Exploring the Digital Era: Has Digital Technology Innovation Reshaped Investment Efficiency in Chinese Enterprises?

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Abstract: In the digital era, advancements in technologies such as artificial intelligence, big data, and cloud computing are revolutionizing corporate investment strategies, yet academic research has struggled to keep pace with these rapid developments. Utilizing data from 2005 to 2021 for Chinese A-share listed companies, this study examines the impact of digital technology innovation on corporate investment efficiency. The findings reveal that firms with higher levels of digital technology innovation tend to have greater investment efficiency. This improvement stems from the role of digital innovation in driving digital transformation, improving information quality, addressing management issues, reducing reliance on short-term financing, and lowering financial risks. Notably, the positive effects are more pronounced in non-state-owned enterprises, high-tech industries, and well-developed financial markets. The article broadens our understanding of the economic effects of digital technology innovation and the factors contributing to corporate investment efficiency growth strategies in a rapidly evolving digital economy.

Keywords: Digital technology innovation; corporate investment efficiency; information asymmetry; digital economy

JEL Classification: G11; G31; O3

1. Introduction

Since the dawn of the 21st century, digital technology has been a catalyst for change in the global economy. Defined as the use of digitized information and communication technologies to generate economic and social value (Opland et al., 2022), digital technology is a driving force in the creation and dissemination of knowledge, products, services, and business models. The transition from traditional information and communication technology to cutting-edge advancements like AI, big data, and blockchain has altered lifestyles and consumption patterns, while significantly boosting corporate efficiency in organization, operations, and finance (Guo and Xu, 2021). A McKinsey Global Institute report highlights the substantial economic contribution of digital technology, which accounts for over 10% of global economic growth, a trend poised to expand (Manyika et al., 2016). China, as a digital revolution frontrunner and the world's second-largest economy, exemplifies this shift. The nation's digital economy has surged to a value of 50 trillion yuan, representing over 36% of its GDP (Peng and Luxin, 2022). Given China's historical reliance on investment for growth (Lin et al., 2023), the evolution of this model in the context of digital innovation warrants examination. This paper zeroes in on the corporate perspective, investigating how digital technology innovation influences

corporate investment efficiency. It conducts both a theoretical analysis and empirical examination of the transformation of China's traditional investment-driven growth model amidst the digital revolution. It offers new insights into the symbiotic relationship between digital progress and corporate investment.

Investment efficiency, as a core indicator reflecting a firm's ability to utilize invested capital, has long received extensive attention from scholars (Benlemlih and Bitar, 2018; Chen et al., 2017). Some scholars have noted that efficient investment strategies can not only drive companies to achieve high-quality development trajectories but can also prevent the waste of resources and the devaluation of assets (Huang, 2022). In China, especially after the reform and opening-up, investment efficiency improved through the rapid growth of rural industrialization and non-state-owned enterprises. However, this growth model did not last long, and issues such as a decline in the domestic share of investment, slow growth of investment efficiency, and imbalances in investment gradually emerged (Jun, 2003). This "extensive" investment growth model has caused a series of economic imbalances at the macro level, and many enterprises at the micro level have gradually shown poor financial performance, inefficiency, and a lack of technological innovation (Zheng et al., 2009). Currently, finding new ways to improve investment efficiency has become an important issue for emerging countries like China.

As a key driver in the fourth industrial revolution, digital technology innovation is profoundly reshaping traditional business models of enterprises, gradually achieving digitization, intelligence, and interconnectivity in various aspects such as production, sales, and operations (Caruso, 2018; Cirillo et al., 2023). Scholars have found that digital technology innovation holds immense potential not only for improving enterprise operations and financial performance but also for enhancing supply chain management capabilities, helping businesses achieve better environmental performance and sustainable development (Guo and Xu, 2021; Wang and Teng, 2022). By fostering innovation in enterprise marketing, digital technology can enhance customer acquisition, retention, and loyalty, increasing sales and overall performance (Jung and Shegai, 2023). Furthermore, the embeddedness of digital technology innovation networks also affects firms' innovative performance since it facilitates the acquisition, analysis, and application of knowledge (Ge et al., 2023). However, despite these studies providing valuable insights, they overlook how digital technology innovation impacts firm investment efficiency. Given that digital technology innovation is a key driver of digital economy development, and the effect of digital technology development on firm investment efficiency reflects the digital economy's capability to serve the real economy (Peng and Luxin, 2022), it means that exploring the relationship between digital technology innovation and firm investment

efficiency has significant practical importance.

However, there still exists a significant gap in the literature discussing the economic consequences of digital technology innovation, with related theoretical issues requiring empirical support. On the one hand, in the current digital economy era, digital technology plays an increasingly important role in assessing the investment potential of regions, industries, enterprises, projects, products, and more (Caruso, 2018; Gao et al., 2023; Ge et al., 2023; Jung and Shegai, 2023). On the other hand, the advent of digital technology has also promoted the transparency and efficiency of public investments, providing useful tools for local government and residents' investment decisions (Kahn et al., 2018). So, in the corporate realm, can digital technology innovation empower corporate investment? What mechanisms produce this effect? Is its performance stable across different firms, industries, and markets? Addressing these questions, this article uses digital technology innovation as an entry point, employing data from Chinese listed companies as the research sample, to explore the driving effects, economic mechanisms, and heterogeneity of digital technology innovation on corporate investment efficiency. The research finds that digital technology innovation has a significant positive impact on firms' investment efficiency. The underlying mechanisms can be explained from several aspects: firstly, at the "information side," digital technology innovation promotes the digital transformation of enterprises and simultaneously improves the quality of their information disclosure; secondly, at the "governance side," such technology helps alleviate agency problems and managerial myopia; at the "financing side," digital technology innovation reduces companies' reliance on short-term borrowing and excessive debt ratios, thereby increasing stock liquidity; finally, at the "risk side," this innovative technology reduces external stock price crash risks and internal financial risks. These factors work together to provide strong support for improving the investment efficiency of companies. Furthermore, this study also explores the heterogeneity of the relationship between digital technology innovation and corporate investment efficiency under different enterprise, industry, and market conditions. The findings indicate that the role of digital technology innovation in improving investment efficiency is particularly significant in non-state-owned enterprises, highly innovative industries, and developed financial markets.

The possible contributions of this paper are mainly reflected in the following three aspects:

Firstly, the paper expands the research on the influencing factors in the field of corporate investment under the background of the digital economy. Corporate investment activities are closely related to long-term development (Gradzewicz, 2021; Manogna and Mishra, 2021), and existing literature has analyzed the driving factors for improving

corporate investment efficiency in areas such as macroeconomic policies, market financing, and corporate financial reporting (Chen et al., 2013; Chen et al., 2011; Biddle et al., 2009). However, as the digital economy has developed rapidly in recent years, the complex dynamics of how corporate digital technology innovation affects investment decisions and, thereby, investment efficiency have largely remained unexplored. Given that existing literature uses annual report keyword metrics to measure the degree of digital transformation, which is conceptually different from digital technology innovation (Huang et al., 2023; Wu et al., 2021), this paper aims to explore the role of digital technology innovation in shaping investment strategies and their corresponding returns, helping to understand changes in corporate investment decisions under the digital economy.

Secondly, the paper analyzes the mechanism of the impact of digital technology innovation on corporate investment efficiency. Existing research explains the internal mechanisms of digital technology driving corporate performance improvement from the perspectives of policy environment, knowledge expansion, and innovation empowerment (Gao et al., 2023; Guo and Xu, 2021). As an extension, this paper explains the possible mechanisms by which digital technology innovation affects corporate investment efficiency from multiple perspectives, including information, governance, financing, and risk, aiming to provide a more comprehensive theoretical analysis framework for revealing the internal logic of digital technology innovation on corporate investment efficiency.

Lastly, the paper conducts a heterogeneity analysis of the research sample based on property rights attributes, industry categories, and market development levels. Since the institutional environment and market environment in which a company operates can lead to differences in the impact and direction of digital technology innovation on corporate investment efficiency, this study not only discusses the impact of digital technology innovation on corporate investment efficiency as a whole but also performs a heterogeneity analysis from the perspectives of different companies, industries, and markets, enriching the economic implications of digital technology innovation.

