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Nonlinear effects of digital development on manufacturing innovation: evidence from China

Qinqin Wu[a,b] and Qinqin Zhuang[c]

[a]Institute of Industrial Economics, Jiangsu University, Zhenjiang, Jiangsu, China; [b]School of Finance and Economics, Jiangsu University, Zhenjiang, Jiangsu, China; [c]Institute of Quantitative & Technological Economics, Chinese Academy of Social Sciences, Beijing, China

ABSTRACT

The digital economy has brought innovative power to the manufacturing transformation. This study aims to investigate the nonlinear effects of digital development on manufacturing innovation using provincial panel data from China from 2011 to 2018. A two-way fixed effects model is used to examine the inverted U-shaped curve that represents the nonlinear impact of digital development on innovation. To explore the reasons behind the nonlinear digital innovation spillover, this study considered both the internal factors and external boundary conditions. We employ a moderation effect model to verify the interaction between digital development and user literacy which has a positive impact on manufacturing innovation. Especially, higher education can help users enhance digital literacy in driving digital innovation spillovers. Threshold effect model is used to examine the boundary conditions such as Internet penetration rate, information resources, and protection of intellectual property rights that contribute to the nonlinear effects. The research findings suggest that when these factors reach a critical point, the positive impact of the digital economy on manufacturing innovation turns towards a declining trend. The study provides insights into the complex relationship between digital development and manufacturing innovation and proposes policy implications.

KEYWORDS

Digital development; manufacturing industry; nonlinear digital innovation spillover; user literacy; boundary conditions

JEL CLASSIFICATION

L86; O14; O33

I. Introduction

The digital economy has become a crucial component of national economies in China, extending into various industrial fields through the new generation of information technology. According to the research report on the development of digital economy in China (2023) by the Institute of Information and Communication (CAICT 2023), the scale of China's digital economy reached 50.2 trillion yuan in 2022, a nominal increase of 10.3% over the same period last year, which has been significantly higher than the nominal growth rate of GDP for 11 consecutive years. The proportion of digital economy in China's GDP reached 41.5%, which is equivalent to the proportion of the secondary industry in the national economy. As the scale of the digital economy continues to expand, new technologies, industries, business types, and models continue to emerge, showcasing significant development advantages. In particular, the manufacturing industry has experienced new opportunities through digital transformation. Digital transformation has made a significant impact on innovation in the manufacturing industry, leading to cost reduction, resource optimization and efficiency improvement. Technological innovation has become the primary driving force in the manufacturing industry, increasingly influenced by digitalization under the digital economy era. Research on the effects of the digital economy on manufacturing innovation in China holds both theoretical and practical significance.

Previous literature has provided valuable insights into the impact of the digital economy on innovation. However, there are several areas that require further investigation. The literature on the impact of the digital economy on innovation has largely focused on developed countries at the firm level (Boland, Lyytinen, and Yoo 2007; Brynjolfsson and Saunders 2009; Han, Song, and Li 2019; Paunov and Rollo 2016; Thomas 2020). There is a need for more research to investigate how the digital economy affects innovation in different industrial contexts, particularly in

CONTACT Qinqin Wu wuqq1025@126.com Institute of Industrial Economics, Jiangsu University, Zhenjiang, Jiangsu 212013, China

developing countries. Many scholars have only acknowledged the direct relationship between the digital economy and innovation (Huang, Yu, and Zhang 2019; Nambisan 2017; Zhao, Zhang, and Liang 2020), without considering the more complex, indirect ways that the digital economy affects innovation. The positive effect of the digital economy is not necessarily sustainable in the long term, and there may be a declining trend. Most research has primarily focused on demonstrating its linear and positive effects while disregarding its nonlinear features. Furthermore, the specific causes and key factors of the nonlinear impact of the digital economy on innovation are also lacking in discussion. Although some studies have explored the impact of user factors on micro-enterprise innovation (Teece 2018), less attention has been given to how users' literacy affects the popularization and application of digitization. The widespread adoption of digital technologies may have unintended consequences such as exacerbating social inequalities or creating environmental risks. Therefore, more research is needed to better understand the boundary conditions that shape the nonlinear effects of the digital economy on innovation.

This study aims to make three significant contributions, which are outlined below. Firstly, it examines the impact of digital development on manufacturing innovation in China from both regional and industrial perspectives. By focusing on regional manufacturing technology innovation, this study provides a deeper understanding of the nonlinear form characteristics of digital innovation spillover, which is shaped like an inverted U-shaped curve. This study explores the new characteristics and applicability of network externalities in the digital age. Secondly, the research emphasizes the moderation effect of user literacy in the context of digital innovation spillovers. In the exploration of digital transformation, much academic attention has been directed towards external forces, often overlooking internal factors, particularly those related to users. Digital literacy can promote the adoption and effective use of digital technologies by businesses and individuals. The study emphasizes that users can be integrated into the manufacturing innovation process. Thirdly, the study uses the threshold effect model to examine the boundary conditions that contribute to nonlinear effects of the digital economy on innovation. The research finds that Internet penetration rate, information resources, and protection of intellectual property rights are the specific factors. When these factors reach a critical point, the positive impact of the digital economy on manufacturing innovation will turn towards a declining trend. The findings of this study can enrich the theoretical framework of boundaries for digital innovation spillover, and provide valuable insights for policymakers and manufacturing companies seeking to promote innovation in the digital era.

II. Theoretical framework and hypothesis development

Manufacturing innovation motivated by digitalization

Innovation economics theory suggests that external factors such as technological progress, market demand, competition, and government policy have a significant impact on technological innovation (Manso 2011). The digital economy has become a driving force for innovation, promoting the development of digital technology and business models that are widely applied to production and daily life. It has great scalability and low entry barriers, which encourages widespread participation and democratizes invention (Yoo, Henfridsson, and Lyytinen 2010). Digital technology as a new generation of information technology is a general purpose technology (GPT) that can leverage innovations (Harris 1998; Helpman and Trajtenberg 1996; Varian 2010) and enhance the technological development of production processes. The implementation of Industry 4.0 practices promote manufacturing innovation through the integration of digital technologies, such as IoT, cloud computing, and smart manufacturing. These digital technologies enable manufacturers to streamline processes, reduce costs, improve innovation efficiency, develop new and high-quality products. The digital economy creates new market spaces that generate demand for manufacturing innovative products and services from users. Traditional marketing models have been disrupted. The existence of the Long Tail theory motivates manufacturers to continuously enrich their personalized product categories to meet specific customer preferences (Ghasemaghaei and Calic 2020). This innovation involves flexibility in production and the ability to adapt to changing market demands. Furthermore, digital development has intensified competition among manufacturers, forcing them to enhance their level of innovation to maintain competitiveness, in line with Schumpeter's hypothesis. Therefore, digital development will promote technological innovation in the manufacturing industry.

