ORIGINAL PAPER

DOI: 10.26794/2308-944X-2026-14-1-37-55
UDC 338.1(045)
JEL G34, O31, O32, O33

The Shifting Influence of Digital Transformation on Breakthrough Innovation in China

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ABSTRACT

The study investigates the relationship between digital transformation (Dt) and breakthrough innovation (Bi) in Chinese A-share listed companies. Specifically, the **subject** of the study is the influence of Dt on Bi, focusing on comparing its effects during normal periods and the global health crisis, with an emphasis on the differing impacts across state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). The **purpose** of the research is to explore how digitalization can enhance innovation under both stable conditions and during external disruptions, while examining the variations in its effects on different types of firms. The **relevance** lies in the increasing role of Dt in driving innovation in today's rapidly evolving global landscape, especially in light of the challenges posed by the COVID-19 crisis. This study provides important insights into how firms can adapt their digital strategies to maintain or accelerate innovation during periods of disruption. The **scientific novelty** lies in the analysis of the heterogeneous impact of Dt on innovation across firm types and external contexts, particularly the comparison between normal and crisis periods. The authors used the **methods** of machine learning-based text-mining techniques to construct indicators for Dt and fixed-effects regression models to estimate its impact on Bi. As part of the study, the author used panel data from Chinese listed companies spanning from 2014 to 2024, applying these advanced methods to uncover the effects of Dt on Bi under different periods and firm conditions. Based on the **results**, it was found that Dt significantly boosts Bi under normal circumstances but that this positive relationship is disrupted during crisis periods, especially in SOEs. Non-SOEs showed no significant impact from Dt in either normal or crisis periods. The author **concluded** that while digital transformation is a key driver of innovation, its effectiveness is contingent upon firm type and the external context, with global disruptions potentially limiting its full potential, particularly for SOEs.

Keywords: digital transformation; breakthrough innovation; machine learning; global health crisis; state-owned enterprises; non-state-owned enterprises; China

For citation: **Pu T., Zulkafli A.H. The shifting influence of digital transformation on breakthrough innovation in China. *Review of Business and Economics Studies*. 2026;14(1):37-55. DOI: 10.26794/2308-944X-2026-14-1-37-55**

ОРИГИНАЛЬНАЯ СТАТЬЯ

Изменение влияния цифровой трансформации на прорывные инновации в Китае

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АННОТАЦИЯ

В данном исследовании изучается взаимосвязь между цифровой трансформацией (ЦТ) и прорывными инновациями (ПИ) в китайских компаниях, А-акции которых котируются на бирже. **Предметом** исследования является влияние ЦТ на ПИ. Проводится сравнение этого влияния в обычные периоды и в условиях глобального кризиса здравоохранения с учетом различного воздействия на государственные и негосударственные предприятия. **Цель исследования** — изучить, как цифровизация может способствовать инновациям в стабильных условиях и во время внешних потрясений, а также исследовать различия в ее влиянии на разные типы фирм. **Актуальность** исследования заключается в возрастающей

роли цифровой трансформации в стимулировании инноваций в современном быстро меняющемся глобальном ландшафте, особенно в свете вызовов, связанных с кризисом COVID-19. Данное исследование предоставляет важные сведения о том, как фирмы могут адаптировать свои цифровые стратегии для поддержания или ускорения инноваций в периоды потрясений. **Научная новизна** заключается в анализе неоднородного влияния цифровой трансформации на инновации в разных типах компаний и внешних условий, в частности, при сравнении периодов нормальных и кризисных ситуаций. Авторы использовали **методы** машинного обучения для анализа текста с целью построения индикаторов цифровой трансформации и регрессионные модели с фиксированными эффектами для оценки ее влияния на прорывные инновации. В рамках исследования авторы применяли панельные данные китайских компаний, котирующихся на бирже, за период 2014–2024 гг., реализуя эти передовые методы для выявления влияния цифровой трансформации на прорывные инновации в разные периоды и при различных условиях деятельности компаний. На основе полученных **результатов** было установлено, что ЦТ значительно повышает ПИ в нормальных условиях, но эта положительная взаимосвязь нарушается в кризисные периоды, особенно в госпредприятиях. В негосударственных предприятиях значительного влияния ЦТ ни в нормальные, ни в кризисные периоды не зафиксировано. Авторы пришли к **выводу**, что, хотя цифровая трансформация является ключевым фактором инноваций, ее эффективность зависит от типа компании и внешнего контекста, а глобальные потрясения ограничивают ее потенциал, особенно для государственных предприятий.

Ключевые слова: цифровая трансформация; прорывные инновации; машинное обучение; глобальный кризис здравоохранения; государственные предприятия; негосударственные предприятия; Китай

Для цитирования: **Pu T., Zulkafli A.H. The shifting influence of digital transformation on breakthrough innovation in China. *Review of Business and Economics Studies*. 2026;14(1):37-55. DOI: 10.26794/2308-944X-2026-14-1-37-55**

Introduction

The rapid advancement of technologies such as artificial intelligence, blockchain, cloud computing, and big data has led to a broad shift toward digital transformation (Dt) across multiple sectors [1–3]. Businesses increasingly recognize the transformative power of digitalization, which not only reshapes traditional business models but also redefines innovation processes [4–5]. Dt is widely regarded as a crucial force in enhancing operational efficiency and improving overall economic outcomes [6–9]. Given its broad impact, it is essential to deeply understand the relationship between Dt and breakthrough innovation (Bi).

Academic discussions on Dt often emphasize its potential to enhance innovation capabilities by facilitating more effective knowledge absorption and promoting value creation [10]. Additionally, the role of the internet in improving information access and dissemination has been shown to significantly influence product innovation, enabling firms to better meet customer needs through internet-based business models [11–15]. However, during the global COVID-19 pandemic (2020–2021), many firms experienced varying degrees of disruption to their innovation activities, particularly in the early stages [16]. As the pandemic persisted, it remained unclear whether companies, through accelerated Dt, were able to uncover new pathways and opportunities for Bi.

