From non-digital to digital: Digitalization of technological innovation and firms' digital transformation performance

Cheng Zhou[a*], Qian Chang[b]
[a] Business and Tourism School, Sichuan Agricultural University, 288, Dujiangyan Jianshe Road, Chengdu, 611,830, China
[b]College of Management, Sichuan Agricultural University, 211, Huimin Road, Chengdu, 611,130, China
* Corresponding author: Cheng Zhou(zhoucheng1017@163.com)

Abstract: In the new wave of technological revolution, information technology is currently the most innovative areas around the world. Technological innovation is increasingly focused on digitalization. However, little research has attempted to investigate method to measure the digitalization of technological innovation and its impact. Based on longitudinal multiple data sources, including comprising patent documents, annual reports of listed Chinese manufacturing firms, a third-party database. We introduce a novel construct, namely digital technology proximity, to capture how firms digitize their technological innovation based on social network. Meanwhile, we consider firms' digital transformation performance, measured by the proportion of digital-related revenue, as the impact of digitalization of technological innovation. Our unbalanced-panel regression and robustness tests reveal a positive link between digitalization of technological innovation and firms' digital transformation performance, supporting the notion that technological innovation digitalization empowers firms' digital transformation. In addition, digital innovation ability exerts a significant mediating effect for digitalization of technological innovation. This research introduces a new method of measuring the digitalization of technological innovation and its impact on digital transformation.

Keywords: Digitalization of technological innovation; Digital technology proximity; Digital transformation performance; Digital innovation ability; Social network

1. Introduction

With the dawn of the digital economy era, digital technology permeates and restructures industrial models and business strategies for economic and social activities by expanding in scope and depth worldwide (Petersen et al., 2022). Many companies use digital technology to promote efficient resource allocation; in other ways, digital technology is expected to reduce their transaction costs by decreasing information uncertainty. Today, firms increasingly rely on data and digital technology beyond its ancillary role in the firms' business activities, and digital technology presents strategic value over time. From the perspective of industry, the R&D and application of digital technology have changed the traditional industry model, improved production efficiency, and injected new vitality into economic development. The digitalization of technology is powerful because it not only enables industrial upgrading but also promotes industrial digital transformation. On one hand, it is widely acknowledged that digital technology has the capacity to revolutionize firms' ability to transfer and restructure both external and internal knowledge. On the other hand, the ongoing advancement of digital technology has minimized the cost of entry for businesses to join trade, encouraging the integration of various industries across borders. (Jain Kashiramka, & Jain, 2019; Rangan & Sengul, 2009) and then enhancing competitive advantage (Pavlou & El Sawy, 2010; Weinman & Euchner, 2015). Accordingly, the conventional claim that "digital technology empowers digital transformation" has been widely accepted (Nambisan, Wright, & Feldman, 2019), especially for the manufacturing industry.

To date, digital transformation is becoming a worldwide topical issue, and it refers to leverage various digital technologies to enable major business improvements (Ciarli et al., 2021; Verhoef et al., 2021; Zhai, Yang, & Chan, 2022). Accordingly, innovation of digital technology plays a fundamental role in achieving digital transformation success (Hess et al., 2016; Si et al., 2022). In fact, technological innovation is a long-term (Al-Emran & Griffy-Brown, 2023), organizations may not consider digitize their innovation process in the outset. With the arrival of digital era, digitalization attracts more and more attention across society. It is noting that the terms “digitization” and “digitalization” are often used synonymously but they have distinct meanings. Digitization refers to shifting from analog data to a binary/digital format (Tilson, Lyytinen, & Sørensen, 2010). Digitalization refers to a socio-technical change, where digitized knowledge is applied to alter processes, social practices, etc. (Parviainen et al., 2017; Legner et al., 2017). In this study, we build our argument is on digitalization. Existing literature also indicates that digitalization has the potential to bolster entrepreneurial activity, as well as generate economic and social benefits at various aspects (Burtch Carnahan, & Greenwood, 2018; Nambisan, Wright, & Feldman, 2019). Drawing on this background, digitalization of technological innovation is also gaining increasing attention from organizations. In this study, digitalization of technological innovation refers to the technological innovation changes from non-digital relevance to digital-related, which is an intricate and dynamic process that enhances knowledge related to digital technology contained in the outcomes of technological innovation. Analyzing here, two concepts are needed to distinguish, namely digitalization of technological innovation and digital innovation. this study summarizes the differences among the two concepts in Table 1. From these summaries, we can conclude that the purpose of technological innovation digitalization is to achieve digital innovation. Due to digitalization is not an immediate process and has critical implications at the corporate, national, and even societal levels, it is crucial to understand the process of digitalization and its impact. Thus, the following three research questions are this study focus:

RQ1. How to measure digitalization of technological innovation?

RQ2. Whether such digitalization can enhance firms’ digital transformation *performance?*

RQ3. What is the potentially impact mechanism of the impact?

Table 1. Comparison of digitalization of technological innovation and digital innovation

	Definition	Status	Focus
Digitalization of technological innovation	The change or creation of technological innovation from non-digital to digital relevance (this study)	Dynamic	Process-oriented of changing or creating from non-digital technology to digital technology
Digital innovation	The use of various digital technologies to create new products or services, or to transform existing business models (Cheng and Wang, 2022)	Static	Application-oriented of digital technology

To address the above questions, we construct a research model (see Figure 1): First, to measure the digitalization of technological innovation, on the basis of economic complexity (Guevara et al., 2016; Rahmati, Tafti, & Hidalgo, 2021) and the interplay between the digitalization of technological innovation and digital innovation, this study proposes a novel construct, namely digital technology proximity (DTP), to measure it based on social network theory. The DTP is relatedness-based, as it symbolled by the distance between non-digital and digital within a technological innovation network. In detail of DTP's quantization, we build a network of various technological fields from patents perspective. The International Patent Classification (IPC), which is recognized as a valid means of identifying various technological innovation fields (Sasaki and Sakata, 2021; Singh, Sharma, & Dhir, 2021), is employed in our approach. We connect two IPC codes when a patent document is in both, showing the expectation that a firm wants to operate in these technological innovation fields. Then, this innovation network is utilized to measure the level of digitalization of technological innovation. DTP enables us to shift our focus towards changes of technological innovation, rather than simple application of information technology (IT). Second, keywords or phases about digital transformation are widely used to measure the degree of digital transformation at firm level (Zhuo & Chen, 2023). This approach may unable to effectively reflect a firm’s digital transformation performance, because the keywords mainly represent the firm’s vision for digital transformation, and there is a possibility that the firm might not take actual actions toward it. That is, there is a “behavior-intention gap” (Hofeditz et al., 2107). Prior literature has indicated that the creation of new products is one of typical outcomes of digital transformation (Bertani, Raberto, & Teglio, 2020). In line with this, product development is another aspect to measure digital transformation performance. In this study, we propose digital revenue, calculated by the ratio of digital-related revenue/total revenue, as an indicator to evaluate firms’ digital transformation performance. Third, drawing on the affordance theory, we apply digital innovation ability as mediator to reveal the latent mechanisms of the effect digitalization of technological innovation on firms’ digital transformation performance.

