



Research article

Has enterprise digital transformation improved the efficiency of enterprise technological innovation? A case study on Chinese listed companies

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Abstract: Digital transformation is a new driving force of enterprise efficiency reform. Enterprises' digital transformation can effectively improve their technological innovation efficiency, thereby promoting their high-quality development. Using the panel data of 930 Chinese A-share listed companies from 2015 to 2020, we have studied the impact and heterogeneity of digital transformation on enterprise technological innovation efficiency with a panel data model. Further, a mediating effect model and a moderating effect model were constructed to study the mechanism of digital transformation affecting the efficiency of enterprise technological innovation. The conclusions are as follows. First, enterprise digital transformation significantly improves the efficiency of enterprise technological innovation. Second, the impact of digital transformation on the efficiency of enterprise technological innovation is heterogeneous, which is reflected in two aspects: the factor intensity and the nature of ownership. Third, financing constraints and equity concentration play a mediating and a moderating role, respectively, in the impact of digital transformation on the efficiency of enterprise technological innovation.

Keywords: digital transformation; enterprise technological innovation efficiency; financing constraints; equity concentration; DEA-BCC

1. Introduction

The rise of digital economy provides new momentum to economic development. For micro

enterprises facing huge challenges brought by demanding customers and increasingly severe market competition, they need to seize the opportunity of digital economy development and carry out a digital transformation [1,2]. Enterprise digital transformation refers to the application of the Internet of Things, cloud computing, big data, mobility and intelligent technologies to enterprises with the help of digital solutions. By planning and implementing a business model transformation and management and operation transformation, enterprises bring new digital value improvement to customers, enterprises and employees, continuously improving the new core competitiveness of enterprises in the digital economy environment [3–5]. Digital transformation endows enterprises with new development momentum, which can comprehensively improve the operation efficiency of enterprises, thus bringing greater possibilities for improving the efficiency of technological innovation [6]. From a practical point of view, the current technological innovation activities of enterprises in developing countries generally have the problem of “large quantity but low efficiency”. Enterprises with low-efficiency innovation will be less competitive than those with high-efficiency innovation in terms of research and development (R&D) cost and technology. If enterprises only pursue quantitative growth and ignore the quality or efficiency of technological innovation, they will not only waste R&D investment, but also increase sunk costs. Therefore, in this context, systematically studying the impact of enterprise digital transformation on technological innovation efficiency will help to effectively guide enterprises to improve technological innovation efficiency.

The search for potential determinants of technological innovation has been a hot topic in academia. The literature in this regard can be summarized from the micro and macro levels. At the micro level, the revolutionary research results of Taymans [7] have provided the basis for enterprises’ further decision-making on decisive innovation. Some researchers believe that the knowledge stock, decision-making, industry sector, corporate strategy, information processing structure, R&D expenditure, infrastructure, national environment and financing constraints are factors that affect the speed of corporate innovation [8–13]. In addition, at the macro level, income, imports, human capital, institutional quality, financial development, debt financing, corruption, knowledge spillovers and investment in R&D are considered important determinants of technological innovation [14–19].

In the context of the digital economy era, the impact of enterprise digital transformation has also become a hot issue in academic research, and many scholars have done in-depth research on it. Existing research mainly examines the impact of digital transformation on business models [20,21], competitive advantages [22–24] and technology entrepreneurship [25]. In recent years, the impact of digitalization on innovation has also begun to receive attention, but there are relatively few studies on the impact of enterprise digital transformation on enterprise innovation at the micro level.

From the perspective of research, the impact of digitization on enterprise innovation is mainly based on the output of technological innovation. Scholars believe that digital transformation can provide enterprises with stronger resource integration ability, information acquisition and data analysis, thereby increasing the number of innovations [24,26]. Moretti et al. [27] pointed out that enterprises can carry out digital or intelligent upgrading and transform existing products through digital transformation, thereby promoting innovation output. In addition, digital transformation also makes the R&D activities of enterprises repeatable and flexible. With the help of digital technology, enterprises can add new functions in the product life cycle, promote the innovation iteration based on digital technology and greatly improve the innovation output of enterprises [28,29]. Yoo et al. [30] analyzed the impact of continuous digitization on innovation and believed that a new layered modular product architecture may appear due to the digitization of products. Therefore, the digitization of

products and the economy is the key to realizing technological innovation. Afonasova et al. [31] and Yuan et al. [32] claimed that digitization has changed business dynamics, institutional quality and organizational structure, thus positively impacting technological innovation. In contrast, Liu et al. [33] took Chinese listed agricultural enterprises as samples to compare the impact of enterprise digital transformation on technological innovation from the perspective of the quantity and quality of technological innovation, and they further studied the impact mechanism and heterogeneity.

In terms of the research conclusions, there is no consensus on the impact of enterprise digital transformation on enterprise innovation. On the one hand, most scholars believe that enterprises' digital transformation can help promote their innovation activities. Using the resource-based view framework, Nwankpa and Roumani [34] found that a digital transformation has a positive impact on enterprise innovation. Ferreira et al. [35] conducted a sample questionnaire survey and a multivariate statistical analysis of 938 companies in Spain, and their findings show that the adoption of new digital processes by companies can help to improve their competitiveness and adapt to the ongoing digitalization transformation, thereby improving the ability to innovate. On the other hand, some scholars hold a negative attitude toward the impact of digital transformation on enterprise innovation. The research results of Stutzmann [36] show that a digital transformation requires a lot of human and material resources investment, and that capital investment accounts for the main part. Therefore, 60–85% of enterprises undergoing digital transformation will break their capital chain and fall into a digital paradox: the dilemma of “death without transformation, death after transformation”, so they cannot continuously obtain the dividends brought by digital transformation, let alone produce the effect of technological innovation. Some scholars believe that the impact of a digital transformation on the technological innovation of enterprises may be in an inverted “U” shape. For example, there are boundaries or thresholds for improving technological innovation efficiency by enterprise digital transformation [33,37].