The remaining parts of the paper are arranged as follows: the second part reports the literature review and research hypothesis; the third part introduces the related data, variables, and research design; the fourth part displays the baseline regression, robustness and endogeneity, economic mechanisms, and heterogeneity studies; and the fifth part concludes with conclusions and policy recommendations.

2. Literature Review and Research Hypotheses

2.1 Literature Review

2.1.1 Digital Technology Innovation

Digital technology innovation can be defined as a multidimensional process that

utilizes digital technologies and data resources to build and implement new knowledge, products, services, and business models, thereby creating additional economic and social value (Kohli and Melville, 2019). This process encompasses not only the integration of technologies such as cloud computing, the Internet of Things (IoT), and big data analytics but also the innovation of cutting-edge technologies like artificial intelligence and blockchain. These technologies provide the core driving force for the digital economy and serve as crucial tools for enhancing the quality of economic development (Ding et al., 2021). Against the backdrop of the rapid development and widespread application of digital technologies, digital technology innovation has gradually become a central strategy for governments and businesses around the world to pursue competitive advantages and achieve sustainable development, making it a subject of in-depth academic discussion.

Research on the consequences of digital technology innovation primarily explores two dimensions: macro and micro. From a macro perspective, the core focus is on how to analyze and measure the impact of digital technology innovation on the overall effect on nations and societies. Li et al. (2020) note that digital technology innovation and digital transformation have become the key pathways for rapid development in several Asian countries. These pathways have propelled these nations to advance comprehensive economic and social transformation through the wave of digitization. Moreover, digital technology innovation is considered a core element for achieving sustainable development. With the continuous strengthening of national innovation capabilities, there is hope for improving domestic carbon emissions, thereby fostering the development of a green economy. On the societal level, scholars are also highly attentive to the effects brought about by digital technology innovation, which includes developing new services and establishing new business models to enhance the welfare of socially vulnerable groups and striving to address social inequalities and exclusion (Qureshi et al., 2021; Parthiban et al., 2021; Qureshi et al., 2018).

Shifting to the micro dimension, research focuses more on the impact of digital technology innovation on businesses and consumers. In today's digital era, technology has become a core determinant of business competitiveness. The depth and breadth of business digitization are increasingly becoming central competitive forces in the modern economy. They not only give rise to new market domains but also greatly advance innovation and transformation in business operations, organizational structure, and process management (Hirt and Willmott, 2014). As the application of digital technology deepens, the rise of emerging business models such as e-commerce and online shopping begins to threaten the long-standing advantages of the traditional retail industry while also reshaping the behavioral patterns and preferences of brick-and-mortar retailers and

consumers (Reinartz et al., 2019). Moreover, digital technology innovation significantly reduces consumers' costs of searching for merchant information. This shift not only forces businesses to improve their competitive strategies but also further promotes the bilateral development of consumer markets (Ratchford, 2019).

However, current research on how digital technology innovation influences a company's investment efficiency, particularly its underlying mechanisms and pathways, remains relatively scarce. This provides a unique research opportunity for this paper to delve deeper into the exploration and analysis of the relationship between digital technology innovation and corporate investment efficiency.

2.1.2 Corporate Investment Efficiency

Research into the factors affecting investment efficiency has always been a core topic in the fields of finance and economics, where theories such as information asymmetry, agency costs, and market frictions have been used to explore factors that could influence corporate investment decisions (Jensen and Meckling, 1976; Myers and Majluf, 1984). As an important metric for measuring corporate operational performance and competitive advantage, investment efficiency is a necessary factor for corporate survival and long-term development (Chen et al., 2011). In recent years, with the development of economic globalization and digitization, research on the factors influencing corporate investment efficiency has entered a new phase. Scholars have primarily explored this from two aspects: the external environment of the enterprise and its internal structure.

In the ongoing evolution of corporate investment decisions, many scholars have delved into the increasingly complex external environment of today. The sustained development of globalization has virtually eliminated legal and regulatory barriers to international investment for businesses in developed economies. At the same time, emerging markets have gradually relaxed restrictions on international investments over the past two decades, not only opening up more financing channels for businesses but also raising the bar for market competitiveness (Stulz, 2009). Domestically, government intervention in business activities can have a distorting effect, as firms with closer government ties often exhibit lower investment efficiency (Chen et al., 2011). Additionally, scholars have pointed out that improvements in domestic transportation networks can enhance the connection between firms and external investors, improving investment efficiency by reducing external monitoring costs and mitigating information asymmetry (Wu et al., 2022).

From an internal perspective, numerous studies have deeply analyzed the multifaceted factors affecting corporate investment efficiency. Information asymmetry and agency issues within firms have long been proven to have a significant impact on their

own investment efficiency (Jensen, 1986; Jensen, 1993). To further enhance corporate investment efficiency and address information asymmetry and agency conflicts, scholars have contributed their insights from the perspectives of financing structure, corporate governance, and accounting information (Tong and Lu, 2005; Aggarwal and Samwick, 2006; Healy and Palepu, 2001). At the same time, the quality of corporate financial reporting is directly linked to its investment efficiency; high-quality financial reporting can enhance the accuracy of investment forecasts, thereby better aligning investment expectations and outcomes and improving investment efficiency (Biddle et al., 2009). However, the role of financial reporting quality in enhancing investment efficiency is primarily concentrated in the banking financing process. If a firm's purpose is to reduce taxes by opting for a lower level of earnings, the positive impact of financial reporting quality on investment efficiency will progressively diminish.

While the aforementioned studies offer valuable insights for understanding the relationship between technological innovation and corporate investment, they do not delve into the relationship between digital technology innovation and corporate investment efficiency, particularly in a country like China, where the digital economy is rapidly developing. Therefore, this paper attempts to explore in depth how digital technology innovation impacts corporate investment efficiency to expand research on the economic consequences of digital technology innovation as well as the determinants of corporate investment efficiency.

2.2 Research Hypotheses

The relationship between corporate digital technology innovation and investment efficiency is grounded in the Information Asymmetry Theory. According to this theory, imbalances in information can lead to inefficiencies or market failures (Akerlof, 1978; Stiglitz and Weiss, 1992). In today's digital era, companies leverage technologies like big data, blockchain, and artificial intelligence to rapidly extract actionable investment insights from vast datasets, reducing the costs of information acquisition and increasing investment efficiency (Goldfarb and Tucker, 2019). A company's high level of digital innovation indicates proficiency with digital tools, which enhances data processing, analysis, and application capabilities. This expertise is crucial in reducing information asymmetry in investment decision-making, thereby improving efficiency. Moreover, as Spence (1973) suggests, in situations of information asymmetry, superior firms can distinguish themselves through signaling to attract favorable investment opportunities. Strong engagement in digital innovation acts as such a signal, reflecting a company's progressive outlook, advanced operations, and competitive position. This, in turn, mitigates the challenges of asymmetric information in financing and investment partnerships, further

boosting investment efficiency.

Based on the Information Asymmetry Theory, it is believed that digital technology innovation boosts corporate investment efficiency through channels such as "information side", "governance side", "financing side", and "risk side".

Firstly, digital technology innovation can facilitate corporate digital transformation and improve the quality of information disclosure through the "informational" channel, thereby mitigating information asymmetry and enhancing corporate investment efficiency. Digital technology innovation has become a key driver for corporate transformation, injecting vitality into traditional business models, operational processes, and decision-making mechanisms. As the level of digital technology innovation rises, it implies that a firm possesses an increasing array of digital resources and capabilities, enabling it to handle vast data more effectively and achieve real-time updates and sharing of information (Bharadwaj et al., 2013), ultimately increasing the efficiency of corporate investment decisions. In terms of information disclosure, existing research has found that higher-quality financial reporting can lead to improved capital investment efficiency (Biddle et al., 2009). In a digitized context, companies can more swiftly and accurately provide external stakeholders, such as investors, partners, and consumers, with information regarding their operational health, market prospects, and strategic plans. The timeliness and accuracy of information significantly alleviate information asymmetry issues, bolstering the confidence of external stakeholders and channeling high-quality funds into corporate investment activities.

