Available Online: 28 July 2026 DOI: 10.54254/2977-5701/2026.35720

Can digital-real integration reverse the low-end-locked dilemma of innovation: the case of China's industrial sector

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Abstract. The digital-real integration is emerging as a strategic approach to invigorate industry and enhance industrial core competitiveness. This paper categorizes industrial innovation into high-end and low-end innovations, and empirically examines the influence of digital-real integration on industrial innovation in China's industrial sector, specifically on the low-end-locked dilemma. The results reveal that digital-real integration substantially fosters industrial innovation and recreates a crucial function in overcoming the challenges of low-end-locked innovation. The empowering effect of digital-real integration on industrial innovation varies under different quantile conditions and its marginal contribution increases as the level of industrial innovation improves. The industrial absorptive capacity positively moderates the driving effect of digital-real integration on industrial innovation. The analysis of heterogeneity in digital-real integration sources indicates that incorporating digital services into the real economy significantly influences high-end innovation more than digital products. This study provides valuable insights for governments to facilitate high-end industrial innovation through digital-real integration.

Keywords: digital-real integration, low-end-locked dilemma, low-end innovation, absorptive capacity

1. Introduction

Developing countries increasingly acknowledge that industrial innovation plays a pivotal role in establishing their core competitive advantage, serving as a vital catalyst for sustained economic growth. Given the progressively intricate global political and economic landscape, innovation in high-tech sectors, advanced manufacturing, and emerging industries has evolved into frontier competition among major powers [1]. However, contradicting the vast scale of industrial output, the majority of China's manufacturing sector remains stuck at the low end of the global value chain, exhibiting a characteristic of "quantity over quality" in industrial innovation. From 2010 to 2022, the proportion of invention patents granted in China consistently fluctuated within the range of 14.6% to 23.6% of the total number of patents issued. By contrast, the ratio for the United States remains around 90% [2]. The *Global Innovation Index Report 2021* shows that China is ranked 12th in the innovation index and is impeded by the issue of low-end-locked, posing a significant and pressing challenge for high-quality economic growth.

Since the advent of the "post-industrialization" era, the profound advancement of digital technology and its rapid penetration into the industrial sector has progressively underscored the benefits of the digital economy in augmenting national competitiveness and global value chain positioning. The digital economy has spawned numerous novel industries and models, propelling digital transformation and ushering in fresh prospects for high-quality economic growth [1]. The *Digital China Development Report (2022)* highlights that China's digital economy expanded to 5.02 trillion yuan in 2022, which accounted for 41.5% of the country's GDP, effectively bolstering the ongoing economic recovery. The report of the *20th National Congress* was put forward to expedite the advancement of the digital economy and foster a profound integration between the digital and real economy. As the primary arena of digital advancement, the profound fusion of the industrial sector with information networks and digital technologies is pivotal in unlocking the boundless potential of new digital industries and models for industrial innovation.

While digital-real integration holds significant promise for industrial innovation by revolutionizing existing production, research and development, and management models, it remains a thought-provoking question whether this strategy can effectively address the challenge of the low-end-locked dilemma in industrial innovation during the digital transformation era. Furthermore, China's industrial landscape encompasses a wide array of sectors with varying technological content and levels of digitization, resulting in uneven absorption capacity and digital coverage across industries. The impact of digital-real integration on different industrial sectors and innovation activities may be heterogeneous. Therefore, how does digital-real integration impact industrial innovation in practical terms? Can it propel the transition from the "low-end" to the "high-end" of industrial innovation? What are the crucial scenario mechanisms involved? Answering these questions is essential and urgent. It will offer the industry a valuable reference for enhancing its innovation capabilities through integration with the digital economy, ultimately contributing to the rapid construction of an innovative nation.