Throughout the above literature review, we can see that, first, existing studies have conducted multidimensional empirical research on the impact of digital transformation on the quantity of enterprise technological innovation, but there is insufficient empirical experience on the impact of a digital transformation on the efficiency of enterprise technological innovation; second, the research conclusions of the impact of a digital transformation on enterprise technological innovation are not unified; third, there is little in-depth and extensive discussion on the theoretical transmission mechanism and heterogeneity of digital transformations affecting enterprise technological innovation. Therefore, based on the above research review, taking all listed enterprises in China as samples, this paper empirically explores the impact of digital transformation on enterprise technological innovation efficiency and its mechanism, and further discusses the impact heterogeneity under different factor intensities and ownership of enterprises. Under the dual backdrop of the digital economy and the post-epidemic era, the research in this paper has important practical significance.

The research contributions of this paper can be summarized in the following two aspects. First, this paper confirms that the enterprise digital transformation improved the efficiency of enterprise technological innovation by some econometric tests and estimations. Second, the impact of digital transformation on the efficiency of enterprise technological innovation is heterogeneous, which is reflected in two aspects: the factor intensity and the nature of ownership. Also, the financing constraints and equity concentration have mediating and moderating effects on the relationship between the digital transformation and technological innovation efficiency of enterprises. This research can not only enrich the content of relevant research, but also provide a reference for the strategic choice of

enterprises and the formulation of government policies.

The rest of this paper is organized as follows. Section 2 elaborates the study design. In this section, the research hypotheses are first proposed, and then the empirical models are set. In addition, the samples, indicators and data are explained in detail. Section 3 presents the measurement test, including the benchmark regression analysis and the robustness test. Section 4 further explores the impact mechanism and heterogeneity of digital transformations with respect to enterprise technological innovation efficiency. Section 5 presents the conclusion.

2. Research design

2.1. Model setting

In general, a digital transformation can breakdown “data silos”, and the full extraction and application of data will help enterprises greatly improve resource allocation and cost management [22], thereby improving the efficiency of technological innovation [38]. Specifically, first, enterprise technological innovation is increasingly dependent on data and information, and digital transformation has improved the efficiency of data processing and analysis [39]. Enterprises can process and deeply analyze massive data with the help of digital technology, thereby providing effective information for enterprise technological innovation activities and improving the efficiency of enterprise technological innovation [40–42]. Second, digital transformation creates more efficient innovation ecological scenarios and provides a more optimized innovation environment. It can fully empower enterprise technological innovation activities and bring greater possibilities to improve the efficiency of enterprise technological innovation [43,44]. Third, in the process of digital transformation, enterprises build digital platforms, apply digital systems and digital technology to the production process, carry out digital intelligent upgrading of large-scale equipment and build a digital industrial chain, which will help to improve the investment and production efficiency of enterprise technological innovation [45,46]. Fourth, the digital upgrading of systems and equipment brought by the digital transformation of enterprises not only improves their production and operation efficiency, but also provides hardware conditions for their technological innovation activities, thus improving the efficiency of technological innovation [47]. Therefore, there is reason to believe that the higher the level of digital transformation, the more it can improve the efficiency of enterprise technological innovation. This paper sets up an econometric model for empirical testing.

In this study, panel data were used in the empirical test. In order to alleviate the endogeneity problem caused by the absence of unobservable important variables, a panel regression model with individual and time effects was set to test the effect of digital transformation on the efficiency of enterprise technological innovation [48]. Besides, the important explanatory variables will be covered in the model as much as possible; also, the two-way fixed-effects estimation method used for the model can largely overcome the omitting variable problem. The benchmark panel model set in this study is shown in Eq (1) [49].

$$TIE_{it} = \alpha + \beta DIGI_{it} + \gamma Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

In Eq (1), TIE_{it} is the explained variable, which represents the technological innovation efficiency of the i th enterprise during a period t ; $DIGI_{it}$ is the core explanatory variable, which indicates the degree of digital transformation of the i th enterprise during a period t ; $Control_{it}$ represents the set of other

enterprise-level control variables that affect *TIE*, including the enterprise performance, percentage of fixed assets and asset-liability ratio. μ_i and δ_t represent the individual effect and the time effect, respectively; ε_{it} stands for the random disturbance term. The parameter β in the model is used to describe the effect of *DIGI* on the efficiency of enterprise technological innovation. After the Hausman test, it was found that the individual and time dual fixed-effects model is more suitable, so the fixed-effects model was selected [50].

2.2. Variable description

2.2.1. Measurement of enterprise technological innovation efficiency

Based on the concept of “relative efficiency evaluation”, data envelopment analysis (DEA) was developed as a new system analysis method commonly used to evaluate the performance and relative efficiency of a group of decision-making units with multiple input indicators and multiple-output indicators [51–53]. In this paper, each sample enterprise is regarded as a production decision-making unit that transforms several inputs into several outputs, and the DEA-BCC model (proposed by Banker et al. [54]) was selected to measure the efficiency of enterprise technological innovation for the following reasons. First, the process of technological innovation includes the innovation input and innovation output, which include multiple variables and different dimensions. The DEA method has unique advantages in terms of relative effectiveness evaluation, and there is no need for dimensionless data processing before the model setting. Second, the DEA method does not need any weight assumption, but it obtains the optimal weight from the actual data input and output of the decision-making unit, eliminating many subjective factors and having strong objectivity. Third, considering the research purpose of this study and the characteristics of enterprise technological innovation activities, we assumed that the returns to scale are not fixed, so the DEA-BCC model was selected to measure the efficiency of enterprise technological innovation [55,56].