This study aims to fill the gap in the literature by examining the impact of Dt on Bi, with a particular focus on comparing its effects during normal periods and crisis periods. By utilizing panel data from Chinese A-share listed firms spanning 2014 to 2024, this study constructs a Dt index using machine learning-based text-mining techniques. The analysis reveals that while Dt generally enhances Bi, this positive effect is significantly interrupted during crisis periods, highlighting the disruptive impact of external shocks on the relationship between Dt and innovation.

In addition, the study examines the heterogeneous effects of Dt on Bi across different types of firms. The results show that state-owned enterprises (SOEs) experience a stronger positive impact of Dt on Bi during normal periods compared to non-state-owned enterprises (non-SOEs). However, this effect is reversed for SOEs during crisis periods, while non-SOEs show no significant impact from Dt in either normal or crisis periods. These findings suggest that the relationship between Dt and Bi is not uniform across firm types, with SOEs benefiting more from Dt under normal conditions but facing greater challenges during crises, whereas non-

SOEs struggle to leverage Dt effectively in both contexts.

This research contributes in several ways. First, by comparing the effects of Dt on Bi during normal periods and crisis periods, it fills a gap in the existing literature on the dynamic relationship between digital transformation and innovation under external shocks. Second, the study employs machine learning-based text-mining techniques to construct a Dt index, providing an innovative methodological approach for researching corporate Dt and its impact on innovation. Third, it uncovers the heterogeneous effects of Dt on Bi under different firm types, offering new theoretical insights into the role of Dt during periods of economic and social turmoil.

The organization of this paper is structured as follows: Section 2 delves into the theoretical framework, providing a comprehensive discussion on the derivation and development of the research hypotheses. Section 3 outlines the methodological approach adopted in this study, detailing the techniques and processes employed. Section 4 presents the empirical findings and conducts a thorough analysis of their reliability and validity. Section 5 presents the heterogeneity analysis, focusing on the differences between state-owned and non-state-owned enterprises in the relationship between Dt and Bi. Lastly, Section 6 concludes by summarizing the key insights and implications derived from the study.

Theoretical foundations and hypothesis development

Agency theory

Agency theory (AT) serves as a potential theoretical framework for explaining the impact of Dt on Bi. At the heart of this theory is the inherent conflict of interests and the information asymmetry that exists between the owners, or shareholders, of the company and the managers tasked with its day-to-day operations [17]. These discrepancies can often result in managerial behaviors that prioritize personal goals over the long-term success of the company. The theory provides a lens through which the relationship between Dt and Bi can be dissected and understood, particularly through the following three key aspects:

First, reduction of information asymmetry. One of the most significant contributions of Dt is its ability to reduce information asymmetry, which has long been a barrier to effective governance in corporations. By integrating advanced information technologies, such as big data analytics, blockchain, and cloud computing, firms are now able to gather, process, and analyze massive datasets in real time [18]. This collection and processing of data substantially diminish the information gaps between managers and owners, making the flow of information far more transparent and accessible. For owners, this increased visibility into managerial actions enables enhanced monitoring of decisions, leading to more informed oversight. As a result, the typical risks associated with moral hazard and adverse selection — common in situations of incomplete information — are notably reduced. With these risks mitigated, owners are more capable of ensuring that managerial activities align with the firm's innovation agenda. Furthermore, the transparency introduced by Dt makes it harder for managers to pursue self-serving projects, as they are now held accountable for their actions in a more transparent environment. This shift encourages a more innovation-driven approach, with managers increasingly directed to invest in projects that foster corporate growth and competitiveness.

Second, innovation incentives. Dt also plays a pivotal role in the enhancement of innovation incentives within the firm. Advanced data analytics, made possible by Dt, allow companies to monitor the progress of innovation projects more accurately and in real time, ensuring that managers remain accountable for meeting both short-term milestones and long-term strategic objectives [19]. This capability creates a dynamic feedback loop, where managers are continuously assessed based on performance metrics linked directly to innovation outcomes. Transparent and precise reward systems, supported by data-driven insights, are designed to ensure that managerial behavior is aligned with the company's broader innovation goals. These incentive structures motivate managers to focus on projects that will have lasting impacts on the firm's innovative capabilities, rather than prioritizing short-term gains or personal interests. Furthermore, Dt enables more efficient performance

evaluations, thus refining the overall managerial incentive system, which, in turn, enhances a firm's ability to sustain and scale its innovation efforts [20].

Third, reduction of agency costs. Another critical aspect of AT is the reduction of agency costs, which represent the expenses incurred due to the conflict of interest between managers and owners. Dt significantly improves the efficiency of monitoring and controlling the execution of innovation projects. For example, cloud computing and blockchain technologies allow for a more transparent and verifiable documentation process regarding the progression of innovation initiatives [21]. This increased transparency not only accelerates the reporting process but also minimizes the need for extensive manual oversight, thereby cutting down on the traditional costs associated with supervisory efforts. As a result, firms can free up resources that would otherwise be used for monitoring and direct these resources toward higher-potential innovation projects. Ultimately, lower agency costs enable firms the flexibility to invest more aggressively in breakthrough innovations, which in turn can improve their competitive standing in an increasingly digitized economy. By streamlining project management and accountability, Dt empowers companies to achieve higher levels of innovation output with fewer internal inefficiencies.

Resource dependence theory

Resource dependence theory (RDT) provides a comprehensive and insightful framework for analyzing the relationship between Dt and innovation. According to RDT, organizations are inherently dependent on external resources for their long-term survival and success [22]. This external reliance not only influences an organization's operational behaviors and strategies but also affects its capacity to innovate. The interaction between Dt and Bi can be better understood through the following key perspectives:

First, expanding access to essential resources. Digital transformation significantly impacts innovation by broadening firms' ability to acquire vital external resources. In highly competitive markets, the capability to effectively gather, integrate, and utilize these resources provides a substantial competitive edge. Leveraging cutting-edge technologies, including big data analytics, cloud computing, and blockchain, firms can systematically extract valuable insights from diverse external sources such as suppliers, markets, and business partners [23]. This improved capacity to process extensive datasets facilitates access to critical knowledge, technological innovations, and financial assets, which serve as fundamental drivers of innovation. By alleviating resource constraints, firms are better equipped to pursue groundbreaking innovations, advancing both technological and commercial frontiers.

