

The Impact of Artificial Intelligence on Firms' Critical Digital Technology Innovation: A Quasi-Natural Experiment Based on National New-Generation AI Innovation Pilot Zones

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Abstract. As a core policy instrument to boost regional and national digital innovation, artificial intelligence (AI) pilot policies facilitate corporate digital transformation via resource agglomeration, institutional guidance and innovation environment optimization. This paper treats the policy of National New-Generation Artificial Intelligence Innovation Development Zones as a quasi-natural experiment. We construct panel data of A-share listed firms in China as research samples and adopt the staggered difference-in-differences (DID) model to empirically examine the causal effects and heterogeneous mechanisms of AI pilot policies on enterprises' critical digital technology innovation. The empirical results show two key findings. First, AI pilot policies significantly elevate firms' critical digital technology innovation performance, and this result remains robust after a series of robustness tests. Second, heterogeneous analysis reveals that the innovation-promoting effect of AI pilot policies is more pronounced for non-manufacturing firms, non-high-tech industrial enterprises and firms operating in highly competitive industries. This study provides micro-level empirical evidence for evaluating the effectiveness of AI pilot policies and offers practical implications for advancing corporate digital innovation.

Keywords: Artificial Intelligence, Critical Digital Technology Innovation, Staggered Difference-in-Differences Model, Industry-University-Research Collaboration.

1. Introduction

As the core driving force of the new round of technological revolution and industrial transformation, artificial intelligence has become a pivotal core technology for countries to seize technological competitive advantages and reshape the global industrial competition landscape (Wu et al., 2020)^[1]. The 15th Five-Year Plan Outline puts forward major strategic deployments including strengthening original innovation, tackling key core technologies and sustaining research and development (R&D) of cutting-edge technologies. To implement these deployments and coordinate the development of the AI industry, the Ministry of Science and Technology issued supporting documents such as the *Guidelines for the Construction of National New-Generation Artificial Intelligence Innovation Development Zones*. These documents jointly build a multi-tiered and coordinated policy support system for artificial intelligence. Guided by such policies, artificial intelligence has penetrated diverse industries and scenarios, continuously injecting new momentum into the advancement of digital technologies.

Meanwhile, critical digital technology innovation emerges as a vital path to fulfill national technological strategies and achieve digital transformation. However, corporate digital innovation activities are inherently high-risk and uncertain (Ciarli et al., 2021)^[2]. Against this backdrop, the implementation of AI pilot policies carries great practical significance. Theoretically, AI pilot zone policies can affect firms' critical digital innovation through two transmission channels. On one hand, these policies generate regional innovation resource agglomeration effects. They build collaborative industry-university-research platforms and deploy fiscal and tax incentives such as R&D subsidies and high-end digital talent recruitment programs. Such measures encourage firms to increase investment in underlying core digital technologies and deliver high-quality critical digital innovation outputs. On the other hand, pilot zones leverage their institutional advantages to upgrade local innovation infrastructure and optimize the overall innovation ecosystem. These improvements lay a

solid external foundation for firms to conduct long-term and stable technological R&D. Given the above context, two research questions arise naturally. Do AI pilot policies exert significant impacts on critical digital technology innovation? How effective are these policies in practice? Answering these questions bears important theoretical and practical value.

Two strands of literature closely relate to our research. The first strand explores driving factors of corporate digital technology innovation from perspectives including firm innovation and digital finance (Fang & Liu, 2024; Firk et al., 2022; Li et al., 2023)^{[3][4][7]}. For firm-level innovation, corporate digital transformation strengthens core competitiveness, eases financing constraints, improves internal control quality and expands R&D investment, thereby promoting digital technology innovation (Fang & Liu, 2024)^[3]. From the executive team perspective, IT or digital expertise among top managers mitigates managerial short-termism and drives corporate digital innovation (Firk et al., 2022; Zhao et al., 2024)^{[4][5]}. In terms of digital finance, tech-finance policies expand the share of patient capital and significantly boost digital innovation. This effect is stronger for firms with looser financing constraints and higher financialization levels (Shao et al., 2025)^[6]. In addition, digital finance stimulates technological innovation by expanding R&D expenditure and boosting consumer demand (Li et al., 2023)^[7].