Table 1. Evaluation indicator system for enterprise technological innovation efficiency.

Primary indicator	Secondary indicator	Indicator description
Input indicator	Number of R&D personnel	Reflecting the human input in enterprise technological innovation
	Amount of R&D input	Reflecting the financial investment in enterprise technological innovation
Output indicator	Number of patent applications	Total number of applications for invention patents, utility models and exterior designs

Enterprise independent innovation is a complex and comprehensive process, and establishing an evaluation indicator system is the basis for assessing the efficiency of enterprise technological innovation. The evaluation index system for enterprise technological innovation efficiency has been designed from the perspective of inputs and outputs, which are divided into two parts. One is the innovation input indicators, including indicators of human input and financial input. The indicator of human input is represented by the number of R&D personnel, and the indicator of financial input is represented by the amount of R&D investment. The second is the innovation output indicators,

including the number of patent applications filed by the company in the current year. Griliches [57] and Croby [58] believe that patent grants are influenced by human factors such as patent institutions, making them more uncertain and prone to abnormal changes [59]. Therefore, in order to better reflect the actual level of innovation output, we chose the number of patent applications to measure innovation output. The evaluation indicator system for enterprise technological innovation efficiency constructed in this study is shown in Table 1. Then, we used DEAP2.1 software to process the data for the enterprise innovation input and innovation output into the BCC model to obtain the evaluation values for the technological innovation efficiency of listed companies.

2.2.2. Other variables

First, the core explanatory variable of this study is enterprise digital transformation. Referring to the research of Liu et al. [33], we collected data from listed companies' annual reports and used the proportion of the digital transformation related part in the year-end intangible assets details disclosed in the notes of the financial reports of listed companies (specifically, the total amount of intangible assets) to measure the degree of enterprise digital transformation. Digital related intangible assets exist in the form of electronic data. They are intangible assets owned or controlled by enterprises in the process of daily sales and production, including financial and logistics software, financial software, management software, computer software, application software, patents and related patent projects.

Second, in terms of control variables, we mainly consider the internal characteristics of enterprises. In order to control the impact of other important factors on the efficiency of enterprise technological innovation, we selected the following control variables: 1) Enterprise performance (Per), where the improvement of enterprise performance can reduce the inhibitory effect of factor market distortion on innovation efficiency to a certain extent, adjust the R&D investment scale, improve the driving force of R&D expenditure and thus improve the efficiency of technological innovation [60]; 2) Percentage of fixed assets (Fixed), where the higher the indicator, the worse the liquidity of enterprise assets and the more negative the attitude of enterprises on carrying out innovation activities, which is unfavorable for the improvement of technological innovation efficiency [61]; 3) Asset-liability ratio (RLT), where the asset-liability ratio reflects the asset-liability situation of the enterprise, and the higher the ratio of an enterprise, the higher the leverage ratio and the greater the financial risk faced by the enterprise, which may inhibit the technological innovation productivity of the enterprise [62].

Third, the mediating variable selected in this study is financing constraints. There are many ways to measure financing constraints, but most of them rely on endogenous financial indicators, so the research conclusions may be biased. Hadlock and Pierce [63] adopted non-intrinsic financial indicators and redesigned the financing constraint variable (the SA index). The specific calculation formula for the financing constraint (SA) is as follows: $SAindex = -0.737 \times \ln 2 - 0.040 \times age$, where size is the natural logarithm of enterprise size (total assets of an enterprise); age represents how long the enterprise has been established. For the convenience of explanation, we have taken the absolute value of the SA index as a proxy variable for financing constraints. The greater the value, the more serious the financing constraints faced by the enterprise.

In addition, we selected equity concentration as a moderating variable [64]. To a certain extent, equity concentration reflects the mutual checks and balances between shareholders and executives. The more concentrated the equity structure, the more efficient the digital transformation decision-making of enterprise management; and, the digital transformation can better improve the technological

innovation efficiency. We used the number of tradable shares held by the top five shareholders in the total number of tradable shares of a company to measure equity concentration. The specific variable description is shown in Table 2.

Table 2. Variable description.

Variable type	Variable name	Variable abbreviation	Variable definition and measurement
Explained variable	Enterprise technology innovation efficiency	TIE	Estimated by the methods mentioned above
Explanatory variable	Digital transformation	DIGI	The proportion of the digital transformation related part in the year-end intangible assets details disclosed in the notes of the financial reports of listed companies as the total amount of intangible assets
Mediating variable	Financing constraints	SA	$SA = 0.043 * Size^2 + 0.737 * Size - 0.04 * Age $ [Size = ln (Total assets / 1,000,000), Age for listing years]
Moderating variable	Equity concentration (top five shareholders)	CRI	Number of tradable shares held by the top five major shareholders / the total number of outstanding shares of the company
Control variable	Enterprise performance	Per	Total profits / total assets at the end of the year
	Percentage of fixed assets	Fixed	Net enterprise fixed assets / total assets
	Asset-liability ratio	RLT	Total liabilities / total assets of the enterprise

2.3. Sample selection and data sources

Based on data availability, we selected China's A-share listed companies from 2015 to 2020 as the research object. The original samples are processed according to the following principles. 1) Special Treatment companies were eliminated. 2) Samples with missing data for relevant variables were eliminated. 3) All continuous variables were winsorized at 1 and 99% quantiles to avoid the influence of outliers on statistical inference. Finally, 930 Chinese A-share listed companies that continuously disclosed relevant data from 2015 to 2020 were obtained as the research samples.