Second, enhancing resource interdependencies. Dt also plays a fundamental role in fostering and strengthening the interdependencies between organizations and their external environment. Through the implementation of digital platforms, firms can build stronger, more interactive relationships with external stakeholders, including customers, suppliers, and strategic partners [24]. These digital platforms create opportunities for co-creation of value, where firms and their partners can collaboratively develop new products or services. Such interdependencies drive continuous innovation, as firms must keep up with or surpass the expectations of their external stakeholders to maintain their competitive edge. The collaborative nature of these interdependencies also facilitates faster and more efficient innovation cycles, enhancing a firm's overall innovation capability.

Third, reducing environmental uncertainty. A central tenet of RDT is the notion that firms innovate not just for growth but also to manage and mitigate the uncertainties present in their external environment. Environmental uncertainty, particularly concerning the availability and reliability of critical resources, can pose significant risks to a firm's innovation endeavors [25]. Dt, with its ability to process real-time data and deploy advanced predictive analytics, enables firms to monitor external conditions and anticipate potential challenges with greater accuracy. By reducing uncertainty about external factors, such as market demand or supply chain disruptions, firms are in a stronger position to make well-informed decisions regarding their innovation investments. This risk mitigation leads to more strategic and calculated inno-

vation activities, minimizing the potential for failure.

Fourth, strategic resource reconfiguration. Another way in which Dt impacts innovation is by empowering firms to reconfigure their resource base more effectively. Dt tools allow companies to optimize how they allocate resources across different innovation projects, making it easier to shift focus to high-potential opportunities while reducing investments in underperforming or obsolete initiatives [26]. This ability to adapt and reallocate resources in response to new digital opportunities enables firms to enhance their innovation outcomes. By continually reconfiguring resources to meet emerging challenges, firms ensure that they remain at the forefront of innovation, effectively navigating a rapidly changing digital landscape. This dynamic reallocation of resources is essential not only for maintaining operational efficiency but also for sustaining long-term innovation success.

Black swan theory

Black swan theory (BST), popularized by Nassim Nicholas Taleb, describes rare and unpredictable events with profound consequences [27]. These events are characterized by three main features: first, they are outliers. Black Swan events fall outside regular expectations and are not anticipated by historical data. They are so rare and unprecedented that past experiences do not indicate their likelihood or impact. Second, they have a massive impact. When such events occur, they have extensive and often transformative effects, disrupting normal processes and systems. The consequences are significant and can lead to systemic changes. Third, retrospective predictability is evident. After the event occurs, there is a tendency to create explanations that make it seem predictable or understandable, even though it was unforeseeable before it happened. This hindsight often overlooks the inherent unpredictability of the event.

The global COVID-19 pandemic can be considered a Black swan event. On the one hand, the pandemic emerged as an anomaly, far exceeding typical expectations and preparedness plans. Previous experiences and historical data on infectious diseases did not anticipate the scale and rapid spread of COVID-19, rendering it an unforeseeable and unprecedented event. On the other hand, the pandemic had a massive impact globally, disrupting economies, healthcare systems, and daily life. The shockwaves affected virtually every sector, including Dt and innovation processes [28]. The scale of the crisis surpassed the anticipations and preparations of most organizations and governments.

Subsequently, there has been a trend to rationalize the pandemic by citing various factors and warning signals that were supposedly evident but previously overlooked. This retrospective reasoning often disregards the inherent unpredictability and magnitude of the crisis. In the context of Dt and innovation, the COVID-19 pandemic underscores how Black swan events can undermine expected outcomes. Initially, it was anticipated that Dt would continuously drive innovation. However, the sudden outbreak and profound impact of the pandemic created conditions that disrupted these anticipated benefits.

Main effect hypothesis

Based on prior literature, this study predicts that Dt enhances Bi among Chinese listed firms.

From the perspective of AT, Dt alleviates information asymmetry between shareholders and managers, a critical issue in innovation activities. Due to the long-term and risky nature of innovation, managers responsible for the daily operations and financial disclosures related to R&D may prioritize their own short-term interests over those of shareholders. This misalignment can lead to agency conflicts and increased costs. Dt improves the transparency of innovation information, enhancing the timeliness and openness of R&D investment disclosures [29]. By reducing the risk of misinformation and lowering agency costs, Dt aligns managerial actions with shareholder interests. Furthermore, the automation of financial data processing through digital technologies further limits human intervention, thereby reducing agency costs associated with R&D investments [18, 30].

From the perspective of RDT, Dt substantially enhances innovation efficiency by transforming the allocation of internal resources and minimizing reliance on external entities. Advanced digital technologies, including artificial intelligence, blockchain, cloud computing, and big

data, diminish dependence on conventional and less effective systems, thereby improving the overall efficiency of innovation processes [31]. Additionally, these technologies facilitate better management of interactions within the innovation network, bridging knowledge gaps between firms and external partners [32]. This improved access and integration support the generation of innovative outcomes. Dt also enhances decision-making efficiency in innovation strategies and enables firms to establish strategic partnerships and alliances [1, 16]. By reducing dependence on single suppliers and fostering knowledge exchange and resource pooling, Dt contributes to more efficient innovation processes. Based on these considerations, we propose the following hypothesis:

H1: Under otherwise similar conditions, Dt has a positive impact on Bi.

