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Financial Digital Intelligence and Innovative Development of Strategic Emerging Industries: Impact Effects and Mechanism Tests

Abstract. *The financial sector has entered the digital intelligence development stage. Innovative development is not only the driving force for the growth of strategic emerging industries, but also the key factors in leading high-quality economic development. The article empirically investigates the effects and mechanisms of financial digital intelligence on the innovative development of strategic emerging industries, utilising a sample of 5,731 data points from 2015 to 2022, which includes 789 listed companies and 114 prefecture-level cities in China. The results indicated that financial digital intelligence remarkably boosts the innovative development of strategic emerging industries. It enhances innovation by improving corporate information disclosure, reducing transaction costs, and strengthening regional industry–university–research collaboration. Moreover, the effects of financial digital intelligence on the innovative development of strategic emerging industries vary across central, eastern, and western regions, as well as capital-intensive and technology-intensive sectors, with no significant impact noted in other regions and industries.*

Keywords: *financial digital intelligence, strategic emerging industries, information disclosure, transaction costs, industry–university–research collaboration.*

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1. Introduction

Strategic emerging industries (SEIs) constitute a pivotal component of modern industrial systems, playing an increasingly vital role in global economic development (Ding et al., 2024). SEI is an increasingly important area, since

innovation is crucial for maintaining national economic growth (Nodehi et al., 2022). The past decade has witnessed the rapid advancement in the field of SEI, especially driven by the convergence of digital technologies and carbon neutrality goals. The development of SEI has now become a pivotal domain that shapes geopolitical dynamics, industrial chain security, and global technological competition among economies (Niemand et al., 2021). One of the greatest challenges is that innovation requires substantial and continuous financial backing (Nugraha et al., 2022). Extensive studies have shown that if financial support is ineffective, it may encounter dangers associated with short-term commercialisation obstacles (Wang, 2023). In China, financial evolution has advanced from the phases of financial electrification and informatization in 2017, followed by financial internalization and mobilization predominantly propelled by internet finance (Bai et al., 2024), to the current phase of digital and intelligent development (Wang et al., 2024). Financial digital intelligence (FiDI) is progressively impacting and reshaping traditional financial ecosystems and economic operational paradigms. It is not known whether FiDI can promote the innovative development of SEI.

The provision of financial support for the development of SEIs is a vital subject of scholarly investigation. Prior research, predominantly from the viewpoints of fintech or digital money, reveals controversies. Some researchers contend that digital finance could promote the advancement of SEIs (Hossain et al., 2024) by facilitating innovation spillover (Hou & Li, 2020) and geographical knowledge spillover (Khalid et al., 2024). And other researchers dispute this viewpoint, claiming that digital finance operates as a "double-edged sword" (Petare et al., 2023). There is a prevailing inclination to neglect technological and innovative competencies, which could jeopardise the real economy and industrial capital, potentially resulting in systemic financial problems (Petare et al., 2023). Existing research encompasses extensive analyses of financial assistance for SEI. However, the influence of FiDI as a new financial growth model on the inventive progress of strategically growing industries is still unclear.

Although the development of strategic emerging industries is of great significance to countries worldwide, we focus on China. China has 24 of the world's top 100 technology clusters, ranking first globally for three consecutive years. By the end of 2023, there were 96,000 industrial enterprises above designated size engaged in the production of strategic emerging industries in China, accounting for 19.5% of all such enterprises. New economic growth drivers such as new energy, new materials, and aerospace are poised to take off, with the installed capacity of new energy storage exceeding 100 million kilowatts, representing over 40% of the global total. Since 2017, advancements in technologies such as the Internet of Things (IoT), big data, blockchain, and artificial intelligence (AI) have dismantled information barriers, facilitating the provision of intelligent and personalised financial services. Fuelled by both policy incentives and the empowerment derived from digital technologies, the financial sector in China has undergone rapid development. This study addresses a significant research gap by examining the role

of financial digital intelligence in promoting SEIs' development in China. The findings contribute not only to the achievement of China's developmental objectives but also offer valuable insights for other economies confronting analogous risks (Nguyen and Phan, 2020). These insights possess a degree of generalisability across diverse institutional settings.

This article analyses the influence of FiDI on the innovative development of SEIs. This investigation concentrates on a panel data of 5731 Chinese listed firms over the period 2015–2022 to examine the impact and mechanism of FiDI on the innovative development of SEIs. This article contributed to the previous literature in several ways. Firstly, it boosts the understanding of the economic consequences of FiDI. Existing research has demonstrated the influence of FiDI on macro aspects, such as financial inclusion, debt trap industrial structure upgrading, green growth and micro firms, such as ESG performance, green innovation, corporate environmental violations. However, research remains scant on the extent to which FiDI influences the innovative development of SEIs. This article reveals the unique role of FiDI in deterring the innovative development of SEIs.