The second strand evaluates the policy effects of innovation pilot programs (Lin & Zhu, 2025; Wang et al., 2026; Li et al., 2025)^{[8][10][12]}. For green development, innovation pilot policies facilitate corporate green innovation by raising operational efficiency, increasing R&D investment and enhancing environmental information disclosure (Lin & Zhu, 2025; Mijit et al., 2025)^{[8][9]}. They also promote urban green innovation via green technological progress and entrepreneurial vitality (Wang et al., 2026)^[10]. From an economic perspective, innovation pilot policies alleviate income inequality and strengthen urban economic resilience by attracting labor agglomeration, optimizing industrial structures and stimulating innovation vitality (Li et al., 2025; Xu et al., 2024)^{[12][11]}. In the long run, these policies boost urban innovation and accelerate corporate digital transformation through technological progress, improved internal control and relaxed financing constraints (Wang & Deng, 2022; Liu et al., 2024)^{[14][13]}. Moreover, innovation pilots deepen industry-university-research cooperation and generate sustainable long-term benefits for enterprises and society (Zeng et al., 2023)^[15]. Existing studies lay a solid analytical framework for understanding how AI pilot policies shape critical digital technology innovation.

Nevertheless, two research gaps remain unaddressed in prior literature. First, most studies on digital innovation drivers focus on broad digital technology innovation (Fang & Liu, 2024; Firk et al., 2022; Zhao et al., 2024)^{[3][4][5]}, while few papers specifically investigate critical digital technology innovation. Second, existing research on AI pilot policies mostly examines their enabling effects on green innovation (Lin & Zhu, 2025; Mijit et al., 2025; Wang et al., 2026)^{[8][9][10]}. Few scholars explore the impact mechanisms and effects of these policies on critical digital technology innovation. Only a small number of studies discuss how national innovative city pilots accelerate corporate digital transformation (Liu et al., 2024)^[13]. Compared with prior work, this paper contributes to the literature in the following dimension. We focus on the causal impact of National New-Generation AI Innovation Development Zones on firms' critical digital technology innovation. Our findings expand research on AI pilot policies and critical digital R&D, and provide empirical evidence for the transmission mechanisms of innovation pilot policies.

2. Research Design

2.1. Sample Selection and Data Sources

This study uses balanced panel data of A-share listed firms in Shanghai and Shenzhen Stock Exchanges from 2014 to 2024 as the research sample. We identify cities included in the National New-Generation Artificial Intelligence Innovation Development Zones based on the 2019 *Guidelines for the Construction of National New-Generation Artificial Intelligence Innovation Development Zones* issued by the Ministry of Science and Technology. We manually collect pilot zone information

from official platforms of the Ministry of Science and Technology and local government public notices. Data on critical digital technology patents come from the Critical Digital Technology Patent Database in the CNRDS database. Firm-level financial indicators and basic corporate information, as well as listed firms' annual reports, are extracted from the CSMAR database. City-level variables are sourced from the *China City Statistical Yearbook* and prefectural-level municipal bureaus of statistics. Non-listed firm data for supply chain spillover analysis are manually collected from Qichacha. We clean the original sample through the following procedures:

- (1) Eliminate firms labeled ST, *ST or PT;
- (2) Exclude firms in the financial industry;
- (3) Drop firm-year observations with less than one full year of trading records;
- (4) Winsorize all continuous variables at the 1% and 99% quantiles to mitigate the influence of outliers.