The externalities of digital development

In the digital economy, information flows at an unprecedented speed, and production, exchange, distribution, and consumption are all closely related to network information, resulting in increasingly prominent network externalities. Network effects arise when the value of a network to a user is dependent on the number of other users within the network. When the value of a network increases as more users join, this is known as a positive network effect. Network externalities are externalities that arise due to network effects (Katz and Shapiro 1985). Network effects are a potent driver of value and often referred to as 'demand-side economies of scale' because they impact the revenue side of a provider's profitability equation by boosting users' willingness-to-pay for its products or services. Metcalf's Law describes the phenomenon of network externalities in economics. The law states that the value of a network is proportional to the square of the number of nodes in the network. Metcalf's law indicates that overall, there is increasing marginal utility in consumption, i.e. demand creates new demand. For consumers, when deciding whether to purchase network products, they consider two types of value: one is the intrinsic value of the product that is independent of the product's user base, and the other is the collaborative value described by Metcalf's law, which is related to the network size and the additional value that existing consumers obtain due to the addition of new consumers. However, if too many users are connected to a network, congestion may occur which reduces speed and efficiency leading to negative externalities and increased connection costs. Therefore, network externalities contain both positive and negative aspects, but positive externalities are relatively more common. Under the influence of network externalities, the shape of the demand curve changes from a monotonic downward slope in traditional economics to an inverted U-shaped curve. Therefore, this study posits that network externality in the digital economy has both positive and negative implications.

User literacy as the intrinsic driving force in the digital innovation spillover effect

In the digital age, the growth of digital technology necessitates individuals to possess essential skills and capabilities for performing tasks and problem-solving in a digital environment (Polizzi 2020; Sarkar 2012; van Deursen, Helsper, and Eynon 2016). These skills are commonly referred to as digital literacy. The concept of digital literacy was first introduced by Gilster (1997) in the late 1990s. He emphasized that the internet enabled people to access seemingly endless ideas and information at lightning speed, but it also placed new responsibilities on users. Users must acquire a broad range of skills to adapt to the digital age. Digital literacy has now become a crucial survival skill (Heredia et al. 2022). These skills encompass operational expertise, information navigation, social interaction, and creativity (van Deursen, Helsper, and Eynon 2016). For instance, competencies in web browsing and information gathering, the ability to create and share knowledge online, transmitting and receiving digital content, as well as engaging in social media interactions, are all crucial components of digital literacy (Brandtweiner, Donat, and Kerschbaum 2010; Calvani et al. 2012; Hargittai 2005; Hargittai and Hsieh 2012).Without a solid foundation in digital literacy, individuals are incapable of effectively utilizing information and communication technology. These skills are imperative for adapting to the ever-evolving digital landscape.

The digital literacy of users plays a pivotal role in the context of digital development and transformation. Given that digital literacy constitutes a set of skills and capabilities employed by individuals when interacting with digital technology (Stordy 2015), it follows that as users' digital literacy improves, the utilization of digital technology becomes more effective (Abedin, Daneshgar, and D'Ambra 2012).

The critical role of employee digital literacy in the context of digital transformation relative to technology has been verified (Cetindamar Kozanoglu and Abedin 2021; Kane 2019; Warner and Wäger 2019). Drawing from the three-gear model employed by (Sharma et al. 2018) and the four-gear model constructed by (Reddy, Sharma, and Chaudhary 2020), this study posits the existence of a gear effect between digital development, user digital literacy, and manufacturing innovation. As digital development propels the widespread adoption of digital technology, it requires users to enhance digital literacy. In the dynamic interplay between digital technology and user literacy, manufacturing enterprises will accelerate their digital transformation. Users will engage with enterprises by enhancing their communication and feedback through digital technology, thereby participating in the technological innovation ecosystem.

The boundary conditions of innovation driven by digital development

Environmental constraints can impact digital nonlinear innovation spillover, resulting from boundary conditions. This study analyzes the boundary conditions of digital innovation spillover.

Firstly, the change of network externality from positive to negative is closely related to the critical point of network penetration rate. The effect of digital economy on manufacturing innovation requires a certain scale of users and network externality. As the number of users increases, the capacity of digital platforms struggles to accommodate the user base, leading to a decrease in network value. Consequently, the impact of the digital economy on innovation shifts from positive to negative, resulting in an inverted U-shaped relationship between digital development and manufacturing innovation. Secondly, the richness of data information, as the core element of digital economy, determines the value of digital resources. However, excessive information, information security, abuse of freedom of speech, and the acceleration of the wealth gap pose challenges to the digital economy.. The focus of innovation subject's attention is limited, which is a scarce resource (Sims 2003, 2006). Under the environment of digital economy, the allocation of attention resources changes (Qinqin et al. 2023). Excessive information can lead to distraction and information waste, reducing the efficiency of work and life. Information overload (IO) exacerbates these challenges. Thirdly, regional intellectual property rights and the non-regionality of the network space lead to network infringement disputes of innovative achievements. Digital resources' anonymous attribute leads to a dilemma of privacy protection and data utilization efficiency. Intellectual property protection in the digital age has reasonable limits to avoid limiting sustainable innovation. Personal information leakage can also incur connection costs, but the privacy paradox is evident when people willingly relinquish private data for incentives (Athey, Catalini, and Tucker 2017). Therefore, factors such as network penetration, the number of information resources and the level of intellectual property protection will limit the actual effect of digital innovation spillover, which needs to be included in the research category as threshold variables.

Based on the above theoretical analysis, three research hypotheses are put forward. In the research framework, shown in Figure 1, we have thoroughly considered both the internal factors (user literacy) and external boundary conditions (Internet popularization rate, information resources, intellectual property protection) that determine the impact of digital development on manufacturing innovation.

H1: The digital development has a nonlinear innovation spillover effect on the manufacturing industry.

H2: The interaction between digital development and user literacy has a significant impact on manufacturing innovation.

H3: The effect of digital development on manufacturing innovation will change significantly under the external boundary conditions.