Secondly, our research magnifies the literature about the determinants of innovative development of SEIs. The existing research has predominantly concentrated on financial factors, such as capital market (Huang et al., 2015), financing constraints (Shi et al., 2015), indirect finance (Li & Yang, 2017), financial support efficiency (Ren, 2021), mechanism of finance, and other factors, such as economy & ecology, intellectual property risks, environmental regulation (Song et al., 2021). Given the paucity of existing literature examining the impact of FiDI on SEIs, this study constructs a causal framework within the context of accelerating global digital transformation and deepening technological revolution.

Thirdly, our research enhances the current literature about the correlation between FiDI's development and the innovative development of SEIs by improving corporate information disclosure, reducing transaction costs, and strengthening regional industry–university–research collaboration. By clarifying the methods by which FiDI influences innovative development of SEIs, we have enhanced our comprehension of this digital empowerment effect.

Finally, this study employs an innovative measurement for FiDI's development level. The current mainstream literature predominantly uses the Peking University Inclusive Finance Index to represent the level of regional digital financial development. However, this index is based on third-party payment data and emphasises inclusiveness but falls short in capturing the digital and intelligent dimensions of financial development. To fill this gap, this study constructs a digital finance lexicon, manually select relevant keywords from the Baidu Index, crawl their daily data, and integrate the number of regional fintech companies to calculate the FiDI index for each region annually. This method provides a significant enhancement to the current measurement of digital finance. Of course, this study also has some shortcomings. First, only listed SEI firms are included, yet numerous strategic emerging sectors thrive within startups, dynamic private enterprises, and university commercial spin-offs. These entities remain crucially reliant on digital

finance and exhibit heightened sensitivity to financial frictions. Consequently, the estimated effect of FiDI likely understates the true impact. Second, in terms of industry classification for heterogeneity analysis, due to the unique institutional background of China and its international applicability, it is divided into labour-intensive, capital-intensive, and technology-intensive industries. However, the internal differences among SEIs still require further in-depth research.

2. Hypothesis development

Financial digit intelligence (FiDI) represents a distinct theoretical construct separate from both FinTech and digital finance. FinTech denotes the technological tools and innovations employed to enhance or disrupt traditional financial services, emphasising the "technology" per se. Digital finance refers to novel financial services, models, and ecosystems enabled by digital technologies – particularly FinTech – focusing on the digital manifestation of financial business activities. In contrast, financial digit-intelligence signifies a systematic process through which traditional financial institutions or systems leverage digital technologies and data as key factors to undertake a deep-seated overhaul and intelligent upgrading of entire business processes, organisational structures, operational models, and decision-making paradigms. It underscores the dynamics and depth of the "transformation." FiDI, an innovation merging "financial digitalisation + financial intelligence," signifies a trend that utilises artificial intelligence technologies to take the financial business to a more sophisticated level. Financial digital intelligence encompasses the integration of advanced digital technologies, particularly artificial intelligence (AI) and its subfields like machine learning and deep learning, into various facets of financial services to enhance decision-making, efficiency, and risk management (Xia et al.,2024; Chen, 2025). Core to financial digital intelligence is the application of AI in critical areas such as risk management, investment decision-making, and personalised banking (Deepu, 2025; Mamatha, 2025).This movement efficiently supports the real economy via astute decision-making, closed-loop systems, and services.

The basis of FiDI is rooted in technological innovation (Wang, 2023). It includes several innovative technologies, such as blockchain and big data, designed to facilitate the expansion of the financial services sector. FiDI is the amalgamation of digital finance and intelligent finance, embodying the progressive tendencies of intelligent technology and unique application attributes within the financial sector. This transformation is driven by the rapid growth of data volume and complexity within the financial industry, necessitating sophisticated analytical methods beyond traditional approaches (Zhu, 2025; Cao et al.,2021). This innovative model utilises the interconnectivity of many information systems in the financial sector, employing accurate customer analysis based on substantial big data, and utilising innovation as a crucial element for achieving sustainable and superior financial growth. In contrast to conventional finance, the deep integration of intelligent technology into financial support has allowed capital resources to deliver financial assistance more efficiently

and economically, substantially reducing information asymmetry and contractual imperfections. Recent study indicates that data has become an essential factor of production for economic and industrial development, displaying traits such as non-rivalry, limited exclusivity, significant synergy with other technologies, and externalities in its application (Wang et al., 2024). The integration of data and capital components is a hallmark of the contemporary movement towards FiDI, effectively encouraging innovative practices among businesses and substantially promoting the expansion of strategic new industries. Hence, we propose Hypothesis 1.