Contextual effect hypothesis

From the perspective of the BST, Dt's typically positive influence on Bi may be disrupted during global health crises due to the extraordinary nature of such events. Black Swan events are characterized by their rarity, extreme impact, and the tendency for individuals to construct post hoc explanations that make these events appear predictable. The COVID-19 pandemic exemplifies a Black Swan event, representing an unprecedented disruption that exceeds the normal scope of organizational risk management and strategic planning [33]. During such crises, the traditional benefits of Dt — such as enhanced transparency, streamlined processes, and increased operational efficiency — can be severely compromised. The pandemic imposes substantial external shocks and operational constraints, leading organizations to prioritize immediate crisis response over long-term innovation efforts.

In this context, the usual mechanisms through which Dt supports Bi — such as improved data accessibility and resource optimization — may be undermined by the urgent need to adapt to rapidly changing and highly uncertain conditions. The crisis introduces a level of unpredictability and instability that disrupts normal innovation workflows and resource allocations. As organizations are forced to reallocate resources and shift focus to short-term survival, the positive impact of Dt on Bi may be significantly attenuated. Thus, while Dt generally enhances innovation under stable conditions, its effectiveness in driving Bi is likely diminished during global health crises due to the amplified and unprecedented challenges posed by such events. In this way, Hypothesis 2 is presented.

H2: The positive impact of Dt on Bi is disrupted during global health crises.

Heterogeneity hypothesis

Building on the theoretical foundations of AT and RDT, we hypothesize that the impact of Dt on Bi will exhibit heterogeneity between SOEs and non-SOEs. Specifically, we propose that the positive impact of digital transformation on breakthrough innovation is stronger in SOEs during normal periods compared to non-SOEs, but this effect is likely to be disrupted during crises for SOEs.

From the perspective of AT, SOEs are typically characterized by a more structured governance framework with stronger oversight from government stakeholders [25]. This enhanced governance structure means that Dt can more effectively reduce information asymmetry and agency costs in SOEs, aligning managerial incentives with long-term innovation goals [27]. During normal periods, this alignment enables SOEs to leverage digital transformation to enhance their breakthrough innovation efforts. The availability of resources and government support further strengthens their capacity to implement digital technologies, which ultimately drives more significant innovation outcomes. However, during crises, SOEs are often subject to more rigid, government-driven constraints, which may lead to a more conservative approach that prioritizes stability over innovation [11]. In such circumstances, the impact of Dt on innovation is likely to be weaker or even reversed, as SOEs may focus more on risk mitigation and short-term survival, rather than leveraging Dt for long-term innovation.

In contrast, non-SOEs may not experience the same level of benefit from Dt during either normal or crisis periods. While they may face fewer government-imposed constraints compared to SOEs, their limited resources and less formalized governance structures may restrict their ability to adopt and implement digital technolo-

gies effectively [31]. This resource constraint, combined with potential organizational inertia, could lead to weaker or insignificant effects of Dt on innovation, regardless of the period. The negative relationship between Dt and breakthrough innovation for non-SOEs in crisis periods further supports this argument, indicating that these firms may not possess the resilience or adaptability to capitalize on digital transformation, even in times of uncertainty. Therefore, we hypothesize:

H3: Compared to non-SOEs, the positive impact of Dt on Bi is stronger in SOEs during normal periods, but this effect is likely to be disrupted during crises for SOEs.

Methodology

Sample and data

This study utilized a comprehensive and unique dataset covering all A-share listed firms in China from 2014 to 2024. Financial information for the analysis was derived from the reputable China Stock Market and Accounting Research Database, known for its detailed and reliable financial and accounting data on Chinese enterprises. Simultaneously, Dt-related terms were meticulously identified from corporate annual reports through text mining methodologies, enabling an in-depth assessment of Dt activities across firms. To measure innovation output, patent data were sourced from the Chinese Research Data Services Database, ensuring precise evaluation of firms' innovation capabilities.

Several rigorous preprocessing steps were applied to enhance the quality and robustness of the dataset. First, financial institutions were excluded from the sample. These firms operate under distinct governance structures and financial performance frameworks compared to non-financial companies, which could introduce bias into the analysis. By excluding financial firms, the study focuses on non-financial enterprises, where Dt and innovation dynamics are more comparable. Second, firms placed under "Special Treatment" (ST) status, meaning they experienced consecutive losses over two years and faced the risk of delisting, were removed. These companies tend to have abnormal financial behaviors, which could skew the results and lead to misinterpretation of the general trends observed in healthier firms.

In addition, data reliability was a key consideration. Therefore, firms with incomplete or missing financial, patent, or Dt-related data were systematically excluded from the analysis. This step ensured that the dataset used for empirical testing was as complete as possible, minimizing the impact of data gaps that could distort the findings. Moreover, to deal with potential biases arising from outliers in the financial data, all continuous variables were winsorized at the 1st and 99th percentiles.

Variable measurement and estimations techniques

Dependent variable

The dependent variable in this study is breakthrough innovation, which is measured using patent-related activities. Consistent with the approach of [34], Bi is quantified as the natural logarithm of one plus the total number of invention patents applied for by the firm each year. This method of measurement captures a firm's efforts to engage in innovative activities, particularly those aimed at developing new, groundbreaking technologies. Invention patents, as opposed to utility or design patents, provide a more stringent measure of innovation because they reflect higher levels of novelty and technological advancement. By taking the natural logarithm, we address potential skewness in the patent count data, ensuring that firms with very high or very low numbers of patent applications do not disproportionately influence the results.

Independent variable

The independent variable in this research is digital transformation (Dt). Since the text in annual reports reflects a firm's strategic orientation, examining these reports provides valuable insights into the firm's emphasis on digital transformation [35]. Following the methodology of Tu and He (2022) [36, 37], this study employs a Python-based crawler to develop the digital transformation metric. The process involves several stages: first, seed terms associated with Dt, such as "digital technology," "information technology," "big data," and "cloud computing," are selected. Python's Jieba and Re modules are then used to extract relevant text, which is subsequently cleaned, matched,

and analyzed for frequency. The corpus for this study is generated through word segmentation and the removal of stop words. Machine learning, specifically the word2vec model, is applied to this corpus to generate word vectors and calculate similarities between terms, thereby identifying semantically related words. Using a seed word dictionary, the frequency of these keywords is determined. Due to the typical right-skewed nature of this data, the keyword frequencies are log-transformed (LN) with an addition of one (LN (keyword frequency +1)) to evaluate the degree of Dt among Chinese A-share listed companies.

