)	0.104***(0.000448)
Age		0.00418(0.00418)
Board		-4.46e-04(5.95e-04)
Size		0.00809***(0.00132)
State		-0.00241(0.00295)
Indep		-0.00511(0.00512)
Capint		-0.00312*(0.00169)
Infor		0.0684***(0.0117)
Dual		-0.00219(0.0045)
Constant	0.177***(0.000747)	-0.109***(0.0365)
Industry fixed effect	Controlled	Controlled
Year fixed effect	Controlled	Controlled

Observed value	28,143	26,378
R^2	0.171	0.174

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.2.3. Mediating effects of financial constraints. In order to deeply analyze whether the financing constraints of enterprises play a mediating effect in the process of digital transformation to promote the improvement of enterprises' innovation performance, this paper conducts a two-stage analysis of the mediating effect. In the first stage of the analysis, Table 5 shows the results of the effect of digital transformation on the ratio of corporate financing constraints to total assets. Although the regression coefficient is relatively small, around 0.3% or so, it is statistically highly significant, which means that digital transformation significantly improves the level of cash holding of enterprises, and hypothesis H2 is valid.

There are multiple possible explanations for this finding. First, digital transformation may induce firms to increase their financing constraints by improving the efficiency of their financial operations and making them more flexible in responding to market changes. Second, digital transformation may have improved firms' performance and increased profitability, which in turn made more funds available for financing constraints.

Finally, digital transformation may have stimulated more investment and capital inflows, further increasing the size of firms' funding.

Table 5. The first phase of the mediation effect is returned

	1	2
VARIABLES	KZ	KZ
DT	0.0317***(0.000397)	0.00337***(0.000418)
Age		-0.000603***(3.27e-04)
Board		-0.0297***(0.00314)
Size		4.25e-04(5.53e-04)
State		-0.00737***(0.00127)
Indep		-0.00231***(0.00277)
Capint		-0.00965**(0.00479)
Infor		-0.00953***(0.00158)
Dual		-0.155***(0.0109)
Constant	0.125***(0.000722)	0.664***(0.0338)
Industry fixed effect	Controlled	Controlled
Year fixed effect	Controlled	Controlled
Observed value	28,143	26,378
R^2	0.047	0.095

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6 shows the second stage of the regression that delves into the mediating effect, using three different innovation performance variables mentioned earlier in the paper, including innovation input (INVEST), innovation output (OUT) and innovation efficiency (EFFECT). The regression results clearly demonstrate that firms' financing constraints have a significant positive impact on innovation performance, and this relationship is robust across different measures of innovation performance. This finding further solidifies the role of corporate financing constraints as a mediating effect in the impact of digital transformation on innovation performance. Specifically, the regression results suggest that firms' digital transformation may contribute to innovation performance by increasing the level of firms' financing constraints. This positive relationship is validated across innovation performance variables, including R&D input, innovation output and innovation efficiency. Although the regression coefficients between financing constraints and innovation performance are relatively small, they are statistically significant and show a consistent positive trend, which implies that digital transformation does positively affect innovation performance with the help of increasing the level of financing constraints, validating Hypothesis II.

Table 6. The second phase of the mediation effect is returned

	1	2	3
VARIABLES	*DT* (*invest*)	*DT* (*out*)	*DT (effect)*
KZ	0.0178***(0.00675)	0.0251***(0.00622)	0.0561***(0.127)
DT	0.0104***(0.000449)	0.00415***(0.000415)	0.218***(0.00827)
Age	0.000427***(3.55e-04)	-0.000576***(3.21e-04)	0.00761***(0.000653)
Board	0.00368(0.00336)	-0.0199****(0.00309)	0.0492(0.0621)
Size	-4.39e-04(5.95e-04)	-1.57e-04(5.47e-04)	-0.000568(0.00112)
State	0.00795***(0.00132)	-0.0138***(0.00122)	0.172***(0.00121)
Indep	-0.00279(0.00295)	-0.0136***(0.00272)	-0.0299(0.0545)
Capint	-0.00527(0.00512)	-0.00385(0.00471)	-0.0445(0.947)
Infor	-0.00329*(0.00169)	0.000399(0.00157)	-0.0922***(0.0211)
Dual	0.0659***(0.0117)	0.385***(0.0107)	5.009***(0.216)
Constant	0.0847**(0.0273)	0.297***(0.0268(	-1.571***(0.573)
Industry fixed effect	Controlled	Controlled	Controlled
Year fixed effect	Controlled	Controlled	Controlled
Observed value	28,143	28,143	28,143
R^2	0.172	0.151	0.212