H1: FiDI will promote the innovative development of SEIs.

High-quality information disclosure enhances external visibility, signalling innovation excellence to markets (ul Haq & Suki., 2025). This significantly lowers investor search costs for R&D information, relaxing corporate financing constraints. By mitigating the manager-investor information asymmetry (Zhao et al., 2023), such disclosure protects minority interests and stimulates R&D engagement. Conversely, poor disclosure quality distorts information environments and exacerbates negative spillovers (Nguyen & Kecskés, 2020). FiDI can significantly enhance information disclosure quality through technological innovation and improved data governance capabilities, facilitating a paradigm shift from "compliance-oriented disclosure" to "investor demand-driven disclosure." This transformation effectively promotes the optimal allocation of capital resources, reduces trial-and-error costs in innovation, and enables precise risk management, thereby better fostering the innovative development of SEIs. Hence, we propose Hypothesis 2.

H2: FiDI promotes the innovative development of SEIs by enhancing quality of enterprises information disclosure.

Elevated transaction costs, including both financing and operational expenditures in credit acquisition, substantially diminish corporate innovation incentives (Amore et al., 2013). These costs may further compel firms to abandon high-quality, long-cycle innovation projects in favour of short-term, rapid-return alternatives, thereby distorting resource allocation and crowding out essential inputs for substantive innovation (Jardak & Ben Hamad, 2022). FiDI constitutes a fundamental driver in optimising the allocation of data and capital resources. Through intelligent capture of enterprise credit information coupled with real-time identification and monitoring of innovation risks, FiDI effectively reduces transaction costs resulting from information opacity and asymmetries. Furthermore, financial digital intelligence enhances financing efficiency substantially by employing tamper-proof data systems and smart contract technologies, among other advanced digital solutions. Hence, we propose Hypothesis 3.

H3: FiDI can promote the innovative development of SEIs through reducing transaction costs.

The effectiveness of industry-university-research (IUR) collaboration is a critical determinant of innovation velocity (Song et al., 2020). Given that R&D activities require sustained and substantial financial commitments (Nugraha et al., 2022) and considering the divergent value orientations among enterprises, universities, and research institutions – the primary R&D actors – the frequent lack

of trust and communication often leads to a theory-practice disconnect (Crespin-Mazet & Ingemansson-Havendvid, 2021). Even in market-driven innovation systems, both demand-side variations and technology-side adaptations necessitate iterative trial-and-error processes across multiple stages. As an emerging financial paradigm, digitally-enabled Foreign Direct Investment (FiDI) demonstrates unique capabilities in: (1) optimising resource allocation; (2) providing innovation financing; and (3) facilitating the convergence of capital, information, and talent flows. Hence, we propose Hypothesis 4.

H4: FiDI promotes the innovative development of SEIs by strengthening regional industry-university-research cooperation.

3. Data and empirical strategy

3.1 Variable definition

3.1.1 Explanatory variables

Financial digital intelligence (FiDI): This study operationalises the concept of financial digital intelligence by systematically distinguishing between the overlapping and substitutive dimensions of "digitisation" and "intelligence" in financial contexts. Through a rigorous document analysis methodology, we identify and extract 50 key terms (presented in Table 1) from nine authoritative industry reports published between 2020-2024, including: The China FinTech and Digital Finance Development Report (2024);The FinTech Development Plan (2022-2025);The Financial Industry Digital Transformation Development Report (2020-2021);The Consumer Finance Digital Transformation Research Report (2023);The Intelligent Financial Innovation and Development Report (2023). Methodologically, we employ web crawler technology to collect search result volumes from Baidu News' advanced search platform. The raw data is aggregated at the regional level and subsequently log-transformed to address right-skewness while preserving the growing trend of financial digital intelligence adoption. This transformation follows established practices for handling skewed distributions in empirical research.