III. Research model

Model setting

To examine the impact of regional digital economy on technological innovation in manufacturing

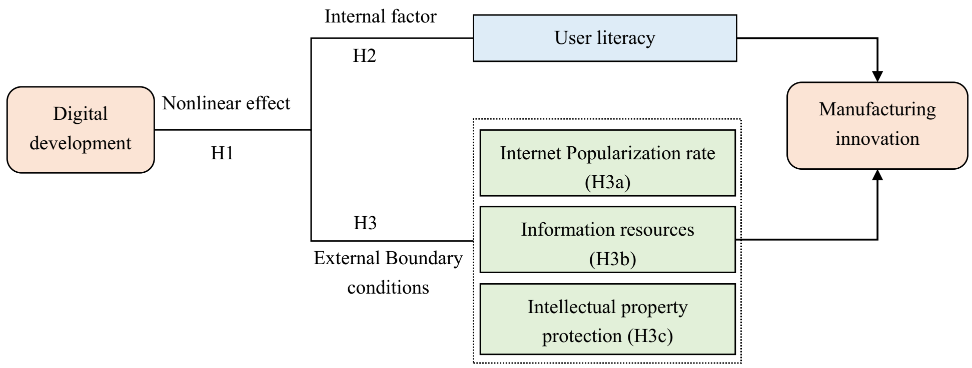

Figure 1. Research framework.

enterprises, this paper constructs a province-time two-way fixed effect model as the benchmark to test:

$$Inno_{jt} = \beta_0 + \beta_1 digital_{jt} + \beta_c Control_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt} \tag{1}$$

Among them, the subscript j and t represent province and year respectively. The explained variable $Inno_{jt}$ represents the technological innovation level of manufacturing enterprises in provinces of each year. From the point of view of innovation output, the number of patent applications of industrial enterprises in each province is used to reflect manufacturing innovation. The explanatory variable $digital_{jt}$ reflects the comprehensive index of regional digital economy development. $Control_{jt}$ is a series of control variables, λ_j is a regional fixed effect, φ_t is a year fixed effect, ε_{jt} is a random error term. If $\beta_1 > 0$, it is considered that digital development can promote technological innovation in the manufacturing industry.

Based on Formula (1), this study also includes lagged explanatory variables to examine the dynamic impact of digital economic development on manufacturing innovation. In order to test the nonlinear characteristics of digital economy development on manufacturing innovation spillover, with reference to the study of (Wang et al. 2021), this paper adds the square term of digital index to the benchmark model. We have conducted the Regression Equation Specification Error Test with an F-test. The p-value is less than 0.05, which indicates the need to include higher-order terms in this multivariate linear regression.

$$Inno_{jt} = \beta_0 + \beta_1 digital_{jt} + \beta_2 digital_{jt}^2 + \beta_c Control_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt} \tag{2}$$

Considering that the interaction between digital development and user literacy will regulate the nonlinear innovation spillover, this study adds the user literacy expressed by per capita years of education and the second column using the proportion of higher education population as the moderating variables. To test hypothesis 2, the study examines the interaction coefficient between user literacy and digital development index ($digital_{jt} \times userl_{jt}$). In order to reduce collinearity, the interaction term after variable centralization is used to further expand the model.

$$\begin{aligned} Inno_{jt} = \beta_0 + \beta_1 digital_{jt} + \beta_2 digital_{jt}^2 + \beta_3 digital_{jt} \times userl_{jt} \\ \beta_4 userl_{jt} + \beta_c Control_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt} \end{aligned} \tag{3}$$

Finally, in order to test the boundary conditions of nonlinear innovation spillover caused by environmental constraints in digital economy, the panel threshold model of Hansen (1999) is used to investigate, and the model is constructed as follows:

$$\begin{aligned} Inno_{jt} = \beta_0 + \beta_1 digital_{jt} \cdot I(q_{jt} \le \gamma) + \beta_2 digital_{jt} \cdot I(q_{jt} > \gamma) \\ + \beta_c Control_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt} \end{aligned} \tag{4}$$

Among them, q_{jt} is the threshold variable, γ is the threshold value to be estimated, and I(·) is the indicator function.

Data sources and variable interpretation

This paper takes thirty provinces in China as the research sample and uses the balanced panel data at the provincial level from 2011–2018 to conduct an empirical test. Due to the lack of samples, the data of Hong Kong, Macao, Taiwan and Xizang are excluded. The indicators of the technological innovation level of the manufacturing industry come from *China Science and Technology Statistical Yearbook*, and the data of digital development are subdivided from *annual China Statistical Yearbook*, *China Internet Development report*, *China City Statistical Yearbook*, *Peking University Digital inclusive Financial Index (2011–2020)*, etc. The data of other control variables and threshold variables come from the statistical database of China Economic Network and the local statistical yearbooks of provinces and cities over the years, and intellectual property protection also uses data such as *Annual report of the State intellectual property Office*. In addition, in order to reduce the interference of outliers, the sample was tailed by 1% before and after.

Explained variable

There are mainly two perspectives in the measurement of technological innovation in the existing literature. The first is innovation investment. The R&D funds and the number of R&D personnel needed for technological innovation are widely used as input indicators; the second is innovation output. The evaluation index of innovation output generally adopts the number of patent applications, the number of patent authorizations and so on. In this paper, the number of patent applications of manufacturing enterprises in various provinces is used as an explained variable to measure the innovation output of regional manufacturing enterprises, and logarithmic processing is made.

Explanatory variable

With the continuous expansion of the connotation and extension of digital economy, a single index can only reflect the local facts of digital development. In order to fully reflect the level of regional digital development, it is necessary to measure the comprehensive index by indexation method. At present, an authoritative index to measure the degree of digital development has not been formed at home and abroad. The international authoritative measurement of the development level of digital economy mainly includes the social informatization index issued by the International Telecommunication Union and the index system constructed by the Organization for Economic Cooperation and Development (OECD) and the United States Bureau of Economic Analysis (BEA). Chinese scholars initially constructed the Internet development index (Han, Song, and Li 2019; Huang, Yu, and Zhang 2019), and further designed different digital economy indicators by adding digital factors such as digital finance or e-commerce (Zhao, Zhang, and Liang 2020).

Referring to the construction ideas of different indicators, and according to the availability, comprehensiveness and science of data, this paper combines the actual situation of the development of digital economy in China. Digital development index is measured from three dimensions: digital infrastructure, digital popularization and application and digital service level. As shown in Table 1.