Control variables

To address potential confounding factors influencing breakthrough innovation, this study incorporates a comprehensive set of control variables. These variables are selected based on their relevance to innovation performance in prior literature. Firm Size (Fs), measured as the logarithm of total assets, accounts for the scale of a company and its potential to support innovation activities. Firm Age (Fa), calculated as the natural logarithm of the number of years since establishment plus one, reflects the maturity and experience of the firm. Financial Leverage (Lev), defined as the ratio of total debts to total assets, captures the firm's financial structure and risk profile. Return on Assets (Roa), represented by net income divided by total assets, provides insight into the firm's profitability and efficiency in utilizing resources. Sales Growth (Gr), measured by the year-over-year change in operating income, indicates the firm's market performance and growth trajectory. Board Size (Bs), expressed as the logarithm of the number of board directors, serves as a proxy for governance and decision-making capacity. Ownership Concentration (To), represented by the percentage of shares held by the largest shareholder, reflects the degree of control exerted by major stakeholders, which may influence strategic innovation decisions. Finally, Institutional Ownership (In), represented by the percentage of shares held by institutional investors, is included to account for the influence of institutional investors on a firm's innovation strategy and decision-making process.

Estimations techniques

The following equation is used to estimate H1 and H3:

$$Bi_{i,t} = \alpha_0 + \alpha_1 Dt_{i,t} + \alpha_2 Fs_{i,t} + \alpha_3 Fa_{i,t} + \\ + \alpha_4 Lev_{i,t} + \alpha_5 Roa_{i,t} + \alpha_6 Gr_{i,t} + \alpha_7 Bs_{i,t} + \\ + \alpha_8 To_{i,t} + \alpha_9 In_{i,t} + Year + Firm + \varepsilon. \quad (1)$$

In the model specification, α_0 represents the intercept term, while $\alpha_1 - \alpha_9$ denote the coefficients associated with the respective independent and control variables, which are to be estimated through regression analysis. This study incorporates dummy variables to control for both year and firm fixed effects, represented by Year and Firm, respectively. These fixed effects account for time-invariant characteristics specific to each firm and temporal factors that could influence the results across different years. The error term, ε, captures unobserved factors that may affect the dependent variable. The subscript iii refers to the cross-sectional dimension, indicating individual firms, while t denotes the time-series dimension, representing different periods over which the data are observed.

Findings

Descriptive statistics and correlation matrix

The descriptive statistics presented in *Table 1* provide a comprehensive overview of the key variables utilized in this study. The dataset comprises 39,440 observations, offering a broad range of data points across different variables.

Starting with the dependent variables, breakthrough innovation (Bi and Bia) both exhibit considerable variability. Bi, representing the natural logarithm of one plus the total number of invention patent applications, has a mean of 1.198, with a standard deviation of 1.353. The range of values for Bi spans from 0 to 5.609, reflecting substantial differences in patenting activities across firms. A similar pattern is seen for Bia, which represents the natural logarithm of one plus the total number of granted invention patents. The mean value of Bia is 0.851, with a standard deviation of 1.110, further illustrating the varied innovation outputs among firms. The discrepancy between Bi and Bia highlights the gap between innovation efforts (applications) and realized outcomes (grants), reinforc-

Table 1
Descriptive statistics

Variables	Count	Mean	Sd	Min	Max
Bi	39440	1.198	1.353	0.000	5.609
Bia	39440	0.851	1.110	0.000	4.970
Dt	39440	1.724	1.412	0.000	5.056
Fs	39440	22.259	1.309	19.630	26.452
Fa	39440	2.065	0.957	0.000	3.466
Lev	39440	0.410	0.205	0.049	0.935
Roa	39440	0.037	0.069	−0.375	0.255
Gr	39440	0.133	0.375	−0.654	3.808
Bs	39440	2.099	0.197	1.609	2.708
To	39440	0.332	0.147	0.074	0.757
In	39440	0.419	0.249	0.001	0.920

Source: Calculated by authors.

Table 2
Pearson correlation

Column number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	**Bi**	**Dt**	**Fs**	**Fa**	**Lev**	**Roa**	**Gr**	**Bs**	**To**	**In**
(1)	1.000									
(2)	0.165***	1.000								
(3)	0.077***	0.026***	1.000							
(4)	−0.172***	−0.039***	0.465***	1.000						
(5)	−0.054***	−0.036***	0.489***	0.379***	1.000					
(6)	0.128***	−0.048***	0.005	-0.254***	-0.369***	1.000				
(7)	0.027***	−0.002	0.038***	-0.071***	0.026***	0.266***	1.000			
(8)	0.016***	−0.056***	0.271***	0.162***	0.139***	0.014***	0.006	1.000		
(9)	−0.015***	−0.117***	0.171***	-0.083***	0.015***	0.171***	0.004	0.010**	1.000	

Source: Calculated by authors.

Note: significance levels are represented by asterisks: *, **, and *** correspond to p-values less than 0.1, 0.05, and 0.01, respectively.

ing the need to analyze both dimensions of innovation.

Turning to the key independent variable, Dt, the data show significant heterogeneity in the adoption of digital technologies across firms. The mean value of Dt is 1.724, with a standard deviation of 1.412, indicating that while some firms have embraced digital technologies more extensively, others are still in the early stages of transformation. The values of Dt range from 0 to 5.056, suggesting varied digital strategies and capabilities among firms.