Table 1. Indicators system for

Indicators	Keywords
Financial digitisation	digital economy, digital currency, mobile payment, digital credit, e-commerce platform, digital RMB, P2P, online loan, online lending, crowdfunding, online lending, Internet investment, network investment, third-party payment, online payment, online payment, QR code payment, fingerprint payment, mobile payment, NFC payment, Internet finance, Internet insurance, network finance, online finance, network car insurance, quantitative investment, financial platform, Internet finance, e-banking, online banking, internet banking, network banking, internet banking alliance, mobile banking, direct bank, digital marketing
Financial intelligence	machine learning, natural language processing, knowledge graph, intelligent customer service, system software, neural network, human-computer interaction, generative AI, deep learning, large model, cloud computing, big data, blockchain, artificial intelligence

Source: Original data from CSMAR database.

3.1.2 Explained variables

Innovative development of SEI (SEIID): This article develops a comprehensive evaluation index framework tailored to assess the innovative development of enterprises within strategic emerging industries. The system integrates both innovation input and innovation output as core indicators, ensuring a holistic assessment of their innovation capabilities. The specific selection of indicators is detailed in Table 2.

Table 2. Indicators system for the innovative development of strategic emerging industries

Primary Indicators	Characterisation indicators	Indicator attributes
Innovation input	Number of R&D personnel	+
	R&D investment/ operating income	+
Innovation output	Annual number of patent applications	+
	Increment of intangible assets/ Total assets at the beginning of the year	+

Source: Original data from CSMAR database.

3.1.3 Control variables

We accounted for variables including enterprise scale, asset-liability ratio, Tobin Q value, technology, and finance policy, return on assets, age, the shareholding ratio of the largest shareholder, all of which have a significant influence the new quality productive forces.

3.2 Model settings

To test the aforementioned hypotheses, the study formulates the following baseline regression mode, presented in equation (1).

$$SEIID_{i,t} = \beta_0 + \beta_1 FiDI_{i,t} + Controls_{i,t} + u_i + \theta_t + \varepsilon_{i,t} \quad (1)$$

In this equation, the *i* represents listed companies in strategic emerging industries, *t* represents the year, β_0 represents the intercept term, β_1 represents the core parameter to be estimated, $Control_{i,t}$ represents the control variable; u_i and θ_t correspond to industry fixed effects and year fixed effects, respectively, while $\varepsilon_{i,t}$ denotes the random error term. The level of innovation and development of strategic emerging industries (*SEIID*) is used as the dependent variable, and the level of regional financial digital intelligence (*FiDI*) is used as the core explanatory variable. ε represents the random disturbance term.

To empirically examine the potential mediating roles of corporate information disclosure quality, transaction costs, and industry-university-research cooperation in the relationship between financial digital intelligence and strategic emerging industries' innovative development, the study specify the models in Equations (2)-(4). Among them, *KV* represents the quality of enterprises information disclosure, *SER* represents transaction cost, and *LNIUR* represents reginal industry-university-research cooperation.

$$SEIID_{i,t} = \beta_0 + \beta_1 FiDI_{i,t} + \beta_2 KV_{i,t} + Controls_{i,t} + u_i + \theta_t + \varepsilon_{i,t} \quad (2)$$

$$SEIID_{i,t} = \beta_0 + \beta_1 FiDI_{i,t} + \beta_2 SER_{i,t} + Controls_{i,t} + u_i + \theta_t + \varepsilon_{i,t} \quad (3)$$

$$SEIID_{i,t} = \beta_0 + \beta_1 FiDI_{i,t} + \beta_2 LNIUR_{i,t} + Controls_{i,t} + u_i + \theta_t + \varepsilon_{i,t} \quad (4)$$

3.3 Data sources

This article constructs the sample based on the following criteria: (1) following the classification of "Strategic Emerging Industry Classification (2018)" by the National Bureau of Statistics of China; (2) including enterprises with a main business revenue share exceeding 20%; (3) excluding firms with stock codes marked as ST or ST*. After rigorous screening, the final sample consists of 5,731 unbalanced panel data observations from 2015 to 2022. Except for replace explanatory variables – the Digital Inclusive Financial Index from Peking University (PKU), the original data of all the variables used in this article are sourced from the CSMAR database, and the data of PKU are sourced from the Peking University Digital Finance Research Centre. Regarding missing values, only the quality of corporate information disclosure (KV) was lacking. However, the missing mechanism was entirely random, with a very low missing rate of merely 5%. Therefore, not processing the missing values had almost no impact on the research results and conclusions.

4. Empirical and results

4.1 Descriptive statistical analysis

Table 3 displays the variable descriptive statistics. The SEIID index shows moderate dispersion (mean = 0.074, SD = 0.101, range = 0.0005-0.552), indicating relatively even distribution. FiDI demonstrates stability (mean = 14.070, SD = 0.821, range = 10.73-15.38) with minimal outliers. All control variables (firm size, leverage, etc.) exhibit normal distributions (see Table 3).

