ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 20, No. 2, 121–153, 2024

DIGITAL TRANSFORMATION AND CORPORATE INNOVATION: EMPIRICAL DISCOVERY BASED ON MACHINE LEARNING

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ABSTRACT

With the flourishing development of the digital economy, the phenomenon of digital transformation at the firm level has attracted scholars' attention regarding its impact on microeconomic activities. However, whether the transformational changes induced by digital technologies affect corporate innovation and the underlying mechanisms have not been fully explored. Based on panel data from Chinese listed firms spanning from 2012 to 2021, this paper constructs a measure of digital transformation using machine learning techniques and investigates its relationship with corporate innovation. The findings suggest that digital transformation effectively promotes corporate innovation, a result robust to a battery of sensitivity checks. Mechanism analysis reveals that digital transformation significantly enhances innovation by increasing R&D input and improving innovation efficiency. Further analysis indicates that the innovation-promoting effect of digital transformation is mainly manifested in high-quality innovation output, with greater benefits observed for state-owned enterprises and non-high-tech industry enterprises. Overall, our study provides valuable policy insights for enhancing innovation levels among enterprises in developing countries like China through digital transformation strategies.

Keywords: Digital transformation, Corporate innovation, Machine learning, R&D input, Innovation efficiency

Received: 14 January 2024; Accepted: 25 July 2024; Published: 27 December 2024

To cite this article: Pu, T., Li, Y., & Zulkafli, A. H. (2024). Digital transformation and corporate innovation: Empirical discovery based on machine learning. *Asian Academy of Management of Accounting and Finance, 20*(2), 121–153. https://doi.org/10.21315/aamjaf2024.20.2.4

To link to this article: https://doi.org/10.21315/aamjaf2024.20.2.4

INTRODUCTION

The emergence of new technologies such as artificial intelligence, blockchain cloud computing and big data has sparked a broader phenomenon known as "digital transformation" across most industries (Butschan et al., 2019; Loonam et al., 2018; Richter et al., 2018; Tu & He, 2022). Firms increasingly recognise the pivotal role of digital transformation, which disrupts traditional business models and innovation approaches (Loonam et al., 2018). In fact, digital transformation holds the potential to stimulate innovation, enhance efficiency and improve economic prospects (Hao et al., 2023). Therefore, exploring the impact of digital transformation on innovation and the underlying mechanisms is of significant value.

Some scholars consider information technologies as a foundational force, that can strengthen a firm's capacity to absorb knowledge, particularly explicit knowledge, thereby fostering a value-creation process (Peng & Tao, 2022; Vial, 2019). Another focal point in the literature revolves around the Internet's influence on corporate innovation, as it facilitates increased information accessibility and dissemination, which, in turn, enhances innovation ability by catering to personalised customer needs through Internet-based business models (Ghezzi & Cavallo, 2020). Simultaneously, the study of digital transformation's role in innovation is gaining momentum. For instance, Ferreira and Teixeira (2019) discovered that it can amplify service and process innovation. In other words, digital transformation has become a strategic choice for companies to seize the opportunities presented by the new wave of technological and industrial changes. The digital development of enterprises provides digital technologies, products, services, infrastructure and solutions for internal innovation (Chan et al., 2018; Ghosh et al., 2022), suggesting that digital transformation should positively impact corporate innovation. However, the existing academic literature has not reached a consensus on its impact mechanisms, and there is limited research on how digital transformation specifically affects corporate innovation. This reveals a disconnect between expected and actual innovation outputs. These gaps are of great concern to governments, enterprises and academia and are the motivation behind this study. Therefore, this paper aims to investigate whether digital transformation affects corporate innovation and, if so, what the possible mechanisms are.

Using a sample of A-share listed companies in China from 2012 to 2021, this study empirically investigates the relationship between digital transformation and corporate innovation. The reason for selecting China as the research sample is its prominent position as the world's second-largest contributor to the digital economy (Sun et al., 2022). According to the White Paper on the Development of China's Digital Economy (2021) issued by the China Academy of Information and Communications Technology, China's digital economy has reached RMB 39.2 trillion (approximately USD 5.4 trillion), which amounts to 38.6% of GDP (Tian et al., 2022). The flourishing development of China's digital economy has prompted numerous enterprises to engage in digital transformation actively (see Figure 1), considering it a pivotal strategic initiative for economic advancement (Guo et al., 2022; Zeng et al., 2022).

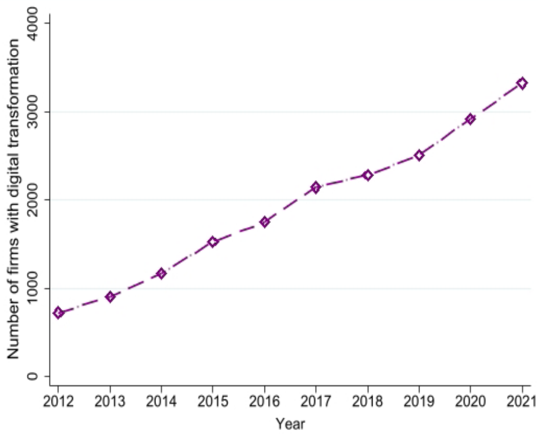

Figure 1: The annual trend of Chinese listed firms with digital transformation (2012–2021) (Source: Annual Reports of Chinese listed firms).

In this article, we used a measure of digital transformation with the help of machine learning to examine the impact of digital transformation on corporate innovation. Specifically, we employ the Word2vec module, a set of related models for generating word vectors. These models are shallow, two-layer neural networks trained to reconstruct the linguistic context of words, thereby significantly enhancing the accuracy of text recognition. The findings demonstrate that digital transformation benefits corporate innovation by adding R&D input (input channel) and improving innovation efficiency (efficiency channel). Further analysis reveals that digital transformation drives high-quality innovation rather than low-quality innovation. Moreover, this promotion effect is more pronounced in state-owned and non-high-tech enterprises.