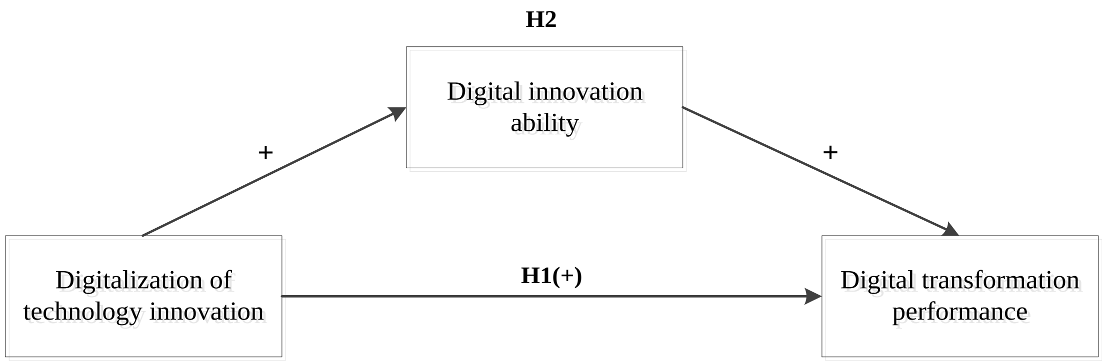


Figure 1. Research model

This study makes several contributions. First, we propose DTP as a theoretical construct of the dynamic process of digitalization of technological innovation and introduce its measurement to shed new light on digital innovation. Second, from the industry level, we introduce digital revenue as a new indicator of digital transformation performance and examine its relationship with DTP, providing valuable recommendations for firms to understand the crucial role of digitalization of technological innovation in fostering firms' digital transformation performance. Third, extending the line of literature on the affordance theory, we explore the underlying mechanisms of the relationship between digitalization of technological innovation and firms' digital transformation performance through digital innovation ability.

2. Theoretical background and hypotheses development

2.1 Digitalization of technological innovation and digital transformation

Digitalization of technological innovation can be described as the innovation process of changing from non-digital to digital. While DT has been defined as the process of using digital technology to fundamentally change how organizations operate value-creation, it is more than just the implementation of digital technology; it involves changing organizational culture, processes, and strategies to embrace digital innovation fully (Majchrzak et al., 2016; Zhai et al., 2022). They are closely related concepts: digitalization of technological innovation can be considered as the driver of digital transformation, while digital transformation creates a platform for continuous technological innovation digitalization.

With the advent of digital technologies, the digitalization of traditional innovation is an inevitable movement forward (Mühleisen, 2018). For example, Njihia and Merali (2013) suggested that the flow of resources among firms can be promoted by the development of digital innovation. Goldfarb and Tucker (2019) revealed that digital innovation in firms can reduce search costs, transportation costs, tracking costs, and so on. In Li's (2020) business model framework, he pinpointed that firms use digital innovation to build and maintain relations with customers. Thus, the more developed and applied the digital technology, the more likely it is to accelerate the speed and efficiency of digital transformation.

2.2 Digitalization of technological innovation and digital transformation performance

As products and services become more sophisticated, firms require more professional technologies to support their development. Firms may be organized as coordinated networks of technologies to develop sophisticated products and services. Previous research has also posited that digitalization of technological innovation improves the production of products and services, as well as the creation of new products and services (Alcacer et al., 2016; Hinings et al., 2018). Thus, digitalization of technological innovation enhances and intensifies the complexity of business processes.

The literature based on resource theory suggests that the ability of a firm's competitors to access digital resources with a network of related industries can be hindered due to social complexity (Teece et al., 1997; Wade & Hulland, 2004). Digitalization of technological innovation enhances firms' digital transformation performance in three ways: It enables the establishment of digital platforms and ecosystems, expands firms' innovation boundaries, and creates new business opportunities. For example, automobile manufacturers develop application platforms that enable access to the digital components integrated within cars. As a result, the manufacturers can derive benefits from the innovation by integrating digital components into their products. Thus, firms can leverage resources from other innovation fields that are seemingly unrelated to their original innovation processes. Based on the theoretical arguments above, we expect that digitalization of technological innovation enables digital transformation performance and posit the following:

H1: *Digitalization of technological innovation is positively related to firms'* *digital transformation performance.*

2.3 Mechanisms of digital innovation ability

The affordance theory serves as a theoretical foundation for exploring the effectiveness of capturing value through innovating actors (Nambisan et al., 2017). Accordingly, technology affordance refers to the potential actions that individuals or organizations with a particular purpose can undertake with a technology (Liu et al., 2023). Such affordance highlights the importance of digital innovation in generating value for firms (Nambisan et al., 2017). Hence, the affordance theory is appropriate for investigating how and why the digitalization of technological innovation can lead to different consequences.

The ability at which innovation occurs is a crucial underlying mechanism for capturing value from the digitalization of technological innovation (Yoo et al., 2012). Innovation ability refers to the capacity of individuals or organizations to generate new ideas, products, or processes that provide value and contribute to positive change (Kessler and Chakrabarti, 1996). Similarly, at firm level, digital innovation ability can be defined as the capacity of firms to harness and leverage digital technologies to drive innovation and create value. Previous research has highlighted the significance of innovation ability in firms' performance (Liu et al., 2023).