Secondly, corporate digital technology innovation can alleviate managerial myopia and ease agency conflicts through the "governance" channel, thus reducing information asymmetry and enhancing company investment efficiency. Existing literature on corporate investment confirms that managers' pursuit of personal benefit maximization can provoke agency conflicts between them and shareholders or external investors, impeding the firm's ability to make optimal investment decisions (Jensen and Meckling, 1976; Chen et al., 2011). When managers have more information than shareholders, they might exploit this informational advantage for personal gain, disregarding the interests of the shareholders. For instance, managers might over-invest in short-term, high-return but riskier projects or manipulate accounting figures to embellish financial statements, securing higher compensation or bonuses and triggering severe agency issues. The application and innovation of digital technology can provide more transparent information and communication mechanisms, allowing shareholders to better monitor and evaluate managers' behavior and performance, thereby curbing self-interested managerial actions. At the same time, advanced data analytics and business intelligence tools can offer

managers real-time feedback and decision-making advice, reducing the likelihood of errors and risks in decision-making. In such an environment, managerial decisions are increasingly based on data and analysis rather than intuition or short-term gains, further enhancing the long-term investment efficiency of the company.

Thirdly, corporate digital technology innovation can improve investment efficiency by adjusting the company's financing structure and reducing the costs of debt through the "financing" channel. As digital technologies such as cloud computing, big data, and artificial intelligence develop, the marginal cost for financial institutions to acquire multi-dimensional credit data on enterprises is continuously decreasing. The criteria for assessing corporate credit have expanded from traditional structured data, such as financial statements and collaterals, to unstructured data, including images, videos, web pages, and texts, which has profound implications for corporate financing strategies (Lai et al., 2023). On the one hand, companies with a high capacity for digital technology innovation are often better at precisely forecasting and managing their financial liquidity needs. This allows them to present their financial situation and operational forecasts more accurately during communications with banks and financial institutions. As a result, these companies are more likely to secure longer-term and more favorable financing conditions, thereby lowering their reliance on short-term liabilities and reducing the likelihood of liquidity risks (Titman and Wessels, 1988). Moreover, high digital technology innovation can bring about improvements in operational efficiency, further reducing the waste of capital and ensuring that funds are used for the most valuable investment opportunities. On the other hand, in the context of direct financing, a company's digital technology innovation capabilities can enhance the quality and depth of its information disclosure, offering external investors more detailed and authentic company operational information. This high degree of transparency can mitigate information asymmetry, enhance the appeal of the company's stock, and may facilitate an increase in stock price, thus lowering the company's financing costs and further boosting investment efficiency.

Fourthly, corporate digital technology innovation can enhance investment efficiency by reducing both internal and external risks through the "risk" aspect. On the one hand, with the application of digital technology innovation, a company can enhance its capability to collect and process information, ensuring timely capture of market dynamics and forecasting possible market changes, thereby reducing decision-making biases due to information asymmetry. Studies have shown that the sensitivity of corporate investment decisions to stock prices mainly depends on the degree of information asymmetry within the company (Chen et al., 2007). For external investors, companies with high digital technology innovation capabilities provide more transparent and timely information

disclosure, which helps to bolster their confidence in the company, reduce panic selling in the market, stabilize stock prices, and ultimately lower the external risk of stock price crashes (Botosan, 1997). On the other hand, leveraging research and application of cutting-edge digital technologies can aid financial teams in rapidly identifying inefficient or high-risk investment projects, thus adjusting investment strategies and reducing internal financial risks. Additionally, companies can use high-level digital technologies to better plan their short-term and long-term financial structures, reduce unnecessary financial costs, optimize the use of funds, and thus mitigate internal financial risks. With enhanced internal and external risk management, a more robust investment environment is created, reducing the instability and uncertainty of investments and ultimately effectively improving investment efficiency from the "risk" side.

In summary, this article proposes the following hypothesis:

H1*: Digital technology innovation contributes to the enhancement of corporate investment efficiency.*

3. Research Design

3.1 Empirical Model

To examine the impact of digital technology innovation (*DTI*) on corporate investment efficiency (*Inv_eff*), this study constructs the following model:

$$\begin{aligned} Inv\_eff_{i,t} = {} & \alpha_0 + \alpha_1 DTI_{i,t-1} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 Roa_{i,t} + \alpha_5 CH_{i,t} + \\ & \alpha_6 Age_{i,t} + \alpha_7 IS_{i,t} + \alpha_8 DC_{i,t} + \alpha_9 MF_{i,t} + \alpha_{10} ID_{i,t} + \alpha_{11} BS_{i,t} + \\ & \omega_t + \rho_j + \pi_c + \xi_{tc} + \vartheta_{tj} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The term $DTI_{i,t-1}$ denotes the level of digital technology innovation for firm i in the year t-1; $Inv\_eff_{i,t}$ is the dependent variable, representing the investment efficiency of firm i in year t. To mitigate the effects of omitted variable bias, the model incorporates control variables including firm size (*Size*), leverage ratio (*Lev*), return on assets (*Roa*), cash holdings (*CH*), firm age since listing (*Age*), institutional shareholding ratio (*IS*), duality of CEO and chairperson roles (*DC*), management expense ratio (*MF*), proportion of independent directors (*ID*), and board size (*BS*). Additionally, to control for unobservable time-varying factors at the industry and city levels that may cause endogeneity, the study includes year-fixed effects (ω_t), industry-fixed effects (ρ_j), city-fixed effects (π_c), "Industry × Year" interaction fixed effects (ζ_{tj}), and "City × Year" interaction fixed effects (ϑ_{tc}). The terms α and ε represent the constant term and the error term, respectively. β_1 is the regression coefficient for digital technology innovation (*DTI*); if β_1 is negative and significant, it suggests that digital technology innovation significantly enhances corporate investment efficiency.

3.2 Variable Definition

3.2.1 Dependent Variable: Investment Efficiency (*Inv_eff*)

Drawing from Richardson (2006), the variable for corporate investment efficiency ($Inv\_eff_{i,t}$) is gauged by the absolute value of the residuals from year-specific OLS regressions of the model below, where a larger absolute value signifies a higher degree of inefficient investment and, consequently, lower investment efficiency. The detailed model is as follows:

$$Inv_{i,t} = \beta_0 + \beta_1 Growth_{i,t-1} + \beta_2 Lev_{i,t-1} + \beta_3 Cash_{i,t-1} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Ret_{i,t-1} + \beta_7 Inv_{i,t-1} + \omega_t + \rho_j + \varepsilon_{i,t} \quad (2)$$

$Inv_{i,t}$ represents the actual new investment expenditures of firm i in year t, equal to the cash paid for constructing fixed assets, intangible assets, and other long-term assets, plus cash outlays for the acquisition and disposal of subsidiaries and other business operations, divided by the average total assets; $Growth_{i,t-1}$ indicates the growth opportunities of firm i in year t-1, measured by Tobin's Q; $Cash_{i,t-1}$ captures the cash flow position of firm in year t-1, computed as the net cash flows from operating activities relative to the total assets; $Ret_{i,t-1}$ reflects the stock return rate of firm i in year t-1, denoted by the annualized return on the stock, inclusive of reinvested cash dividends; $Inv_{i,t-1}$ is the new investment expenditures of firm i in year t-1; $\varepsilon_{i,t}$ represents the residual from the model estimation. The definitions for $Lev_{i,t-1}$, $Age_{i,t-1}$, and $Size_{i,t-1}$ correspond with those in model (1). In addition, this model adjusts for time effects (ω_t) and industry effects (ρ_j).

3.2.2 Independent Variable: Digital Technology Innovation (*DTI*)

Drawing on the studies by Huang et al. (2023), Li et al. (2020), Lai et al. (2023), Wang et al. (2023), and others, this paper measures the level of digital technology innovation of sample firms through the quantity of patent applications in the digital economy domain. This data is compiled by aligning the "Statistical Classification of Digital Economy and Its Core Industries (2021)" and the "Correlation Table between International Patent Classification and National Economic Industry Classification (2018)" released by China's National Bureau of Statistics, which identifies the technical fields of digital technology innovation and their corresponding IPC codes. Considering that the number of patent applications typically follows a right-skewed distribution, this study takes the natural logarithm of the variable after incrementing by one to mitigate heteroscedasticity issues. Furthermore, given the lag in the impact of digital technology patents on corporate investment decisions, the variable of digital technology innovation lagged by one period in the analysis. In the robustness section, the paper cross-validates with digital economy invention patents and digital economy utility model patents separately to enhance the credibility of the research.