This study offers these contributions. First, it uses text mining techniques based on machine learning in conjunction with information from annual reports to construct a comprehensive digital transformation indicator for firms. This indicator established serves as a benchmark for assessing firms' progress towards digital transformation and gauging their success. Second, the research identifies and tests the input and efficiency channels through which digital transformation influences corporate innovation, shedding light on the "black box" of its impact. By doing so, it not only expands the study of the economic effects and mechanisms of digital transformation but also enriches the exploration of the factors influencing corporate innovation, in line with the needs of the digital economy era for high-quality innovation-driven development. Third, the study explores the heterogeneous effects of digital transformation on corporate innovation, considering both firm-level characteristics and innovation quality levels. This provides an in-depth understanding of the economic benefits of firms' digital transformation and informs the design of differentiated policies.

The rest of this article is as follows: the second part provides a brief review of related literature and proposes hypotheses development; the third part explains the methods used in this study; the fourth part discusses the findings and robustness checks; and the final part concludes this research.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Literature on Digital Transformation and its Application

A large number of recent studies have focused on digital transformation, with a general agreement on its definition as an organisation's adoption and implementation of digital technology to develop new or modify existing products, services, and operations by translating business processes into a digital format. For instance, Vial (2019) defines digital transformation as an organisation's adaptation to environmental changes by changing its value creation process using digital technologies such as mobile computing, artificial intelligence and cloud computing. Hess et al. (2020) define digital transformation as the implementation of state-of-the-art technology resulting in new product offerings, innovative methods for value creation and restructuring of the organisation. In addition, Gong and Ribière (2021) provide an objective definition of digital transformation as a significant change fuelled by digital technologies, resulting in the creation of innovative and improved value.

Following the integration of digital technologies into corporate operational frameworks and the implementation of intelligent support systems, digital transformation is often regarded by enterprises as an integral component of value creation, organisational change and strategic financial restructuring (Holopainen et al., 2023; Matarazzo et al., 2021). A widely held view is that digital technologies can help firms overcome internal resource and capability constraints, allowing them to leverage external resources for strategic expansion into new markets and new product development (Chan et al., 2018). Alternatively, scholars argue that firms that embrace digital transformation can improve their production processes by leveraging consumer data (Earley, 2014), changing their organisational structures (Kretschmer & Khashabi, 2020), and modifying their value creation methods (Rachinger et al., 2019). Moreover, digital transformation also extends the reach of firms by strengthening connections and collaborations within supply chains (Reuschl et al., 2022). This technology allows firms to enhance their operational efficiency, generate value and foster innovation by utilising ecosystems and platforms (Ghosh et al., 2022; Gong & Ribière, 2021; Rachinger et al., 2019).

Related Work on Digital Transformation and Corporate Innovation

Corporate innovation is influenced by multiple factors such as investment in research and development (R&D), efficiency of innovation, ownership structure and regional heterogeneity. Numerous researchers have confirmed that R&D is one of the decisive factors for the success of innovation activities (e.g., Liu et al., 2020; Wang et al., 2017; Zhang et al., 2022). Innovation efficiency regulates the output level that a firm can achieve in the same amount of time (Hou et al., 2017; Zhang et al., 2022). Additionally, corporate innovation is affected by the ownership structure, with state and institutional ownership positively influencing innovation performance (Choi et al., 2011; O'Connor & Rafferty, 2012). Moreover, spatial heterogeneity exists in innovation performance across regions (Fei et al., 2019; Miao et al., 2021).

The early research on the impact of digital transformation on corporate innovation focused mainly on the Internet (e.g., Paunov & Rollo, 2016; Xu et al., 2019). The extensive acceptance of the internet has led to the quick spread of information and knowledge. This, in turn, has stimulated corporate innovation (Dahlman et al., 2016; Hess et al., 2020; Peng & Tao, 2022; Vial, 2019). Moreover, Ferreira and Teixeira's (2019) studies in the area of corporate innovation focused on service and process innovation, providing evidence that digital transformation can expand innovation in these areas.

In brief, the extant literature on digital transformation focuses on defining digital transformation, and investigating its influence on the business models, organisational structures, and management approaches of firms. However, the investigation and understanding of the impact of digital transformation on corporate innovation remain limited.

Hypothesis Development

In the fiercely competitive market environment, continuous investment in R&D enables firms to continually introduce new products and technologies, maintaining a technological advantage and leading position in the market (Chang et al., 2019). Concurrently, innovation efficiency determines whether firms can swiftly validate the feasibility of new ideas and technologies, reducing resource and cost inputs while mitigating the risk of R&D failure (Min et al., 2020). In other words, R&D investment and innovation efficiency are two pivotal factors driving corporate innovation. Indeed, the relationship between digital transformation and corporate innovation can be framed within existing theoretical frameworks such as agency theory (Eisenhardt, 1989) and resource dependence theory (Reitz et al., 1979). The former elucidates how digital transformation can mitigate insufficient R&D investment due to agency costs. At the same time, the latter emphasises the imperative for firms to extract resources from their surrounding environment, thus supporting the interdependence and interaction between digital transformation and organisational environments to enhance innovation efficiency.

On the one hand, firms' R&D investment involves many agency issues, which digital transformation can alleviate. Previous literature suggests that R&D investment constitutes a long-term and risky process, possibly sacrificing some firms' short-term performance, jeopardising managers' reputations (Kong et al., 2021; Ooi & Hooy, 2022; Wang et al., 2017; Yuan & Wen, 2018). This exacerbates agency conflicts between managers and shareholders (e.g., Hooy et al., 2019; Iqbal et al., 2020; O'Connor & Rafferty, 2012). Managers, responsible for the daily operation of innovation activities and disclosure of financial information (including R&D investment), hold an information advantage over shareholders, potentially leading to managers reducing high-risk R&D investments through information asymmetry (Min et al., 2020; Tian et al., 2022; Zeng et al., 2022). Digital transformation can mitigate information asymmetry between shareholders and managers, serving as a solution to internal agency conflicts (Ilvonen et al., 2018). Specifically, the role of digital transformation manifests in two aspects: first, enterprises can enhance the transparency of innovation information through digital transformation, improving the timeliness and openness of information dissemination related to R&D investment, thus mitigating shareholders' information disadvantage in managerial competition (Ferreira et al., 2019; Guo et al., 2022; Ilvonen et al., 2018; Iqbal et al., 2020). Second, enterprises can leverage new digital technologies to automate financial data processing, limiting human intervention in R&D investment (Ilvonen et al., 2018; Llopis-Albert & Rubio, 2021), ensuring the sustainability of R&D investment.