For the control variables, the firms in the sample exhibit an average firm size (Fs) of 22.259, measured as the natural logarithm of total assets, and an average firm age (Fa) of 2.065 years. The financial leverage (Lev) has a mean value of 0.410. The return on assets (Roa) shows a mean of 0.037, indicating relatively modest profitability across the sample. The growth rate

(Gr) has a mean of 0.133, suggesting that firms experience moderate growth. The board size (Bs) has an average value of 2.099, while ownership concentration (To) is on average 0.332. Additionally, the institutional ownership (In) variable, which represents the proportion of shares owned by institutional investors, has a mean of 0.419 and a standard deviation of 0.249.

The correlation matrix in *Table 2* shows the relationships between the key variables in this study. Notably, Bi and Dt are positively correlated (0.165***), suggesting that firms with higher digital transformation levels tend to engage in more breakthrough innovation. The correlation between Bi and Fs is also positive (0.077***), indicating that larger firms are more likely to engage in innovation activities. There is a negative relationship between Bi and Lev (–0.054***), implying that firms with higher leverage may invest less in breakthrough innovation. Dt is negatively correlated with Fa (–0.039***), suggesting that older firms might be slower to adopt digital transformation strategies. Moreover, the correlation between Dt and To is negative (–0.117***), suggesting that firms with higher ownership concentration may be less likely to embrace digital transformation. Overall, the coefficient values are all less than 0.5, indicating no concerns about multicollinearity in the model.

Analysis of benchmark regression

We begin our analysis by exploring the impact of Dt on Bi using a panel data model that incorporates two-way fixed effects. This methodological approach allows us to control for both firm-specific unobservable heterogeneity and time-specific macroeconomic shocks, thereby providing more reliable estimates of the relationship between Dt and Bi. The regression outcomes are summarized in *Table 3*.

In columns (1) and (2) of *Table 3*, we present models where Bi serves as the dependent variable. These columns reveal a significantly positive effect of Dt on Bi, regardless of whether control variables are included. Specifically, Dt has a coefficient of 0.019 in the model without control variables (column 1) and 0.012 in the model with control variables (column 2), both significant at the 1% and 5% levels, respectively.

From a theoretical perspective, these findings are consistent with the resource-based view, which suggests that Dt enhances firms' ability to acquire, process, and utilize information resources, thereby improving innovation efficiency and supporting complex knowledge recombination processes required for Bi [38]. Digital technologies can reduce information asymmetry, enhance cross-functional collaboration, and improve the quality of R&D decisions, ultimately strengthening firms' long-term innovation capacity [39]. Therefore, the results provide empirical support for Hypothesis 1.

In columns (3) and (4), we extend our investigation to the non-crisis period to evaluate whether the positive influence of Dt on Bi persists under relatively stable external conditions. The results continue to show positive and statistically significant coefficients for Dt, with a coefficient of 0.016 in column (3) and 0.013 in column (4), both significant at the 5% and 10% levels, respectively.

These results further reinforce the theoretical argument that Dt serves as a strategic capability that enhances firms' ability to sense and exploit innovation opportunities when external environments are relatively stable. Under such conditions, firms are more willing to allocate digital resources toward exploratory innovation activities, which is consistent with the long-term innovation investment logic suggested by the innovation incentive [40].

However, when we shift focus to the sample period encompassing the global health crisis of 2020–2021 (In-Crisis, columns 5 and 6), the effect of Dt on Bi becomes statistically insignificant. The coefficients for Dt in columns (5) and (6) are –0.020 and –0.022, respectively, neither of which is statistically significant.

Importantly, these crisis-period results can also be interpreted within the theoretical framework of AT and RDT when combined with the logic of BST, rather than contradicting these core theoretical predictions. BST suggests that rare, extreme, and highly unpredictable events can fundamentally disrupt existing organizational decision-making patterns and resource allocation structures.

From an AT perspective, Black Swan-type crisis events significantly intensify short-term performance pressure and managerial risk aversion. Under such extreme uncertainty, managers

Table 3
Benchmark results

Column number	(1)	(2)	(3)	(4)	(5)	(6)
Type	**Full**	**Full**	**No-Crisis**	**No-Crisis**	**In-Crisis**	**In-Crisis**
Variables	Bi	Bi	Bi	Bi	Bi	Bi
Dt	0.019***	0.012**	0.016**	0.013*	−0.020	−0.022
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Fs		0.112***		0.114***		0.205***
		(0.01)		(0.01)		(0.06)
Fa		−0.010		−0.025		0.064
		(0.01)		(0.02)		(0.07)
Lev		−0.126***		−0.132***		−0.129
		(0.04)		(0.05)		(0.16)
Roa		0.263***		0.312***		−0.031
		(0.08)		(0.09)		(0.20)
Gr		−0.015		−0.015		−0.060**
		(0.01)		(0.01)		(0.02)
Bs		−0.061		−0.077*		0.043
		(0.04)		(0.05)		(0.11)
To		0.223***		0.252***		0.738**
		(0.08)		(0.09)		(0.33)
In		−0.098*		−0.130**		−0.092
		(0.05)		(0.06)		(0.20)
_cons	1.165***	−1.154***	1.110***	−1.161***	1.336***	−3.617***
	(0.01)	(0.28)	(0.01)	(0.30)	(0.04)	(1.34)
Year-FE	√	√	√	√	√	√
Firm-FE	√	√	√	√	√	√
N	39370	39370	26189	31237	7432	7432
adj. R^2	0.752	0.752	0.732	0.739	0.870	0.870

Source: Calculated by authors.

Note: robustness standard errors are displayed within brackets. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

are more likely to prioritize liquidity preservation, operational continuity, and short-term survival over long-term exploratory innovation investment, even when Dt capabilities are already in place. In this context, although Dt enhances transparency and monitoring efficiency, the governance benefits of digital transparency may not fully translate into increased Bi investment during systemic crisis periods.