The data sources include two parts. 1) The patent application data required to measure the technological innovation efficiency of listed companies using the DEA-BCC model came from the Chinese Research Data Services platform. 2) Other micro data at the enterprise level were taken from the China Stock Market & Accounting Research Database. Regarding the preliminary statistics of the collected data, the descriptive statistical results are shown in Table 3.

Table 3 shows the basic statistical information of various variables. It can be seen that there is no singular value for each variable, which meets the basic requirements of empirical studies. Among them,

the average value of the explained variable *TIE* was greater than the median, indicating that the technological innovation efficiency of some enterprises is high, which makes the average enterprise technological innovation efficiency higher. The mean value of the explanatory variable *DIGI* was 0.0450, which is greater than the median value of 0.0360; the standard deviation was 0.0430.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Median	Std	Min	Max
TIE	5580	0.0530	0.0260	0.0900	0	1
DIGI	5580	0.0450	0.0360	0.0430	0	0.655
SA	5580	-3.653	-3.597	0.250	-4.397	-2.089
CRI	5580	0.519	0.517	0.140	0.166	0.943
Per	5580	121.7	148.7	125.4	0.00600	299.8
Fixed	5580	0.213	0.188	0.135	0.00200	0.876
RLT	5580	0.414	0.411	0.189	0.0200	2.290

3. Econometric test of the impact of digital transformation on enterprise technological innovation efficiency

3.1. Benchmark regression results analysis

Table 4 reports the benchmark regression results of digital transformation on enterprise technological innovation efficiency, which were obtained by using the two-way fixed-effects estimation method. First, without considering the control variables, the mixed ordinary least square model was adopted to estimate the impact of digital transformation on enterprise technological innovation efficiency, so as to preliminarily judge whether there is a positive impact. The results are shown in Column (1) of Table 4. After the Hausman test, a two-way fixed-effects model was applied, and further proof is achieved without the control variable. The results are shown in Column (2) of Table 4. Then, the control variables were added to re-fit the dual fixed-effects model; the results are shown in Column (3) of Table 4.

The results in Table 4 show that digital transformation significantly promotes the efficiency of enterprise technological innovation. The regression coefficients of digital transformation (*DIGI*) in Columns (1)–(3) are all positive, and they all have passed the significance test with a confidence level of 1%. This means that the higher the degree of digital transformation of an enterprise, the more significantly its technological innovation efficiency will be improved. In the regression results of the fixed-effects model with control variables, the regression coefficient of digital transformation (*DIGI*) was 0.161, indicating that, for every 1 percentage point increase in the digital transformation level of an enterprise, its technological innovation efficiency will increase by 0.161 percentage points.

The improvement of technological innovation efficiency by enterprise digital transformation can be explained from the following aspects. First, enterprise digital transformation can accelerate the informatization process of enterprises and realize the transformation from traditional manufacturing to intelligent manufacturing through the application of new technologies such as big data, cloud computing, blockchain and the Internet of Things, thereby improving technological innovation capabilities of enterprises. Second, digitalization has changed the innovation mode of enterprises, which helps to improve the efficiency of technological innovation. Finally, digital transformation can

realize the coordination of internal R&D design and supply chain management of enterprises, as well as expand the exchange and sharing of data and knowledge between the internal systems of enterprises, thereby accelerating the transformation from individual innovation to industrial collaborative innovation, thus promoting the improvement of technological innovation efficiency.

Table 4. Benchmark regression results.

	M(1) TIE	M(2) TIE	M(3) TIE
DIGI	0.119*** (0.0281)	0.151*** (0.0434)	0.161*** (0.0436)
Per			0.000121 (0.00788)
Fixed			-0.0376* (0.0196)
RLT			-0.0308** (0.0120)
Constant	0.0474*** (0.00175)	0.0460*** (0.00213)	0.0516 (0.959)
Individual effect	NO	YES	YES
Time effect	NO	YES	YES
N	5580	5580	5580
R-squared	0.003	0.602	0.602

3.2. Robustness test

In order to obtain reliable research conclusions, we conducted a series of robustness tests [65]. First of all, the impact of enterprise digital transformation on the efficiency of technological innovation may vary greatly due to the inconsistency of industry types to which they belong. Considering industry differences, we carried out robustness tests in three ways. The first way is to replace the model that controls the individual and time effects in the benchmark regression with the model that controls the industry and time effects to re-conduct the regression. The second way is to measure the level of digital transformation by the indicator adjusted by the industry average, that is, to subtract the industry average from the original value. This indicator reflects the relative level of the enterprise digitalization degree in the industry, and it is recorded as *DIGI_b*. In the third method, the level of enterprise digital transformation is measured by the indicator adjusted by the industry median, that is, we subtract the industry median from the original value, and the indicator is recorded as *DIGI_c*. Second, considering the possible endogeneity of control variables, the systematic GMM [66] is used to re-estimate the model, and the results are shown in Table 5.

The results in Table 5 show that the benchmark regression results are robust no matter whether the proxy variable of enterprise digital transformation is changed or the estimation method is changed. In several different robustness test results, the influences of the estimated regression coefficients of digital transformation on the technological innovation efficiency are significant and positive at least at the level of 1%. The fourth column in Table 5 is the result of the GMM. We can see that the first-order lag of the dependent variable *L.TIE* is significant. Also, the experimental results show that the first-order difference of the disturbance term of the model, according to the autoregressive test, has first-order autocorrelation, and the second-order difference does not have autocorrelation, indicating that

the estimators obtained by the GMM are consistent. Besides, the Hansen test of over-identification shows that the p-value was equal to 0.208, which means that the instrument variables are valid. These results indicate that digital transformation has significantly promoted the efficiency of enterprise technological innovation.