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.2.4. Analysis of moderating effects. To test the moderating effect of intellectual property protection in the process of digital transformation affecting firms' innovation performance (including horizontal and vertical synergies). The results of the analysis are shown in Table 7. Models 11 and 13 tested the moderating effect of intellectual property protection capacity on enterprise innovation performance affecting horizontal synergy, and the results of model 11 showed that intellectual property protection had a significant positive effect on enterprise innovation performance (β =0.323, P<0.001), and the results of model 13 showed that the interaction term of digital transformation and intellectual property protection had a significant positive effect (β =0.115, P<0.001), and model 13's R^2 is significantly higher compared to model 11, indicating that the moderating interaction term of intellectual property protection has a larger contribution, and hypothesis H3 is established.

Table 7. Test of regulatory effects

Variable		Dependent variable			
		Digital transformation			
		Model 11	Model 13	Model 12	Model 14
Control variable	Size	0.031	0.007	0.045	0.016
	Age	-0.041	-0.039	-0.067	-0.041
	Dual	0.019	-0.147	0.029	-0.131
	Infor	0.034	-0.025	0.058	-0.007
Independent variable	*DT*	0.437***	0.307***	0.452***	0.408***
Regulating variable	*Ipp*	0.323***	0.207***	0.315***	0.209***
Interaction term	*DT×Ipp*		0.115***		0.337***
Model fitting	R^2	0.286	0.561	0.285	0.59
	Ad-R^2	0.267	0.549	0.269	0.552
	F	15.011***	46.54***	17.278***	54.117***

Note: ***1%, **5%, *10%

4.3. Robustness Tests

4.3.1. Parallel trend hypothesis testing. A prerequisite for ensuring that DIT results satisfy unbiasedness is that the parallel trend assumption is met. If the experimental group and the control group have time trend differences before the event, then the change in corporate innovation performance can be caused not by digital transformation but by different ex ante time trends. Therefore, in order to verify the appropriateness of the DIT model in this paper, it is necessary to verify whether parallel trends existed in firms' innovation performance before digital transformation. Whether the parallel trend hypothesis is valid or not is tested using event analysis to observe the dynamic relationship between digital transformation and corporate innovation performance. The sample interval selected in this paper is 2013-2023, using the year of enterprise digital transformation set above as the center point, and examining the differences between the experimental group and the control group in the first three years and the last six years of digital transformation, a total of nine time points. In order to make the test results more intuitive, this paper plots the regression results after de-trending, as shown in Figure 1, in the first year, the first two years and the first three years before the digital transformation, the difference between the experimental group and the control group is not obvious, indicating that there is no significant difference in the level of enterprise innovation between the experimental group and the control group before the digital transformation of the enterprise, whereas after the digital transformation, the treatment effect shows a significant increase, which indicates that The number of patent applications of enterprises implementing digital transformation is significantly higher than that of enterprises not implementing digital transformation, and the DIT model in this paper meets the parallel trend hypothesis.

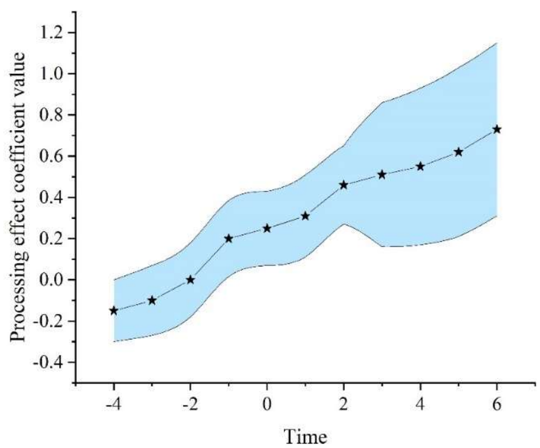

Fig. 1. The time trend chart for digital transformation and enterprise innovation performance

4.3.2. Placebo test. For the conclusions of this paper, the statistical significance of digital transformation and firms' innovation performance may stem from some random factors. For this reason, this paper constructs a placebo test to determine whether the facilitating effect of digital transformation on firms' innovation performance is due to other random factors. This paper adopts the method of randomly generating the treatment group and experimental period to construct the placebo test, and repeats the regression for 4500 times, and counts the t-value of digital transformation in these 4500 regressions, makes the corresponding kernel density plot of the t-value of digital transformation under the explanatory variables as shown in Fig. 2, and compares and analyzes it with the t-value of digital transformation in the column (2) of Table 4. By observing Figure 2, it can be found that for the explanatory variable of digital transformation, the t-values of the regressions are all far away from the t-values of the true regression coefficients in column (2) of Table 4, and only a very small number of regressions have t-values greater than 1, which suggests that the role of digital transformation on the innovation performance of the enterprise is robust, and it does indeed contribute to the enhancement of the innovation performance of the enterprise.