On the other hand, from the perspective of resource dependence theory, digital transformation significantly enhances the efficiency of innovation activities by reshaping internal resource sharing and the degree of environmental dependence. First, digital transformation reduces reliance on traditional and inefficient platforms through technologies such as artificial intelligence, blockchain, cloud computing and big data (Şimşek et al., 2019; Sousa-Zomer et al., 2020; Yoo et al., 2012), strengthening internal processes and improving the operational efficiency of innovation activities. Second, digital technologies facilitate interaction between firms and other participants in the innovation network, reducing the knowledge gap between firms and external social networks (Goldfarb & Tucker, 2019; Martin et al., 2020; Şimşek et al., 2019), facilitating more efficient generation of innovation outcomes. Third, as innovation strategies are complex, digital technologies can enhance decision-making efficiency in innovation activities (Guo et al., 2022; Loebbecke & Picot, 2015; Pagani & Pardo, 2017). Fourth, digital platforms and networks allow firms to establish strategic partnerships and alliances, reducing reliance on a single resource supplier (Ferreira et al., 2019; Kohli & Melville, 2018; Xia et al., 2016), enabling knowledge exchange, resource aggregation and collaborative innovation, thereby enhancing the efficiency of innovation activities (Gupta et al., 2022; Helfat & Raubitschek, 2018; Yoo et al., 2012).

In summary, we predict that digital transformation will enhance corporate innovation by increasing R&D input and improving innovation efficiency. Based on the above arguments, we propose the following hypothesis:

H1: The digital transformation of firms has a positive impact on corporate innovation.

H1a: The digital transformation of firms has a positive promoting effect on R&D input.

H1b: The digital transformation of firms has a positive promoting effect on innovation efficiency.

DATA AND RESEARCH METHODOLOGY

Sample and Data

The original sample of the study consisted of all Chinese A-share listed firms from 2012 to 2021. Financial information was acquired from the China Stock Market and Accounting Research Database, and data on digital transformation were collected from annual reports, while patent information was obtained from the

Chinese Research Data Services Database. Additionally, the data underwent the following pre-processing steps. First, financial firms were excluded because they have different governance and performance systems than non-financial Chinese firms. Second, "special treatment" firms (i.e., firms with continuous losses for two consecutive years and facing the risk of delisting) were excluded to avoid the influence of abnormal financial conditions. Third, in order to reduce the impact of missing values on the results, sample data with missing information were deleted, in consideration of data availability and accuracy. Fourth, all continuous variables were winsorised at the 1st and 99th percentiles to minimise the influence of extreme values.

Variable Measurement and Estimation Techniques

The dependent variable of this study was corporate innovation (Patent), following prior studies (e.g., Iqbal et al., 2020; Ding et al., 2022), the measure of Patent, is the natural logarithm of one plus firm's total patents applied, including invention patents, design patents and utility patents. In addition, another indicator that serves as a robustness test is Patent grant, which is the natural logarithm of one plus firm's total patents granted.

The independent variable of our focus is digital transformation (DT). Since the words and phrases in annual reports are indicative of the strategy and future direction of a firm, text analysis of annual reports can effectively reflect the strategic orientation of the firms (Kindermann et al., 2021).

Following Tu and He (2022), the paper uses a Python crawler for the construction process of the digital transformation measures to collect the annual reports of selected sample firms as follows: first, this research employed terms such as "digital transformation", "digital technology", "information technology", "big data" and "cloud computing" as seed words; second, Python's Jieba and Re modules were utilised to extract all textual content, followed by text cleansing, matching and word frequency statistics. This process involved word segmentation and the removal of stop words to create the corpus for this study; third, the Word2vec model of machine learning was employed to train on the corpus, generating word vectors and calculating similarities between words. This allowed for the identification of semantically related words to the seed words; fourth, the seed word dictionary is used to determine the frequency of keyword occurrences.

Due to the typical "right-skewed" nature of this type of data, the frequencies were then subjected to a natural logarithmic transformation with an addition of one that is, LN (keyword occurrence frequency +1), which is used to measure all Chinese A-share listed firms' degree of digital transformation.

This study controlled for a series of factors that may be related to corporate innovation. Specifically, following past studies (e.g., McGuinness et al., 2017; Yuan & Wen, 2018; Jia et al., 2019; Kong et al., 2021; Ding et al., 2022; Liu & Lv, 2022), we control for Firm Size (the book value of total assets), Firm Age (the number of years since the firm's establishment plus one), Financial Leverage (the book value of total debts divided by total assets), Return on Assets (the book value of net income divided by total assets), Sale Growth (the ratio of the operating income changed to the operating income in the last year), Board Size (the natural logarithm of the total number of directors on a firm's board), Ownership Concentration (the percentage of shares owned by the largest shareholder) and Institutional Ownership (the number of shares held by institutional investors divided by the total shares). Table 1 provides variables and measurements used in our study. The following equation is used to estimate the hypotheses:

$$\begin{aligned} Patent_{i,t} &= \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 FS_{i,t} + \alpha_3 FA_{i,t} + \alpha_4 LEV_{i,t} + \alpha_5 ROA_{i,t} \\ &+ \alpha_6 SG_{i,t} + \alpha_7 BS_{i,t} + \alpha_8 OC_{i,t} + \alpha_9 IO_{i,t} + Year + Firm + \varepsilon \end{aligned} \tag{1}$$

Where α_0 denotes the intercept; and $\alpha_1 - \alpha_9$ are the coefficients to be estimated. This study added dummy variables that control for year and firm fixed effects (Year and Firm), ε is the error term; i denotes the cross-sectional dimension for firms; and t denotes the time series dimension.