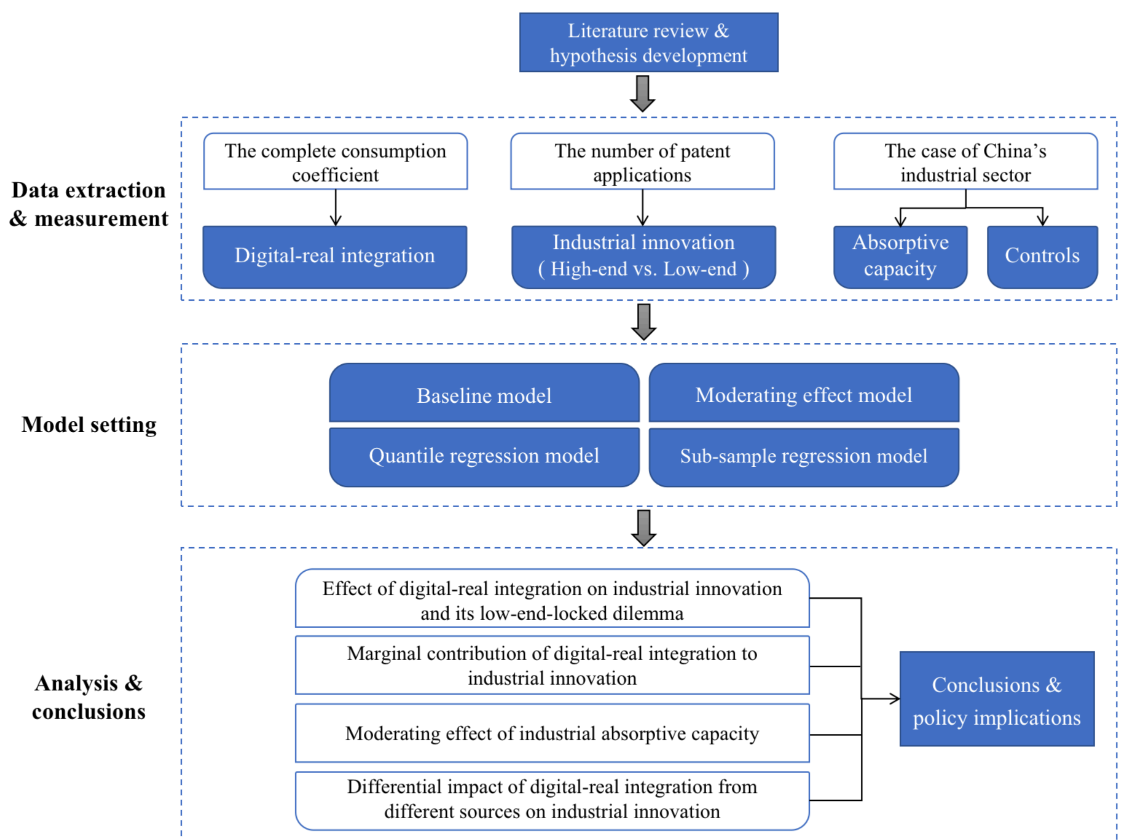

Figure 1. Research process and analysis procedure

The rest of this article is arranged as follows. Section 2 reviews the literature. Section 3 provides the theoretical basis and hypothesis. Section 4 presents the research methods and data. Section 5 shows the findings and offers a comprehensive analysis. The conclusion is presented in Section 6. Figure 1 shows the research process and the analysis procedure in the following sections.

2. Literature review

The digital economy has significantly influenced economic and social development, attracting considerable attention from academia due to its technological and service advantages in recent years. However, there lack of comprehensive theoretical and empirical research focusing on the influence of digital-real integration on industrial innovation. The current literature discusses the concept of digital-real integration, economic implications of digital economy, and its connection with innovation activities, which holds relevance for this paper.

The digital-real integration refers to the digitalization and intelligence of the real economy, encompassing various novel concepts and domains brought by the digital economy, like data elements, the sharing economy, and the platform economy [3]. The shared and interconnected nature of the digital economy establishes the groundwork for the convergence of digital and real economies. As Hong and Ren [4] outlined, digital-real integration involves the entire process of digital technologies and data elements penetrating into the real economy, which propels the enhancements of quality, efficiency, capabilities, and production methods in the real economy.

Regarding the economic effects of the digital economy, previous studies generally acknowledge its substantial assistance to economic development, total factor productivity, industrial structure optimization, and sustainable development [5]. The digital economy has the ability to enable traditional production systems to achieve enhanced and sustainable economic performance through optimizing resource allocation, enhancing efficiency in supply and demand alignment, and fostering technological innovation [6]. Taking 271 cities in China, Ren et al. [7] provide evidence that the digital finance facilitates industrial structure upgrading with regional variations. Xu et al. [8] performed an empirical analysis involving 210 Chinese manufacturing firms, revealing a positive correlation between digital transformation and the sustainable development of enterprises. Hao et al. [9] employed a spatial econometric model to explore how digitization affects green economic growth and revealed that digitization has the potential to stimulate green economic benefits by fostering innovation in green technology.

The existing exploration has not reached a unified consensus regarding the correlation between the digital economy and innovation activities. Most studies provide a positive outlook on the innovation impact of digital economy [10]. At the enterprise level, the representative literature suggests that the digital economy is a considerable driver of innovation for non-state enterprises, small and medium-sized enterprises. Digital technologies, platforms, and infrastructure offer unparalleled tools and opportunities for enterprise innovation, but the persisting issue of prioritizing quantity over quality remains largely unaddressed [11]. At the regional innovation level, only a few studies have investigated the comprehensive impact of the digital economy on innovation, which highlights the significance of alleviating financing constraints and expanding collaboration channels as crucial mechanisms for effectively driving innovation through the digital economy [12, 13]. There are different opinions among scholars regarding this matter. Ghasemaghaei and Calic [14] conducted an empirical study using questionnaire data from the US and discovered that different aspects of big data have varying effects on firm innovation performance, with quantitative characteristics showing minimal effect.

The above literature offers a plethora of valuable insights for this study but several areas for improvement. First, while numerous prior studies acknowledge the positive influence of digital economy in stimulating enterprise innovation, there remains an inadequate focus on its potential impact on the industrial predicament of low-end-locked innovation. Second, the current research primarily focuses on the economic benefits and innovation impacts of the digital economy from the standpoint of digital economy itself or digital transformation, neglecting the empowerment role of digital-real integration, a new direction and stage of digital economy development. Third, digital-real integration encompasses the entire process of applying, penetrating, and reshaping digitalization within the non-digital real economy. Unfortunately, the current research falls short of providing a valid quantification of the digital-real integration degree.