Table 3. The descriptive statistical characteristics of each variable

Variables	Sample	Mean	SD	Min	Median	Max
SEIID	5731	0.074	0.101	0.0005	0.027	0.552
FiDI	5731	14.070	0.821	10.730	14.227	15.380
KV	5731	0.413	0.234	0.002	0.380	1.625
SER	5731	0.078	0.110	0	0.049	4.843
LNIUR	5731	4.165	2.245	0	4.369	7.653
SIZE	5731	22.490	1.236	19.410	22.358	27.190
LEV	5731	0.426	0.197	0.014	0.423	1.687
TBQ	5731	2.312	1.591	0.641	1.828	22.570
TREAT	5731	0.746	0.436	0	1	1
FIX	5731	0.164	0.133	0.0004	0.131	0.876
AGE	5731	2.947	0.296	1.792	2.996	3.714
TOP1	5731	28.840	13.360	2.120	26.5	80.010

Source: Original data from CSMAR database.

4.2 Benchmark regression results

The article uses a panel two-way fixed effects model to test the impact of financial digital intelligence on the innovative development of strategic emerging industries (SEI). Given the panel data imbalance, potential heteroscedasticity, and intra-annual serial correlation, this study employs the cluster-robust standard error for two-way clustering between firms and years proposed by Petersen (2009).

Table 4 presents the results of the benchmark regression. Among them, columns (1) – (4) are the regression results without adding fixed effects and control, adding year and industry fixed effects, adding only control variables, and adding both control variables and year and industry fixed effects, respectively. The results show that the coefficient of FiDI is significant at the $P = 0.01$ level, robust to the inclusion of fixed effects and control variables, indicating that FiDI promotes the innovative development of strategic emerging industries. Thus, Hypothesis 1 is verified.

Table 4. Benchmark regression results

	(1)	(2)	(3)	(4)
	SEIID	SEIID	SEIID	SEIID
FiDI	0.0116*** (0.0027)	0.0114*** (0.0027)	0.0146*** (0.0037)	0.0169*** (0.0036)
FIX			-0.0169 (0.0188)	-0.0107 (0.0212)
SIZE			0.0066** (0.0026)	0.0091*** (0.0025)
LEV			-0.0076 (0.0110)	-0.0107 (0.0120)
TBQ			0.0047** (0.0015)	0.0025* (0.0012)
AGE			-0.0057 (0.0097)	0.0137 (0.0096)
TREAT			-0.0095 (0.0079)	-0.0139 (0.0079)
TOP1			-0.0002 (0.0002)	-0.0002 (0.0002)
_CONS	-0.0898** (0.0375)	-0.0863* (0.0373)	-0.2548** (0.0778)	-0.3926*** (0.0744)
YEAR	NO	YES	NO	YES
IND	NO	YES	NO	YES
N	5731	5729	5731	5729
Adj. R2	0.0088	0.0621	0.0164	0.0729

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with robust standard error-values in parentheses.

Source: Original data from CSMAR database.

4.3 Endogenous test

This article further employs instrumental variable estimation and GMM dynamic panel analysis to mitigate the endogenous issues.

4.3.1 Instrumental variables estimation

This study employs the number of electronic accounts (NEA), including Internet payment accounts and their associated bank accounts, as an instrumental variable in the IV-SIS estimation analysis. And use the cluster-robust standard error of two-way clustering between firms and years. The results are presented in Table 5, with column (1) displaying the first-stage regression results and column (2) showing the second-stage regression results. When NEA is used as an instrumental variable, the results in Table 5 indicate that it successfully passes the IV relevance, lack of identification, and weak IV tests. The lack of identification test indicates that the p-value of Kleibergen-Paap rk LM statistic is 0.0062, which is statistically significant at the 1% level. Weak instrumental variable test indicates that Kleibergen-Paap rk Wald F statistic is 217.958, which is greater than the critical value of the Stock-Yogo weak instrumental variable identification F-test at the 10% significance level. In the first-stage regression, the coefficient of NEA is estimated to be 0.0178, with a t-statistic value of 14.76, significant at the 1% level. After excluding the instrumental variable, the first-stage F-statistic is 217.96. In the second-stage regression, the coefficient of financial digital intelligence is estimated to be 0.0228, significant at the 5% level. After addressing the potential endogeneity of the key explanatory variables, the conclusions drawn in the previous section remain robust and consistent with the initial findings.