Table 1
Summary of variable description and measurement

Variable	Measurement	References
Panel A: Dependent variables		
Corporate Innovation (Patent)	The natural logarithm of one plus firm's total patents (invention, design and utility) applied.	(Iqbal et al., 2020)
Panel B: Independent variables		
Digital Transformation (DT)	The natural logarithm of the frequency of digital-related words plus one in financial annual reports.	(Tu & He, 2022)
Panel C: Control variables		
Firm Size (FS)	The book value of total assets (unit: billions of RMB).	(Ding et al., 2022)
Firm Age (FA)	The number of years since the firm's establishment.	(Liu & Lv, 2022)
Financial Leverage (LEV)	The book value of total debts divided by total assets.	(Yuan & Wen, 2018)

(*Continued on next page*)

Table 1 (*Continued*)

Variable	Measurement	References
Return on Assets (ROA)	The book value of net income divided by total assets.	(Yuan & Wen, 2018)
Sale Growth (SG)	The ratio of the operating income changed to the operating income in the last year.	(Kong et al., 2021)
Board Size (BS)	The natural logarithm of the total number of directors on a firm's board.	(McGuinness et al., 2017)
Ownership Concentration (OC)	The percentage of shares owned by the largest shareholder.	(Jia et al., 2019)
Institutional Ownership (IO)	The number of shares held by institutional investors divided by the total shares.	(Yuan & Wen, 2018)
Panel D: Other variables		
R&D intensity (R&D)	The ratio of R&D expenditure to sales.	(Sunder et al., 2017)
Innovation efficiency (IE)	The number of patents applied per unit of R&D investment	(Hirshleifer et al., 2013)
DT_dummy	A dummy variable, is defined as 1 if a firm's annual report contains words associated with digital transformation, and 0 otherwise.	(Sun et al., 2022)
Patent_grante	The natural logarithm of one plus firm's total patents granted.	(Ding et al., 2022)
Patent_hq	The natural logarithm of one plus firm's invention patents applied.	(Hu et al., 2020)
Patent_lq	The natural logarithm of one plus firm's design and utility patents applied.	(Hu et al., 2020)

Table 2
Descriptive statistics

Variables	N	Mean	Std	Min	Max
Patent	29,108	2.622	1.721	0.000	6.690
DT	29,095	1.410	1.387	0.000	5.056
FS	29,094	4.202	2.668	0.369	228.091
FA	29,094	18.320	1.384	4.998	33.016
LEV	29,094	0.412	0.204	0.050	0.893
ROA	27,239	0.041	0.063	–0.239	0.222
SG	27,234	0.169	0.390	–0.544	2.445
BS	29,053	2.120	0.197	1.609	2.708
OC	29,056	34.383	14.817	8.630	74.180
IO	29,025	44.234	25.232	0.321	94.529
R&D	29,108	0.042	0.047	0.000	0.256
IE	29,108	0.140	0.093	0	0.332
DT_dummy	29,109	0.660	0.473	0	1
Patent_grante	29,108	2.451	1.643	0.000	6.408
Patent_hq	29,108	1.845	1.519	0.000	5.974
Patent_lq	29,108	2.083	1.652	0.000	6.073

Note: this table presents the descriptive statistics of the main variables defined in Table 1 for the sample period 2012–2021.

Table 3
Pearson correlation

Variables	Patent	DT	FS	FA	LEV	ROA	SG	BS	OC	IO	VIF
Patent	1.000										–
DT	0.167***	1.000									1.04
FS	0.293***	0.032***	1.000								1.78
FA	–0.036***	0.016***	0.183***	1.000							1.06
LEV	0.081***	–0.061***	0.533***	0.178***	1.000						1.71
ROA	0.076***	0.019***	–0.003	–0.080***	–0.358***	1.000					1.35
SG	0.027***	0.043***	0.037***	–0.043***	0.021***	0.259***	1.000				1.10
BS	0.046***	–0.074***	0.274***	0.057***	0.156***	–0.003	–0.024***	1.000			1.12
OC	–0.006	–0.115***	0.186***	–0.084***	0.051***	0.127***	–0.010*	0.017***	1.000		1.39
IO	0.045***	–0.083***	0.440***	0.053***	0.208***	0.102***	0.028***	0.230***	0.485***	1.000	1.66

Note: this table shows the correlation coefficients for the main variables defined in Table 1. The lower triangle in this table shows the Pearson correlation coefficients. VIF indicates the variance inflation factor. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FINDINGS AND DISCUSSION

Descriptive Statistics and Correlation Matrix

The descriptive statistics for the main variables in our study are shown in Table 2. It shows the mean, standard deviation, minimum and maximum values of those variables. The mean and standard deviation of Patent are 2.622 and 1.721, respectively, which demonstrate that there is some difference in the measures of innovation among sample firms. The maximum (5.056), minimum (0) and mean (1.410) values of digital transformation indicate that most Chinese listed firms are in the industrialisation stage and are in low-level digital transformation.

In terms of control variables, the firms in our sample have an average firm size of 22.200, firm age of 2.908, financial leverage of 0.412, return on assets of 0.041, sale growth of 0.169, board size of 2.120, ownership concentration of 34.383, and institutional ownership of 44.234. Additionally, the average R&D intensity in the sample is 0.042, innovation efficiency is 0.140, the dummy variable of digital transformation is 0.660, the number of patents granted is 2.451, and the numbers of high-quality and low-quality patent applications are 1.845 and 2.083, respectively.

The Pearson correlation matrix of the major variables is shown in Table 3. Generally, the correlation coefficients between independent and control variables are almost less than 0.50, and this study further conducts a multicollinearity diagnostic test among the continuous variables. Each of the control variables shows a low variation inflation factor (VIF) from the test (less than 2), which indicates no serious multicollinearity issue in our model. Furthermore, Table 3 demonstrates that Patent is significantly positively correlated with most variables. Specifically, DT, FS, LEV, ROA, SG, BS and IO are all positively correlated with the number of patents. This suggests that higher levels of digital transformation, larger firm size, higher financial leverage, higher return on assets, faster sales growth, larger board size and greater institutional ownership are associated with a greater number of patents. Meanwhile, FA shows a significant negative correlation with the number of patents, while OC has an insignificant and nearly non-existent correlation with the number of patents. Nevertheless, further discussion is needed to validate the final relationship.

Univariate Analysis

Table 4 displays the results of the univariate tests for the dependent variable in this study. The mean of Patent is 2.813 for the firms having digital transformation and 2.249 for the firms without digital transformation, and the differences are both statistically significant at the 1% level. Additionally, the positively sloped linear regression line in Figure 2 indicates a positive correlation between DT and Patent. These findings imply that firms undergoing digital transformation exhibit higher levels of innovation output compared to those that do not engage in digital transformation.