To bridge these limitations, this study adds knowledge related to digital-real integration and endeavors to contribute in the following aspects. First, the input-output model is adopted to measure the integration degree of the digital economy and real industrial sector, based on which the impact mechanism of digital-real integration on industrial innovation and the potential to mitigate the low-end-locked challenge in industrial innovation are explored. Enriching the research framework of the digital economy's role in empowering industrial innovation, this spreads up a unique research perspective for harnessing the digital dividend. Second, this paper attempts to investigate the moderating function of knowledge absorption in the process of digital-real integration affecting industrial innovation, taking into account variances in research and development cost, the technological complexity, and risk degree, between industrial high-end and low-end innovations. This is helpful to clarify the scenario mechanism of digital-real integration reversing the low-end-locked dilemma compared with existing studies. Third, this paper explores the internal logic of digital-real integration improving industrial innovation quality from perspectives of digital service penetration and digital product application, given the diverse sources of digital-real integration. This can provid the feasibility for industrial sector to leverage appropriate digital-real integration strategies to achieve a high-end innovation leap, compared with previous studies.

3. Theoretical basis and assumptions

3.1. The relationship between digital-real integration and industrial innovation

The digital economy era is characterized by data-driven, resource-sharing, and network interconnections. The fusion of digital and real industrial elements presents significant incentives for industrial innovation, which can be observed through various aspects. First, digital-real integration enhances the ability of innovation entities to gain insights from external information, thus catalyzing industrial innovation by uncovering hidden issues and identifying avenues for improvement. The data, including production data, market data, and user data, is a valuable information resource [14]. By acquiring, mining, analyzing, and engaging with such information, micro-enterprises can leverage these resources to gain a competitive edge in innovation. This enables them to accurately navigate market trends, enhance Research and Development (R&D) efficiency, mitigate innovation risks, and ultimately transform untapped data resources into tangible innovation outcomes [15]. Second, digital-real integration enhances the collision and crossover of technology, knowledge, and experiences across various domains, effectively stimulating fresh perspectives on innovation. This interdisciplinary integration and communication foster innovative ideas within the industrial sector, prompting a departure from traditional innovation modes and thinking frameworks, thereby accelerating the progress of innovation activities [16]. Third, leveraging its technological advantages and the vast reach of the Internet platform, the digital economy has established a robust foundation for sharing resources across time and space, facilitating collaborative innovation. This allows industrial enterprises to use external innovation resources and reduce innovation costs entirely. Building upon this premise, the paper puts forth the hypothesis:

H1. The digital-real integration is exerting a positive influence on industrial innovation.

When it comes to innovation activities for industries, they can be classified into two categories based on their research and development process, areas of focus, and development objectives. One is low-end innovation, which typically involves improving and optimizing existing products and services. This type of innovation is characterized by low income, low levels of knowledge and technology complexity, low risk, and small investment. High-end innovation falls into the second category, which is characterized by high returns but high levels of knowledge and technology complexity, high risks, and large investments. High-end innovation typically involves disruptive technologies, new business models, and strategies, primarily leading industry development, promoting technological progress, and driving industrial upgrading. Compared to the "quick and easy" low-end innovation, high-end innovation demands a higher level of knowledge and technology intensity, and may be driven more digital-real integration strategy.

On the one hand, low-end innovation, represented by utility models and designs, is a strategic industry behavior with low reliance on knowledge. Constantly, the complexity of high-end innovation makes its R&D process more reliant on innovative resources and advanced technologies, resulting in a stronger sensitivity to the spillover effects of data knowledge and digital technologies under digital-real integration [17]. On the other hand, using digital technologies like virtual reality, 3D printing, and computer-aided design accelerates the creation and testing of product prototypes and compresses the R&D cycle, which is more evident in high-end innovation [13]. As an emerging economic paradigm, digital economy promotes the formation and development of digital innovation ecosystem to promote the cross-border flow of knowledge and talent. This can break down technological barriers and enable industrial sectors to escape from low-end-locked innovation [10]. Therefore, this study proposes that:

H2. Digital-real integration has a stronger driving effect on high-end innovation; that is, digital-real integration can reverse the low-end-locked dilemma of industrial innovation.

3.2. The scenario mechanism of digital-real integration affecting industrial innovation

According to the theory of innovation, the inherent variability within an industry significantly influences its innovative behavior [18]. Absorptive capacity means the industry's capability to identify, extract, deconstruct, and analyze knowledge and technology to learn, enhance, and translate them into its own output. This capacity plays a vital role in shaping innovation activities [19]. This paper integrates absorptive capacity into a situational analysis framework to thoroughly examine the impact of digital-real integration in enabling innovation.