Table 5. Regression results of instrumental variables

	(1) Phase 1	(2) Phase 2
NEA	0.0178*** (0.0012)	
FiDI		0.0228** (0.0065)
Control variables	YES	YES
YEAR	YES	YES
IND	YES	YES
N	5729	5729
F	125.52	4.94
Non-identifiability test(Kleibergen-Paap rk LM statistic)		7.485 (0.0062)
Weak instrumental variables(Kleibergen- Paap rk Wald F statistic)		217.958 [16.38]

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with robust standard error-values in parentheses. The bracket contains the critical value of the Stock-Yogo weak instrumental variable identification F-test at the 10% significance level.

Source: Original data from CSMAR database.

4.3.2 GMM dynamic panel analysis

This study employs GMM regression to address the serial correlation issue in the ongoing innovative development of strategic emerging industries (SEI). The results presented in Table 6 show that the coefficients for the lagged SEI innovation and development index (LSEIID) and financial digital intelligence (FiDI) are 0.33

and 0.031, respectively. Both coefficients are significantly positive at the 1% and 5% significance levels, respectively. These findings confirm that the lagged SEIID and its endogenous effects, particularly the impact of financial digital intelligence on the innovation and development levels of strategic emerging firms, persist. The robustness of the previous conclusion is thus further validated.

Table 6. Regression results of system GMM

	SEIID
L.SEIID	0.33*** (0.041)
FiDI	0.031** (0.015)
Control variables	YES
YEAR	YES
N	4825
AR(1)	0.000
AR(2)	0.579
Hansen	0.227

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

4.4 Robustness test

To verify the robustness of the baseline estimates, the study conducts comprehensive sensitivity analyses through the following approaches.

4.4.1 Replace explanatory variables

This article utilises the Digital Inclusive Financial Index from Peking University (PKU) as an alternative core explanatory variable to test the robustness of the benchmark regression model. The results are presented in Table 7, column (1). The findings indicate that even after substituting the core explanatory variable, financial digital intelligence continues to significantly promote the innovative development of SEI.

Table 7. Regression results of robustness test

variables	Replace	Adjust sample		transform
	explanatory variables (1)	excludes data from 2015 (2)	excludes data from municipalities (3)	regression model (4)
PKU	0.000*** (5.157)			
FiDI		0.016*** (6.117)	0.022*** (7.330)	0.239*** (4.589)
_CONS	-0.295*** (-7.455)	-0.387*** (-8.166)	-0.484*** (-8.590)	-8.915*** (-9.327)
Control variables	YES	YES	YES	YES

variables	Replace explanatory variables (1)	Adjust sample		transform regression model (4)
		excludes data from 2015 (2)	excludes data from municipalities (3)	
YEAR	YES	YES	YES	
IND	YES	YES	YES	
Log- pseudolikelihood				-1305.933
Wald chi2				55.760
Pseudo R2				0.028
N	5729	5049	4201	5729

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, in the first three columns with t-values in parentheses. In the fourth column with z-values in parentheses.

Source: Except for PKU, original data from CSMAR database, and the data of PKU are sourced from the Peking University Digital Finance Research Centre.

4.4.2 Adjust sample data

The article excludes data from 2015 due to the stock market crash that year, which had a substantial impact on industrial innovation. Additionally, statistics from municipalities are omitted, given their unique economic characteristics that may lead to significant differences in economic development and enterprise innovation. The results are presented in Table 7, columns (2) – (3). The findings indicate that regardless of whether these specific samples are excluded, the estimated coefficient remains significantly positive at the 1% level.

4.4.3 Transform regression model

Given that the indicators employed in this study to measure the innovation and development levels of strategic emerging enterprises are decimal values ranging between 0 and 1. So the Poisson Pseudo Maximum Likelihood (PPML) model is selected to further examine the relationship between financial digital intelligence and the innovation and development levels of these enterprises, which is consistent under heteroscedasticity, can deal with zero weight or fractional variable effectively, and can accommodate the fixed effect of enterprise and year without imposing distribution assumption. The results are presented in Table 7, column (4). The study using the PPML censored regression model corroborates the persistent positive impact of financial digital intelligence, with coefficients remaining significant at the 1% level.