Table 5. Robustness test results.

	M(1) TIE	M(2) TIE	M(3) TIE	M(4) TIE
DIGI	0.0683** (0.0293)			0.114* (0.0609)
DIGI _b		0.131*** (0.0440)		
DIGI _c			0.146*** (0.0442)	
L.TIE				0.395** (0.199)
Per	1.68e-05* (9.53e-06)	-0.000460 (0.00788)	-0.000239 (0.00788)	6.29e-06 (7.99e-06)
Fixed	0.00220 (0.00944)	-0.0375* (0.0196)	-0.0375* (0.0196)	-0.0426 (0.0425)
RLT	-0.00228 (0.00657)	-0.0299** (0.0120)	-0.0301** (0.0120)	-0.0312 (0.0226)
Constant	0.0481*** (0.00371)	0.129 (0.959)	0.101 (0.959)	0.0498*** (0.0167)
Industry effect	YES	NO	NO	NO
Individual effect	NO	YES	YES	YES
Time effect	YES	YES	YES	YES
N	5579	5580	5580	4650
R-squared	0.064	0.602	0.602	-
Hansen test p	-	-	-	0.208

Note: DIGI represents the original value of digital transformation, DIGI_b represents the digital transformation adjusted by the industry mean and DIGI_c represents the digital transformation adjusted by the industry median.

3.3. Heterogeneity analysis

3.3.1. Heterogeneity test based on enterprise factor intensity

Considering that the development level of enterprise digital transformation varies in different industries, and that there are great differences among the environments of technological innovation in different industries, it is necessary to further analyze whether there is industry heterogeneity in the impact of a digital transformation on the efficiency of enterprise technological innovation [67]. We first divided the industries of listed companies according to the “Guidelines for Industry Classification of Listed Companies” revised and issued by China Securities Regulatory Commission in 2012, and the proportion of fixed assets and the proportion of R&D expenditure were selected as the classification indicators. Then, we applied a cluster analysis method to classify the listed companies according to the factor intensity of the industry. Among them, the proportion of fixed assets = net value of fixed assets

/ total assets; the proportion of R&D expenditure = R&D expenditure / employee compensation payable. The reasons for selecting these two classification indicators are as follows. The proportion of fixed assets reflects the importance of fixed assets in production factors. The larger the proportion of fixed assets in the industry, the more important capital is for the industry, so the industry is capital-intensive. The proportion of R&D expenditure reflects the importance of R&D expenditure in production factors. The larger the proportion of industry R&D expenditure, the greater the gap between R&D expenditure and employee compensation, indicating that technical factors are more important than labor factors for the industry, so the industry is technology-intensive. For the cluster analysis, we used the widely used sum of squared deviation method to divide the samples into three sub-samples according to the industries to which they belong: labor-intensive, capital-intensive and technology-intensive. See Table 6 for the corresponding sub-industries of different sub-samples.

Table 6. Enterprise factor intensity classification.

Factor intensity type	Subdivision of industry
Labor-intensive	A03 (livestock), B06 (coal mining and washing), B09 (nonferrous metal mining and dressing), B11 (mining activities), C13 (agricultural and side food processing), C14 (food manufacturing), C15 (wine, beverage and refined tea manufacturing), C17 (textile), C18 (textile, clothing, apparel), C19 (leather, fur, feathers and its products and footwear), C20 (wood processing and wood, bamboo, rattan, palm, grass products), C21 (furniture manufacturing), C24 (culture, education, beauty, sports and entertainment manufacturing), C41 (other) Manufacturing, C42 (comprehensive utilization of waste resources), E48 (civil engineering construction), E50 (building decoration and other construction), F51 (wholesale), F52 (retail), L72 (business services), N77 (ecological protection and environmental management), R85 (news and publishing), R86 (radio, television, film and television recording production)
Capital-intensive	C22 (paper and paper products), C23 (printing and recording media reproduction), C25 (petroleum processing, coking and nuclear fuel processing), C26 (chemicals), C28 (chemical fiber manufacturing), C29 (rubber and plastics), C30 (non-metal minerals), C31, C32, C33, C36 (automotive), C37 (railway, shipping, aerospace and other transportation equipment manufacturing), D44 (power, thermal production and supply), D45 (gas production and supply), D46 (water production and supply), G54 (road transportation), G59 (storage)
Technology-intensive	C27 (pharmaceutical manufacturing), C34 (general equipment manufacturing), C35 (special equipment manufacturing), C38 (electrical machinery and equipment manufacturing), C39 (computer, communications and other electronic equipment manufacturing), C40 (instrument manufacturing), I63 (telecommunications, radio and satellite transmission services), I64 (Internet and related services), I65 (software and information technology services), J69 (other financial industry), M74 (professional services)

Based on the benchmark regression Model M(1), we estimated the impact of the digital transformation of labor-intensive enterprises, capital-intensive enterprises and technology-intensive enterprises on the technological innovation efficiency, whose parameter estimation results are shown in Columns (1)–(3) of Table 7, respectively.

Table 7. Heterogeneity test results.