The existing literature highlights that the decision-making for industrial innovation in the digital economy is influenced by its absorptive capacity. Industries possessing higher absorptive capacity are more likely to prioritize high-end innovations over low-end ones. This preference is attributed to absorptive capacity determining the extent to which enterprises and organizations embrace and leverage digital technology and data resources. When an industry exhibits limited understanding and awareness of digital technology and lacks the necessary infrastructure and skilled workforce, its participation and impetus for innovation through digital-real integration may be constrained, potentially resulting in missed opportunities to gain a competitive advantage from digitalization-driven innovation [20]. Conversely, industries with robust absorptive capacity are more inclined to adopt digital technologies across various aspects, such as production, management, and marketing. They seize technological opportunities, foster innovators and users in the digital age, and adeptly adapt to market demands by strengthening collaborations and enterprise alliances. Consequently, the integration of digital and real industrial economy significantly facilitates industrial innovation in these sectors. Thus, this paper hypothesizes that:

H3. Absorptive capacity can positively moderate the promoting effect of digital-real integration on industrial innovation.

H4. Industries with robust absorptive capacity are likelier to engage in high-end innovation through digital-real integration.

Figure 2 illustrates the conceptual model and hypotheses proposed in this study.

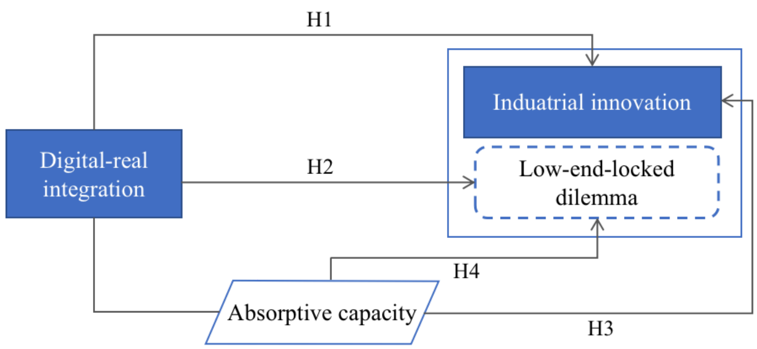

Figure 2. Conceptual model

4. Estimation model and data

4.1. Model setting

To examine the practical implications of digital-real integration on industrial innovation, this study performs econometric analysis using panel data on China's industrial sector from 2010 to 2020. Following the approach by Razzaq and Yang [21], this paper establishes the subsequent model (Equation (1)):

$$II_{it} = \beta_0 + \beta_1 DRI_{it} + \sum_{k=2}^{5} \beta_k cvs_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

where β_0, … β_5 represent the estimated coefficients, the subscript i denotes the industrial sector, and t represents the year. Variable II corresponds to industrial innovation, while DRI indicates the degree of digital-real integration. Additionally, cvs_{it} represents the control variables. The terms μ_i and θ_t denote the fixed effects, and ε_{it} reflects the impact of random error. In examining the potential of digital-real integration to counteract the low-end-locked phenomenon in industrial innovation, the dependent variable will be successfully substituted with High-end Innovation (HII) and Low-end Innovation (LII). Consistent with Hypothesis 1, this study conjectures that $\beta_1 > 0$.

Moreover, to investigate the situational mechanisms of digital-real integration affecting industrial innovation, the following moderating effect model (Equation (2)) is constructed in this paper, referring to Bendig et al. [22]:

$$II_{it} = \varphi_0 + \varphi_1 DRI_{it} + \varphi_2 M_{it} + \varphi_3 DRI_{it} \times M_{it} + \sum_{k=4}^{7} \delta_k cvs_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

where φ_0, …φ_8 denote the estimated coefficients, while M_{it} represents the moderating variable known as industry absorptive capacity. This paper employs Industry Size (IS) and Research and Development Capital Investment (RD) as proxy variables to capture this capacity. The significance of the estimated coefficients φ_1 and φ_3 suggests absorptive capacity acts as a moderator of digital-real integration affecting industrial innovation.

Given that the above analyses rely on the mean value model, which solely assesses the average impact of DRI on II, it becomes challenging to visually comprehend the distinct effects of digital-real integration on industrial innovation across various conditional positions. Extreme values within the variables may lead to instability in the parameter estimation. Hence, this study constructs the panel quantile regression model (Equation (3)) to examine whether industrial sectors with different innovation levels benefit equally from the digital-real integration development strategy.

$$Q_\tau(II) = \alpha_0 + \alpha_1 DRI_{it} + \sum_{k=2}^{5} \alpha_k cvs_{it} + \varepsilon_{it} \tag{3}$$

where α_0, … α_5 represent the estimated coefficients. τ represents the quantile points. The parameter τ is employed to denote the specific quantile points. To get a better picture of the conditional distribution, five quantile points of 0.10, 0.25, 0.50, 0.75, and 0.90 are selected for estimation in this paper, following the practice of existing studies [23]. This approach is aimed at offering a comprehensive and nuanced analysis of the research subject.