4.5 Mechanism analysis

The preceding analysis establishes that financial digital intelligence contributes to SEIs' innovative development via three transmission channels: enhancing quality of enterprises information disclosure, alleviating transaction costs, and improving regional industry-university-research cooperation. This article aims to validate the logic and investigate the mechanism by which financial digital intelligence

influences the innovative development of strategic emerging industries, selecting enterprise information disclosure quality, transaction costs, and regional industry-university-research cooperation as the variables for analysis. (1) Referring to Kim & Verrecchia (2001), the article chooses “KV value to represent the quality of enterprises information disclosure. (2) Referring to Huang et al. (2019), the article chooses “sales expense ratio (SER)” to represent transaction cost. (3) The acritical choose “the natural logarithm of the number of regional industry-university-research patents plus 1” to represent the regional industry-university-research cooperation.

As shown in Column (1) of Table 8, the coefficient of FiDI on KV is - 0.039 and statistically significant at the 1% level, suggesting that greater financial digital intelligence (FiDI) reduces the KV value – consistent with higher-quality corporate information disclosure. This supports the notion that digitalisation enhances transparency. Column (2) further reveals that the coefficient of KV on SEIID is -0.019, indicating that weaker information disclosure quality (higher KV) suppresses firm innovation. Notably, the absolute magnitude of FiDI’s coefficient in Column (2) (0.015) is smaller than in the baseline regression (0.017), implying partial mediation. In sum, these results demonstrate that FiDI promotes innovative development in SEISs by elevating information disclosure quality, thereby confirming Hypothesis 2.

Table 8. Regression results of mechanism analysis

	KV (1)	SEIID (2)	SER (3)	SEIID (4)	LNIUR (5)	SEIID (6)
FiDI	-0.039*** (-6.766)	0.015*** (5.490)	-0.006*** (-3.861)	0.012*** (4.847)	2.109*** (72.709)	0.011*** (3.153)
KV		-0.019*** (-3.055)				
SER				-0.076*** (-3.148)		
LNIUR						0.003*** (2.577)
Control variables	YES	YES	YES	YES	YES	YES
_CONS	-0.051 (-0.490)	-0.329*** (-6.889)	0.324*** (12.379)	-0.276*** (-5.954)	-28.099*** (-52.916)	-0.311*** (-5.661)
N	5220	5220	5309	5309	5729	5729
YEAR	YES	YES	YES	YES	YES	YES
IND	YES	YES	YES	YES	YES	YES

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

Table 8 Column (3) reveals a statistically significant negative relationship between FiDI and SER (coefficient = -0.006, p<0.01), suggesting that financial digital intelligence effectively reduces firms' transaction costs. Furthermore, Column (4) shows SER's significant negative impact on SEIID (coefficient = -0.076, p<0.01),

indicating that higher transaction costs constrain corporate innovation. The mediation analysis demonstrates partial mediation, as FiDI's coefficient in Column (4) (0.012) is smaller in absolute value than in the baseline regression (0.017). These findings collectively support Hypothesis 3, confirming that FiDI fosters innovative development in SEIs through transaction cost reduction.

Table 8 Column (5) demonstrates a significant positive association between FiDI and LNIUR ($\beta = 2.109, p < 0.01$), indicating that financial digital intelligence enhances regional industry-university-research collaboration. The positive coefficient of LNIUR on SEIID ($\beta = 0.003, p < 0.05$) further suggests that such collaboration facilitates corporate innovation. Mediation analysis reveals partial mediation, with FiDI's coefficient in Column (6) ($\beta = 0.011$) being smaller than the baseline estimate ($\beta = 0.017$). These results collectively support Hypothesis 4, confirming that financial digital intelligence stimulates innovation in strategic emerging industries by fostering regional industry-university-research cooperation.

4.6 Heterogeneity analyses

4.6.1 Heterogeneity of region

To examine regional variations in the impact of FiDI on the innovative development of SEIs, we conduct subsample regressions across China's eastern, central, western, and northeastern regions. According to the differences in the development of various regions in China and the general geographical division of China, China is divided into four major regions: the east, the central region, the west, and the northeast. The results, presented in Table 9, reveal statistically significant coefficients for FiDI in the eastern, central, and western regions (all significant at the 1% level), while the northeastern region shows no significant effect. The magnitude of the effect follows a descending order: central region (strongest), western region, and eastern region. To formally test for regional heterogeneity, we perform a Chow test and report the results in Table 10. The interaction term ($Z_PROTOTYPE$) between FiDI and the regional dummy variable yields a coefficient of 0.005 (significant at the 5% level), confirming statistically significant differences in FiDI's effects across regions. Specifically, the central region exhibits the strongest influence on corporate innovation (coefficient = 0.041), followed by the eastern (0.025) and western regions, with the northeastern region showing no material impact. The 0.016 gap between the central and eastern regions further underscores this divergence.