Table 4
Univariate analysis

Variable	Dummy (DT) = 1		Dummy (DT) = 0		Differences *t*-value
	N	Mean	N	Mean	
Patent	19,239	2.813	9,869	2.249	0.564***

Note: This table presents the results of univariate analysis on the mean difference of the corporate innovation indicator (Patent) between firms having digital transformation and firms having no digital transformation. The *t*-values for mean differences are based on *t*-tests. ***denotes significance at the 1% level.

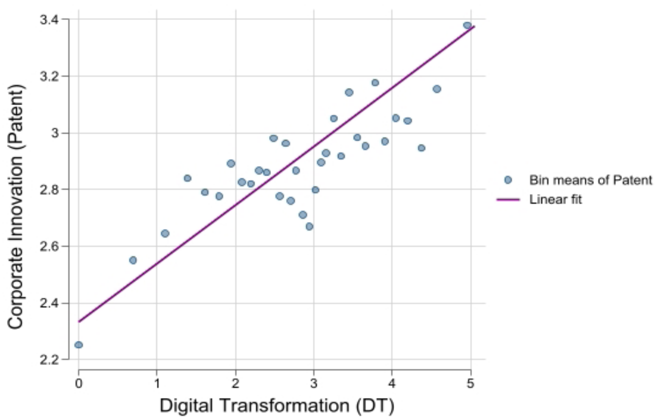

Figure 2: The linear fit of digital transformation and corporate innovation (Source: Annual Reports of Chinese Listed Firms and CNRDS Database).

Note: due to the large number of observations involved in the linear fitting of the sample, this study divides Patents into 100 equally sized groups for analysis in Figure 2

Multivariate Analysis

Table 5 tests the relationship between digital transformation (DT) and corporate innovation (Patent) to examine H1. All regression models incorporate both year and firm fixed effects to mitigate the heterogeneity of firms and the potential impact of other policies and shocks in specific years. Moreover, this study employs a robust estimation method of corrected standard errors clustered at the firm level to yield robust estimates of the test statistics.

Column (1) reports the regression results that test the DT and Patent relationship in the study. The coefficient on DT is significantly positive at the 1% significance level (α = 0.070), which indicates that the overall impact of DT on Patent is significantly positive without control variables. Next, control variables were successively added to construct columns (2) to (3), and the data analysis showed that even after including various control variables, the regression coefficient of DT on Patent remained positive and passed the significance test at the 1% level. Thus, it can be concluded that digital transformation significantly enhances corporate innovation regardless of including multiple control variables.

In terms of control variables, the coefficient for FS is significantly positive at the 1% level, indicating a positive correlation between firm size and innovation output. LEV is significantly negative, suggesting that firms with higher leverage face greater financial pressure and are able to afford fewer innovation expenses. This finding is consistent with previous research results (e.g., Hou et al., 2017; Pu & Zulkafli, 2024; Sunder et al., 2017). However, variables such as FA, AT, SG, BS, OC and IO did not have a significant impact on Patent.

Overall, our study confirms a positive relationship between the digital transformation indicators obtained through machine learning and patent output, emphasising a focus on technological innovation. While the innovation measure in this study differs from the one used by Ferreira and Teixeira (2019), who employed new product development as a measure of corporate innovation, the conclusions drawn are similar. Our findings also resonate with earlier views on the positive impact of digitalisation on corporate innovation. Specifically, the widespread use of digital technologies in enterprises can rapidly facilitate the dissemination of knowledge and information while reducing the costs associated with information search, replication, transmission, tracking and verification, thereby fostering corporate innovation (Fang et al., 2022). From a resource-based perspective, firms undergoing digital transformation tend to have higher absorptive capacities, enabling them to derive greater innovation benefits from network utilisation (Müller et al., 2021). Additionally, the application of digital technologies, such as the internet, can reduce agency costs and significantly promote R&D investment (Gherghina et al., 2021). Our evidence further supports the notion that digital transformation enhances innovation capabilities by breaking organisational boundaries and bridging information gaps.

Table 5
Multivariate results

Variable	(1)	(2)	(3)
DT	0.070***	0.027**	0.027**
	(0.01)	(0.01)	(0.01)
FS		0.477***	0.479***
		(0.03)	(0.03)
FA		–0.159	–0.135
		(0.18)	(0.18)
LEV		–0.261***	–0.258***
		(0.10)	(0.10)
ROA		0.047	0.043
		(0.15)	(0.15)
SG			0.004
			(0.02)
BS			0.100
			(0.08)
OC			0.001
			(0.00)
IO			–0.001
			(0.00)
Cons	2.536***	–7.442***	–7.805***
	(0.02)	(0.82)	(0.86)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj. R^2	0.757	0.771	0.772
N	28,577	26,731	26,620

Note: this table presents the results of the impact of digital transformation (DT) on corporate innovation (Patent). The dependent variable is Patent, the independent variable is digital transformation (DT). All regressions including year fixed effects and firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are defined in Table 1.

Robustness Tests

So far, the estimation indicates a positive relationship between digital transformation and corporate innovation. This section conducts a variety of additional tests to check the robustness of the baseline results.