When constructing synthetic indicators, it is necessary to determine the weight or importance of each individual indicator that goes into the calculation. There are two main approaches to determining weights: subjective weighting and objective weighting. Objective weighting uses mathematical or statistical methods to derive weights based on empirical data and is generally considered more objective and reliable. Among the various objective weighting methods, the CRITIC *(Criteria Importance Through Intercriteria Correlation)* method is one approach that can be used to generate weights that comprehensively consider the variability and

Table 1. The index system of digital development.

First-level index	Second-level index	Unit
Digital infrastructure	Proportion of IPv4 addresses	%
	Number of domain names with ten thousand users	Units/person
	Length of long-distance optical cable line	Kilometers
Digital popularization and application	Proportion of netizens	%
	Digital inclusive financial index	-
Digital service level	Total amount of express delivery business	Ten thousand pieces
	Revenue from Post and Telecommunications	100 million yuan
	Proportion of employees in information transmission, computer services and software industry	%

correlation of indicators. This method takes into account both the intercorrelations and the variability of the indicators, and has been widely used in academic research and practical applications. Therefore, the design of weights is more accurate (Yalcin and Ünlü 2018). The weights are as follows:

$$w_i = \frac{C_i}{\sum_i^n C_i} i = 1, 2, \ldots, n \tag{5}$$

Among them, $C_i = \sigma_i \sum_j^n (1 - r_{ij}) i = 1, 2, \ldots, n, i \neq j$, σ_i is the standard deviation of index i, and r_{ij} is the correlation coefficient between i and j.

Control variables

Referring to the existing research, the main control variables used in this paper include: urbanization level *(urban)*, financial support *(gov)*, financial development level *(fin)*, private economic development level *(pe)*, foreign investment proportion *(fdi)*, proportion of tertiary industry and secondary industry *(stru)* and so on. These control variables can isolate the potential impact on the innovation of regional manufacturing enterprises.

Moderating variable

In this paper, user literacy is added as a moderating variable to analyse the interaction with digital development. User literacy is often considered a school-based competence, but it is introduced and cultivated in other informal learning environments (Meyers, Erickson, and Small 2013). Considering that user literacy is closely related to their level of education, this study uses two proxy variables to represent user literacy: one is the proportion of highly educated individuals *(userla)*, and the other is the average years of education per capita[1] in each province *(userlb)*.

Threshold variables

The threshold regression model is used to analyse the boundary conditions affecting digital innovation spillover, and three threshold variables are selected respectively. ***Network penetration rate (intpjl).*** The study selects the regional Internet penetration rate as the threshold variable to verify network externalities. Network externalities occur when the value of Internet increases as more people use it, leading to a positive feedback loop of adoption and usage. ***The number of information resources (info).*** The study selects two types of threshold variables to represent the level of information resources. One is the average number of bytes (KB) of each web page. Another is the mobile data usage (GB) of each phone. In addition to browsing web pages for information resources online, in the era of mobile Internet, using mobile apps to read or search for news has become a mainstream trend. ***Intellectual property protection (ipr).*** With the popularization and application of digitalization, the knowledge spillover effect is strengthened. But it will also cause negative effects such as infringement on original inventors. The ending rate of patent infringement cases is selected to reflect the regional intellectual property infringement situation and law enforcement efficiency.

Based on the above analysis, summarize the main variables' definitions of this article, as shown in Table 2.

Descriptive statistics

The descriptive statistics of the main variables in this paper are shown in Table 3. The statistical results show that the logarithmic average of the number of patents of industrial enterprises in different provinces and cities is 9.065, and the standard deviation is 1.436. There are great differences in the level of technological innovation in different provinces. The average value of digital development index is 0.279, the minimum value is 0.075, and the maximum value is 0.639, which reflects the great difference in regional digital development. In Table 4, correlation test shows that the absolute value of the correlation coefficient between any two variables is less than 0.8, indicating that collinearity is not severe.

IV. Empirical results

Benchmark regression results

The benchmark regression results of the spillover effects of digital development on manufacturing

[1]Average years of education = (number of illiterate people × 1 + number of people with primary school education × 6 + number of people with junior high school education × 9 + number of people with senior high school and technical secondary school education × 12 + number of people with college or above education × 16)/total population over the age of six.

Table 2. Definitions of main variables.

Category	Variable name	Definitions
Explained variable	lnpatent	The number of patent applications of provincial manufacturing enterprises and takes the natural logarithm
Explanatory variable	digital	Comprehensive index of provincial and municipal digital development
Control variables	urban	Proportion of urban population to total population at the end of the year
	gov	Fiscal expenditure accounts for a proportion of GDP
	fin	Proportion of total deposits and loans of financial institutions to GDP
	pe	Proportion of the number of private enterprises
	fdi	The proportion of total foreign investment in GDP
	stru	Ratio of tertiary industry to secondary industry
Moderating variable	userl	Proportion of higher education enrollment
		Per capita number of years of education
Threshold variables	intpjl	The number of netizens in the district accounts for the proportion of the total population
	info	Average number of bytes per web page (KB)
		The mobile data usage(GB) of each phone
	ipr	Ratio of the number of patent infringement cases closed to the number of cases filed

Table 3. Descriptive statistics of main variables.

VarName	Mean	SD	Min	Max	Obs
lnpatent	9.065	1.436	5.124	11.89	240
digital	0.279	0.099	0.075	0.639	240
urban	0.571	0.123	0.350	0.893	240
gov	0.246	0.101	0.110	0.585	240
fin	25.38	15.99	2.231	71.23	240
pe	0.506	0.135	0.128	0.766	240
fdi	6.479	1.347	3.343	9.176	240
stru	1.125	0.633	0.518	4.348	240

Source of information: Compiled based on the calculation results from Stata software.

Table 4. Correlation test.

	digital	urban	gov	fin	pe	fdi	stru
digital	1						
urban	0.433***	1					
gov	−0.209***	−0.385***	1				
fin	0.374***	−0.177***	−0.347***	1			
pe	0.002	−0.143**	−0.331***	0.277***	1		
fdi	0.553***	0.707***	−0.755***	0.314***	0.164**	1	
stru	0.473***	0.567***	0.073	−0.226***	−0.450***	0.299***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Enterprise innovation are shown in Table 5. Column (1) is not added with two-way fixed effects. And column (2)-(5) adds all of control variables and province-year two-way fixed effects. The result in column (2) show that digital development can promote the technological innovation of regional manufacturing industry, and the influence coefficient significantly positive at 1% confidence level. For every 1 unit increase of digital economy index, the innovation output of regional manufacturing industry will increase by 2.061 units. The (3) (4) columns examined the dynamic impact of digital economic development on manufacturing innovation, with the addition of lagged digital economic indices for periods 1 and 2. The results show that as the lag order of the digital economic index increases, the spillover effect of digital innovation reaches its peak in the first period and then weakens, indicating a dynamically decaying relationship between digital economic development and manufacturing enterprise innovation.