3.2.3 Control Variables

In reference to prior research (Liu et al., 2023), this study incorporates a set of control variables into Model (1). Specifically, these include: company size (*Size*), measured by the natural logarithm of total corporate assets; leverage ratio (*Lev*), defined as the ratio of total liabilities to total assets; return on assets (*Roa*), expressed as the proportion of net profit to total assets; the level of cash holdings (*CH*), defined as the end-of-period cash and cash equivalents balance as a percentage of total assets; the age of the firm since listing (*Age*), measured by the natural logarithm of the number of years the company has been listed; the percentage of shares held by institutional investors (*IS*), defined as the proportion of shares held by institutional investors to the total number of shares outstanding; dual leadership (*DC*), a dummy variable that takes a value of 1 when the chairman and general manager are the same person and 0 otherwise; management expense ratio (*MF*), which is the ratio of management expenses to operating income; the proportion of independent directors (*ID*), the ratio of the number of independent directors on the board to the total number of directors; and board size (*BS*), measured by the natural logarithm of the number of board members.

3.3 Data Sources

The data for this study is derived from Chinese A-share listed companies from 2005 to 2021, and the sample was filtered according to the following criteria: First, companies that were designated as ST, *ST, PT, or delisted during the sample period were excluded. Second, companies in the financial and real estate sectors were eliminated. As a result, this study obtained 30,352 sample observations. To avoid the influence of outliers, the continuous variables were winsorized at the 1% and 99% levels. Moreover, the number of patent applications in the digital economy field was sourced from the CNRDS database, while other company-level data were drawn from the CSMAR database. The descriptive statistical results of the main variables are presented in Table 1.

Table 1 Variable descriptive statistics

Variable	*Mean*	*p50*	*SD*	*Min*	*Max*	*N*
Inv_eff	0.041	0.026	0.050	0.001	0.301	30352
DTI	0.607	0.000	1.120	0.000	4.852	30352
Size	22.252	22.072	1.287	19.878	26.245	30352
Lev	0.449	0.447	0.200	0.063	0.890	30352
Roa	0.035	0.034	0.061	-0.251	0.195	30352
CH	0.150	0.121	0.112	0.010	0.558	30352
Age	2.165	2.303	0.736	0.693	3.296	30352
IS	0.455	0.478	0.237	0.004	0.907	30352

DC	0.239	0.000	0.426	0.000	1.000	30352
MF	0.086	0.069	0.069	0.008	0.428	30352
ID	0.373	0.333	0.053	0.300	0.571	30352
BS	2.143	2.197	0.202	1.609	2.708	30352

The correlation coefficients of the main variables are shown in Table 2. Table 2 conveys at least two types of information: On the one hand, the correlation coefficient between digital technology innovation (*DTI*) and corporate investment efficiency (*Inv_eff*) is -0.029, which preliminarily indicates a positive relationship between the two, suggesting that digital technology innovation contributes to the enhancement of corporate investment efficiency. On the other hand, with the absolute values of the correlation coefficients ranging between 0 and 0.504, it is evident that there are no serious multicollinearity issues among the variables.

Table 2 Correlation coefficient matrix

Variable	*Inv_eff*	*DTI*	*Size*	*Lev*	*Roa*	*CH*	*Age*	*IS*	*DC*	*MF*	*ID*	*BS*
Inv_eff	1											
DTI	-0.029	1										
Size	-0.108	0.104										
Lev	-0.062	-0.046	0.447	1								
Roa	0.055	0.037	0.042	-0.344	1							
CH	0.009	0.067	-0.188	-0.365	0.254	1						
Age	-0.125	-0.116	0.379	0.297	-0.132	-0.148	1					
IS	-0.022	-0.080	0.414	0.214	0.131	0.007	0.243	1				
DC	0.050	0.070	-0.127	-0.123	0.012	0.041	-0.208	-0.213	1			
MF	0.116	0.022	-0.341	-0.271	-0.178	0.131	-0.072	-0.178	0.064	1		
ID	0.017	0.041	0.022	-0.021	-0.026	0.014	-0.029	-0.083	0.121	0.037	1	
BS	-0.044	-0.029	0.236	0.155	0.038	-0.038	0.123	0.254	-0.189	-0.100	-0.504	1

4. Empirical Results and Analysis

4.1 Baseline Regression Results

The baseline regression results of corporate digital technology innovation on investment efficiency are presented in Table 3. Columns (1) to (3) control for year-fixed effects (*Year*), industry-fixed effects (*Industry*), city-fixed effects (*City*), "Industry × Year" interaction fixed effects, and "City × Year" interaction fixed effects, respectively, without the inclusion of control variables. The results indicate that the regression coefficient of digital technology innovation (*DTI*) on corporate investment efficiency (*Inv_eff*) is significantly negative at the 1% level. This outcome suggests that corporate digital technology innovation can significantly enhance investment efficiency. To mitigate the omitted variable bias, columns (4) to (6) incorporate a series of control variables. The findings reveal that the regression coefficient of *DTI* remains negative and significant at

the 1% level, further corroborating that digital technology innovation can effectively improve corporate investment efficiency. This aligns with the hypothesis ***H1***.

The reasons could be, on the one hand, that digital technology innovation strengthens the firms' capacity to process, analyze, and utilize external information. This enables companies to identify investment opportunities, assess risks, and respond based on real-time data, thereby reducing the wastage of resources and increasing the return on investments more accurately (Sotnyk et al., 2020). On the other hand, digital technology innovation can enhance internal controls and management, effectively reducing agency costs and moral hazards. A high level of digital technology application can provide real-time, high-quality data streams on enterprise operations, thus enhancing transparency in internal management to diminish information asymmetry between shareholders and managers. This can lead to lower corporate agency costs, decreasing the likelihood of managers engaging in self-interested activities based on informational advantages and thus reducing the risk of internal errors and fraudulent activities within the firm. This, in turn, promotes the efficient allocation of resources and ultimately improves corporate investment efficiency.

Table 3 The impact of digital technology innovation on corporate investment efficiency: Baseline regression results

Variable	(1) *Inv_eff*	(2) *Inv_eff*	(3) *Inv_eff*	(4) *Inv_eff*	(5) *Inv_eff*	(6) *Inv_eff*
DTI	-0.0016***	-0.0016***	-0.0018***	-0.0016***	-0.0016***	-0.0016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size				-0.0024***	-0.0025***	-0.0027***
				(0.001)	(0.001)	(0.001)
Lev				0.0162***	0.0175***	0.0168***
				(0.003)	(0.003)	(0.003)
Roa				0.0671***	0.0708***	0.0596***
				(0.007)	(0.007)	(0.008)
CH				-0.0116***	-0.0091**	-0.0093**
				(0.003)	(0.004)	(0.004)
Age				-0.0074***	-0.0072***	-0.0068***
				(0.001)	(0.001)	(0.001)
IS				0.0053***	0.0066***	0.0075***
				(0.002)	(0.002)	(0.002)
DC				0.0030***	0.0031***	0.0034***
				(0.001)	(0.001)	(0.001)
MF				0.0708***	0.0759***	0.0694***
				(0.007)	(0.008)	(0.009)
ID				0.0063	0.0076	0.0064
				(0.008)	(0.008)	(0.009)

BS				-0.0072***	-0.0064***	-0.0064**
				(0.002)	(0.002)	(0.003)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Year × Industry	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Year × City	*No*	*No*	*Yes*	*No*	*No*	*Yes*
_cons	0.0424***	0.0424***	0.0425***	0.1083***	0.1047***	0.1103***
	(0.000)	(0.000)	(0.000)	(0.011)	(0.011)	(0.012)
N	30352	30352	30352	30352	30352	30352
R^2	0.041	0.068	0.206	0.070	0.094	0.228

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

4.2 Robustness and Endogeneity Tests

4.2.1 Replacement Variables

To further bolster the credibility of the conclusions in this article, the study substitutes related variables. On the one hand, following the approach of Guo et al. (2023), this study measures the level of digital technology innovation in firms by utilizing both invention patents and utility model patents to examine whether the impact of different types of patent applications on investment efficiency is consistent. Invention patents and utility model patents represent two distinct forms of patent protection, varying in application requirements, examination procedures, authorization durations, and fee schedules. Different types of patent applications may reflect varying motivations, capabilities, and strategies of firms in digital technology innovation. As can be seen in columns (1) and (2) of Table 4, which replace the core explanatory variables, invention patents, and utility model patents significantly enhance the investment efficiency of firms (the coefficients are negative and significant at the 1% level), with little deviation from the baseline regression results. This indicates that the main findings of the study are robust and not invalidated by differences in patent types.