4.2. Variable definitions and data sources

4.2.1. Dependent variable

As for industrial innovation, scholars generally quantify it in two ways: innovation inputs and innovation outputs. However, the digital transformation of industries necessitates investments in capital and personnel, which may have crowding out and synergistic effects on Research and Development (R&D) investment. Furthermore, R&D investment only partially translates into industrial innovation due to factors such as competitive environment, organizational management, and technological challenges [24]. Therefore, this paper focuses on the innovation outputs and employs the number of patent applications as a quantitative indicator of industrial innovation. And the invention and non-invention patent applications are used as proxies for high-end and low-end innovation in the industry, based on the value of patents and the stringency of patent applications.

4.2.2. Core explanatory variable

This paper employs the *Statistical Classification of the Digital Economy and Its Core Industries (2021)* as the standard for classifying digital industries. Subsequently, the industrial sectors are consolidated into 22 categories based on the *Input-Output Tables* of China. Building upon this foundation, a complete consumption coefficient is utilized to comprehensively evaluate the extent of integration and penetration of the digital economy within the industrial real sector. This approach effectively captures the direct and indirect relationship between the two sectors [25].

4.2.3. Moderating variable

Absorptive capacity refers to the industry's ability to effectively incorporate and leverage new technologies and knowledge. It is widely acknowledged among scholars that the industry's capacity for learning and adaptation, as well as its potential to foster creativity and motivation, tends to improve with larger industry sizes and more significant R&D investments [26]. Therefore, this study utilizes Industry Size (IS) and R&D Capital Investment (RD) as proxy variables of industrial absorptive capacity. IS is expressed by the rate of the industry's primary business income to the number of employees, while RD is measured by the logarithm of the R&D expenditures, including both internal and external investments.

4.2.4. Control variables and data sources

To minimize the interference associated with hidden and confounding variables, the following four control variables that potentially impact industrial innovation are selected in this paper. Industry Competitiveness (IC) is assessed based on the industry's total assets. Labor Demand (LD) is quantified by the number of industrial workers employed. Foreign Direct Investment (FDI) is represented by the total assets of foreign-invested enterprises to the total assets of industrial enterprises. Capital Intensity (CI) is quantified by the rate of total industrial assets to the workers employed. The original data were obtained from reliable sources such as the *Input-Output Tables* and *China Industry Statistical Yearbook*. All economic indicators are deflated to eliminate the effect of inflation.

5. Results and discussion

5.1. Benchmark regression

In order to determine the most suitable approach for addressing the problem at hand, a Hausman test was performed. Based on the Hausman test result presented in Table 1, a significant value of 68.06 suggests that the fixed effect model is preferred. To prevent the interference of time variation, this study further constructs a time and industry double fixed model, with the estimation results shown in model (3). The coefficient of DRI exhibits a significant positive value, suggesting that a 1% increase in digital-real integration corresponds to a 0.444% rise in industrial innovation. Therefore, Hypothesis 1 is confirmed.

Table 1. Benchmark regression results

Dependent variable	II	II	II	HII	LII
Variable	(1)-RE	(2)-FE	(3)-FE	(4)-FE	(5)-FE
DRI	0.391***	0.137***	0.444***	0.522***	0.411***
	(8.52)	(5.33)	(9.44)	(9.72)	(9.00)
IC	-0.437***	-0.424***	-0.457***	-0.386**	-0.487***
	(-2.85)	(-3.38)	(-2.94)	(-2.18)	(-3.23)
LD	0.367**	0.478***	0.411***	0.342**	0.441***
	(2.46)	(3.91)	(2.72)	(1.98)	(3.01)
FDI	-0.567***	-0.041	-0.679***	-0.676***	-0.680***
	(-3.56)	(-0.29)	(-4.23)	(-3.70)	(-4.37)
CI	0.411***	0.468***	0.437***	0.400***	0.452***
	(3.40)	(4.61)	(3.57)	(2.87)	(3.81)
_cons	0.427	-0.524**	0.246	0.063	0.324
	(1.43)	(-2.39)	(0.79)	(0.18)	(1.07)
Industry fixed	No	Yes	Yes	Yes	Yes
Year fixed	No	No	Yes	Yes	Yes
Hausman		68.06***			
R^2	0.498	0.401	0.552	0.556	0.537
Obs.	242	242	242	242	242

Note: The values in brackets are *T*-value, ***, ** and * represent significant at the 1%, 5%, 10% levels.

This finding is consistent Tian et al. [27] that the digital economy enriches innovation factors. New production factors are rapidly generated by leveraging intelligent devices to screen and mine massive amounts of data. Furthermore, the deepening integration of digital and real production components contributes to an improved innovation network. It eliminates spatial barriers among innovation agents, weakening disciplinary boundaries and promoting collaborative innovation. This integration has the capacity to optimize the assignment of resources and reduce R&D risks, cycles, and costs associated with innovation, as supported by Dong and Netten [28]. The digital economy era has also witnessed an explosion of data from diverse sources. This has significantly changed industrial development concepts, industrial forms, and business models. As a result, the internal and external environment for industrial innovation has been optimized, creating opportunities for companies to foster breakthroughs and inspire innovation [29].