	Based on factor intensity			Based on enterprise ownership	
	M(1) TIE	M(2) TIE	M(3) TIE	M(4) TIE	M(5) TIE
DIGI	-0.0811 (0.104)	0.473*** (0.114)	-0.0345 (0.0617)	0.169*** (0.0454)	0.241* (0.134)
Per	-0.000970 (0.0258)	-0.00414 (0.0138)	0.00298 (0.00969)	0.00695 (0.00979)	-0.00733 (0.0158)
Fixed	-0.123* (0.0712)	-0.0652* (0.0336)	0.00198 (0.0240)	-0.0168 (0.0221)	-0.0903* (0.0473)
RLT	-0.0111 (0.0489)	-0.0188 (0.0195)	-0.0453*** (0.0148)	-0.0552*** (0.0140)	0.00921 (0.0271)
Constant	0.235 (3.413)	0.537 (1.602)	-0.289 (1.162)	-0.681 (1.058)	1.225 (2.509)
Individual effect	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES
Control variable	YES	YES	YES	YES	YES
N	876	1,572	2,970	3,702	1,554
R-squared	0.542	0.647	0.616	0.608	0.599

The results in Table 7 show that the impact of digital transformation on enterprise technological innovation efficiency varies in industries with different factor intensities. Digital transformation mainly promotes the technological innovation efficiency of capital-intensive enterprises, with no significant effect on labor-intensive and technology-intensive enterprises. Columns (1) and (3) in Table 7 show that the effects of the regression coefficients of the digital transformation of both labor-intensive and technology-intensive enterprises on the enterprise technological innovation efficiency are not significant, and that the regression coefficient of the digital transformation of capital intensive enterprises in Column (2) is 0.473, which has passed the significance test with a confidence level of 1%. It can be seen that there is industry heterogeneity in the impact of digital transformation on enterprise technological innovation efficiency.

The possible reasons for this conclusion are as follows. Generally speaking, values created by labor-intensive enterprises depend more on the improvement of employees' labor efficiency, while the demand for technological innovation is relatively low. Enterprises in labor-intensive industries prefer to use technology spillovers inside and outside of the industry rather than investing a lot of resources in independent research and development. Moreover, such enterprises do not have too much demand for digital transformation. Therefore, for labor-intensive enterprises, digital transformation has no

obvious effect on improving enterprise technological innovation efficiency. Capital-intensive enterprises use relatively more machinery and equipment in the production process, and the depreciation expense of fixed assets accounts for a high proportion of the product cost. It is necessary for such enterprises to take a variety of measures to reduce the unit product cost in order to obtain a sustainable competitive advantage. On the one hand, they can carry out technological innovation activities to promote the improvement of the technological process and the effective utilization of original machinery and equipment, thereby further reducing the product cost. On the other hand, it is beneficial to strengthen enterprises' equipment manufacturing and creative ability if they pay attention to the improvement of technological innovation efficiency while carrying out innovation activities. The promotion of digital transformation enables enterprises to process and deeply analyze a large amount of data, such as machinery and equipment or process flow data, by using digital technology, providing effective information for enterprise technological innovation activities. Therefore, for capital-intensive industries, the improvement of digital transformation will significantly promote the efficiency of enterprise technological innovation. From the perspective of enterprise development in developing countries, labor-intensive and capital-intensive enterprises develop earlier and are relatively mature, while most technology-intensive enterprises are still in the growth stage, and their awareness of promoting digital transformation is still weak; particularly, they lack the driving force for a digital transformation [68]. Although technology-intensive enterprises are highly dependent on mechanical equipment with high technical content and high technical requirements in the production process and they often pay more attention to the investment in technological innovation, it is difficult to form an effective feedback loop for the efficiency of technological innovation due to the insufficient driving force of digital transformation.

3.3.2. Heterogeneity test based on the nature of enterprise ownership

In the context of different enterprise ownership, there may be significant differences in the impacts of enterprise digital transformation on technological innovation efficiency, so the heterogeneity test was carried out based on the nature of enterprise ownership [69]. Columns (4) and (5) display the parameter regression results for the effects of digital transformation of non-state-owned enterprises and state-owned enterprises on the technological innovation efficiency, respectively.

It can be seen that the impact of enterprise digital transformation on the technological innovation efficiency varies among enterprises with different ownership attributes. Digital transformation can promote the technological innovation efficiency of both state-owned and non-state-owned enterprises; but, in comparison, digital transformation has a greater role in promoting the technological innovation efficiency of state-owned enterprises. In Column (4) of Table 7, the effects of the regression coefficient of the digital transformation of non-state-owned enterprises on the technological innovation efficiency is 0.169, which has passed the significance test with a confidence level of 1%. In Column (5), the effects of the regression coefficient of the digital transformation of Chinese state-owned enterprises on the technological innovation efficiency is 0.241, which passes the significance level with a confidence level of 10%.

The possible explanations are as follows. State-owned enterprises enjoy the support of national reputation and have relatively abundant resources, so, in the context of the rapid development of a digital economy, they can give better play to the advantages of digital transformation, speed up the combination of digital resources and enterprise technological innovation, improve production

technology by maximizing the use of useful information of enterprise technology and mining the possibility of technological innovation, thereby improving technological innovation efficiency. For non-state-owned enterprises, on the one hand, they are facing the pressure of market competition that, if they do not advance, they will fall back, so they have a strong desire to engage in innovative transformation activities to obtain enough market share and create a greater competitive advantage. To this end, non-state-owned enterprises have sufficient motivation to promote digital transformation to improve the enterprise technological innovation efficiency. On the other hand, because non-state-owned enterprises are at a disadvantage compared with state-owned enterprises in terms of resource acquisition and market share, most of them have severe resource constraints, which will have an adverse impact on the enterprise technological innovation efficiency to a certain extent. Therefore, compared with state-owned enterprises, the effect of a digital transformation on the improvement of technological innovation efficiency of non-state-owned enterprises is slightly weaker.