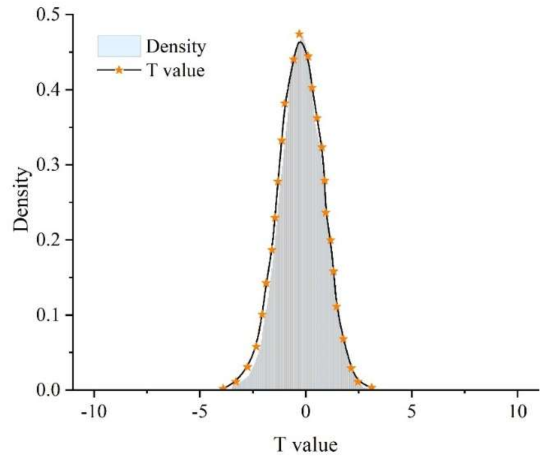

Fig. 2. Digital transformation and the t value of innovation performance regression

4.4. Heterogeneity analysis

4.4.1. Size Heterogeneity Test. In this paper, the median enterprise size is used as the criterion for the grouping test, and enterprises with total assets greater than the annual industry median belong to large-scale enterprises, and enterprises with total assets less than the annual industry median belong to small-scale enterprises. The regression results are shown in Table 8, in large-scale enterprises, the coefficient of digital transformation and innovation performance is 0.176, which is significant at the 1% level, but in small-scale enterprises, digital transformation does not have a significant effect on innovation performance, the possible reason is that large-scale enterprises can invest more resources in digital transformation, and the digital transformation can exert a larger and wider impact and produce scale effects.

Table 8. Heterogeneity test

Variable	Large-scale enterprise	Small-scale enterprise
DT	0.176***(13.24)	0.034(2.46)
Age	0.17(0.45)	0.295***(2.572)
Board	0.451***(0.087)	0.795(-6.278)
Size	0.088(1.78)	-0.251***(0.138)
State	0.022(0.78)	0.175**(1.94)
Indep	-0.255***(-4.11)	-0.3541***(-4.751)
Capint	0.391***(4.51)	-0.573(2.743)
Infor	0.065**(2.48)	0.091(0.08)
Dual	0.033**(-3.51)	0.176(1.01)
Constant term	-17.536***(-35.71)	-12.221***(-11.84)
Year,Industry effect	Control	Control
Observed value	6987	6351
R^2	0.542	0.337

Note: Standard errors in parentheses, ***, **, and * represent significant at the 1%, 5%, and 10% levels, respectively.

4.4.2. The nature of the enterprise and the territorial policy test. Table 9 presents tests for heterogeneity between local policies and firm regions. (Columns (1) and (2) address the heterogeneity of firm ownership and report the results of the tests for the samples of SOEs and non-SOEs, respectively. When implementing enterprise development strategies, SOEs will cooperate with and implement national economic and industrial goals, enjoy many credit advantages, R&D resources, policy support, etc., which can better realize the synergistic effect of innovation and the scale effect of R&D, and quickly promote the effective integration of the industrial chain, the supply chain, and the innovation chain, which will bring about a more significant innovation performance. Columns (3) and (4) of Table 9 report the test results for the samples from high and low innovation resource regions, respectively, with respect to the regional external environment of the firms. The results show that the estimated coefficients on firms' digital transformation are positive and pass the significance test in both types of regional samples. Similarly, combining the results of the Chow test with the estimated coefficient values shows that the enhancement effect of firms' digital transformation on their innovation performance is significantly larger in high innovation resource regions. Generally speaking, in areas with abundant innovation resources such as talents, information, knowledge, and funds, the better the external environment in terms of innovation policies, laws and regulations, scientific research facilities, and market culture, which is more conducive to the innovation activities of scientific research institutions, institutions of higher learning, and enterprise entities.