On the other hand, the study further explores the dependent variable by examining underinvestment and overinvestment as alternatives to the investment efficiency indicator. In Table 4, columns (3) and (4), these two conditions replace the original measure of investment efficiency. Underinvestment can cause firms to miss out on valuable investment opportunities, potentially hindering long-term growth, while overinvestment may lead to resource misallocation, undermining profitability. Both are indicative of a firm's investment inefficiency. Drawing from Richardson (2006), the type of inefficient investment is identified by the regression residuals in model (2): positive residuals suggest overinvestment, whereas negative ones point to underinvestment. The magnitude of

investment inefficiency, whether under or overinvestment, is quantified by the absolute value of these residuals, with smaller values signifying a reduced level of inefficiency.

Table 4 Robustness and endogeneity tests: Replacement variables

Variable	(1) *Inv_eff*	(2) *Inv_eff*	(3) *Under-inv*	(4) *Over-inv*
DTI-I	-0.0016***			
	(0.000)			
DTI-U		-0.0020***		
		(0.000)		
DTI			-0.0008**	-0.0028***
			(0.000)	(0.001)
CVs	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*	*Yes*
_cons	0.1109***	0.1118***	0.1364***	0.0875***
	(0.012)	(0.012)	(0.012)	(0.022)
N	30352	30352	18549	11803
R^2	0.228	0.228	0.295	0.345

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

The findings presented in Table 4 suggest that digital technology innovation decreases the likelihood of both underinvestment and overinvestment—the associated impact coefficients are negative and statistically significant. This supports the study's primary findings, reinforcing the notion that digital innovation plays a crucial role in fostering investment efficiency.

4.2.2 Considering Time Lags

When constructing the baseline model, this study lagged the digital technology innovation (*DTI*) of enterprises by one period, which is primarily based on two considerations. Firstly, digital technology innovation in this study is measured by the number of patent applications filed by enterprises, and it takes a considerable amount of time for these applications to be reviewed and for the patents to be granted and then applied in production. In addition, from the time a patent is granted until it is directly applied in production also requires a period. Enterprises need to consider factors such as the technical maturity of the patent, market demand, and cost-benefit analysis, and they must conduct further research and testing based on actual market conditions. Therefore, digital technology innovation requires a certain period to be implemented, applied, and optimized on the ground before it can fully enhance investment efficiency.

Table 5 Robustness and endogeneity tests: Considering time lags

Variable	(1) *Inv_eff*	(2) *Inv_eff*	(3) *Inv_eff*
lag2. DTI	-0.0017***		
	(0.000)		
lag3. DTI		-0.0017***	
		(0.000)	
lag4. DTI			-0.0014***
			(0.000)
CVs	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*
_cons	0.1084***	0.1124***	0.1114***
	(0.012)	(0.013)	(0.013)
N	29018	26065	22930
R^2	0.227	0.234	0.237

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

To ensure that the selection of the time lag in this study is not merely based on subjective bias and refers to the research experience of predecessors (Lai et al., 2023), this study further extends the time window for verification. Specifically, in addition to considering digital technology innovation with a lag of one period, the study also considers different time windows, aiming to explore the long-term impact of digital technology innovation (*DTI*) on investment efficiency (*Inv_eff*). The results are displayed in Table 5, where columns (1) to (3) represent the lagged variables of digital technology innovation for two, three, and four periods, respectively. It is apparent that, under a longer time window, enterprise digital technology innovation still promotes the improvement of investment efficiency (the impact coefficients are all negative and significant at the 1% level). This further confirms the robustness of the results of this study and is conducive to more accurately capturing the intrinsic relationship between digital technology innovation and investment efficiency.

4.2.3 Reverse Causality

The possibility exists that investment efficiency might inversely influence digital technology innovation. For instance, when a firm achieves or approaches optimal investment, the resulting financial benefits—such as increased funds, decreased debt, and higher profits—could boost the firm's ability and willingness to innovate digitally. To circumvent the issue of reverse causality, this study utilizes the difference in digital

technology innovation as the dependent variable and investment efficiency as the explanatory variable. Robustness checks are performed in column (1) of Table 6. It can be observed that the regression coefficient of investment efficiency (*Inv_eff*) on the difference in digital technology innovation (*ΔDTI*) is not significant. This indicates that the primary conclusions of this study are not compromised by reverse causality.

Table 6 Robustness and endogeneity tests: Reverse causality, excluding special samples and instrumental variable

Variable	Reverse causality (1)	Excluding special samples (2)	(3)	IV first stage (4)	IV second stage (5)
	ΔDTI	*Inv_eff*	*Inv_eff*	*DTI*	*Inv_eff*
Inv_eff	0.0234				
	(0.078)				
DTI		-0.0023***	-0.0013***		-0.0037***
		(0.000)	(0.000)		(0.001)
IV				0.8347***	
				(0.042)	
CVs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Kleibergen-Paap rk LM				285.189***	
Kleibergen-Paap rk Wald F				403.346	
_cons	-0.0530	0.0963***	0.1323***		
	(0.070)	(0.016)	(0.014)		
N	30352	22185	22158	28452	28452
R^2	0.140	0.266	0.227	-	0.027

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

4.2.4 Excluding Special Samples

To verify whether the main conclusions of this study are affected by specific samples, the study has excluded data from certain enterprises. On the one hand, according to Zhai et al. (2022), enterprises located in four major Chinese cities—Beijing, Shanghai, Shenzhen, and Guangzhou—were excluded. As economic hubs and pioneers of development in China, these cities have distinct economic development levels, policy environments, and market competition characteristics that might impact the relationship between digital technology innovation and investment efficiency, thus obscuring the true situation in other

regions. To estimate the relationship more reliably between digital technology innovation and investment efficiency, the study decided to exclude enterprise samples from these four cities. The results, displayed in column (2) of Table 6, show that digital technology innovation can still enhance enterprise investment efficiency after excluding regional samples (the effect coefficient is negative and significant at the 1% level). This is consistent with the results of the study's baseline regression, indicating that the conclusions are robust.

On the other hand, the study also excluded samples from the financial crisis period (2007 and 2008) and the COVID-19 pandemic period (2020 and 2021). These periods represent significant global financial market turbulence and public health crises, respectively, and their impacts on enterprises are global and extensive, potentially affecting this study's research differently from other periods. To ensure that the conclusions of the study are not affected by these extreme conditions, enterprise samples from these periods were removed. The results, shown in column (3) of Table 6, indicate that digital technology innovation continues to promote enterprise investment efficiency after excluding time samples (the effect coefficient is negative and significant at the 1% level), suggesting that the study's conclusions are robust.

4.2.5 Instrumental Variable (IV)

To further address the potential endogeneity issues in the primary conclusions of this article, we construct relevant instrumental variable for testing. Following Xiao et al. (2023), the instrumental variable is composed of the interaction term between "Broadband China Pilot Cities" (*BCPC*) and the "Average Digital Technology Innovation in the Firm's Industry in the Current Year (excluding the firm itself)" (*DTI_IM*). The selection rationale is as follows: On the one hand, in terms of the relevance assumption, BCPCs were designated by Chinese government agencies from 2013 to 2015 as pilot cities for broadband network construction and application promotion. These cities benefited from government financial support, policy incentives, and technical guidance, which provided conditions and motivation for local firms' digital technology development, hence highly correlated with the level of digital technology innovation. The *DTI_IM* reflects the average digital technology trend within the industry. For a given firm, the innovative activities of other firms in the industry can act as a proxy for market trends or industry benchmarks, exerting a direct or indirect influence on the firm, thereby also correlating with a particular firm's level of digital technology innovation. Thus, the interaction term of these two variables can impact corporate digital technology innovation from both policy and industry relevance perspectives, aligning with the relevance assumption for an instrumental variable. On the other hand, regarding the exogeneity assumption, *BCPC* as a macro policy variable is

exogenous relative to firm investment decisions. The *DTI_IM* reflects the aggregate level of digital technology development within an industry. Given that this article has excluded the influence of the firm's own digital technology level, there is no direct, discernible link between the *DTI_IM* and a particular firm's investment efficiency. Consequently, this satisfies the criterion for the assumption of exogeneity.