2.2. Model Specification

To identify the impact of AI pilot policies on critical digital technology innovation, we construct the staggered difference-in-differences regression model as follows:

$$KDTI_{i,t} = \alpha + \beta AIPZ_{i,t} + \gamma \sum Control_{i,c,t} + \lambda_i + \mu_t + \varepsilon_{i,c,t} \quad (1)$$

In Equation (1), subscript i denotes individual firms, t denotes years, and c denotes cities. The dependent variable $KDTI_{i,t}$ measures the level of critical digital technology innovation. The core independent variable $AIPZ_{i,t}$ is the dummy variable for AI pilot policy. If city c where firm i locates is approved as a national AI innovation pilot zone in year t , $AIPZ_{i,t}$ equals 1 for year t and all subsequent years; otherwise, it takes the value of 0. $\sum Control_{i,c,t}$ represents a full set of firm-level and city-level control variables. λ_i and μ_t capture firm fixed effects and year fixed effects respectively, and $\varepsilon_{i,c,t}$ is the random error term.

2.3. Variable Definition

2.3.1. Dependent Variable

Critical Digital Technology Innovation ($KDTI_{i,t}$). Following Tao et al. (2023)^[16], we preprocess raw patent data and extract the primary classification number of each patent. We then screen patents falling into seven categories of critical digital technologies under the *Classification System for Critical Digital Technology Patents (2023)*: artificial intelligence, high-end chips, quantum information, internet of things, blockchain, industrial internet and metaverse. We aggregate the annual number of patent applications and granted critical digital patents by city. Finally, we match listed firms and their holding subsidiaries with patent applicants to calculate the annual volume of critical digital patents obtained by each listed firm.

2.3.2. Independent Variable

AI Pilot Policy ($AIPZ_{i,t}$). We define treatment firms as enterprises located in prefectural-level cities approved as national AI innovation pilot zones ($Treat_i=1$), while all other firms serve as the control group ($Treat_i=0$). Pilot zones were launched in three batches: the first batch took effect in 2019, the second in 2020, and the third in 2021. We construct a time dummy variable $Post_t$, which equals 1 for the policy implementation year and all later years, and 0 for years before policy launch. The policy interaction term $AIPZ_{i,t}$ is generated by multiplying $Treat_i$ and $Post_t$. This interaction term identifies the micro-level causal effect of AI pilot policies on listed firms' critical digital technology innovation.

2.3.3. Control Variables

We select multiple firm- and city-level indicators as control variables that may affect corporate digital innovation outcomes.

Firm-level control variables include:

- ① Firm Age (Age): Number of years since the firm's IPO;
- ② Firm Size (Size): Natural logarithm of total annual assets;
- ③ Asset-Liability Ratio (Lev): Year-end total liabilities divided by year-end total assets;
- ④ Return on Total Assets (ROA): Earnings before interest and tax divided by average total assets;
- ⑤ Top 3 Shareholding Ratio (Top3): Shares held by the top three major shareholders divided by total outstanding shares;
- ⑥ CEO-Chairman Duality (Dual): Equals 1 if the chairman and CEO are the same person, and 0 otherwise;
- ⑦ Board Size (Board): Natural logarithm of the number of board directors.

City-level control variables include:

- ① Science and Technology Input (SciTech): Local fiscal expenditure on science and technology divided by total general fiscal expenditure;
- ② Government Intervention (GovInterv): Local general fiscal budget expenditure divided by regional GDP;
- ③ Fiscal Pressure (FisPress): The gap between local general fiscal expenditure and fiscal revenue, scaled by regional GDP.

Table 1 reports the descriptive statistics of all major variables.