Table 9. Regression results by region grouping

Variables	Eastern (1)	Central (2)	western (3)	north-eastern (4)
FiDI	0.015*** (4.418)	0.041*** (4.041)	0.025*** (4.700)	0.001 (0.049)
Control variables	YES	YES	YES	YES
_CONS	-0.330*** (-5.804)	-0.658*** (-3.837)	-0.605*** (-5.423)	-0.423* (-1.731)
Year	YES	YES	YES	YES

Variables	Eastern (1)	Central (2)	western (3)	north-eastern (4)
Industry	YES	YES	YES	YES
N	4241	658	619	211

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

Table 10. Intergroup coefficient difference test of regions

	SEIID
FiDI	0.009** (2.196)
Z_PROTOTYPE	0.005** (2.374)
Control variables	YES
CONS	-0.283*** (-4.509)
YEAR	YES
IND	YES

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

4.6.2 Heterogeneity of industry

To investigate industry-specific effects of FiDI on innovative development of SEIs, we classify sample firms into three categories: labour-intensive, capital-intensive, and technology-intensive. Table 11 presents the regression results, revealing distinct patterns across industries. While FiDI shows no significant effect on labour-intensive firms, it demonstrates statistically significant positive impacts on both capital-intensive and technology-intensive firms ($p < 0.01$). To formally assess inter-industry differences, we conduct a Chow test. As shown in Table 12, the interaction term (Z_INDTYPE) between FiDI and the industry dummy variable yields a positive and significant coefficient, confirming substantial heterogeneity in FiDI's effects across industry types. Specifically, the analysis indicates that: (1) Capital-intensive enterprises exhibit the strongest response to FiDI; (2) Technology-intensive firms show a moderate but still significant effect; (3) Labor-intensive firms display negligible impact. These findings highlight the varying efficacy of financial digitalisation across different industrial structures, with capital-intensive operations benefiting most substantially from FiDI-driven innovation enhancement.

Table 11. Regression results by industry group

	labour-intensive (1)	capital-intensive (2)	technology- intensive (3)
FiDI	-0.002 (-0.243)	0.028*** (5.049)	0.015*** (5.128)
Control variables	YES	YES	YES
CONS	-0.002	-0.571***	-0.370***

	labour-intensive (1)	capital-intensive (2)	technology-intensive (3)
N	(-0.019)	(-5.396)	(-6.954)
YEAR	450	757	4522
IND	YES	YES	YES

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

Table 12. Intergroup coefficient difference test of industries

	SEIID
FiDI	0.023*** (2.793)
Z_INDTYPE	0.000*** (2.933)
Control variables	YES
_CONS	-0.386*** (-2.841)
YEAR	YES
IND	YES

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with t-values in parentheses.

Source: Original data from CSMAR database.

5. Conclusions

This article integrates financial digital intelligence (FiDI) and the innovative development of strategic emerging industries (SEIs) within a unified analytical framework. By employing a sample of 5,731 data points spanning the period from 2015 to 2022, which includes data from 789 publicly listed firms and 114 prefecture-level cities in China, the study empirically investigates the impacts and mechanisms through which financial digital intelligence influences the innovative development of strategic emerging industries. The study finds that financial digital intelligence significantly boosts the innovation of strategic emerging industries, with consistent findings across robustness tests. It enhances innovation by improving corporate information disclosure, reducing transaction costs, and strengthening regional industry–university–research collaboration. Moreover, the effects of financial digital intelligence on the innovative development of strategic emerging industries vary across central, eastern, and western regions, as well as capital-intensive and technology-intensive sectors, with no significant impact noted in other regions and industries.

Drawing from the aforementioned conclusions, the article proposes the following countermeasures. First, advancing artificial intelligence and large-scale model applications is critical, particularly in fostering a dynamic, collaborative innovation ecosystem. This requires a comprehensive digital and intelligent

transformation across financial infrastructure, customer engagement channels, operational processes, product offerings, and managerial decision-making frameworks. Second, developing differentiated digital finance use cases and promoting a secure, well-functioning digital financial ecosystem can enhance the precision of financial services by empowering innovation. However, extant studies examining the nexus between financial digital intelligence and strategic emerging industries' innovative development faces inherent limitations. Data processing and analytical approaches may vary depending on researchers' methodological preferences and technical expertise, potentially affecting the reliability and validity of empirical findings.

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