We argue that digitalization of technological innovation influences firms' digital innovation ability in two ways. First, digital innovation's convergence emphasizes the integration of separate parts in the firms internal (Nambisan et al., 2017). Drawing on this, firms can digitize their technological innovation to bring previously separate parts, which not only bring novel ideas to the firms but also enhance the firms' capabilities to adapt to rapid changes. For example, Volvo Cars launches a digital platform to collaborate with Spotify's music service and Pandora radio (Svahn et al., 2017). Second, digital innovation's generative implies that innovation is i malleable and provides an insight into existing inventions how to induce the future inventions (Ahuja et al., 2013). Following this logic, digitalization of technological innovation enables firms to move toward digital-related products and services. Such shift allows the firms to adapt to changes quickly. Taken together, we propose that:

H2: *Digital innovation ability exerts a mediating effect on the relationship between digitalization of technological innovation and firms' digital transformation performance; that is, digitalization of technological innovation increases firms' digital innovation ability, and in turn enhances firms' digital transformation performance.*

3. Methodology

3.1 Research setting and data collection

In recent years, digital transformation has been widely focused in manufacturing industry. For example, in Germany, manufacturing digital transformation is called "Industrie 4.0" (Kagermann et al., 2013), and "industrial internet" describes a similar transformation in the United States (Vogelsang et al., 2018); in China, the term "Made-in-China 2025" is common (Li, 2018). Increasing digitalization shapes actual and future value-creation processes, enabling business improvements and leading to fundamental changes in manufacturing (Liere-Netheler et al., 2018). Today, more and more manufacturing firms are recognizing the need to define digital transformation strategies in their operations. As mentioned above, digital transformation is about digital technology that reconstructs the way of doing business processes massively. Consequently, the integration and application of digital technology is erasing the boundaries between manufacturing firms (Lucke et al. (2008). Many terms, such as the "second machine age," have been coined to depict the substantial impact of digital technology on the manufacturing industry (Brynjolfsson & McAfee, 2014). Much of the literature has reported that advanced digital technology is a key element of digital transformation (Jones, Hutcheson & Camba, 2021). With the deep digitalization of traditional technology, manufacturing firms have gradually built a strategic vision for digital technology through their digital transformation. In summary, manufacturing digital transformation starts with the adoption and implementation of digital technology, followed by radical internal and external changes (Zhang et al., 2021).

To construct our data sample, listed Chinese manufacturing firms on the Shanghai and Shenzhen A-share exchanges from 2012 to 2021 are selected as the research object. We conducted this selection for three reasons: (1) China is currently experiencing a crucial period of upgrading, making it crucial to study the digitalization of technological innovation of manufacturing firms (Zhang et al., 2021). (2) As early as 2012, the Chinese government prioritized digital technology and launched a series of policies to empower the digital transformation of manufacturing industry (Zhang et al., 2021). (3) As digital transformation is a long-term process, firms listed on Shanghai A-share exchanges for at least two years are the focal sample. Drawing on these reasons, we collected data from 2012 to 2021, consisting of 12,701 observations.

For this study, the empirical data are retrieved from two main sources. First, to measure DTP (independent variable), we use a 4-digit level of IPC codes for patent documents (in total of 349,722 documents) collected from the China National Intellectual Property Administration (CNIPA) of listed Chinese manufacturing firms from 2012 to 2021. Second, the data of dependent, meditator and control variables come mainly from the Market Accounting Research (CSMAR) database, a popular firm database in China (Chen et al., 2018).

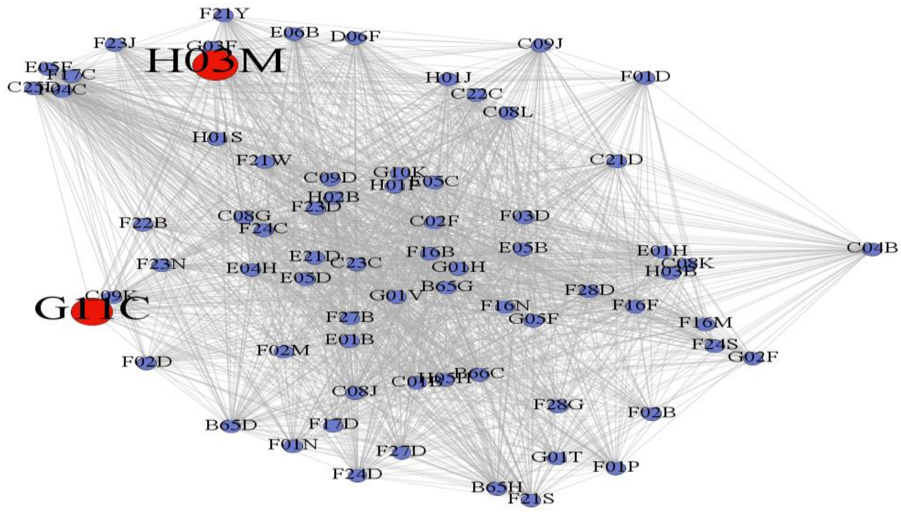
3.2 Technology space network

A technology space network is established to measure digitalization of technological innovation at firm and year level. First, we classified the IPC codes (a total of 492 codes) into two groups: digital and non-digital technologies. Previous research has indicated that digital technologies were closely related to IT (Ciarli et al., 2021); thus, we defined IPC codes associated with IT as digital technological fields, including G06F, G06K, G06N, G06Q, G06T, H03H, H03M, H04L, G011B, G11C, and the other codes as non-digital technological fields. For example, H03H is described as “impedance networks by using digital technologies”, GO6F refers to electric digital data processing; thus, it is appropriate to be used to determine a patent whether belong to digital technology innovation or not.

Second, a criterion is used to present a visualization of the technology space network: a link between two IPC codes if at least one patent document reports them both. Following this criterion, Figures 2–4 present visualizations (Gephi is used) of the technology space network. We used three accumulated time window (2012–2014 as time window 1, 2012–2017 as time window 2, and 2012–2021 as time window 3) to understand the details and changes of technology space metwork well. As the figures show, manufacturing firms gradually attach importance to digital technologies because more and more digital IPC codes appear in the technology space network over time. Meanwhile, the nodes of the digital IPC are getting closer to the center positions of the technology space network. In addition, non-digital technologies are becoming closer to digital technologies (the edges between digital IPC and non-digital IPC are increasing). Therefore, the technology space network models the complementarities between digital and non-digital technologies.