To further examine the nonlinear effects of digitalization spillover on manufacturing innovation, the study adds the square term of the digitalization index in column (5). The result of nonlinear model indicates that while the influence coefficient of the digital economy index remains significantly positive, its square term is – 3.479, significant at a 5% level. This suggests that the impact of digital development on manufacturing innovation follows an inverted U-shaped curve. Within a certain range, as digitalization deepens, there is an improvement in manufacturing technology innovation levels.

Table 5. Benchmark regression results of digital innovation spillover effects.

	(1)	(2)	(3)	(4)	(5)
Models	OLS	FE	FE	FE	FE+nonlinear
Variables	lnpatent	lnpatent	lnpatent	lnpatent	lnpatent
digital	3.231***	2.061***			6.002***
	(0.440)	(0.764)			(1.884)
digital^2					−3.479**
					(1.523)
Lag1_digital			2.164**		
			(0.879)		
Lag2_digital				1.888*	
				(1.047)	
urban	4.521***	6.082***	5.805***	5.641***	5.197***
	(0.776)	(1.147)	(1.296)	(1.494)	(1.199)
gov	−2.017**	2.306**	2.229**	2.314**	2.507***
	(0.789)	(0.912)	(0.951)	(1.027)	(0.907)
fin	0.0148***	−0.00100	−0.00232	−0.00361	−0.000132
	(0.00408)	(0.00473)	(0.00497)	(0.00542)	(0.00470)
pe	0.340	−0.322	−0.792*	−0.705	−0.369
	(0.386)	(0.375)	(0.430)	(0.460)	(0.372)
fdi	0.0539	−0.0803	−0.0656	−0.0499	−0.0667
	(0.0606)	(0.0620)	(0.0624)	(0.0645)	(0.0616)
stru	−0.521***	−0.565***	−0.712***	−0.697***	−0.584***
	(0.0971)	(0.109)	(0.118)	(0.133)	(0.108)
Province fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes
Constant	5.768***	5.794***	6.382***	6.478***	5.389***
	(0.456)	(0.872)	(0.934)	(1.048)	(0.881)
Observations	240	240	210	180	240
R-squared	0.731	0.989	0.991	0.992	0.990

Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

However, due to the existence of Metcalfe's Law, when digital development exceeds a certain limit, positive externality turns into negative externality for innovation spillover. It can be observed that digitalization has both positive and negative impacts on society and economy. While it creates efficient and connected networks for innovation and improves resource allocation efficiency for innovations, it also brings network overload problems along with security issues which may lead to disorderly competition among innovators. Negative feedback appears in enterprise innovation. Therefore, hypothesis 1 is verified.

Robustness test

Change explanatory variable and explained variable

To further ensure the reliability of the results, the study conducts regression analysis by changing both the explanatory and explained variables in Table 6. The explained variable is replaced with innovation input, which is represented by the logarithm of R&D expenditure to indicate technological innovation levels in manufacturing industries. The coefficients in the first column indicate that the digital economy has a positive and significant impact on innovation input of manufacturing enterprises. But the coefficient of the squared term is negative and not significant. Meanwhile, invention patent is also used as a new explanatory variable for testing to verify the impact of the digital economy on manufacturing innovation quality. The result in column (2) is comparable to the benchmark regression, but with significantly larger coefficients. Additionally, the study selects the China Digital Economy Innovation and Entrepreneurship Index (IRIEDEC) (Ruochen et al. 2021) as the new explanatory variable to make robustness test. It effectively portrays the dynamic evolution and spatial distribution of digital industry innovation and entrepreneurship development in various regions of China, reflecting the regional digital development. The regression analysis in column (3) shows that the new explanatory variable (lnIRIEDEC) continues to have a significant impact on manufacturing innovation, which follows an inverted U-shaped curve.

Endogenous test

There may be a reverse causal relationship between digital development and manufacturing innovation, and endogenous problems need to be solved.

Table 6. Robustness and endogeneity tests.

	(1)	(2)	(3)	(4)	(5)
				First stage	Second stage
Variables	lnrd	lninvention	lnpatent	digital	lnpatent
digital	3.108**	8.452***			
	(1.408)	(2.426)			
digital^2	−0.0736	−4.207**			
	(1.138)	(1.962)			
lnIRIEDEC			0.339***		
			(0.0823)		
lnIRIEDEC ^2			−0.0689***		
			(0.0175)		
IV				0.328***	
				(0.035)	
digital					2.505*
					(1.385)
Constant	10.94***	5.132***	6.312***	0.429***	4.412***
	(0.658)	(1.135)	(0.785)	(0.0612)	(1.325)
LM statistic				73.10	
Wald F statistic				85.85	
Control variables	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	240	240	240	240	240
R-squared	0.993	0.982	0.982	0.986	0.343

In the third column, we selected a new explanatory variable by taking the logarithm of the China Digital Economy Innovation and Entrepreneurship Index (IRIEDEC). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrument variable approach is a common practice to deal with mutual causality. With reference to Huang et al. (2019), this study selects the interaction between the number of post offices per million people and the number of employees in the information industry in 2006 as an instrument variable for measuring digital economy index. The results are presented in columns (4) and (5) of Table 6. In the first stage, there is a significant positive impact of instrument variable on digital economy index. The result in second stage reveals that digital development has a significantly positive effect on technological innovation of manufacturing industry, which is consistent with previous findings. The Kleibergen-Paap rk LM statistic value is 73.10, which strongly rejects original hypothesis of underidentification test. Wald-F statistic value is greater than all critical values indicating weak identification test passed successfully. Thus the instrumental variable is both reasonable and effective at addressing mutual causality concerns.