To test Hypothesis 2, this study performed separate regression analyses for high-end innovation and low-end innovation using the subset of data. The corresponding results are presented in models (4) and (5). The estimated coefficients of digital-real integration on both types of innovation are significantly positive, indicating a noteworthy enhancing effect on innovation in both segments. Additionally, it is noteworthy that the coefficient for digital-real integration on high-end innovation is notably larger than that on low-end innovation. That is, the driving effect of digital-real integration on high-end innovation is more pronounced. This finding suggests that digital-real integration aids in overcoming the low-end-locked dilemma in industrial innovation, providing support for Hypothesis 2 put forth in this paper. As demonstrated by Zhang et al. [30], the digital era presents novel technological tools, business models, and market opportunities for the industrial sector, enabling it to transcend the confines of the conventional "low-end" paradigm and achieve remarkable breakthroughs in technological innovation. By capturing production and market data, the industrial sector can significantly enhance its understanding of product performance and shifts in demand. This comprehensive insight paves the way for targeted innovation and improvements, effectively circumventing the pitfalls of "short and fast" low-end innovation [31].

5.2. Panel quantile regression

The baseline regression results confirm a significant contribution of digital-real integration to industrial innovation. However, the marginal influence of digital-real integration on industrial innovation across different levels of innovation is rarely revealed. Specifically, do industries at various levels of innovation benefit equally from digital-real integration? To address this question, this study employs a quantile regression model using five quartiles (0.10, 0.25, 0.50, 0.75, and 0.90) to assess the marginal contribution of digital-real integration to industrial innovation. As presented in Table 2, the regression coefficients for each quantile are 0.014, 0.022, 0.025, 0.196, and 0.308. All of them are statistically significant, except for the 0.10 quantile. These findings indicate a positive influence of digital-real integration on industrial innovation.

Table 2. Quantile regression results

Dependent variable: II					
Variable	QR-(0.10)	QR-(0.25)	QR-(0.50)	QR-(0.75)	QR-(0.90)
DRI	0.014***	0.022***	0.025	0.196***	0.308***
	(2.84)	(6.78)	(0.55)	(3.05)	(4.85)
Control	Yes	Yes	Yes	Yes	Yes
_cons	-0.256	-0.404***	-0.411***	-0.609***	-0.783***
	(-1.57)	(-6.13)	(-6.27)	(-6.05)	(-5.51)
R^2	0.172	0.273	0.326	0.430	0.534

Note: The values in brackets are *T*-value, ***, ** and * represent significant at the 1%, 5%, 10% levels.

Illustrated in Figure 3, the marginal effect of digital-real integration exhibits an increasing trend, with the 0.5 quantile representing a pivotal turning point. This suggests that the digital-real integration development strategy yields a more substantial innovation-enabling effect for industries with higher levels of innovation.

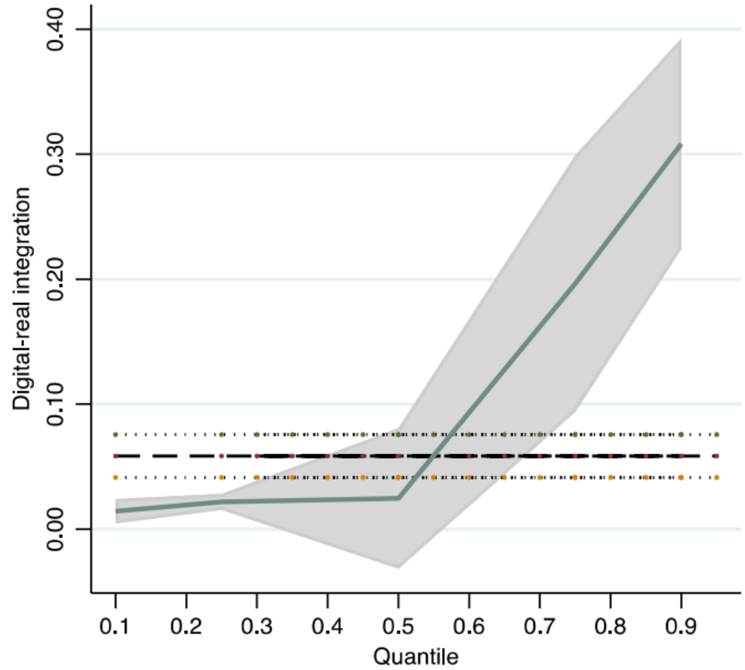

Figure 3. Quantile regression graph

Possible reasons for this phenomenon can be attributed to several factors. Industries with lower levels of innovation often suffer from technological and talent deficiencies. Their limited adoption of digital transformation hinders their ability to actively pursue innovation and adapt to the changing landscape, causing them to miss out on the opportunities presented by the digital economy [32]. In contrast, industries with higher levels of innovation are typically driven by technology, possess greater flexibility and adaptability, and benefit from a stronger economic foundation, a pool of skilled information professionals, and a robust ecosystem for digitalization and innovation. As a result, they can better embrace and leverage the digital economy, which amplifies the effect of digital-real integration on their innovation capabilities [33]. Consequently, the marginal impact of digital-real integration on industrial innovation becomes more pronounced as the level of innovation rises.