Third, drawing on the built technology space network, this study novelty proposes DTP to measure digitalization of technological innovation. Prior research on economic complexity has attempted to represent the ability of a firm’s technological structure to develop diverse products (Hartmann et al., 2017; Hidalgo & Hausmann, 2009). To develop various products and services, a firm needs a productively functioning network to enable its operations, such as technological infrastructure and coordinating processes smoothly (Hartmann et al., 2017; Hidalgo, 2015). In this study, DTP is position-based of firms in a technology space network, highlighting the potential positive impact that digital connectivity can have on a firm digital development. This definition is in line with previous literature showing that geographic proximity is closely associated with business relatedness between firms. Accordingly, DTP allows firms to access markets, resources, and knowledge that may be geographically distant. This expands opportunities for innovation, trade, and collaboration, which in turn can contribute to economic complexity. Firms apply digital innovation by coordinating multiple positions in the network. In practice, to achieve a higher level of digitalization, a firm may require complex social structures (e.g., business processes and managerial structures) to address the challenges caused by the complexities of digitalization (Rahmati et al., 2021). Drawing on economic complexity, this study considers DTP to be innovative owing to the following characteristics: (1) it is built on the outcome-based construct, which captures a firm's technological innovation investment and capability; (2) it is a network-based construct, capturing a firm's technological innovation position toward digitalization in a work, meanwhile, revealing the dynamic effects of other firms' technological innovation digitalization on the focal firm; (3) DTP displays firms' actual levels of the digitalization of technological innovation, which other measures such as IT intensity (Mittal & Nault, 2009) do not capture. Thus, based on these characteristics, DTP helps investigate the digitalization of technological innovation and complements other extant constructs.

To sum up, for a firm, collective knowledge in a network is specific; therefore, high DTP means high social complexity. Complex digital innovation resources and capabilities indicate that the current level of firms' proximity to digital innovation in the innovation network space results from specific paths. Firms that grow in DTP have built a combination of digital innovation capabilities, and they can identity and leverage new business progress through this combination.



Note: Nodes (in black and bigger) are digital technologies; visualized using a Force Altas algorithm.

Figure 2. Technology space network for the time window 2012–2014

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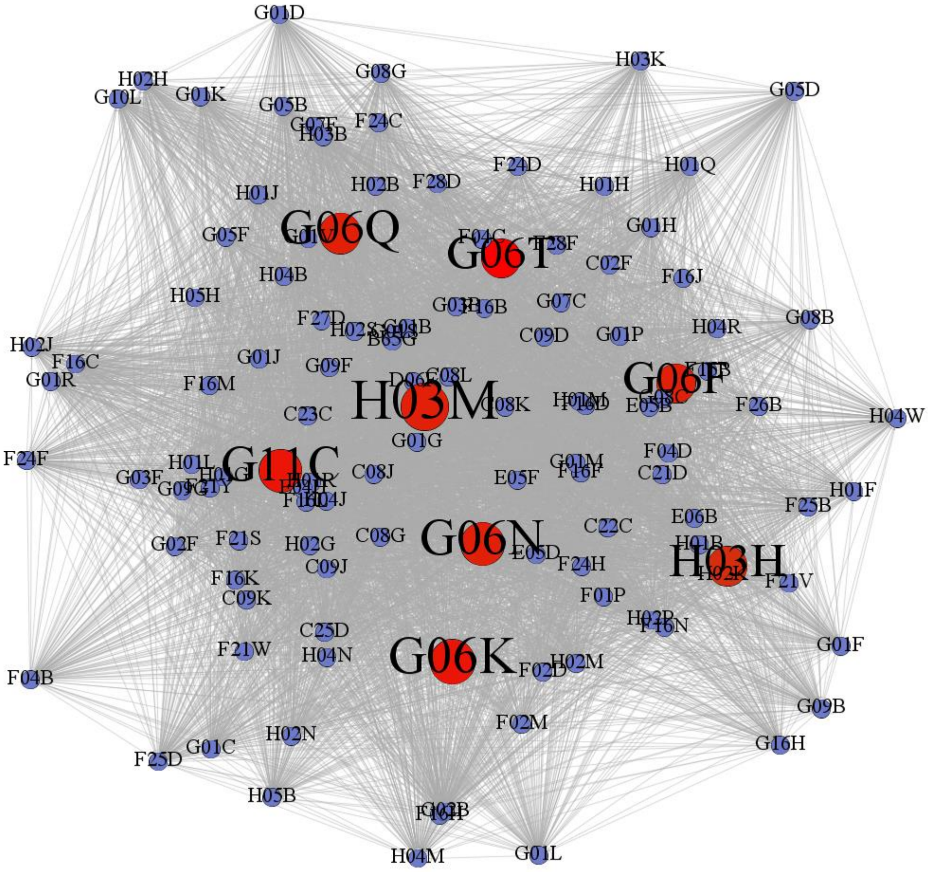