Table 9. Heterogeneity test

Variable	State-owned enterprise	Non-state enterprise	High innovation resources area	Low innovation resources area
DT	1.8521***(0.1421)	1.4131***(0.0857)	1.6125***(0.0754)	1.3756***(0.1257)
Age	2.9511***(0.3871)	2.8827***(0.2014)	0.08167***(0.0403)	2.8749***(0.3451)
Board	0.0721***(0.3847)	0.0968***(0.0192)	0.9178***(0.1378)	0.0238(0.0367)
Size	0.8015(0.0534)	1.1128***(0.1203)	0.6542***(0.1195)	-0.2273(0.1976)
State	1.3824***(0.0238)	0.7837***(2.4814)	2.1482**(0.2871)	1.4623***(0.4614)
Indep	2.4921(0.0841)	-0.2319***(0.0748)	0.1963**(0.4512)	2.6713***(0.2149)
Capint	0.0517***(0.1842)	1.6498***(0.7328)	1.2438***(0.2041)	3.1572***(0.2467)
Infor	0.3428***(0.0251)	-0.0515***(0.1245)	2.5729***(0.5781)	0.2383**(0.0841)
Dual	0.0473***(0.0156)	0.0471***(0.5813)	0.6255***(0.0233)	0.2162**(0.1792)
Constant term	1.8639***(0.2831)	-0.4827***(0.1054)	0.7463***(0.1358)	0.6158***(0.1159)
Year fixed effect	Yes	Yes	Yes	Yes
Regional fixation effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Observed value	4821	12572	12545	5128
R^2	0.40781	0.2761	0.2743	0.3257
Group coefficient difference	0.4271***		0.1225	
Chow test value	238.76[0.0000]		4.09[0.0193]	

5. Conclusion

In order to investigate the impact of digital transformation on enterprise innovation performance and its mechanism, this paper selects the data of a listed enterprise from 2018 to 2023 as a research sample for empirical analysis. Firstly, the impact of digital transformation on innovation performance is examined, and secondly, the mechanism of the role between digital transformation and enterprise innovation performance is analyzed through the perspective of financing constraints. In further analysis, the role of enterprise innovation performance on enterprise digital transformation is analyzed through the perspective of intellectual property protection. Finally, in order to verify the robustness of the empirical results and the corresponding conclusions, the robustness test and heterogeneity analysis are conducted successively. The analysis found that there is a significant positive relationship between digital transformation and enterprise innovation performance. This suggests that the more capital and human resources are invested in R&D for enterprises with a higher degree of digitalization, and that financing constraints play a partial mediating role between enterprise digital transformation and enterprise innovation performance. Intellectual property protection plays a positive moderating role between digital transformation and firm innovation performance. Heterogeneity analysis finds that the facilitating effect of digital transformation on innovation performance is more prominent among large-scale firms.

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References

[1] Chen, P., & Kim, S. (2023). The impact of digital transformation on innovation performance-The mediating role of innovation factors. Heliyon, 9(3).

[2] Li, R., Rao, J., & Wan, L. (2022). The digital economy, enterprise digital transformation, and enterprise innovation. Managerial and Decision Economics, 43(7), 2875-2886.

[3] Schwertner, K. (2017). Digital transformation of business. Trakia Journal of Sciences, 15(1), 388-393.

[4] Pflaum, A. A., & Gölzer, P. (2018). The IoT and digital transformation: toward the data-driven enterprise. IEEE pervasive computing, 17(1), 87-91.

[5] Plekhanov, D., Franke, H., & Netland, T. H. (2023). Digital transformation: A review and research agenda. European management journal, 41(6), 821-844.

[6] Ulas, D. (2019). Digital transformation process and SMEs. Procedia computer science, 158, 662-671.

[7] Li, S., Gao, L., Han, C., Gupta, B., Alhalabi, W., & Almakdi, S. (2023). Exploring the effect of digital transformation on Firms' innovation performance. Journal of Innovation & Knowledge, 8(1), 100317.

[8] Liu, Y., Ni, Z., Karlsson, M., & Gong, S. (2021). Methodology for digital transformation with internet of things and cloud computing: A practical guideline for innovation in small-and medium-sized enterprises. Sensors, 21(16), 5355.

[9] Anim-Yeboah, S., Boateng, R., Odoom, R., & Kolog, E. A. (2020). Digital transformation process and the capability and capacity implications for small and medium enterprises. International Journal of E-Entrepreneurship and Innovation (IJEEI), 10(2), 26-44.