1. *Alternative dependent variable*: Patent granted was introduced to serve as alternative dependent variables. Different from the previous use of applying numbers to reflect innovation, the patent granted is a description of innovation activities from the perspective of legitimacy and effectiveness (Ding et al., 2022). As shown in column (1) of Table 6, after using the alternative innovation measure of Patent_grante, the regression coefficient of DT on Patent_grante remained positive and significant at the 1% level, so the results further confirmed the robustness of the baseline regression.
2. *Alternative independent variable*: In addition to utilising the natural logarithm of the frequency of digital transformation keywords plus one in the annual reports as a proxy for digital transformation in the baseline regression, this study also adopts the measurement approach proposed by Sun et al. (2022). Specifically, this approach involves the use of a binary variable (DT_dummy) to assess whether digital transformation keywords are present in the annual reports of firms. A value of 1 indicates their presence, while 0 indicates their absence. The results in column (2) of Table 6 indicate that the coefficient of DT_dummy is positive and statistically significant at the 1% level, suggesting the robustness of the original baseline findings.
3. *Subsample regression test*: Considering that exogenous shocks from the COVID-19 period may interfere with the innovative activities of firms, to obtain a more reliable result, the study dropped the 2020 and 2021 samples. The results of DT in column (3) of Table 6 support the previous regression results.
4. *Application of Tobit method*: As not all firms in the sample have a patent record, the dependent variable is susceptible to truncation at some range. To address the issue of truncation in patent data, this study takes inspiration from the approach of Kim et al. (2017) and uses the Tobit model to rerun the baseline regression. Overall, the results from the Tobit model in column (5) of Table 6 are consistent with the conclusions from the previous main regression model.
5. *Additional fixed effects*: In order to mitigate potential issues arising from the omission of time-invariant industry, province, and city-specific characteristics, this section re-estimates Equation (1) by including industry fixed effect, province fixed effect and city fixed effect when utilising Patent as the dependent variable. The results presented in column (5) of Table 6 indicate that the estimated coefficient for the variable DT is statistically significant at the 5% level. This suggests that our research findings are not driven by these time-invariant specific features.

Table 6
The results of robustness tests

Variable	(1) DV2	(2) IV2	(3) Subsample	(4) Tobit	(5) Additional FE
	Patent_grante	Patent	Patent	Patent	Patent
DT	0.027** (0.01)		0.023* (0.01)	0.055*** (0.01)	0.026** (0.01)
DT_dummy		0.068*** (0.02)			
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes
Province FE	No	No	No	No	Yes
City FE	No	No	No	No	Yes
Adj. R^2	0.791	0.772	0.790		0.775
Log likelihood				–3,8864.131	
N	26,620	26,620	19,824	27,163	26,619

Note: this table reports the regression results using alternative innovation indicator of Patent_grante (column 1), alternative digital transformation indicator of DT_dummy (column 2), excluded subsamples from the COVID-19 period (column 3), Tobit model (column 4) and additional fixed effects (column 5). The dependent variables are Patent and Patent_grante, the independent variable are DT and DT_dummy. Robust standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are defined in Table 1.

Endogenous Treatment

Based on concerns regarding sample selection bias, managerial ability interference and the potential for reverse causality causing endogeneity, this research proceeded to address endogeneity through three specific treatments applied to the research sample.

Correcting selection bias by using Heckman two-step estimation

There is an issue of endogeneity in the dependent variable, as not all firms tend to apply for patents. The propensity to apply for patents may not be random across firms, which could lead to self-selection bias. Following the approach of Zhang et al. (2022), this section employs a Heckman two-stage selection model to address the potential sample selection bias. In the first stage, a probit model is estimated with a binary dummy variable (Dummy_Patent) as the dependent variable, which equals 1 if a firm has ever applied for a patent and 0 otherwise. The following probit model is used to estimate the probability of firms applying for patents.

$$Probit(Dummy\_Patent)_{i,t} = \alpha_0 + \alpha_1 FS_{i,t} + \alpha_2 FA_{i,t} + \alpha_3 ROA_{i,t} + \alpha_4 LEV_{i,t} + \alpha_5 SG_{i,t} + \alpha_6 BS_{i,t} + \alpha_7 OC_{i,t} + \alpha_8 IO_{i,t} + Year + Firm + \varepsilon \quad (2)$$

The calculated probability is expressed as an inverse mill's ratio, namely IMR, which is obtained from Equation (2). In the second stage, this study re-run Equation (1), but with the IMR included to mitigate heterogeneity in a firm's propensity to innovate. The results from the second stage regression are presented in column (1) of Table 7. As IMR has a significantly positive and large coefficient, this result suggests that a firm's propensity to innovate is an important determinant of its patent output. After correcting for selection bias, the estimated coefficients of DT consistently have the same signs as the previous coefficients and are still statistically significant. Therefore, potential selection bias does not ruin our main findings.

Controlling managerial ability by application of the two-stage DEA model

Managers play a crucial role in corporate innovation, and thus differences in their capabilities can significantly influence innovation outcomes (Chen et al., 2015). Specifically, managerial ability (MA) is manifested in the manager's role in transforming company resources—such as the allocation of capital, labour and other assets. Although many firms may have similar innovation decisions and R&D investments, differences in managers' control over other resources may lead to varying innovation outputs. Therefore, MA may be considered as a potentially omitted driving factor.

To address the variations in MA among our sample firms, following Yuan and Wen (2018), we adopt a two-step procedure developed by Demerjian et al. (2012) to estimate managerial ability. In the first step, we employ Data Envelopment Analysis (DEA) to assess the relative corporate efficiency of peer decision-making units. The overall efficiency of a firm depends on the resources utilised by the company, including the contributions of both the firm and the managers. In the second step, we separate managerial contributions from corporate efficiency by running a Tobit regression model, controlling for firm-specific factors (such as size, free cash flow, competition and age) within industries to obtain the residuals of the Tobit model. This measure has been widely applied in accounting, finance and management research (e.g., Wang et al., 2017; Yuan & Wen, 2018).

In Equation (1), we introduce MA as a new control variable and conduct regression analysis. The results in column (2) of Table 7 indicate a significant negative impact of MA on innovation output, suggesting that excessive managerial control over resources indeed hampers firms' innovation output. However, the sign and significance level of the DT coefficient remains consistent with our previous findings, indicating that MA is unlikely to drive our research results.

Generalised Method of Moments Estimation

In the benchmark regressions, the paper has controlled for a range of factors affecting the corporate innovation of firms, as well as firm and time-fixed effects. However, in addition to omitted variables, the issue of endogeneity arising from two-way causality may also lead to biased regression results. The Generalised Method of Moments (GMM) approach is well-suited to mitigate reverse causality and omitted variable bias (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009). Therefore, this section employs the two-step system GMM estimation approach to alleviate distortions caused by endogeneity issues arising from reverse causality and omitted variables that might affect the relationship between digital transformation and corporate innovation.

Column (3) of Table 7 displays the two-step system GMM regression findings of regressing DT on Patent. After passing the Arellano-Bond test and the Hansen test of overid, the coefficient of DT is significantly positive at the 5% level, which suggests that the regression findings are still robust.