Figure 3. Technology space network for the time window 2012–2017

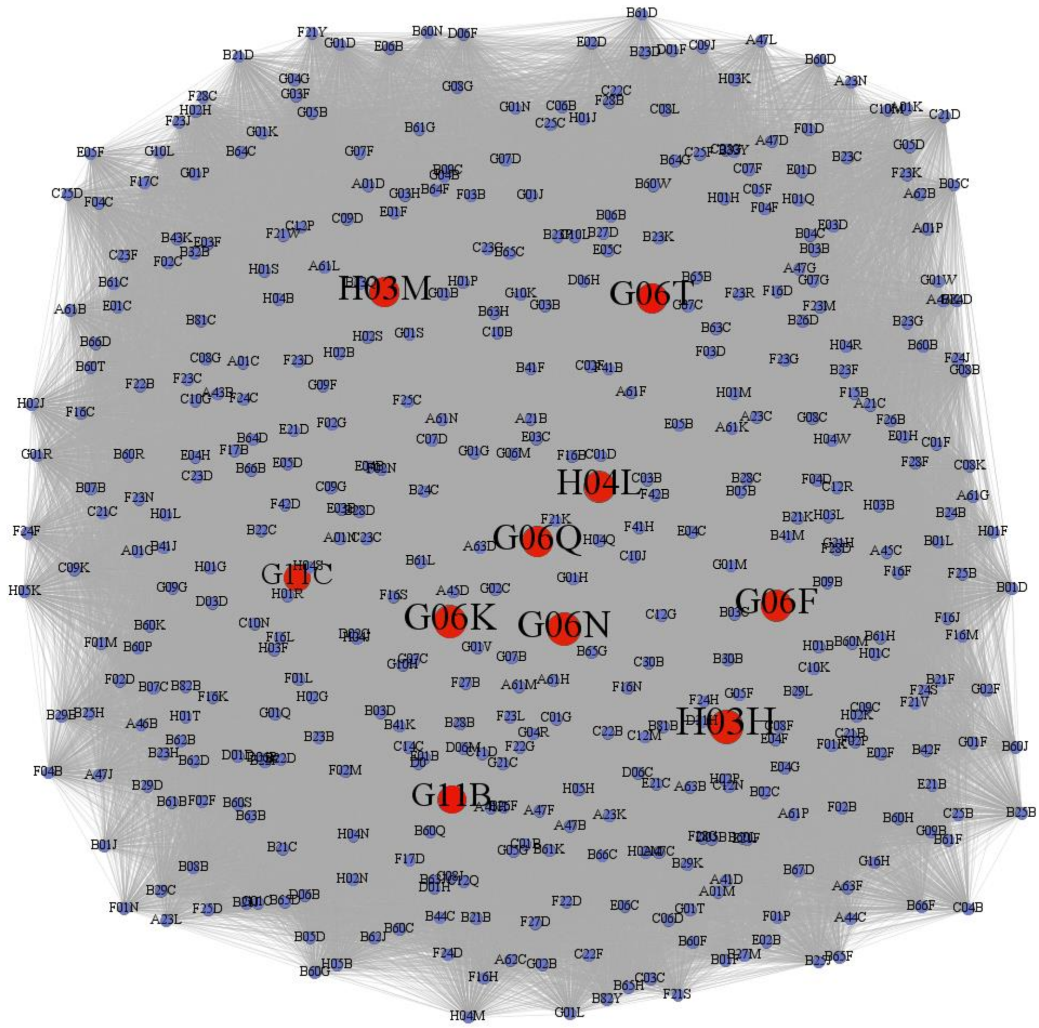

Figure 4. Technology space network for the time window 2012–2021

3.3 Measurement

Dependent variable: *Digital transformation performance* (*Performance*), we measure this variable by the ratio of digital revenue to total revenue in year t. The CSMAR divides the revenue of the listed firms into 19 primary industries and 90 secondary industries. According to Rahmati et al. (2021), we classify four industries related to digital economy from the secondary industries, including software and information technology industry, Internet and related industry, computer and communication industry, telecommunications and electronic industry. Thus, the

Performance is calculated as follows:

$$Performance_{i,t} = \frac{\sum Digital\_revenue_{i,t}}{Total\ \ revenue_{i.t}} \quad (1)$$

where $Performance_{i,t}$ denotes the digital transformation performance of firm i in year t, $\sum Digital\ \ revenue_{i,t}$ denotes the sum digital revenue of firm i in year t.

Independent variable: *Digital technology proximity* (*DTP*). As the discussion above shows, the technology space network shows specific relations between digital technologies and non-digital technologies, suggesting manufacturing enterprises' opportunities for digitizing traditional technology. To capture this position, the average shortest paths based on Dijkstra's algorithm, from one IPC code to digital IPC codes, are calculated. In practice, a patent document may report multiple IPC codes, and the first IPC code is usually considered the focal code that reports the technological field of the patent (Leydesdorff et al., 2014; Perez-Molina & Mejia, 2021). Drawing on these arguments, we compute each firm's DTP at the year level using Eq. (2). DTP captures a manufacturing firm's change in focus from non-digital technologies to digital technologies and presents its diversification. An enterprise gains high DTP scores if it includes technology that has high complementarities with digital technology in its R&D or if the firm develops directly in digital technology. Accordingly, a firm with higher DTP scores is ahead of its competitors in the digitalization of technological innovation.

$$DTP_{i,t} = \frac{\sum_{j=1}^{n} \frac{1}{1 + \sum_{k=1}^{m} shortest\_path_{j,k,t}}}{n}, \quad (2)$$

where $DTP_{i,t}$ denotes the average DTP of firm i in year t, $\sum_{k=1}^{m} shortest\_path_{j,k,t}$ denotes the sum shortest path between focal IPC class j and digital IPC code k of firm i in year t, and n denotes the count of focal IPC codes of firm i in year t.

Meditator variable: *Digital innovation ability* (*Innovation*) is measured by the number of patents that belong to the digital technology fields (if a patent's focal IPC code belongs to Table 1) in year t to measure it.

Control variables: Referring to previous studies on the same topic (Li et al., 2022; Rahmati et al., 2021; Zhang et al., 2021), we control for other variables at the firm level: firm age (*Age*), number of the firm's employees (*Size*), return on assets (*ROA*). *R&D* is transformed using the natural log, and sales (*Sales*) is transformed using the natural log. Meanwhile, two network-related factors are controlled: structural holes (*Holes*) and closeness centrality (*Closeness*). Finally, industry competition (*HHI*) is considered the influence of an external factor.

The summary statistics are shown in Table 1. Furthermore, the VIF of independent, meditator and control variables is between 1.021 and 5.510, which are all below 10. Hence, we conclude that multicollinearity is not a severe issue.

Table 1. Descriptive statistics for the variables

Variable	Mean	SD	Min	Max
DTP	0.601	0.667	0.000	1.000
Performance	0.021	0.057	0.001	0.350
Innovation	1.657	1.148	0.000	9.000
Age	6.472	2.601	3.000	28.000
Ln(*Size*)	13.681	1.164	8.779	27.486
Ln*(R&D)*	34.273	13.168	13.978	60.481
ROA	0.042	0.043	-0.067	0.134
Ln *(Sales)*	21.949	1.158	18.217	31.104
Holes	0.332	0.092	0.000	3.000
Closeness	0.056	0.014	0.001	2.132
HHI	0.325	0.241	0.019	0.786

4. Empirical results

4.1 Model specification

We apply firm-level fixed effects models (comparing the results of random effects and fixed effects show that the Hausman test is significant, thus indicating that the fixed effects model is preferred for hypothesis testing) to test our hypotheses. Potential confounding effects are controlled, such as size, age, ROA, and R&D. The models are specified as follows:

$$Performance_{i,t+2} = \beta_0 + \beta_1 DTP_{i,t} + \beta_2 Control_i + Year_i + Regional_i + \varepsilon \quad (3)$$

$$Innovation_{i,t+1} = \beta_0 + \beta_1 DTP_{i,t} + \beta_2 Control_i + Year_i + Regional_i + \varepsilon \quad (4)$$

$$Performance_{i,t+2} = \beta_0 + \beta_1 Innovation_{i,t+1} + \beta_2 Control_{i+1} + Year_{i+1} + Regional_{i+1} + \varepsilon \quad (5)$$

$$Performance_{i,t+2} = \beta_0 + \beta_1 DTP_{i,t} + \beta_2 Innovation_{i,t+1} + \beta_2 Control_i + Year_i + Regional_i + \varepsilon \quad (6)$$

Where model (3) is used to test H1, and models (4) - (6) are used to test the mediation mechanism of digital innovation ability.