From a RDT perspective, Black swan events drastically increase uncertainty regarding the availability, reliability, and continuity of critical external resources. Even when digital technologies improve internal coordination and infor-

Table 4
Robustness checks

Column number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Type	**Full**	**No-Crisis**	**In-Crisis**	**Full**	**No-Crisis**	**In-Crisis**	**Full**	**No-Crisis**	**In-Crisis**
Variables	Bia	Bia	Bia	Bi	Bi	Bi	Bi	Bi	Bi
Dt	0.017***	0.021***	0.017	0.013**	0.013**	−0.020	0.012**	0.013**	−0.017
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Controls	√	√	√	√	√	√	√	√	√
Year-FE	√	√	√	√	√	√	√	√	√
Firm-FE	√	√	√	√	√	√	√	√	√
N	39370	31237	7432	39370	31237	7432	31258	24329	4918
adj. R^2	0.718	0.719	0.836	0.753	0.739	0.870			

Source: Calculated by authors.

Note: robustness standard errors are displayed within brackets. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

mation processing capabilities, firms may still face severe constraints in accessing external financing, technological knowledge spillovers, and stable supply chain resources. This external resource disruption weakens firms' ability to effectively convert Dt investments into Bi outcomes.

Overall, our findings suggest that while Dt generally enhances Bi under stable conditions, its innovation effects are contingent upon external environmental stability. These findings extend the existing literature by demonstrating that Dt should be viewed as a context-dependent strategic capability rather than a universally innovation-enhancing factor. Consistent with Wu et., al (2024) [41], Dt improves innovation-related information transparency and investment disclosure efficiency, but our results further suggest that the realization of these benefits depends on macroeconomic and environmental stability.

Robustness tests

To ensure the robustness and reliability of our findings, we perform several robustness checks using alternative specifications and methodologies. The results, presented in *Table 4*, confirm the consistency of our primary findings under different model assumptions.

First, we replace the dependent variable in our analysis to test the robustness of the relationship between Dt and Bi. In columns (1), (2), and (3), we use the number of granted invention patents (Bia) instead of patent applications as the measure of innovation. Given that granted patents are considered a more authoritative indicator of innovation due to their validation in the patenting process, we find that the coefficients for Dt remain positive and statistically significant in columns (1) and (2). However, in column (3), the relationship becomes statistically insignificant during crisis periods. This variation in significance reinforces the robustness of our results across different measures of innovation.

Second, we introduce additional fixed effects to further control for potential confounding factors. In columns (4), (5), and (6), we include industry, province, and city fixed effects in addition to firm and year fixed effects. This specification controls for unobserved heterogeneity across industries, regions, and firms, and the results remain consistent with our main findings. The coefficients for Dt continue to demonstrate significance, further validating our initial results.

Third, we substitute our regression methodology with a Poisson count model to test the robustness of our results under a different estimation method. Columns (7), (8), and (9) present the results from this alternative approach, where the dependent variable is modeled as a count

Table 5
Digital transformation and breakthrough innovation: SOEs vs. non-SOEs in normal and crisis periods

Ownership	SOEs		non-SOEs	
Column number	(1)	(2)	(3)	(4)
Period	**No-Crisis**	**In-Crisis**	**No-Crisis**	**In-Crisis**
Variables	Bia	Bia	Bia	Bia
Dt	0.023***	−0.018	0.004	−0.023
	(0.01)	(0.03)	(0.01)	(0.02)
Controls	√	√	√	√
Year-FE	√	√	√	√
Firm-FE	√	√	√	√
N	20832	2270	27521	5162
adj. R^2	0.769	0.907	0.747	0.849

Source: Calculated by authors.

Note: robustness standard errors are displayed within brackets. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

variable. Even with this different estimation technique, the coefficients for Dt continue to show similar patterns, confirming the stability of the relationship between digital transformation and breakthrough innovation under varying model specifications.

Heterogeneity analysis

We explore the differential effects of Dt on Bi by comparing SOEs and non-SOEs. The results presented in *Table 5* reveal substantial differences in how Dt influences innovation across these two types of firms, particularly under normal and crisis conditions.

For SOEs, as shown in columns (1) and (2), Dt has a significant positive effect on Bi during normal periods (0.023***), suggesting that digital transformation boosts the innovation capabilities of SOEs. This positive relationship could stem from the fact that SOEs often have more stable access to resources and government support, which enables them to effectively adopt digital technologies and pursue innovation. However, during crisis periods, the effect reverses, with a negative and statistically insignificant coefficient (−0.018, column 2). This may indicate that the typical advantages of digital transformation, such as enhanced transparency and data-driven decision-making, are not as effectively utilized in times of crisis. One possible explanation is that the unique characteristics of SOEs, such as stronger government involvement and more conservative decision-making, could hinder their ability to adapt quickly in uncertain conditions. In crisis situations, SOEs may prioritize stability and risk-averse strategies over the potential for innovation, thus diminishing the positive impact of Dt on breakthrough innovation.

In contrast, for non-SOEs, the results in columns (3) and (4) show weaker and statistically insignificant relationships between Dt and Bi, both during normal periods (0.004) and crisis periods (−0.023). This suggests that non-SOEs may not fully leverage the benefits of digital transformation in driving innovation, regardless of the economic context. It is possible that non-SOEs face more constraints in terms of resources, access to advanced technologies, and expertise, which limits their ability to adopt and implement digital transformation effectively. Furthermore, the negative effect during the crisis suggests that non-SOEs may be more vulnerable to external shocks, as they often lack the financial buffers and institutional support that SOEs benefit from. In times of crisis, these firms may be forced to focus on short-term survival rather than long-term innovation, further

weakening the impact of Dt on breakthrough innovation.

These findings suggest that digital transformation has heterogeneous effects on breakthrough innovation depending on the type of firm and the economic context. SOEs benefit more from Dt during normal times, but their ability to innovate is reduced during crises, potentially due to their more conservative strategies and reliance on government support. In contrast, non-SOEs show a weaker response to Dt overall, possibly due to limited resources and adaptability, and are particularly vulnerable during crises.