V. Further analysis

The moderation effect of user literacy on digital innovation spillover

Table 7 presents the regression results of the moderation effects, with the first column using the proportion of higher education population as the moderating variable, and the second column using per capita years of education. The moderation effect test is based on the previous nonlinear two-way fixed effects model. The research finds that the inverted U-shaped nonlinear relationship between digital development and manufacturing innovation remains valid even after adding moderating variables. The results show that both years of users' education and the proportion of higher education population positively interact with digital development, with coefficients of 5.577 and 0.548. These results indicate that user literacy has a positive moderation effect on digital innovation spillovers. The finding suggests that education, especially higher education, can be a significant factor in driving digital innovation spillovers in the context of manufacturing industry. Users with higher levels of education are more receptive to digital technology and business models, making it more conducive for manufacturing companies to integrate digital resources for innovation purposes.

However, it should be noted that per capita years of education and the proportion of higher education population alone have negative impact coefficients on manufacturing innovation within a 1% confidence interval. This indicates that relying solely on user literacy cannot directly produce

Table 7. Results of the moderation effect test.

VARIABLES	(1) Inpatent	(2) Inpatent
digital	6.375***	6.908***
	(1.888)	(1.943)
digital^2	−5.105***	−4.981***
	(1.716)	(1.743)
digital_userla	5.577**	
	(2.647)	
userla	−2.306*	
	(1.233)	
digital_ userlb		0.548*
		(0.292)
userlb		−0.145*
		(0.0858)
Control variables	Yes	Yes
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	5.061***	5.639***
	(0.917)	(1.233)
Observations	240	240
R-squared	0.990	0.990

The moderating variable in first column is the proportion of higher education population, and the second column using per capita years of education. The interaction terms of user literacy are mean-centred in order to reduce collinearity. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

positive effects on manufacturing innovation – the real positive impact comes from the synergy between education and digital development. This is because the digital literacy of users plays a pivotal role in the context of digital development and transformation. As users' digital literacy improves, the utilization of digital technology becomes more effective in order to unleash its innovative spillover effects. In the digital era, users become the key elements in innovation activities. Feedback from users can force enterprises to update iterative technology in time and improve innovation efficiency. It's essential to build an innovation network of value co-creation between enterprises and users. Therefore hypothesis 2 is tested.

Boundary conditions of digital innovation spillover: analysis of threshold effect

Although the overall nonlinear innovation spillover effect of digital development on manufacturing industry is significant, the innovation spillover effect will be affected by external environmental factors and change significantly. There are some boundary conditions. According to the above analysis, the Internet penetration rate, information resources and intellectual property protection are respectively taken as threshold variables and added into the threshold model for analysis.

First, check whether the threshold effect is significant. According to the test results, the Internet penetration rate, information resources and intellectual property protection level are significant only by a single threshold test. Secondly, the threshold model is used to test the boundary conditions of digital innovation spillover. The regression of threshold values based on different influencing factors is shown in Table 8. The results show that the trend of digital innovation spillover changes after reaching the threshold values of environmental influencing factors, and hypothesis 3 is verified.

Internet penetration rate

Internet penetration rate has a single threshold effect on digital innovation spillover, and the corresponding threshold value is 29.13. This indicates that when the proportion of regional Internet users is lower than 29.13%, the influence coefficient of digital development on manufacturing technology innovation is 1.662, which is only significant within

Table 8. Results of threshold model regression.

	intpjl	info		ipr
		bytes per web page (KB)	mobile data usage(GB)	
Boundary conditions	(1)	(2)	(3)	(4)
threshold value	29.13	43	2.69	0.746
digital_1	1.662***	4.170***	2.539***	3.764***
	(0.602)	(0.478)	(0.722)	(0.452)
digital_2	3.069***	3.778***	2.020***	3.444***
	(0.423)	(0.437)	(0.684)	(0.427)
Constant	5.509***	5.375***	4.177***	5.212***
	(0.435)	(0.429)	(0.653)	(0.433)
Observations	240	240	240	240
R-squared	0.783	0.783	0.606	0.778

The estimated coefficients of digital development index for different threshold intervals are denoted as digital_1 to digital_2. The "bootstrap" method is used for repeated sampling 300 times. Due to space constraints, the results of the control variable regression are omitted.

the 10% confidence interval. When this threshold is crossed, the influence coefficient of digital development on manufacturing technology innovation reaches 3. 069, and the significance increases. This verifies that network externality and Metcalfe's Law are still valid in the digital age, and the innovation spillover of digitalization to the manufacturing industry will gradually increase with the expansion of the user scale of digital resources.

Information resources

The abundance of information resources also has a single threshold effect on digital innovation spillover. The results show that when the average number of bytes per web page is lower than 43KB, the impact coefficient of digital development on manufacturing technology innovation is 4.170, while when the number of information resources exceeds this threshold, the spillover of digital innovation is reduced to 3.778. For the mobile internet, when the average mobile data usage per person exceeds 2.69GB, the impact coefficient of digital development on manufacturing innovation will decrease from 2.539 to 2.02. The results indicate that although information is conducive to the facilitation of enterprises to obtain innovation resources, the 'information explosion' will increase the demand for network capacity, potentially causing issues such as congestion, latency, downtime, flooding of junk and false information. When users have limited attention resources, excessive use of digital resources can lead to 'information overload', which hinders innovative activities.

Intellectual property protection

Regional intellectual property protection level is positively correlated with digital innovation spillover, and there is a single threshold effect. When the patent infringement settlement rate is lower than 74.6%, the influence coefficient of digital development on technological innovation of manufacturing enterprises is 3.764, which is significantly positive at 1% confidence interval. When this threshold value is crossed, the influence coefficient of digital innovation spillover decreases to 3.444. The results show that, on the one hand, the high rate of patent infringement settlement reflects the effective protection and efficient law enforcement of intellectual property rights, which is conducive to guaranteeing the original achievements of manufacturing enterprises in the digital environment and encouraging technological innovation activities. On the other hand, when the intensity of intellectual property protection is too large, strict laws and regulations will inhibit the spillover of digital innovation, which will constrain the development of new technologies and new business forms under the digital economy.