4.2 Regression results

First, we examine the relationship between digitalization of technological innovation and digital transformation performance. As shown in Table 2, column (1) is a baseline regression that includes only the independent variable, and column (2) includes all the variables. The results display a positive and significant effect of DTP on digital transformation performance when controlling for firm and year level variables. Thus, H1 is supported.

Table 2. Empirical regression results

Variable	（1） *Performance*	（2） *Performance*
DTP	0.041**	0.065***
	（2.59）	(3.34)
Age		0.032***
		(3.18)

Ln*(Size)*		0.003***
		(4.23)
Ln*(R&D)*		0.078***
		(4.76)
Ln *(Sales)*		2.8e-05
		(1.56)
ROA		0.001
		(1.05)
Holes		-0.246
		(-1.56)
Closeness		0.578
		(1.24)
HHI		-0.143***
		(-3.61)
_cons	0.002***	0.000***
	(22.34)	(13.25)
Year-fixed	Yes	Yes
Firm-fixed	Yes	Yes
Observations	9701	9323
R^2	0.417	0.506

Note: t-statistics' values in parentheses are adjusted for clustering at the firm level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Same below.

Second, we examine the mediation effect of digital innovation ability. As shown in Table 3, column (2) certifies the positive relationship between digitalization of technological innovation and firms' digital innovation ability. Column (3) verifies the positive relationship between the mediator, *Innovation*, and firms' digital transformation performance. Column (4) is involved to test the indirect effects, indicating that the digitalization of technological innovation can improve firms' digital innovation ability, and then enhance their digital transformation performance. Thus, H2 is supported. Furthermore, the Sobel tests (*Innovation*: Z=2.89,$\rho < 0.01$) confirm the existence of the indirect effects.

Table 3. Mechanism analysis results

	(1)	(2)	(3)	(4)
	Step 1: X→Y	Step 2: X→M	Step 3: M→Y	Step 4:X,M→Y
	Performance	*Innovation*	*Performance*	*Performance*
DTP	0.053***	0.017***		0.043***
	(3.73)	(4.42)		(3.34)
Innovation			0.012***	0.008**
			(5.85)	(2.65)
Age	0.032***	0.066***	0.055**	0.016***
	(3.18)	(3.85)	(2.50)	(3.18)
Ln*(Size)*	0.003***	0.012**	.056**	0.003***
	(4.23)	(2.43)	(2.02)	(4.23)
Ln*(R&D)*	0.078***	0.015**	0.036**	0.014***
	(4.76)	(2.20)	(2.41)	(4.76)
Ln *(Sales)*	2.8e-05	0.018	0.049	0.028
	(1.56)	(0.32)	(0.69)	(0.98)
ROA	0.001	0.066*	0.083	0.001
	(1.05)	(1.85)	(0.61)	(0.75)
Holes	-0.246	0.006**	0.001**	0.005
	(-1.56)	(2.50)	(2.15)	(1.56)
Closeness	0.578	0.004**	0.004**	0.001***
	(1.24)	(2.70)	(2.19)	(4.88)
HHI	-0.143***	-0.030	0.000	0.157***

	(-3.61)	(-0.96)	(1.34)	(4.15)
Year-fixed	Yes	Yes	Yes	Yes
Regional-fixed	Yes	Yes	Yes	Yes
Observations	9323	10,217	10,217	9323
R^2	0.506	0.478	0.447	0.512

4.3 Robustness checks

To validate the main findings, we conduct additional analyses. First, in the main analysis, the weight of the edges in the network defaults to 1. Thus, we set the edge weights as the number of links between two IPC classes. Eq. (2) is rewritten as follows:

$$DTP_{i,t} = \frac{\sum_{j=1}^{n} \frac{1}{1 + \sum_{k=1}^{m} shortest\_path_{j,k,t}} * Weight_{j,k,t}}{n}. \quad (7)$$

The re-estimated results shown in Table 4, the coefficient of DTP is significantly positive, which further supports the previous results.

Table 4. Results for robustness checks

	(1)	(2)	(3)	(4)
	Step 1: X→Y	Step 2: X→M	Step 3: M→Y	Step 4:X,M→Y
	Performance	*Innovation*	*Performance*	*Performance*
DTP(weighted)	0.014***	0.009***		0.021***
	(2.89)	(3.51)		(4.61)
Innovation			0.019**	0.010***
			(2.02)	(2.84)
Control variables	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Regional-fixed	Yes	Yes	Yes	Yes

Observations	9323	10,217	10,217	9323
R^2	0.312	0.319	0.356	0.332

Second, we assess the robustness of the identified relationship between DTP and digital transformation performance by adopting an instrumental variable (IV) approach. In the main research setting, we use the average shortest paths between the focal IPC class and digital-related IPC classes. In this study, instrumental variable (IV) is defined as the average shortest paths between the neighbor IPC classes of the focal IPC class to the digital-related IPC classes. We call this IV as *second-order digital technology proximity* (SDTP) and argue that SDTP should have no direct effect on firms' digital transformation performance because the focal IPC class is the firms' main concern. However, SDTP has a direct effect on DTP, as neighboring IPC classes can drag the focal IPC class into the digital-related IPC classes, and in turn influences the shortest paths. The construction of SDTP is in accordance with the construction of DTP. Table 5 presents the results of IV estimation, all results show positive and significant coefficients, providing further support for our main findings.

Table 5. Instrumental variable analysis

	(1)	(2)	(3)	(4)	(5)
	First-stage	Step 1: X→Y	Step 2: X→M	Step 3: M→Y	Step 4: X,M→Y
	DTP	*Performance*	*Innovation*	*Performance*	*Performance*
SDTP	0.027***	0.028***	0.014***		0.019***
	(6.31)	(5.98)	(5.25)		(3.92)
F-statistics	244.621				
Innovation				0.019**	0.013***
				(2.02)	(2.84)
Control variables	Yes	Yes	Yes	Yes	Yes

Year-fixed	Yes	Yes	Yes	Yes	Yes
Regional-fixed	Yes	Yes	Yes	Yes	Yes
Observations	10,217	9323	10,217	10,217	9323
R^2	0.267	0.312	0.319	0.356	0.332

Third, digital transformation is a spontaneous and selective decision made by a manufacturing firm. Thus, self-selection issue may introduce bias into the study. To further investigate the robustness of the identified relationship between DTP and digital transformation performance, we implement the matching technique to create a group of manufacturing firms that conduct digitalization of technological innovation (the treatment group) and a group of manufacturing firms that are similar to those in the treatment group but do not conduct digitalization of technological innovation (the control group). Then, difference-in-difference (DID) technique is used to the main regression specification.