4. Mechanism analysis of the impact of digital transformation on enterprise technological innovation efficiency

4.1. Mediating effect test

Enterprise digital transformation, namely, the digital processing of enterprise operation data, can alleviate the enterprise financing constraints to a certain extent [70]. First, enterprises, which are undergoing digital transformation, have better development prospects in the era of a digital economy. Such enterprises can also get more attention in the market, which can strengthen the market's positive expectations and alleviate the financing constraints. Second, in the process of digital transformation, enterprises can use the processed information to improve their own operation and obtain market demand information through data processing, which helps enterprises to adjust the operation scale and improve the quality and efficiency of production and operation, thereby obtaining financing in the capital market more easily. Moreover, the loan interest rate of such enterprises in banking institutions will be relatively more favorable, which can effectively alleviate the problem of financing constraints. In addition, under the condition of effectively processing and outputting information, enterprises will be more willing to "push" information to the market in order to obtain the support of more external investors. This increase in the amount of two-way access to information significantly reduces the information asymmetry, which is also helpful for enterprises to improve financing availability and alleviate liquidity constraints [71,72].

Meanwhile, corporate financing constraints can improve the enterprise technological innovation efficiency [73]. On the one hand, since internal financing has small risks and low costs, when companies are subject to certain internal financing constraints, they will realize their bad capital situation, thus speeding up technological innovation and achievement transformation. From this perspective, the internal financing constraints have a certain positive effect on the technological innovation efficiency of enterprises. On the other hand, when enterprises are faced with certain external financing constraints, they will limit some irrational and low-yield investments, thereby reducing the probability of inefficient innovation investment projects and thus improving the technological innovation efficiency. Therefore, we argue that financing constraints can play a mediating role in the impact of digital transformation on technological innovation efficiency.

Table 8. Mechanism test results.

Empirical results of the mediating effect	Empirical results of the mediating effect			Empirical results of the moderating effect		
	M(1) TIE	M(2) SA	M(3) TIE	M(4) cTIE	M(5) cTIE	
DIGI	0.161*** (0.0436)	- 0.0730*** (0.0212)	0.170*** (0.0436)	cDIGI	0.161*** (0.0436)	0.149*** (0.0436)
SA			0.115*** (0.0302)	cCRI		-0.0289 (0.0227)
Per	0.000121 (0.00788)	- 0.0136*** (0.00383)	-0.00145 (0.00788)	cDC		1.085*** (0.274)
Fixed	-0.0376* (0.0196)	0.0557*** (0.00953)	-0.0312 (0.0197)	cPer	0.000121 (0.00788)	-0.00117 (0.00788)
RLT	- 0.0308** (0.0120)	- 0.0669*** (0.00583)	- 0.0385*** (0.0122)	cFixed	-0.0376* (0.0196)	-0.0397** (0.0196)
_cons	0.0516 (0.959)	-1.986*** (0.466)	-0.178 (0.959)	cRLT	-0.0308** (0.0120)	- 0.0335*** (0.0120)
	0.161*** (0.0436)	0.0730*** (0.0212)	0.170*** (0.0436)	_cons	-1.35e-05 (0.000848)	0.0528*** (0.000847)
Individual effect	YES	YES	YES	Individual effect	YES	YES
Time effect	YES	YES	YES	Time effect	YES	YES
Control variable	YES	YES	YES	Control variable	YES	YES
N	5580	5580	5580	N	5580	5580
R-squared	0.602	0.988	0.604	R-squared	0.602	0.604

In order to test whether the impact of a digital transformation on the technological innovation efficiency of enterprises can be realized through financing constraints, we set the following mediating effect model:

$$TIE_{i,t} = \alpha_0 + \alpha_1 DIGI_{i,t} + \gamma Control_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

$$SA_{i,t} = \beta_0 + \beta_1 DIGI_{i,t} + \gamma Control_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

$$TIE_{i,t} = \theta_0 + \theta_1 DIGI_{i,t} + \theta_2 SA_{i,t} + \gamma Control_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

Equations (2)–(4) are the three models included in the mediating effect models, where SA represents the financing constraint; the meanings of the other variables are consistent with Eq (1). Based on Eqs (2)–(4), we adopted the improved causality test in a stepwise regression method to test, referring to the practice of Wen and Ye [74]. The specific steps are as follows:

The first step is to examine the regression coefficient α_1 in Eq (2), proceeding to the second step if α_1 is significant; otherwise, the test will be stopped.

In the second step, the regression coefficients of β_1 and θ_2 in Eqs (3) and (4) are checked in turn. If they are significant, it indicates that there is a mediating effect, and the test will proceed to the third

step. If at least one of them is not significant, the bootstrap method is used to test the significance of $\beta_1 \times \theta_1$. If it is significant, the test will continue to the third step; otherwise, there is no mediating effect and the test should be stopped.

The third step is to test the significance of the estimated value of θ_1 in Eq (4). If the estimated value is significant, it means that there is a partial mediating effect; if the estimated value is not significant, it means that there is a complete mediating effect.

Based on the mediating effect model set above, the test results of the mediating effect of financing constraints were derived, as shown in Columns (1)–(3) in Table 8. These results indicate that financing constraints have a partial mediating effect on digital transformation affecting the efficiency of technological innovation. In Table 8, the regression coefficient of *DIGI* in Column (1) is 0.161, which is significant at 1% significance level, indicating that *DIGI* has passed the first-step test of the mediating effect model. The regression coefficient of *DIGI* in Column (2) is -0.0730 and significant at a 1% significance level, indicating that *DIGI* has passed the second-step test of the mediating effect model. The regression coefficient of *DIGI* in Column (3) is 0.170, which is higher than that in Column (1). The regression coefficient of SA (financing constraint) is 0.115, which also passes the significance test with a confidence level of 1%. The results of three-step regression show that a digital transformation can affect the efficiency of technological innovation by alleviating financing constraints.