Table 7
The results of endogenous treatment

Variable	Patent		
	(1) Heckman	(2) MA	(3) GMM
DT	0.028** (0.01)	0.028** (0.01)	0.089** (0.04)
IMR	1.509*** (0.30)		
MA		-0.884*** (0.11)	
L.Patent			0.350*** (0.03)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj. R^2	0.773	0.771	

(*Continued on next page*)

Table 7 (*Continued*)

Variable	Patent		
	(1) Heckman	(2) MA	(3) GMM
No. of firms			3,829
No. of instruments			27
AR1 *p*-value			0.000
AR2 *p*-value			0.281
Hansen *p*-value			0.116
N	26,620	25,049	24,470

Note: This table reports the regression results using Heckman two-step selection model (column 1), controlling managerial ability through a two-step DEA model (column 2) and dynamic two-step system GMM estimation (column 3). The dependent variable is Patent, the independent variable is digital transformation (DT). Robust standard errors [clustered at the firm level] are reported in parentheses (3) [column (1) and column (2)]. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are defined in Table 1.

Mechanism Analysis

As discussed in the hypothesis development section, sustained R&D investment and efficient innovation processes imply that firms can effectively utilise resources such as capital, manpower and time to drive innovation output. Clearly, the enhancement of R&D input and innovation efficiency are two crucial aspects driving innovation output for firms. As firms transition into a digitalised, dynamic environment, shareholders gain access to more information, crucially mitigating the information disadvantage they face in competing with executives, which is vital for reducing agency costs during the R&D process (Gong & Ribière, 2021; Sun et al., 2022). Simultaneously, adopting efficient digital processes can reshape internal resource sharing and the level of environmental dependency within firms, thereby improving the efficiency of innovation output. To ascertain whether digital transformation contributes to corporate innovation through increased R&D input (input channel) and enhanced innovation efficiency (efficiency channel), we examine the impact of digital transformation on R&D investment and innovation efficiency.

We employ two measures proposed in the innovation literature to capture the pathways of firms' innovation activities (e.g., Campbell et al., 2006; Hirshleifer et al., 2013; Sunder et al., 2017; Yuan & Wen, 2018). The first measure is R&D intensity, calculated as R&D expenditure divided by sales, with missing values set to zero. The second measure is innovation efficiency, calculated as the number of patents applied per unit of R&D investment.

As shown in Table 8, column (1) represents R&D intensity, while column (2) represents innovation efficiency. The estimated coefficients for DT in both columns are positive and statistically significant at the 1% or 10% levels, confirming the potential impact of digital transformation on the input and efficiency channels affecting corporate innovation. Thus, hypotheses H1a and H1b are supported.

Table 8
The results of mechanism analysis

Variable	Input channel	Efficiency channel
	(1) R&D	(2) IE
DT	0.001*** (0.00)	0.001* (0.00)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj. R^2	0.851	0.742
N	26,620	26,620

Note: This table reports the regression results of mechanism analysis. The dependent variable included R&D and IE; the independent variable is digital transformation (DT). All regression including year fixed effects and firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are defined in Table 1.

Further Analysis

To further elucidate the differential impacts of digital transformation on corporate innovation, this study further disaggregates corporate innovation into high-quality innovation and low-quality innovation, and conducts cross-sectional tests based on property rights and the technological characteristics of industry.

High-quality innovation vs. low-quality innovation

For a long time, despite significant progress made by Chinese listed firms in areas such as technological R&D, product innovation, and business model innovation, there remains room for improvement compared to international benchmarks (Liu & Lv, 2022). Some firms may lean towards low-quality imitation and incremental improvements, lacking the capacity to enhance innovation quality truly. This is evidenced by the low quality of patents filed by numerous enterprises, leading to a patent bubble (Hu et al., 2020). Particularly in the context of digital transformation, firms may be incentivized by the market to submit a large number of low-quality patent applications to showcase their innovative activities, yet many of these patents may lack substance and serve merely to boost quantity rather than drive genuine innovation (Cao et al., 2024). High-quality innovation typically yields patents of substantive and enduring value, while low-quality innovation may contribute to the inflation of the patent bubble (Li, 2012). Therefore, examining the impact of digital transformation on high-quality and low-quality innovation from the perspective of patent quality can provide a more comprehensive assessment of the actual influence of digital transformation on corporate innovation.

Considering that the measurement indicators for corporate innovation encompass three distinct categories of patents; invention patents in China must meet the requirements of "novelty, inventiveness and practicality" to be approved. In contrast, utility or design patents only require the absence of similar previous applications. Therefore, invention patents exhibit the highest level of novelty and technological content. In this study, to further investigate the differential impact of digital transformation on high-quality and low-quality innovation, following the approach of Hu et al. (2020), the paper treats the application for invention patents as a proxy for high-quality innovation outcomes (Patent_hq), while applications for utility and design patents serve as a proxy for low-quality innovation outcomes (Patent_lq).

The analysis results for innovation quality are presented in Table 9. In the first column (Patent_hq) and the second column (Patent_lq), DT exhibits statistically significant positive effects in the first column (coefficient = 0.046; p-value < 0.01), but not in the second column. This suggests that digital transformation not only contributes to enhancing high-quality innovation outcomes but also alleviates concerns regarding the emergence of low-quality innovation bubbles.

Table 9
The results of further analysis

Variable	High quality	Low quality	SOEs	Non-SOEs	High-Tech	Non-High-Tech
	(1) Patent_hq	(2) Patent_lq	(3) Patent	(4) Patent	(5) Patent	(6) Patent
DT	0.046*** (0.01)	0.013 (0.01)	0.044** (0.02)	0.017 (0.01)	0.006 (0.01)	0.084*** (0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	26,620	26,620	9,503	17,034	17,334	9,241
N	0.761	0.746	0.826	0.735	0.753	0.752

Note: This table reports the regression results of further analysis. The dependent variable included Patent, Patent_hq and Patent_lq, the independent variable is digital transformation (DT). All regression including year fixed effects and firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are defined in Table 1.