To construct the treatment and control groups, we use all control variables as match specifications to derive the sample. The propensity score matching (PSM) results based on the one-on-one nearest-neighbor matching approach are shown in Table 6. The absolute values of all t-statistics are lower than 1.96, indicating that the control group is comparable to the treatment group before the intervention. Then, Eq. (8) is considered the DID regression specification:

$$Performance_{i,t+1} = \alpha + \beta_1 du_{i,t} + \beta_2 dt_{i,t} + \beta_3 (du_{i,t} \times dt_{i,t}) + \gamma Controls_{i,t} + Year_i + Regional_i + \varepsilon \quad (8)$$

where $du_{i,t}$ is a dummy that equals 1 if DTP is greater than the average level of manufacturing firm i in year t and 0 otherwise, and $dt_{i,t}$ is a time dummy variable that equals 1 if the year t is on or after the development and application of digital technology of manufacturing firm i and 0 otherwise. The coefficient of β_3 captures the changes in the digitalization of technological innovation.

The estimated results are shown in Table 7. In column (1), the coefficient of

$du \times dt$ is positive and significant. The results of weighting for DTP in column (2) are also statistically significant. Furthermore, we perform a one-on-three nearest-neighbor matching approach to re-derive the sample (see column (3)). All estimated results are consistent with the previous findings.

Table 6. Balance testing of the matched sample

Variable	Mean		Bias（%）	t-statistic
	Treatment	Control		
Age	4.6045	4.5362	1.0	0.31
Size	8.1764	8.1813	-0.4	-0.15
R&D	10.782	10.45	4.4	1.54
Sales	11.406	14.098	-5.6	-1.18
ROA	0.7484	0.7361	2.3	0.78

Table 7. PSM-DID results

Variable	（1） 1：1 matching	（2） 1：1 matching （weighted）	（3） 1：3 matching
$du \times dt$	0.058***	0.025**	0.039***
	(4.77)	(2.78)	（3.11）
dt	0.016***	0.014***	0.018***
	(4.81)	(3.57)	（2.91）
Control variables	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes
Observations	7263	7263	9684
R^2	0.354	0.343	0.387

5. Discussion

Digital technology empowers digital transformation, especially for the manufacturing industry. However, technological change is a dynamic process from non-digital to digital. Digitalization of technological innovation has been widely received much attention, whereas limited research has provided an empirical measurement of digitalization of technological innovation and examined the relationship between digitalization of technological innovation and digital transformation performance. In this study, we propose a new construct, called digital technology proximity, to measure the digitalization of technological innovation from a social network perspective. Meanwhile, we measure digital transformation performance by the ratio of digital-related revenue/total revenue at firm level. Combining multiple data resources (patent documents, annual reports, and a third-party database), we take Chinese A-share listed manufacturing firms from 2012 to 2021 as the sample and examine the empowerment of digital technology digitalization in digital transformation performance. The results support our hypothesis, namely, that digitalization of technological innovation (digital technology proximity) positively related to firms' digital transformation performance. The mechanism analysis shows that digital innovation ability mediates the positive relationship between digitalization of technological innovation and firms' digital transformation performance.

This study has important research implications. First, we theorize digitalization of technological innovation and propose a novel network-based construct to measure it. Digitalization of technological innovation is a dynamic process, indicating that the change of technological innovation from non-digital to digital. Based on economic proximity and social network (Boschma et al., 2015; Rahmati et al., 2021), we propose DTP to measure the digitalization of technological innovation. Differs to traditional IT investment-based measures, DTP captures a firm's position in a technology space network when evaluating their degree of digitalization of technological innovation. Second, we provide another aspect of firms' digital transformation performance. Previous studies have measured the extent in which digital transformation by using the word frequency (Zhai et al., 2022; Zhuo and Chen, 2023), this study identifies digital-related industries and use the share of digital revenue to measure firms' digital transformation performance. Third, we perform a mechanism analysis by digital innovation ability, such mediation model unpacks the black box of the impact of digitalization of technological innovation on firms' digital transformation performance, offering a more comprehensive understanding regarding the internal mechanism of technological innovation digitalization how to work.

The findings of this study also have several contributions to practice. First, our work highlights the importance of digitalization of technological innovation for empowering firms' digital transformation performance. We show how the change of innovation activities of firms from non-digital to digital. Therefore, firms need strategic insight into digital innovation. Second, we theorize a new practical approach for measuring the digitalization of technological innovation. This approach responds to call for research that alternative methods of capturing digitalization (Greenstein et al., 2013). Our digital technology proximity provides a new tool for policymakers to measure the dynamic process toward the digitalization of technological innovation.

Although this study provides new insight into the relationship digitalization of technological innovation and digital transformation performance, it also has several limitations that can be addressed in future research. First, our empirical model is tested in the context of Chinese data, which might make it difficult to generalize our findings to other countries. Thus, future research could further examine our model using a variety of data samples, such as manufacturing firms in USA and EU, showing similarities and differences. Second, although we perform an instrumental variable analysis to mitigate potential endogeneity concerns, the data limited our ability to construct other instrumental variables. Thus, future research could explore more instrumental variables to correct for endogeneity bias. Third, IT-related elements are used to identify digital-related IPC classes. Not all firms hold digital patents, however, this does not mean that the firms do not have any digital innovation activities. Future research could attempt to apply text-based indicator for measuring the degree of digitalization of technological innovation (Zimmermann et al., 2023).

References

Ahuja, G., Lampert, C. M., & Novelli, E. (2013). The second face of appropriability: Generative appropriability and its determinants. *Academy of Management Review*, 38(2), 248-269.

Al-Emran, M., & Griffy-Brown, C. (2023). The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society*, 102240.

Bertani, F., Raberto, M., & Teglio, A. (2020). The productivity and unemployment effects of the digital transformation: an empirical and modelling assessment. *Review of Evolutionary Political Economy*, 1, 329-355.

Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, 24(1), 223-250.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. *WW Norton & Company*.

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science*, 64(12), 5497-5520.

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7), 104289.

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, 57(1), 3-43.