Using IV-GMM model, the results are shown in columns (4) and (5) of Table 6. It can be observed that, after the inclusion of the instrumental variable, the relationship between firm digital technology innovation and investment efficiency remains consistent with the baseline regression results (the effect coefficient remains negative and significant at the 1% level). Moreover, the under-identification test (Kleibergen-Paap rk LM) rejects the null hypothesis that "the instrumental variable is not related to the endogenous explanatory variable," and the weak identification test (Kleibergen-Paap rk Wald F) rejects the null hypothesis of "weak instrumental variable." This indicates that the instrumental variable tests conducted in this article are reasonable and valid, further enhancing the reliability of the baseline regression results.

4.2.6 Placebo Test

To rule out the interference of unobservable random factors on the endogeneity of the baseline model, this study conducted a placebo test following the approach of Lai et al. (2023). The primary procedure of the test is as follows: First, the sequence of the digital technology innovation variable is randomized to create a new random variable (*Random-DTI*). Second, this *Random-DTI* variable is inserted into the baseline regression model for retesting; if the coefficient is significant, it would suggest that the original effect of the digital technology innovation variable on investment efficiency is spurious, and the baseline model is influenced by random factors. Conversely, if the coefficient is not significant, this supports the validity of the core conclusions of this article. Third, the above process is repeated 1,000 times to obtain the distribution of the *Random-DTI* coefficients and *P-values* after 1,000 regressions, which is represented in a kernel density plot.

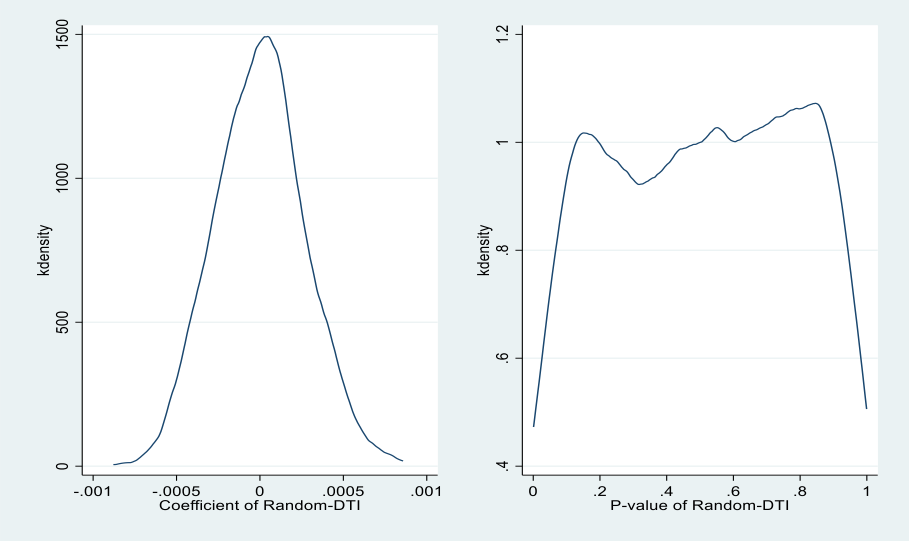

Figure 1 Placebo Test

Figure 1 shows the distribution of the regression coefficients of *Random-DTI* on firm investment efficiency and their *P-values*. The coefficients of *Random-DTI* are approximately normally distributed, mainly concentrated around zero, indicating that most coefficients are not statistically significant. Furthermore, the distribution of the *P-values* of the coefficients is also presented, with the majority exceeding 10%, signifying that the impact coefficients do not pass the significance test, which is consistent with the distribution of the *Random-DTI* regression coefficients. Therefore, the results of the placebo test indicate that the impact of corporate digital technology innovation on investment efficiency is not driven by random factors, thereby ensuring the robustness of the baseline regression in this article.

4.3 Potential Economic Mechanisms

Building on the content above, this paper has substantiated the significant impact of digital technology innovation on enhancing corporate investment efficiency. Nevertheless, this segment of the research did not fully delve into the potential economic pathways' mechanisms. Considering this, the present study elaborates further, within the theoretical hypothesis framework, on how digital technology innovation could bolster investment efficiency through four primary channels. Firstly, on the "information side," *DTI* accelerates corporate digital transformation (*Dig_ tra*) and concurrently elevates the quality of information disclosure (*KV*). Secondly, on the "governance side," *DTI* aids in alleviating agency conflicts (*AC*) and curtails managerial myopia (*MM*). Thirdly, on the "financing side," *DTI* diminishes firms' reliance on short-term borrowing (*STDD*), thereby circumventing the predicament of over-indebtedness (*OD*) and concurrently enhancing the liquidity of company stocks (*Illiquidity*). Lastly, on the "risk side," *DTI* contributes to the reduction of market-level stock price crash risk (*NCSKEW*) as well as corporate

financial risk (*DD_KMV*).

Columns (1) and (2) of Table 7 illustrate the "information side" pathway through which digital technology innovation enhances investment efficiency. The results indicate that corporate digital technology innovation (*DTI*) can expedite the digital transformation (*Dig_ tra*) of firms and improve the quality of information disclosure (*KV*)[1], aligning with the hypotheses previously set forth. By optimizing information management systems and employing advanced data analytics tools, firms are better poised to comprehend and utilize digital technological tools such as big data, thereby achieving in-depth data mining and intelligent analysis. This process propels the comprehensive development of digitization, informatization, and intelligence across the company's production, operational, and governance dimensions. It not only heightens the efficiency and accuracy of internal decision-making but also strengthens relationships with external stakeholders through higher-quality information disclosure. Consequently, this enhances overall investment efficiency, realizing "information" empowerment.

Columns (3) and (4) of Table 7 reveal the "governance side" processes through which digital technology innovation boosts investment efficiency. It is evident that digital technology innovation (*DTI*) can mitigate agency conflicts (*AC*) and alleviate managerial myopia (*MM*)[2], which aligns with the paper's initial hypotheses (both are negative indicators with negative impact coefficients and are significant at the 1% level). Digital technology innovation enables businesses to establish more transparent and efficient management systems, which clarifies and rationalizes the internal decision-making process, thus reducing agency conflicts arising from information asymmetry between shareholders and management. Moreover, through the utilization of big data and artificial intelligence, management can monitor market dynamics in real-time, better understand and anticipate future business trends, and thus devise more visionary investment

[1] To construct a measure for corporate digital transformation (*Dig_ tra*), this study follows the approach of Tian et al. (2022), building a keyword lexicon that encapsulates the essence of digital foundations and applications from the perspectives of big data, artificial intelligence, cloud computing, and blockchain technology. Leveraging this lexicon, the study employs Python tools to perform text mining on the annual reports of listed companies. The process involves matching and extracting occurrences of "digitalization"-related keywords from the reports. The frequency of these keywords is then tallied and incremented by one before being logarithmically transformed using the natural logarithm. The higher the resultant value, the more advanced the level of digital transformation is presumed to be.
As for the construction of the information disclosure quality (*KV*), the methodology of Kim and Verrecchia (2001) is referenced. In this approach, the coefficient of the impact of trading volume on returns—termed the KV index—is used to reflect the level of a company's information disclosure quality. A higher KV index suggests a lower quality of company information disclosure, as it implies that the information disclosed is not sufficiently reducing asymmetry in the market, thereby requiring a larger volume of trades to correct or respond to new information.

[2] The measurement of agency conflicts (*AC*) is based on the approach of Luo et al. (2018) and Jiang et al. (2010), which employ the calculation of the funds occupation rate. The funds occupation rate is defined as the proportion of other receivables to total assets, where a larger value indicates more severe agency conflicts.
Regarding the variable for managerial myopia (*MM*), the study follows the methodology of Hu et al. (2021), which utilizes machine learning and text analysis techniques to generate a managerial myopia dictionary based on the Management Discussion and Analysis (MD&A) sections of listed companies' annual reports. Subsequently, a calculation is performed using the dictionary method to determine the total frequency of "short-term horizon" vocabulary (such as "within days", "several months", "within a year", etc.) as a proportion of the total word frequency in the MD&A. This proportion is then multiplied by 100 to derive the managerial myopia index. A higher index value indicates greater managerial myopia.

strategies. This governance empowerment serves as a catalyst in enhancing the firm's investment efficiency.