Discussion

The results of this study underscore the transformative potential of Dt in promoting Bi within Chinese listed companies. Our analysis reveals that, under stable conditions, Dt enhances Bi significantly, validating the idea that digitalization can fundamentally improve innovation processes. By enabling better access to data, more efficient resource management, and improved decision-making processes, Dt helps firms increase their innovation output. This is in line with existing literature that highlights the role of digital tools in driving operational efficiencies and enhancing corporate innovation [41–51].

That said, the study also reveals a critical insight: during crisis periods, the positive relationship between Dt and Bi is disrupted. This disruption is particularly evident during the global health crisis, where the usual benefits of digital transformation were attenuated. Firms, especially those in the most affected sectors, struggled to effectively leverage digital technologies to sustain or accelerate their innovation activities. The findings suggest that while digital transformation is a crucial driver of innovation in stable environments, its effectiveness is contingent upon the external environment's stability. In times of crisis, firms often shift their priorities to focus on short-term survival, cutting back on innovation activities and reducing the strategic importance of digital transformation. This result aligns with the Black swan theory, which posits that rare and unpredictable events — such as global crises — can disrupt even the most well-established organizational processes, including innovation [52].

The heterogeneity analysis adds further complexity to our understanding of the digital transformation-innovation relationship. Our results indicate that, during normal periods, SOEs experience a significantly stronger positive impact from Dt on Bi. This can likely be attributed to the institutional advantages of SOEs, such as greater access to resources, stable government support, and more formalized governance structures. These factors enable SOEs to effectively harness digital technologies and apply them toward innovation [53, 54]. Additionally, the relatively rigid and bureaucratic nature of SOEs may also contribute to their ability to systematically implement and monitor digital strategies, ensuring that these technologies contribute meaningfully to breakthrough innovation [55–57].

On the other hand, during crisis periods, this advantage seems to diminish. The increased regulatory scrutiny, government intervention, and a more cautious decision-making approach often found in SOEs may hinder their ability to quickly pivot or adapt to external shocks [58–60]. In contrast, non-SOEs show no significant impact from Dt on breakthrough innovation, regardless of whether conditions are normal or crisis-driven. This suggests that non-SOEs face significant challenges in implementing digital transformation strategies effectively. Their limited access to resources, lack of institutional support, and lower digital adoption rates might prevent them from capitalizing on digital technologies to foster innovation. These findings are consistent with previous research, which argues that SOEs, due to their institutional backing and resource availability, are better positioned to implement successful digital strategies, while non-SOEs often lack the necessary infrastructure and governance to do so [60–63].

Conclusion and implications

Drawing on a comprehensive dataset of Chinese A-share listed companies spanning from 2014 to 2024, this study provides both theoretical and empirical insights into the relationship between digital transformation and breakthrough innovation. Our analysis reveals a positive correlation between Dt and Bi, confirming our initial hypothesis that, under normal circumstances, digital transformation significantly enhances firms' ability to achieve breakthrough innovation. However, our

results also indicate that this positive influence is notably reduced during times of crisis, such as the global health crisis. This attenuation suggests that while digital transformation generally fosters innovation, its effectiveness is contingent upon the broader external environment, and its benefits can be undermined by significant disruptions.

Moreover, our heterogeneity analysis highlights important differences in the effects of digital transformation on breakthrough innovation between SOEs and non-SOEs. The results show that Dt has a stronger positive impact on innovation in SOEs during normal periods compared to non-SOEs, emphasizing the role of governance structures and resource access in facilitating innovation. However, this effect is attenuated or even reversed for SOEs during crises, underscoring the vulnerability of even well-resourced and structured firms in the face of unexpected disruptions. In contrast, non-SOEs show less significant impacts from Dt in both normal and crisis periods, suggesting that they may face greater challenges in leveraging digital technologies for innovation due to resource constraints and structural limitations.

These findings have significant implications for both theoretical frameworks and practical applications. From a theoretical standpoint, the positive association between Dt and Bi supports Agency Theory and Resource Dependence Theory, illustrating how digital transformation can reduce information asymmetry and improve firms' access to and utilization of external resources, thereby enhancing their innovative capabilities. However, the diminished impact of Dt during the global health crisis, interpreted through Black Swan Theory, highlights the vulnerability of even robust digital strategies to unforeseen and disruptive events. The heterogeneity observed between SOEs and non-SOEs further suggests that the benefits of Dt are not uniform across different firm types, and that ownership structure plays a critical role in determining the extent to which Dt can drive innovation.

On the practical front, these results underscore the importance for firms to develop resilient and adaptable digital strategies. While digital transformation should be harnessed to drive innovation, firms must also ensure their strategies are flexible enough to respond to unforeseen crises. The reduction in the effectiveness of Dt amid external shocks indicates that firms need to proactively anticipate potential resource constraints and shifts in priorities. Specifically, SOEs should focus on balancing government influence with innovation-driven strategies, while non-SOEs may need to address structural limitations and resource gaps to fully capitalize on digital transformation. By adjusting digital initiatives to address these challenges, firms can better navigate volatile environments and maintain their competitive edge.

Future research should examine how external shocks influence the relationship between digital transformation and innovation, and explore strategies that firms can adopt to mitigate these disruptions. While this study focuses on Chinese A-share listed companies, the applicability of the findings to other countries or regions with different institutional settings may be limited. The sample's specific focus on Chinese companies, particularly the emphasis on SOEs and their unique governance structures, may not fully capture the dynamics of digital transformation in firms from other markets. Understanding how companies in different countries or industries maintain innovation through digital transformation during crises will be crucial for sustaining a competitive edge in today's rapidly changing and uncertain business environment. Future studies could also explore how variations in institutional environments, regulatory frameworks, and market conditions might influence the effectiveness of digital transformation in fostering innovation across different geographical settings.

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Conflicts of Interest Statement: The authors have no conflicts of interest to declare.
The article was submitted on 19.01.2026; revised on 09.02.2026 and accepted for publication on 01.03.2026. The authors read and approved the final version of the manuscript.