Greenstein, S., Lerner, J., & Stern, S. (2013). Digitalization , innovation, and copyright: What is the agenda?. *Strategic Organization*, 11(1), 110-121.

Guevara, M. R., Hartmann, D., Aristarán, M., Mendoza, M., & Hidalgo, C. A. (2016). The research space: using career paths to predict the evolution of the research output of individuals, institutions, and nations. *Scientometrics*, 109, 1695-1709.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for Formulating a Digital

Transformation Strategy. *MIS Quarterly*, (2), 123-139.

Hofeditz, M., Nienaber, A. M., Dysvik, A., & Schewe, G. (2017). "Want to" versus "have to": Intrinsic and extrinsic motivators as predictors of compliance behavior intention. *Human Resource Management*, 56(1), 25-49.

Jain, S., Kashiramka, S., & Jain, P. K. (2019). Cross-border M&As: integration practices from emerging economies. *Journal of Business Strategy*, 41(3), 21-33.

Jones, M. D., Hutcheson, S., & Camba, J. D. (2021). Past, present, and future barriers to digital transformation in manufacturing: A review. *Journal of Manufacturing Systems*, 60, 936-948.

Kagermann, H., Helbig, J., Hellinger, A., & Wahlster, W. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 *Working Group. Forschungsunion.*

Kessler, E. H., & Chakrabarti, A. K. (1996). Innovation speed: A conceptual model of context, antecedents, and outcomes. *Academy of Management Review*, 21(4), 1143-1191.

Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., ... & Ahlemann, F. (2017). Digitalization: opportunity and challenge for the business and information systems engineering community. *Business & Information Systems Engineering*, 59, 301-308.

Leydesdorff, L., Kushnir, D., & Rafols, I. (2014). Interactive overlay maps for US patent (USPTO) data based on International Patent Classification (IPC). *Scientometrics*, 98, 1583-1599.

Li, F. (2020). The digital transformation of business models in the creative industries: A holistic framework and emerging trends. *Technovation*, 92, 102012.

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

Liere-Netheler, K., Packmohr, S., & Vogelsang, K. (2018). Drivers of Digital Transformation in Manufacturing. *In 51st Hawaii International Conference on System Sciences (HICSS)*, Waikoloa, Hawaii (2018) (pp. 3926-3935). Shidler College of Business.

Lucke, D., Constantinescu, C., & Westkämper, E. (2008). Smart factory-a step towards the next generation of manufacturing. *In Manufacturing systems and technologies for the new frontier* (pp. 115-118). Springer, London.

Majchrzak, A., Markus, M. L., & Wareham, J. (2016). Designing for digital transformation. *MIS Quarterly*, 40(2), 267-278.

Mittal, N., & Nault, B. R. (2009). Research note—Investments in information technology: Indirect effects and information technology intensity. *Information Systems Research*, 20(1), 140-154.

Mühleisen, M. (2018). The long and short of the digital revolution. *Finance & Development*, 55(002), 6-8.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1), 223-238.

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), 103773.

Njihia, J. M., & Merali, Y. (2013). The broader context for ICT4D projects: a morphogenetic analysis. *MIS Quarterly*, 37(3), 881-906.

Parviainen, P., Tihinen, M., Kääriäinen, J., & Teppola, S. (2017). Tackling the digitalization challenge: how to benefit from digitalization in practice. *International Journal of Information Systems and Project Management*, 5(1), 63-77.

Pavlou, P. A., & El Sawy, O. A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, 21(3), 443- 471.

Perez-Molina, E., & Mejia, C. (2021). Assessment of technology integration based on patent analysis—Three archetypal case studies: Computer generated animation, regenerative medicine and computer tomography. *World Patent Information*, 66, 102058.

Petersen, J. A., Paulich, B. J., Khodakarami, F., Spyropoulou, S., & Kumar, V. (2022).

Customer- based execution strategy in a global digital economy. *International Journal of Research in Marketing*, 39(2), 566-582.

Rahmati, P., Tafti, A., & Hidalgo, C. (2021). When All Products Are Digital: Complexity and Intangible Value in the Ecosystem of Digitizing Firms. *MIS Quarterly*, 45(3), 1025-1058.

Rangan, S., & Sengul, M. (2009). Information technology and transnational integration: Theory and evidence on the evolution of the modern multinational enterprise. *Journal of International Business Studies*, 40(9), 1496-1514.

Sasaki, H., & Sakata, I. (2021). Identifying potential technological spin-offs using hierarchical information in international patent classification. *Technovation*, 100, 102192.

Shan, P., Song, M., & Ju, X. (2016). Entrepreneurial orientation and performance: Is innovation speed a missing link?. *Journal of Business Research*, 69(2), 683-690.

Si, S., Hall, J., Suddaby, R., Ahlstrom, D., & Wei, J. (2022). Technology, entrepreneurship, innovation and social change in digital economics. *Technovation*, 102484.

Singh, S., Sharma, M., & Dhir, S. (2021). Modeling the effects of digital transformation in Indian manufacturing industry. *Technology in Society*, 67, 101763.

Svahn, F., Mathiassen, L., & Lindgren, R. (2017). Embracing digital innovation in incumbent firms: how volvo cars managed competing concerns. *MIS Quarterly*, 41(1), 239-253.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901.

Vogelsang, K., Liere-Netheler, K., Packmohr, S., & Hoppe, U. (2018). Success factors for fostering a digital transformation in manufacturing companies. *Journal of Enterprise Transformation*, 8(1-2), 121-142.

Weinman, J., & Euchner, J. (2015). Digital Technologies and Competitive Advantage. *Research- Technology Management*, 58(6), 12-17.

Yoo, Y., Boland Jr, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization science*, 23(5), 1398-1408.

Zhai, H., Yang, M., & Chan, K. C. (2022). Does digital transformation enhance a firm's performance? Evidence from China. *Technology in Society*, 68, 101841.

Zhang, T., Shi, Z. Z., Shi, Y. R., & Chen, N. J. (2021). Enterprise digital transformation and production efficiency: mechanism analysis and empirical research. *Economic Research-Ekonomska Istraživanja*, 1-12.

Zhuo, C., & Chen, J. (2023). Can digital transformation overcome the enterprise innovation dilemma: Effect, mechanism and effective boundary. *Technological Forecasting and Social Change*, 190, 122378.

Zimmermann, T., Kalscheuer, U., & Fischer-Kreer, D. (2023). A text-based measure for digital innovation-uncovering digital innovation and its impact on firm performance. *Paper presented at the ECIS 2023.*