5.3. Moderating effect of absorption capacity

In the theoretical analysis, variations in industry absorptive capacity resulting from information technology infrastructure, human resources, and industrial models may affect the role of digital-reality integration in promoting industrial innovation. This paper examines the moderating effect of industry absorptive capacity by introducing a cross-term. Large enterprises, as opposed to small and medium-sized enterprises, possess the advantage of scale and demonstrate a more vital capacity to absorb knowledge spillovers. The IS and its cross-term with digital-real integration are introduced in Equation (2). The regression results of model (1)-(3) are in Table 3. The positive coefficient of DRI aligns with the baseline regression findings. The influence coefficients of DRI*IS on overall innovation, high-end innovation, and low-end innovation are 0.789, 1.096, and 0.659, respectively. These results demonstrate that industry absorptive capacity is favorable moderator in industrial innovation driven by digital-real integration. The digital-real integration development strategy empowers industries with robust absorptive capacity to undertake more high-end innovation activities and alleviate the low-end-locked predicament in industrial innovation. These findings align with the theoretical expectations.

Table 3. Regression results for the moderating effect of absorptive capacity

Dependent variable:	II	HII	LII	II	HII	LII
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DRI	0.350***	0.391***	0.332***	0.250***	0.285***	0.236***
	(7.30)	(7.42)	(7.02)	(5.27)	(5.45)	(4.97)
DRI*IS	0.789***	1.096***	0.659***			
	(5.26)	(6.62)	(4.44)			
DRI*RD				0.386***	0.471***	0.349***
				(7.77)	(8.63)	(7.06)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.606	0.635	0.578	0.669	0.695	0.640
Obs.	242	242	242	242	242	242

Note: The values in brackets are *T*-value, ***, ** and * represent significant at the 1%, 5%, 10% levels.

For the accuracy of the econometric results, the RD and its cross-term with digital-real integration are further introduced into equation (2) to test the moderating effect. As illustrated in models (4)-(6) presented in Table 3, the estimated coefficients for both DRI and DRI*RD are significantly positive, with a larger coefficient observed for high-end innovation. This signifies that the innovation-enabling benefits of digital-real integration are more prominent in industries with a robust absorptive capacity, aligning with previous findings. Compared with low-end innovation, industries with a stronger absorptive capacity excel at leveraging data resources and digital technology to drive high-end innovation, thereby mitigating the prevailing trend of "short and quick" innovation. This discovery is corroborated by Liu and Pang [34], who found that industries with a higher absorptive capacity typically possess superior comprehension and application capabilities regarding technology. Moreover, these industries exhibit remarkable proficiency in recognizing the opportunities presented by the digital economy, discerning prevailing market trends, consumer demands, and prospects for innovation [35]. Therefore, Hypotheses 3 and 4 have been confirmed.

5.4. Heterogeneity analysis of digital-real integration sources

This section divides digital-real integration into two distinct types, considering the sources of the digital economy consumed by the industrial real sector in the input-output table: the integration of the Digital Product Sector and the Real Industrial Sector (DPRI), the integration of the Digital Service Sector and the Real Industrial Sector (DSRI). Drawing upon this, this study constructs the sub-sample regression model for heterogeneity analysis. This endeavor aims to unravel the essential digital factors driving industrial innovation and develop accurate policy guidance. Table 4 offered the practical results founded on the source heterogeneity of digital-real integration.

Table 4. Regression results based on source heterogeneity of digital-real integration

Dependent variable:	II	HII	LII	II	HII	LII
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DPRI	0.390***	0.464***	0.359***			
	(10.28)	(10.82)	(9.68)			
DSRI				1.095***	1.369***	0.978***
				(6.03)	(6.66)	(5.56)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.576	0.587	0.557	0.455	0.467	0.440
Obs.	242	242	242	242	242	242

Note: The values in brackets are *T*-value, ***, ** and * represent significant at the 1%, 5%, 10% levels.

First, as depicted in models (1) and (4), the coefficients for DPRI and DSRI are notably positive, underscoring the role of both types of digital-real integration in fostering industrial innovation. Upon comparison, it becomes evident that a 1% increase in DPRI corresponds to a 0.390% rise in industrial innovation, while a 1% increase in DSRI results in a more substantial 1.095% boost in industrial innovation. These findings suggest that the convergence of digital services exerts a stronger driving force on industrial innovation than digital products. Second, according to models (2), (3), (5), and (6) presented, the impact coefficients of DPRI and DSRI on high-end innovation outweigh their influence on low-end innovation. This observation indicates that both types of digital-industrial integration prove advantageous for enabling industrial innovation to escape from the low-end-locked dilemma. Notably, the estimated coefficient of 1.369 is nearly three times higher than that of 0.464, signifying that the incorporation of digital services significantly enhances the quality of industrial innovation compared to the utilization of digital products.

The rationale behind this observation may be that the adoption of digital products often necessitates industrial firms to undergo system transitions and adaptations. This entails investments in acquiring new technologies and tools, adjusting work processes, and training employees [36]. The presence of switching costs and complexities can pose additional challenges for companies in implementing innovation activities, thereby delaying the immediate return on digital equipment input. On the other hand, the digital service industry leverages digital technologies such as information and communication and big data to serve as conduits for knowledge and information collection and transfer [37]. Such digital services emphasize innovative value and differentiation, empowering the real industrial sector to grasp market trends, foster innovative thinking, and establish open collaborative systems. Consequently, it exerts a more potent driving force toward achieving high-quality innovation.