State-owned enterprises vs. non-state-owned enterprises

Due to variations in property rights among firms, the impact of firms' digital transformation on innovation may vary. Indeed, many state-owned enterprises in emerging economies are intricately linked to the bureaucratic system, maintaining close ties with politicians, businessmen and government officials (Mansha et al., 2022; Tee et al., 2022; Wong & Hooy, 2018; 2024). Due to these political connection, state-owned enterprises often gain access to greater resources for digital infrastructure development, and governments may implement policies to facilitate the implementation of digital transformation within these entities (Liu et al., 2024). This political support and resource advantage empower state-owned enterprises to drive digital transformation and play a pivotal role in innovation activities.

In contrast, non-state-owned enterprises may face constraints due to financial limitations, which may restrict their investments and efforts in digital transformation. These enterprises may rely more heavily on their own profitability to support the process of digital transformation (Li & Xia, 2008), potentially impacting the effectiveness of their innovation activities. Additionally, non-state-owned enterprises may encounter pressures from market competition, leading them to prioritise short-term profits and survival over long-term investments and innovation (Sun et al., 2022). Consequently, compared to state-owned enterprises, non-state-owned enterprises may encounter greater challenges in driving digital transformation.

To test this hypothesis, this study conducted sub-sample analyses on state-owned enterprises and non-state-owned enterprises separately in columns (3) and (4), as shown in Table 9. The results indicate that the coefficient of digital transformation for state-owned enterprises is statistically significant at the 1% level, while the coefficient for non-state-owned enterprises is not significant. Thus, the impact of digital transformation on corporate innovation is more pronounced in state-owned enterprises.

High-tech industry vs. non-high-tech industry

With the continuous development and widespread adoption of digital technology, an increasing number of enterprises are accelerating their pace of digital transformation. In China, firms increasingly leverage advanced technologies such as artificial intelligence, big data analytics, cloud computing and blockchain to expedite product development cycles and enhance product quality, thereby boosting innovation levels (Peng & Tao, 2022). Indeed, firms in high-tech industries possess higher innovation capabilities, largely relying on knowledge innovation and intellectual capital (Wang & Du, 2022). These firms often adopt asset-light strategies, prioritising intangible assets and their relatively fixed business models are less susceptible to influence from digital technologies (Yoo et al., 2010). Conversely, firms in non-high-tech industries with higher fixed asset ratios are more likely to benefit from digital transformation, improving production processes, enhancing research and development efficiency, and driving collaboration along the upstream and downstream of the industry chain (Wang & Du, 2022). Therefore, this study anticipates a stronger positive impact of digital transformation on innovation among firms in non-high-tech industries.

Columns (5) and (6) of Table 9 reveal the disparity in the impact of digital transformation on innovation between high-tech and non-high-tech industries. Specifically, the promotion effect of digital transformation on innovation is only significant and positive in firms of non-high-tech industries. This finding suggests that the relationship between digital transformation and corporate innovation exhibits pronounced heterogeneity based on the technological characteristics of industry.

CONCLUSION AND IMPLICATION

Using panel data of Chinese listed firms from 2012 to 2021, this study uses machine learning methods to construct a measure of digital transformation and discusses the influence of digital transformation on corporate innovation, along with the underlying mechanisms and heterogeneous impact factors. The main conclusions are as follows:

1. Digital transformation facilitates corporate innovation. This conclusion is robust, validated through five rigorous tests (substitution of dependent variable, substitution of independent variable, subsample regression test, Tobit model and additional fixed effects test) and three endogeneity treatments (Heckman two-stage model, controlling managerial ability using a two-stage DEA model and two-step system GMM estimator).
2. Digital transformation significantly promotes corporate innovation by increasing R&D investment and enhancing innovation efficiency.
3. This facilitative effect is particularly pronounced in the context of high-quality innovation output, with a more significant impact observed in state-owned enterprises and non-high-tech industry enterprises.

Our findings have some important contributions as follows: first, this study utilises text mining techniques of machine learning and combines them with information extracted from annual reports to construct a comprehensive digital transformation indicator for companies.

This indicator serves as a valuable reference for evaluating the extent of a firm's digital transformation and assessing its innovation outcomes. Second, there is limited literature addressing the overall impact of digital transformation on innovation activities (input, output and efficiency). By focusing on patent output and examining the dynamic changes in input and efficiency, we contribute to enriching the literature on the multifaceted effects of digital transformation on innovation. Third, our study supplements the evidence of digital transformation alleviating information asymmetry (R&D investment). Moreover, in enhancing the efficiency of innovation activities, our findings align with the previously emphasised perspective of resource dependence (e.g., Han-Song & Tian, 2022; Loonam et al., 2018; Peng & Tao, 2022; Sun et al., 2022), affirming digital transformation as a nexus of interdependence and interaction between firms and digital technologies. These insights not only deepen our understanding of the economic effects and mechanisms of digital transformation but also enrich theoretical research on factors influencing corporate innovation. Fourth, this study examines the heterogeneous effects of digital transformation on corporate innovation based on the characteristics of innovation quality, property rights and technological characteristics of the industry, providing a deeper and more comprehensive understanding of the economic benefits of corporate digital transformation and informing the development of differentiated policies.

Based on the above analysis, the government should consider implementing targeted policies. First, the government should strengthen the construction of digital technology infrastructure to support enterprises' digital transformation. Second, it is crucial to develop policies that aim to reduce the financial burden of digitalisation on non-state-owned and high-tech industry enterprises. Third, regulatory mechanisms for knowledge protection should be enhanced to facilitate the flow of innovation elements. Additionally, managers, especially those in non-state-owned and high-tech industries, should fully recognise the role of digital transformation in driving innovation within firms, thereby narrowing the innovation gap with industry leaders.

While our results highlight how digital transformation of firms contribute to innovation success, this study still has a few limitations. First, it only relies on the overall frequency of digital transformation to measure the degree of digital transformation. For comparative analysis, future studies could consider dividing digital transformation into more specific subdomains (such as artificial intelligence, blockchain, cloud computing and big data). Second, the sample of this study is limited to Chinese listed companies. In future studies, there is potential for greater insight into the impact of digital transformation on innovation by incorporating other transitioning economies into the sample.

ACKNOWLEDGEMENTS

The authors would like to acknowledge Universiti Sains Malaysia for GOT Incentive R502-KR-GOT001-000823021-K134.

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