VI. Conclusions and policy implications

Conclusions

Based on a panel data from 30 provinces in China between 2011 and 2018, the study uses a nonlinear two-way fixed effects model to reveal that digital economy has a positive impact on technological innovation in the manufacturing industry, with clear nonlinear spillover effects. The focus of this study is the discovery of inverted U-shaped nonlinear feature of digital innovation spillover. This discovery validates Metcalfe's Law, which states that as digitization deepens and user scale increases, the overall value of the digital economy will first experience exponential growth but will eventually decline beyond a certain threshold due to redundant resources and low environmental capacity for innovation activities. However, high-quality user literacy can positively moderate digital innovation spillover effects through better integration with demand feedback into manufacturing industry. The approach in this paper bears similarities to the work of Cetindamar Kozanoglu and Abedin (2021). While they demonstrated the impact of employees' digital literacy, our paper places emphasis on the users' digital literacy. Moreover, there are boundary conditions contributing to the digital innovation spillover effects. The study has examied the effect of threshold variables such as Internet penetration rate, information resources and intellectual property protection on digital innovation. Internet users increase network externality while excessive information weakens the efficiency of innovations. Reasonable intensity of intellectual property protection is conducive to guaranteeing original achievements, but excessive protection leads to fewer technological innovations.

Policy implications

The empirical findings of this study offer valuable insights for policymakers to harness the potential of digital development to drive technological innovation within the manufacturing industry. The following policy implications are proposed based on the research findings and conclusions.

Firstly, it is essential to speed up manufacturing enterprises' integration with new technologies, forms, and models of the digital economy with real economies. This can be achieved by fostering new types of digital industries based on major technological breakthroughs that enhance competitiveness within key links in industrial chains. Secondly, strengthening education and training programs aimed at improving digital literacy for users is necessary. Digital literacy is considered as an indispensable driver of digital innovation spillover. Policymakers should prioritize the development and implementation of comprehensive digital literacy programs. Building an interaction mechanism between users and enterprises through community platforms will achieve value co-creation while ensuring market-oriented demand-driven technical design processes that consider diversity among user needs. Thirdly, policymakers should continue efforts to expand Internet access and usage. The growth of Internet penetration is linked to increased network externality, which can stimulate digital innovation. Initiatives that address the digital divide and aim to incorporate more users into the digital economy are critical for realizing the potential of digital development. Fourthly, proper management of information resources will enhance the efficiency of innovation activities. Policymakers should design and implement strategies to oversee information resources effectively, ensuring their accessibility, relevance and quality for innovative endeavours. Lastly but not least important is improving governance structures around intellectual property protection.

Limitations and future research

Our study still has some limitations. The study relies on provincial level panel data from China. In future research, it may be better to use city panel data to test in econometric settings. Our study primarily focuses on the relationship between digital development and manufacturing innovation, but it may not fully address the issue of endogeneity. Other unobserved factors or reverse causality might influence the results.

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ORCID

Qinqin Wu http://orcid.org/0000-0003-4993-2784

Data availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Authors Contributions

Qinqin Wu designed the study, made theoretical analysis and empirical test, wrote the first draft, and submitted it. Qinqin Zhuang helped in data analysis, writing – review & editing, validation.

References

Abedin, B., F. Daneshgar, and J. D'Ambra. 2012. "Do Nontask Interactions Matter? The Relationship Between Nontask Sociability of Computer Supported Collaborative Learning and Learning Outcomes." *British Journal of Educational Technology* 43 (3): 385–397. https://doi.org/10.1111/j.1467-8535.2011.01181.x.

Athey, S., C. Catalini, and C. Tucker. 2017. The Digital Privacy Paradox: Small Money, Small Costs, Small Talk. *National Bureau of Economic Research Working Paper Series, No. 23488*. https://doi.org/10.3386/w23488.

Boland, R. J., K. Lyytinen, and Y. Yoo. 2007. "Wakes of Innovation in Project Networks: The Case of Digital 3-D Representations in Architecture, Engineering, and Construction." *Organization Science* 18 (4): 631–647. https://doi.org/10.1287/orsc.1070.0304.

Brandtweiner, R., E. Donat, and J. Kerschbaum. 2010. "How to Become a Sophisticated User: A Two-Dimensional Approach to E-Literacy." *New Media & Society* 12 (5): 813–833. https://doi.org/10.1177/1461444809349577.

Brynjolfsson, E., and A. Saunders. 2009. *Wired for Innovation: How Information Technology is Reshaping the Economy*. Cambridge, Mass, USA: Mit Press.

CAICT. 2023. *White Paper on the Development of China's Digital Economy*. Beijing. http://www.caict.ac.cn/kxyj/qwfb/bps/202304/P020230427572038320317.pdf.

Calvani, A., A. Fini, M. Ranieri, and P. Picci. 2012. "Are Young Generations in Secondary School Digitally Competent? A Study on Italian Teenagers." *Computers & Education* 58 (2): 797–807. https://doi.org/10.1016/j.compedu.2011.10.004.

Cetindamar Kozanoglu, D., and B. Abedin. 2021. "Understanding the Role of Employees in Digital Transformation: Conceptualization of Digital Literacy of Employees as a Multi-Dimensional Organizational Affordance." *Journal of Enterprise Information Management* 34 (6): 1649–1672. https://doi.org/10.1108/JEIM-01-2020-0010.

Ghasemaghaei, M., and G. Calic. 2020. "Assessing the Impact of Big Data on Firm Innovation Performance: Big Data is Not Always Better Data." *Journal of Business Research* 108:147–162. https://doi.org/10.1016/j.jbusres.2019.09.062.

Gilster, P. 1997. *Digital Literacy*. New York: Wiley Computer Pub.

Hansen, B. E. 1999. "Threshold Effects in Non-Dynamic Panels: Estimation, Testing, and Inference." *Journal of Econometrics* 93 (2): 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1.

Han, X.-F., W.-F. Song, and B.-X. Li. 2019. "Can the Internet Become a New Momentum to Improve the Efficiency of Regional Innovation in China." *China Industrial Economics*, 7:119–136. https://doi.org/10.19581/j.cnki.ciejournal.2019.07.007.

Hargittai, E. 2005. "Survey Measures of Web-Oriented Digital Literacy." *Social Science Computer Review* 23 (3): 371–379. https://doi.org/10.1177/0894439305275911.

Hargittai, E., and Y. P. Hsieh. 2012. "Succinct Survey Measures of Web-Use Skills." *Social Science Computer Review* 30 (1): 95–107. https://doi.org/10.1177/0894439310397146.

Harris, Richard G. 1998. "The Internet as a GPT: Factor Market Implications." In *General purpose technologies and economic growth*, edited by E. Helpman, 145–166. Cambridge, Mass, USA: MIT Press.

Helpman, E., and M. Trajtenberg. 1996. "Diffusion of General Purpose Technologies." *National Bureau of Economic Research Working Paper Series*. https://doi.org/10.3386/w5773.