4.2. Moderating effect test

Equity concentration may strengthen the role of enterprise digital transformation in improving enterprise technological innovation efficiency. As a new development mode, whether the digital transformation of enterprises can play a significant role in the business process depends on the support of investors with the right to speak [75]. In the context of the current digital economy era, digital transformation has become an important direction of enterprise reform and transformation, and it has also been the focus of investors and management. Generally speaking, the power of major shareholders to influence enterprise management and business decision-making increases with the increase of equity concentration. Therefore, the relatively concentrated equity makes the major shareholders have the motivation and ability to supervise the digital transformation decisions made by the enterprise management [76,77]. In other words, the more centralized the ownership structure, the higher the efficiency of the digital transformation decision-making of enterprise management. Therefore, equity concentration has a positive moderating effect on the relationship between digital transformation and technological innovation efficiency. In order to test the moderating effect of equity concentration, we constructed the following model:

$$cTIE_{i,t} = \alpha_0 + \alpha_1 cDIGI_{i,t} + \alpha_2 cCRI_{i,t} + \alpha_3 cDC + \gamma Control_{it} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (5)$$

where *cDIGI* and *cTIE* represent the digital transformation and the equity concentration after mean centralization, respectively. The purpose of centralized processing is to reduce the collinearity problem caused by introducing the multiplication term to the model. *cDC* represents the multiplication term of *cDIGI* and *cCRI*, and the definitions of the other variables are consistent with those in Eq (1). If the regression coefficient α_3 of the multiplication term *cDC* is significant, it indicates that equity concentration has a moderating effect [78]. If α_3 is positive, it indicates that equity concentration has a positive moderating effect on the impact of digital transformation on technological innovation efficiency [79].

Based on the moderating effect model set above, the empirical results of the moderating effect of equity concentration were derived, as shown in Columns (5) and (6) in Table 8, which indicate that equity concentration can significantly enhance the promotion effect of digital transformation on the efficiency of technological innovation of enterprises. In Column (5), the regression coefficient of the digital transformation level ($cDIGI$) is 0.149 and the regression coefficient of the interaction term (cDC) for the digital transformation level ($cDIGI$) and ownership concentration ratio ($cCRI$) to the technological innovation efficiency of enterprises is 1.085. They all passed the significance test at the 1% confidence level. This means that equity concentration has a positive moderating effect on the impact of digital transformation on the efficiency of technological innovation of enterprises.

5. Conclusions

Based on the data of 930 listed enterprises in China, we constructed econometric models to study the impact of digital transformation on the efficiency of technological innovation, and to further study the impact mechanism and heterogeneity. The main conclusions are as follows.

First, enterprise digital transformation can significantly improve the efficiency of enterprise technological innovation, as shown in the benchmark regression model estimation and a series of robustness test results. The reason is that a digital transformation can accelerate the informatization process of enterprises, change their innovation mode and accelerate the transformation from individual innovation to industrial collaborative innovation, thereby improving the efficiency of enterprise technological innovation.

Second, the impact of a digital transformation on the enterprise technological innovation efficiency is heterogeneous, which is reflected in two aspects: the factor intensity and the nature of ownership. On the one hand, digital transformation mainly promotes the technological innovation efficiency of capital-intensive enterprises, but not that of labor-intensive and technology-intensive enterprises. On the other hand, digital transformation significantly promotes the technological innovation efficiency of both state-owned and non-state-owned enterprises, but, in comparison, digital transformation has a greater role in promoting the technological innovation efficiency of state-owned enterprises.

Third, financing constraints and equity concentration play a mediating role and a moderating role, respectively, in the impact of digital transformation on enterprise technological innovation efficiency. On the one hand, digital transformation can affect enterprise technological innovation efficiency by acting on financing constraints. The key is that, by promoting digital transformation, enterprises can reduce the degree of information asymmetry and thus alleviate their financing constraints. Meanwhile, when faced with financing constraints, enterprises will limit irrational innovation investments, thereby improving the efficiency of technological innovation. On the other hand, the higher the equity concentration, the stronger the effect of digital transformation on the technological innovation efficiency of enterprises. The relatively concentrated shareholding gives major shareholders the motivation and ability to supervise the digital transformation decisions made by the enterprise management, so a digital transformation can better improve the efficiency of technological innovation of enterprises.

Based on the above conclusions, we propose the following policy implications. First, the government should further optimize the system and mechanism to create a good external environment for enterprises to implement digital transformation [80]. On the one hand, the government should

introduce targeted fiscal and tax policies to help enterprises in need complete digital and intelligent transformation, strengthen the construction of big data platforms and shared factories and provide hardware conditions for enterprise technological innovation activities, thereby improving the efficiency of enterprise technological innovation [81]. On the other hand, the government should establish relevant systems for the confirmation, opening, circulation and transaction of data resources, as well as strengthen the intellectual property protection of digital technology and data assets.

Second, enterprises should accelerate digital transformation, especially, non-state-owned enterprises should focus on promoting digital transformation. First of all, enterprises should speed up the innovation and application of digital technology and continue to release the potential to improve technological innovation efficiency in the transformation and upgrading of digital technology. Second, enterprises should strengthen the construction of information infrastructure and information-sharing platforms to realize the efficient transmission and communication of resources and information. Third, enterprises should use digital technology to shorten the distance between enterprises and consumers, as well as carry out targeted technological innovation around customer needs.

Third, the equity concentration of enterprises should be properly increased, and the equity incentive systems of listed enterprises should be improved further. This is conducive to improving the decision-making efficiency of digital transformation, thereby enhancing the promoting effect of digital transformation on technological innovation efficiency.

Conflict of interest

The authors declare that there is no conflict of interest.

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