5.5. Robustness test

The robustness tests through four procedures are conduced, and the outcomes are documented in Table 5. First, to address potential bias arising from omitted variables, this study incorporates industry Energy Consumption (EC) and Market Environment (ME) into the equation, thereby re-estimating the impact of digital-real integration on industrial innovation (as depicted by model (1)). Second, the direct consumption coefficient is used to measure the integration degree among industries, providing a more direct reflection of the extent to which the digital economy permeates the real industrial sector. It is representative and reliable as a proxy for the core explanatory variables (as shown in model (2)). Third, considering the inherent lag in the patent application and mitigating reverse causality between digital-real integration and industrial innovation, this study employs the t+1 period of the dependent variable for re-regression (as presented in model (3)). Fourth, to address potential endogeneity concerns within the model, this paper incorporates the Two-Stage Least Squares (TSLS) method to reduce estimation errors (as demonstrated by model (4)). Table 5 demonstrates that digital-real integration exhibits a significantly positive.

Table 5. Robustness results

Variables	(1)	(2)	(3)	(4)
	Adding control variables	Replace the core explanatory variable	Replace the dependent variable	Two stage least square method
DRI	0.432***	0.804***	0.423***	0.890***
	(9.21)	(8.51)	(9.04)	(9.03)
EC	-0.091***			
	(-2.63)			
ME	0.053*			
	(1.74)			
Control	Yes	Yes	Yes	Yes
_cons	0.503	0.408	0.258	-0.189
	(1.51)	(1.26)	(0.78)	(-0.51)
Industry fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
R^2	0.569	0.525	0.554	0.917
Obs.	242	242	220	220

Note: The values in brackets are *T*-value, ***, ** and * represent significant at the 1%, 5%, 10% levels.

6. Conclusion and policy implication

6.1. Conclusions

The emergence of the digital-real integration strategy has garnered significant attention across diverse industries, offering the potential to invigorate industrial sectors and facilitate a transition towards high-quality advancements. To empirically investigate the relationship between digital-real integration and industrial innovation, and to explore its capacity for breaking the cycle of low-end innovation, this study conducts an econometric analysis focusing on Chinese industrial sectors. The main findings are as follows:

(1) Digital-real integration can facilitate industrial innovation and overcome the challenges associated with low-end innovation.

(2) The marginal contribution of digital-real integration on industrial innovation increases with the innovation level of the industry.

(3) The development strategy of digital-real integration promotes high-end innovation activities, particularly in industries with strong absorptive capacity.

(4) Regarding the digital-real integration from various sources, the convergence of digital services into the real industrial sector has notably alleviated the low-end-locked dilemma in innovation, in contrast to digital products.

6.2. Policy implications

First, it is imperative to implement a comprehensive range of measures to foster digital-real integration. Government agencies should establish a unified framework for the development planning of both traditional industries and the digital economy. This entails nurturing and expanding emerging digital sectors like artificial intelligence and cybersecurity while facilitating the synergistic growth of industrial digitization and digital industrialization. Additionally, alongside maintaining conventional infrastructure, expediting the construction of new infrastructure is essential. Emphasis should be placed on fostering a thriving data marketplace, ensuring the availability of digital technologies and a diverse pool of skilled professionals, thus laying a solid groundwork for advancing digital reality integration. Moreover, the establishment of a robust regulatory system for the digital economy market is pivotal in promoting data sharing and resource integration. Consequently, it becomes crucial to bolster legislation concerning data and enhance governance over digital platforms for the robust growth of the digital economy. Such efforts can augment the industry's vitality while injecting new impetus into industrial innovation.

Second, given that the industry's ability to incorporate new knowledge and technologies affects the empowering effect of digital-real integration, the industry should progressively enhance its absorptive capacity while undertaking digital transformation. On the one hand, it should bolster talent development and knowledge management by increasing R&D funds and highly skilled personnel. On the other hand, it should establish collaborations with academic and research institutions to access the most recent research findings and technological trends, thereby facilitating the transfer and application of knowledge and technology. These measures will enable the industrial sector to continuously enhance its absorptive capacity, effectively adapt to and utilize new technologies and knowledge, and achieve high-quality innovation.

Third, the varying degrees of digital-real integration across industries result in a biased impact on overall innovation, high-end innovation, and low-end innovation. Therefore, it is necessary to develop targeted policies to drive digital economy penetration. For instance, different industries have diverse demands for digital technology, face distinct technical challenges, and operate in unique application scenarios. Moreover, their requirements concerning data security and privacy protection also differ. Hence, the formulation of digital integration policies should take into full account the characteristics and needs of each industry, avoiding a one-size-fits-all approach. This will ensure the rationality and effectiveness of policies and cultivate favorable conditions for industrial innovation.

Funding

The Anhui Office of Philosophy and Social Science (AHSKYQ2024D081)

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