Table 7 Potential economic mechanisms: "Information side" and "Governance side"

	"Information side"		"Governance side"	
Variable	(1)	(2)	(3)	(4)
	Dig_ tra	*KV*	*AC*	*MM*
DTI	0.2272***	-0.0029**	-0.0008***	-0.3466***
	(0.016)	(0.001)	(0.000)	(0.130)
CVs	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-1.2177***	0.7567***	0.0272***	-42.9362***
	(0.386)	(0.031)	(0.010)	(3.874)
N	29430	30074	30338	29327
R^2	0.525	0.410	0.287	0.472

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

Columns (1) to (3) of Table 8 illustrate the "financing side" pathways through which digital technology innovation (*DTI*) enhances investment efficiency. The findings indicate that *DTI* diminishes firms' reliance on short-term borrowing (*STDD*), thus averting the pitfalls of over-indebtedness (*OD*)[3]; on the equity financing side, *DTI* creates favorable conditions for the improvement of stock liquidity (*Illiquidity*)[4], which corroborates the hypotheses posited earlier. The likely explanation is that digital technology innovation can refine a firm's information structure and augment transparency, thereby opening up broader channels of financing and more efficient resource allocation, which in turn significantly boosts investment efficiency and market performance. Moreover, by enhancing decision quality and execution efficiency through smart technologies and data analytics, firms can further reduce operational and capital costs, creating a more robust and sustainable development environment. This not only helps firms avoid excessive

[3] The measurement of the short-term debt dependence (*STDD*) indicator is defined by the formula: (Short-term borrowings + Current portion of long-term debt) / (Total assets). A higher value of this index indicates a greater reliance by the firm on short-term borrowing as a financing mechanism, and a correspondingly shorter average maturity of debt financing relative to the firm's total assets. As for the over-indebtedness (OD) metric, the methodology proposed by Harford et al. (2009) and Denis and McKeon (2012) is employed to gauge the degree of a firm's financial overextension. This is done by comparing the firm's actual debt ratio against its target debt ratio, with a greater disparity suggesting a more pronounced level of over-indebtedness.

[4] For constructing the stock illiquidity (*Illiquidity*) measure, the research approach of Amihud (2002) is adopted, where stock liquidity is measured by the average of the daily absolute stock return to daily trading volume ratio. This indicator denotes the sensitivity of the stock price to trading volumes, that is, the degree of price change elicited by each unit of trading volume. The higher this indicator, the worse the stock's liquidity.

dependence on short-term borrowing but also bolsters the appeal of their stock, thereby enhancing liquidity. These advancements provide "financing" empowerment, facilitating the improvement of corporate investment efficiency.

Columns (4) and (5) of Table 8 illustrate the "risk side" pathways through which digital technology innovation enhances investment efficiency. The results in the table indicate that digital technology innovation (*DTI*) can reduce both market-level stock price crash risk (*NCSKEW*) and corporate financial risk (*DD_KMV*)[5], aligning with the hypotheses inferred in this paper. The likely rationale is that the efficient data processing and analytical capabilities on the "information side" enable firms to better monitor their financial health and market conditions, leading to more targeted investment decisions and risk management. This enhances decision-making efficiency and precision, ultimately diminishing the market-level stock price crash risk and corporate financial risk. Furthermore, increased transparency can help firms gain trust from investors and stakeholders on the "financing side," facilitating broader financing channels and methods and lowering financing costs and difficulties, strengthening the firm's risk resistance and investment vitality. This provides a "risk" empowerment for improving the company's investment efficiency.

Table 8 Potential economic mechanisms: "Financing side" and "Risk side"

	"Financing side"			"Risk side"	
Variable	(1)	(2)	(3)	(4)	(5)
	STDD	*OD*	*Illiquidity*	*NCSKEW*	*DD_KMV*
DTI	-0.0079***	-0.0029***	-0.0011***	-0.0089*	0.0446**
	(0.001)	(0.001)	(0.000)	(0.005)	(0.018)
CVs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
_cons	0.1847***	0.8276***	0.5191***	0.1077	11.1948***
	(0.035)	(0.015)	(0.013)	(0.132)	(0.747)
N	28031	29845	30352	29929	30139
R^2	0.556	0.882	0.609	0.204	0.551

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

[5] Regarding the stock price crash risk indicator (*NCSKEW*), following the methodology of Chen et al. (2001), we calculate the annual *NCSKEW* for each company based on the market capitalization-weighted weekly returns. This metric captures the probability and magnitude of stock price declines. A larger *NCSKEW* value indicates a higher risk of a stock price crash. In terms of measuring financial risk (*DD_KMV*), we adopt Merton's (1974) KMV model, which estimates a firm's asset value, asset volatility, and default point, thereby calculating the firm's distance to default and the probability of default. A smaller *DD_KMV* value signals a higher probability of default and, thus, greater financial risk.

4.4 Heterogeneity Analysis

In the preceding discussion, this paper has verified from a holistic sample perspective that digital technology innovation exerts a significant positive impact on enhancing corporate investment efficiency. To delve deeper into the mechanisms of digital technology innovation and its enabling effects across diverse firms, this study, drawing on the research of Wan et al. (2023), introduces a heterogeneity analysis from the perspectives of property rights attributes, industry background, and market development levels. This aims to uncover the preferential impact of digital technology innovation on corporate investment efficiency.

4.4.1 Enterprise Heterogeneity: State-owned Enterprises (SOE) vs. Non-state-owned Enterprises (Non-SOE)

At the enterprise level, this paper examines the heterogeneous effects of ownership structure on the relationship between digital technology innovation (*DTI*) and investment efficiency (*Inv_eff*). The results presented in Table 9 indicate that digital technology innovation (*DTI*) does not significantly enhance the investment efficiency of state-owned enterprises (SOE), as shown in columns (1) and (2). Conversely, non-state-owned enterprises (Non-SOE) are more likely to benefit from the spillover effects of high-level digital technology (with a negative coefficient that is significant at the 1% level).

The possible explanations include, on the one hand, that SOE generally possess more abundant resources and government support, granting them a superior market position and resource allocation capabilities. This results in diminishing marginal benefits from improvements in digital technology, making significant gains in investment efficiency challenging to achieve (Dou and Gao, 2022). Moreover, SOE are often more affected by macro policies and political factors, which could restrict their autonomy in innovation and efficiency improvements. On the other hand, due to their lack of resources and policy support, Non-SOE often have a more urgent need for innovation, which is advantageous in fierce market competition. Furthermore, Non-SOE tend to have more flexible organizational structures, allowing them to quickly respond to market changes and optimize products and services. Therefore, they can better utilize digital technology for timely adjustments in investment decisions.

4.4.2 Industry Heterogeneity: High-tech Industries (High-Tec) vs. Non-high-tech Industries (Non-HT)

At the industry level, our study explores whether a background in the high-tech sector among the sampled firms affects the relationship between digital technology innovation and investment efficiency. As evidenced in columns (3) and (4) of Table 9, firms within the high-tech sector can leverage advancements in digital technology innovation to drive improvements in investment efficiency (as indicated by a negative coefficient significant at

the 1% level). Conversely, firms in non-high-tech industries find it challenging to enhance investment efficiency through the same means.

The likely reason is that companies within the high-tech industries tend to be more forward-looking and open, capable of rapidly adapting to and adopting new technological innovations (Wan et al., 2023). Digital technologies can fully unleash their potential in such environments, not only enabling firms to allocate their resources more effectively but also allowing them to enhance operational efficiency and market responsiveness by leveraging modern technologies like big data and artificial intelligence, thereby increasing investment efficiency. In contrast, non-high-tech industries tend to rely on traditional business models and technologies, which limits the application of emerging digital technologies within these firms. This limitation is not merely a matter of technology acceptance; it is also because firms in non-high-tech industries may lack the necessary technical infrastructure and expertise to fully capitalize on digital technology, preventing them from reaping the benefits associated with advancements in digital technology levels.

4.4.3 Market Heterogeneity: Developed Financial Markets (Dev-Fin) vs. Underdeveloped Financial Markets (Under-DF)

From the market perspective, this study posits that the degree of market development in a firm's locale is an important factor that induces heterogeneity in the relationship between digital technology innovation and investment efficiency. The results, as shown in columns (5) and (6) of Table 9, indicate that firms operating in highly developed financial markets (Dev-Fin) are better positioned to reap the benefits of digital technology innovation during the investment process (as reflected by a negative coefficient that is significant at the 1% level). However, for firms in locales where financial markets are less developed (Under-DF), the impact of digital technology innovation on the investment process is less pronounced.