Heredia, J., M. Castillo-Vergara, C. Geldes, F. M. Carbajal Gamarra, A. Flores, and W. Heredia. 2022. "How Do Digital Capabilities Affect Firm Performance? The Mediating Role of Technological Capabilities in the "New normal"." *Journal of Innovation & Knowledge* 7 (2): 100171. https://doi.org/10.1016/j.jik.2022.100171.

Huang, Q., Y. Yu, and S. Zhang. 2019. "Internet Development and Productivity Growth in Manufacturing Industry: Internal Mechanism and China Experiences." *China Industrial Economics*, 8:5–23. https://doi.org/10.19581/j.cnki.ciejournal.2019.08.001.

Kane, Gerald. 2019. "The Technology Fallacy." *Research-Technology Management* 62 (6): 44–49. https://doi.org/10.1080/08956308.2019.1661079.

Katz, M. L., and C. Shapiro. 1985. "Network Externalities, Competition, and Compatibility." *The American Economic Review* 75 (3): 424–440.

Manso, G. 2011. "Motivating Innovation." *The Journal of Finance* 66 (5): 1823–1860. https://doi.org/10.1111/j.1540-6261.2011.01688.x.

Meyers, E. M., I. Erickson, and R. V. Small. 2013. "Digital Literacy and Informal Learning Environments: An Introduction." *Learning, Media and Technology* 38 (4): 355–367. https://doi.org/10.1080/17439884.2013.783597.

Nambisan, S. 2017. "Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship." *Entrepreneurship Theory and Practice* 41 (6): 1029–1055. https://doi.org/10.1111/etap.12254.

Paunov, C., and V. Rollo. 2016. "Has the Internet Fostered Inclusive Innovation in the Developing World?" *World Development* 78:587–609. https://doi.org/10.1016/j.worlddev.2015.10.029.

Polizzi, G. 2020. "Digital Literacy and the National Curriculum for England: Learning from How the Experts Engage with and Evaluate Online Content." *Computers & Education* 152:103859. https://doi.org/10.1016/j.compedu.2020.103859.

Qinqin, W., S. A. Qalati, R. Y. Hussain, H. Irshad, K. Tajeddini, F. Siddique, and T. C. Gamage. 2023. "The Effects of enterprises' Attention to Digital Economy on Innovation and Cost Control: Evidence from A-Stock Market of China." *Journal of Innovation & Knowledge* 8 (4): 100415. https://doi.org/10.1016/j.jik.2023.100415.

Reddy, P., B. Sharma, and K. J. I. J. O. T. Chaudhary. 2020. "Digital Literacy: A Review of Literature." *International Journal of Technoethics* 11 (2): 65–94. https://doi.org/10.4018/IJT.20200701.oa1.

Ruochen, D., W. Aizhao, C. Binkai, and Z. Xiaobo. 2021. *Index of Regional Innovation and Entrepreneurship in Digital Economy in China (IRIEDEC)*. Retrieved from: https://doi.org/10.18170/DVN/EYCVSP

Sarkar, S. 2012. "The Role of Information and Communication Technology (ICT) in Higher Education for the 21st Century." *Science* 1 (1): 30–41.

Sharma, B., F. I. J. Lauano, S. Narayan, A. Anzeg, B. Kumar, and J. Raj. 2018. "Science Teachers Accelerated Programme Model: A Joint Partnership in the Pacific Region." *Asia-*

Pacific Journal of Teacher Education 46 (1): 38–60. https://doi.org/10.1080/1359866X.2017.1359820.

Sims, C. A. 2003. "Implications of Rational Inattention." *Journal of Monetary Economics* 50 (3): 665–690. https://doi.org/10.1016/S0304-3932(03)00029-1.

Sims, C. A. 2006. "Rational Inattention: Beyond the Linear-Quadratic Case." *American Economic Review* 96 (2): 158–163. https://doi.org/10.1257/000282806777212431.

Stordy, P. 2015. "Taxonomy of Literacies." *Journal of Documentation* 71 (3): 456–476. https://doi.org/10.1108/JD-10-2013-0128.

Teece, D. J. 2018. "Profiting from Innovation in the Digital Economy: Enabling Technologies, Standards, and Licensing Models in the Wireless World." *Research Policy* 47 (8): 1367–1387. https://doi.org/10.1016/j.respol.2017.01.015.

Thomas, A. 2020. "Convergence and Digital Fusion Lead to Competitive Differentiation." *Business Process Management Journal* 26 (3): 707–720. https://doi.org/10.1108/BPMJ-01-2019-0001.

van Deursen, A. J. A. M., E. J. Helsper, and R. Eynon. 2016. "Development and Validation of the Internet Skills Scale (ISS)." *Information, Communication & Society* 19 (6): 804–823. https://doi.org/10.1080/1369118X.2015.1078834.

Varian, H. R. 2010. "Computer Mediated Transactions." *American Economic Review* 100 (2): 1–10. https://doi.org/10.1257/aer.100.2.1.

Wang, F.-Z., X.-L. Lliu, Z. Lei, and C. Wen-Chao. 2021. "Does Digitalization Promote Green Technology Innovation of Resource-Based Enterprises?" *Studies in Science of Science* 40 (2): 332–344. https://doi.org/10.16192/j.cnki.1003-2053.20210824.001.

Warner, K. S. R., and M. Wäger. 2019. "Building Dynamic Capabilities for Digital Transformation: An Ongoing Process of Strategic Renewal." *Long Range Planning* 52 (3): 326–349. https://doi.org/10.1016/j.lrp.2018.12.001.

Yalcin, N., and U. Ünlü. 2018. "A Multi-Criteria Performance Analysis of Initial Public Offering (IPO) Firms Using CRITIC and VIKOR Methods." *Technological and Economic Development of Economy* 24 (2): 534–560. https://doi.org/10.3846/20294913.2016.1213201.

Yoo, Y., O. Henfridsson, and K. Lyytinen. 2010. "Research Commentary—The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research." *Information Systems Research* 21 (4): 724–735. https://doi.org/10.1287/isre.1100.0322.

Zhao, T., Z. Zhang, and S. Liang. 2020. "Digital Economy, Entrepreneurship, and High-Quality Economic Development: Empirical Evidence from Urban China." *Management World* 36 (10): 65–76. https://doi.org/10.19744/j.cnki.11-1235/f.2020.0154.