[10] Liang, S., & Li, T. (2022). Can digital transformation promote innovation performance in manufacturing enterprises? The mediating role of R&D capability. Sustainability, 14(17), 10939.

[11] Zhao, Y., Xu, H., Liu, G., Zhou, Y., & Wang, Y. (2023). Can digital transformation improve the quality of enterprise innovation in China?. European Journal of Innovation Management.

[12] Kommisetty, P. D. N. K. (2022). Leading the Future: Big Data Solutions, Cloud Migration, and AI-Driven Decision-Making in Modern Enterprises. Educational Administration: Theory and Practice, 28(03), 352-364.

[13] Yan, J., Chen, C., & He, Z. (2024). Research on Human Resource Allocation Strategy in Enterprise Strategic Transformation. In SHS Web of Conferences (Vol. 196, p. 03004). EDP Sciences.

[14] Tian, M., Chen, Y., Tian, G., Huang, W., & Hu, C. (2023). The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. International Journal of Production Economics, 262, 108929.

[15] Järvenpää, A. M., Kunttu, I., Jussila, J., & Mäntyneva, M. (2021, April). Data-driven decision-making in circular economy SMEs in Finland. In The International Research & Innovation Forum (pp. 371-382). Cham: Springer International Publishing.

[16] Gao, J., Zhang, W., Guan, T., Feng, Q., & Mardani, A. (2023). The effect of manufacturing agent heterogeneity on enterprise innovation performance and competitive advantage in the era of digital transformation. Journal of Business Research, 155, 113387.

[17] Xing, X., Chen, T., Yang, X., & Liu, T. (2023). Digital transformation and innovation performance of China's manufacturers? A configurational approach. Technology in Society, 75, 102356.

[18] Diván, M. J. (2017, December). Data-driven decision making. In 2017 international conference on Infocom technologies and unmanned systems (trends and future directions)(ICTUS) (pp. 50-56). IEEE.

[19] Kolasani, S. (2023). Innovations in digital, enterprise, cloud, data transformation, and organizational change management using agile, lean, and data-driven methodologies. International Journal of Machine Learning and Artificial Intelligence, 4(4), 1-18.

[20] Zhu, X., & Li, Y. (2023). The use of data-driven insight in ambidextrous digital transformation: How do resource orchestration, organizational strategic decision-making, and organizational agility matter?. Technological Forecasting and Social Change, 196, 122851.

[21] Bratasanu, V. (2018). Leadership decision-making processes in the context of data driven tools. Quality-Access to Success, 19.

[22] Liu, Y., & He, Q. (2024). Digital transformation, external financing, and enterprise resource allocation efficiency. Managerial and Decision Economics, 45(4), 2321-2335.

[23] Liu, Y., & Wei, H. (2024). Digital transformation and enterprise financial asset allocation. Applied Economics, 1-18.

[24] Wang, Y., & Li, L. (2023). Digital Management Mode of Enterprise Human Resources under the Background of Digital Transformation. Journal of Information & Knowledge Management, 22(04), 2350027.

[25] Yu, J., Wang, J., & Moon, T. (2022). Influence of digital transformation capability on operational performance. Sustainability, 14(13), 7909.

[26] Wang, D., Shao, X., Song, Y., Shao, H., & Wang, L. (2023). The effect of digital transformation on manufacturing enterprise performance. Amfiteatru Economic, 25(63), 593-608.

[27] Wang, Y., Wang, T., & Wang, Q. (2024). The impact of digital transformation on enterprise performance: An empirical analysis based on China's manufacturing export enterprises. PloS one, 19(3), e0299723.

[28] Lai Chien Hung & Chien Min Chen. (2025). The Impact of Digital Transformation in Manufacturing on Firm Performance: A Deleveraging Perspective. Journal of Applied Economics and Policy Studies(1),23-29.

[29] Manuel Arana Jiménez,M. Carmen Sánchez Gil,Atefeh Younesi & Julio Lozano Ramírez. (2024). An enhanced hybrid interval slacks-based DEA model with super-efficiency and application. Computational and Applied Mathematics(1),76-76.

[30] Hongfang Han,Runde Gu & Yangyang Yang. (2025). Impacts of low-carbon city pilot policy on ecological well-being performance across Chinese cities: A spatial difference-in-difference analysis. Sustainable Cities and Society105864-105864.