One possible explanation is that firms in developed markets typically have easier access to advanced technologies and financial resources, facilitating the effective application of digital technology to enhance investment efficiency and competitiveness (Hitt et al., 2000). Furthermore, developed financial markets often have a more mature and stable legal and regulatory environment, safeguarding firms' innovations and applications of digital technology and encouraging their proactive utilization in investment activities. This allows firms to optimize their business processes and investment decisions through advanced digital technologies. On the other hand, firms in underdeveloped markets may face a host of challenges. These markets often lack essential technological infrastructure, such as high-speed internet and data centers, severely constraining firms' abilities to adopt and implement advanced technological solutions, thereby diminishing the potential of

digital technology innovation in the realm of investment decision-making. Moreover, the underdevelopment of local financial markets not only exposes firms to funding shortages but may also impact their decision-making processes and willingness to invest due to insufficient intellectual property protection or unstable regulatory policies, reducing the driving effect of digital technology on firm investment.

Table 9 Heterogeneity test of digital technology innovation on corporate investment efficiency

Variable	Enterprise trait		Industry trait		Market trait	
	SOE	Non-SOE	High-Tec	Non-HT	Dev-Fin	Under-DF
	(1)	(2)	(3)	(4)	(5)	(6)
	Inv_eff	*Inv_eff*	*Inv_eff*	*Inv_eff*	*Inv_eff*	*Inv_eff*
DTI	-0.0008	-0.0020***	-0.0020***	-0.0004	-0.0021***	-0.0010
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
CVs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
_cons	0.1086***	0.0945***	0.0864***	0.1286***	0.1022***	0.1184***
	(0.018)	(0.022)	(0.019)	(0.017)	(0.016)	(0.019)
N	13297	16530	15105	15247	18751	11601
R^2	0.317	0.273	0.264	0.318	0.231	0.247

Note: ***, **, and * suggest statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent standard errors clustered at the firm level.

5. Conclusion and Policy Recommendations

This article examines the impact of corporate digital technology innovation on investment efficiency from the perspective of the digital economy's development. Through an analysis of data from Chinese A-share listed companies from 2005 to 2021, the study finds that: (1) Digital technology innovation significantly enhances corporate investment efficiency. After undergoing tests for endogeneity and robustness, such as instrumental variable tests, placebo tests, and reverse causality assessments, the findings consistently support this assertion. (2) By alleviating information asymmetry, digital technology innovation enhances corporate investment efficiency from the standpoints of information processing, financing, governance, and risk management. (3) The effect of digital technology innovation on investment efficiency is heterogeneous; non-state-owned enterprises, those in high-tech industries, and those in regions with more developed

financial markets exhibit a more pronounced spillover effect of digital technology innovation on investment efficiency.

Based on the conclusions of this paper, the following policy recommendations are proposed: First, the government should increase support for digital technology innovation. As the core engine of the digital economy and a decisive factor in enhancing corporate competitiveness, digital technology innovation should be met with increased fiscal input and substantial financial support. The establishment of specialized funds to bolster the R&D, application, and dissemination of digital technologies can ignite the spirit of exploration in basic, applied, and industrialized research, thereby enhancing the quality of digital technology innovation.

Second, the government should advance the construction of a digital governance system and strengthen the integration and sharing of information resources. Promoting the creation of industry-wide information-sharing platforms can be an effective approach, guiding companies to adopt cutting-edge information technologies to fill the gaps caused by information asymmetry, thereby reducing the costs and time associated with information collection and enhancing trust and collaboration among enterprises. Moreover, strengthening the exchange of information between government and businesses can facilitate timely adjustments to regulatory frameworks and guidance, allowing for efficient governance throughout the digital development and transformation of enterprises.

Finally, resources should be preferentially allocated to areas that can foster the efficient development of the digital economy. The government should provide technology transfer and training services to enterprises in their initial stages with limited resources, as well as offer tax relief and R&D subsidies to encourage more investment in digital technology innovation. This will not only accelerate the role of digital technology in boosting social investment growth but also help enhance the overall output level of the nation. Concurrently, the government should also promote deep collaboration between enterprises and digital technology research institutions, establish joint R&D platforms, and guide research institutions to align with the actual needs and challenges of the industry more closely. This approach ensures that the sophisticated research advantages are fully leveraged to yield results that are both valuable in application and significant in scientific research.

Authorship contribution statement

Xiaobing LAI: conceptualization, methodology, data curation, writing-review, and editing. Lei QUAN: conceptualization, writing-original draft, writing-review. Chong GUO: formal analysis, writing-original draft, and validation. Xing GAO: methodology and data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets used during the current study are available from the corresponding author on reasonable request.

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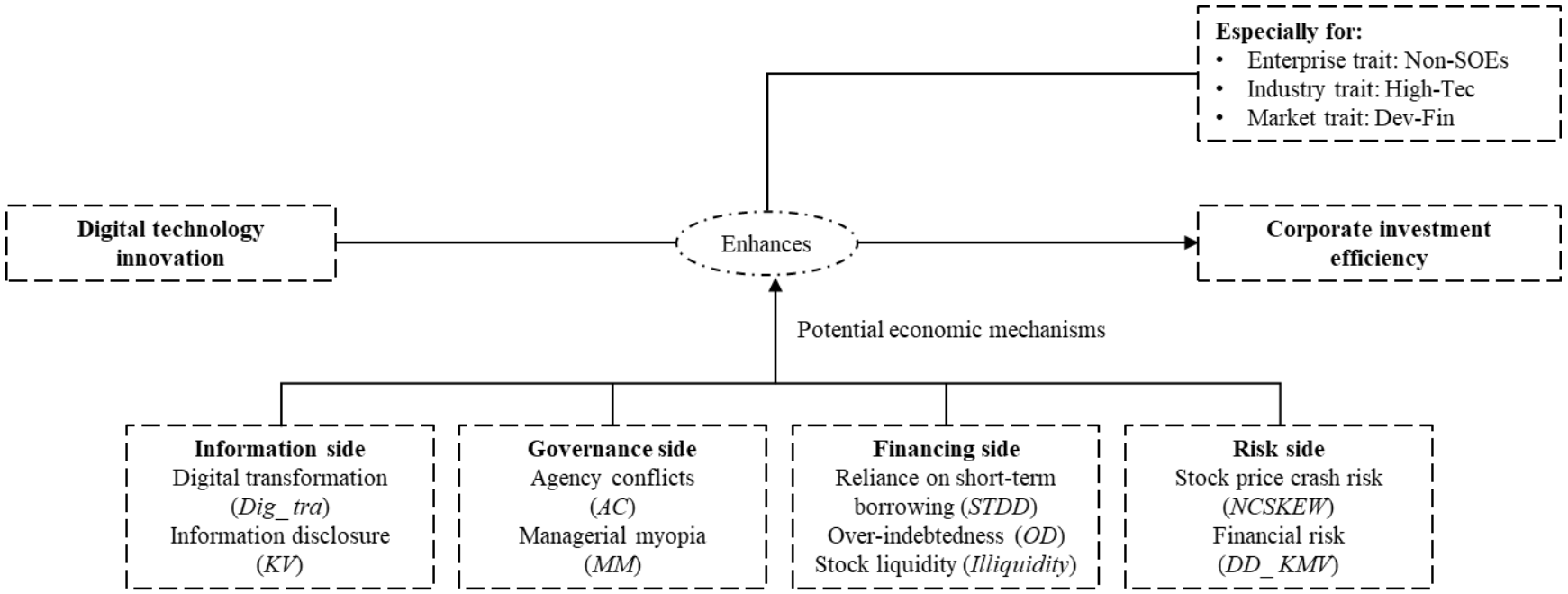
Graphical Abstract



Highlights

- Digital technology innovation significantly enhances corporate investment efficiency.
- Digital technology innovation boosts corporate investment efficiency through channels such as "information side", "governance side", "financing side", and "risk side".
- The positive impact of digital technology innovation on corporate investment efficiency is more pronounced in non-state-owned firms, sectors that prioritize innovation, and in well-developed financial markets.
- This article extends the research on the economic outcomes of digital technology innovation as well as the determinants of corporate investment efficiency, offering novel perspectives on the growth strategies of businesses in the thriving digital economy.