Table 1. Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
<i>AIZPZ</i>	29,628	0.264	0.441	0.000	1.000
<i>KDTI</i>	29,628	0.870	1.160	0.000	4.644
<i>Age</i>	29,628	11.989	8.015	1.000	29.000
<i>Size</i>	29,628	22.404	1.312	19.756	26.245
<i>Lev</i>	29,628	0.435	0.204	0.057	0.912
<i>ROA</i>	29,628	0.031	0.068	-0.238	0.208
<i>Top3</i>	29,628	0.468	0.154	0.157	0.850
<i>Board</i>	29,628	2.223	0.177	1.792	2.773
<i>Dual</i>	29,628	0.291	0.454	0.000	1.000
<i>SciTech</i>	29,628	0.007	0.005	0.001	0.020
<i>GovInterv</i>	29,628	0.156	0.052	0.064	0.344
<i>FisPress</i>	29,628	0.050	0.049	-0.008	0.266

3. Empirical Results and Analysis

3.1. Baseline Regression

Table 2 presents the baseline regression results of AI pilot policies on critical digital technology innovation. Columns (1) and (2) show estimation results without control variables. Column (1) regresses critical digital innovation only on the AI pilot policy dummy. Column (2) further adds firm and year fixed effects on the basis of Column (1). Column (3) incorporates all control variables alongside firm and year fixed effects. The coefficient of *AIPZ* remains significantly positive at the 1% statistical level across all specifications, regardless of whether control variables and fixed effects are included. This finding confirms that AI pilot policies significantly raise firms' critical digital technology innovation performance.

Table 2. Baseline Regression Results

Variable	(1)	(2)	(3)
<i>AIPZ</i>	0.502*** (0.054)	0.117*** (0.017)	0.108*** (0.017)
<i>Age</i>			0.034 (0.022)
<i>Size</i>			0.293*** (0.014)
<i>Lev</i>			-0.202*** (0.043)
<i>ROA</i>			-0.681*** (0.083)
<i>Top3</i>			-0.120 (0.077)
<i>Dual</i>			0.013 (0.013)
<i>Borad</i>			0.051 (0.043)
<i>SciTech</i>			5.675** (2.420)
<i>GovInterv</i>			-0.009 (0.365)
<i>FisPress</i>			0.640 (0.436)
<i>Consatant</i>	0.738*** (0.016)	0.840*** (0.006)	-6.147*** (0.385)
<i>Control Variables</i>	NO	NO	YES
<i>Firm Fixed Effects</i>	NO	YES	YES
<i>Year Fixed Effects</i>	NO	YES	YES
<i>Observations</i>	29,628	29,609	29,609
<i>R²</i>	0.036	0.767	0.774

Notes: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are reported in parentheses. All subsequent tables follow this notation unless otherwise stated.

3.2. Parallel Trend Test

The parallel trend assumption serves as the core identification prerequisite for the DID model. It requires that the gap in critical digital patent outputs between treatment and control firms stays stable before AI pilot policies launch. We follow Jacobson et al. (1993)^[17] to conduct parallel trend tests. First, we generate dummy variables for all sample years. Next, we construct interaction terms between relative policy time dummies and the treatment group dummy. We add these interaction terms to the regression model to trace the dynamic impacts of AI pilot policies on corporate critical digital innovation. The extended regression model is specified as Equation (2):

$$KDTI_{it} = \alpha + \sum_{t=2014, t \neq 2018}^{2024} \beta_t Policy_i * Year_t + \gamma \sum Control_{i,c,t} + \lambda_i + \mu_t + \varepsilon_{i,c,t} \quad (2)$$

In Equation (2), *KDTI* represents critical digital technology innovation measured by the number of independent critical digital invention patents obtained by firms. *Policy_i* is the treatment dummy indicating whether a firm belongs to the treatment group, and *Year_t* denotes year dummy variables. All other notations are consistent with Equation (1). We set the year prior to policy implementation as the benchmark period, with all other model settings identical to the baseline regression. Figure 1 illustrates the test results. All estimated coefficients β_t hover around zero before policy

implementation, and their 95% confidence intervals cross the zero horizontal line. This evidence verifies that no significant innovation gaps exist between treatment and control firms pre-policy, satisfying the parallel trend assumption. The policy effect rises visibly after the launch of AI pilot zones, proving that these policies improve critical digital technology innovation.

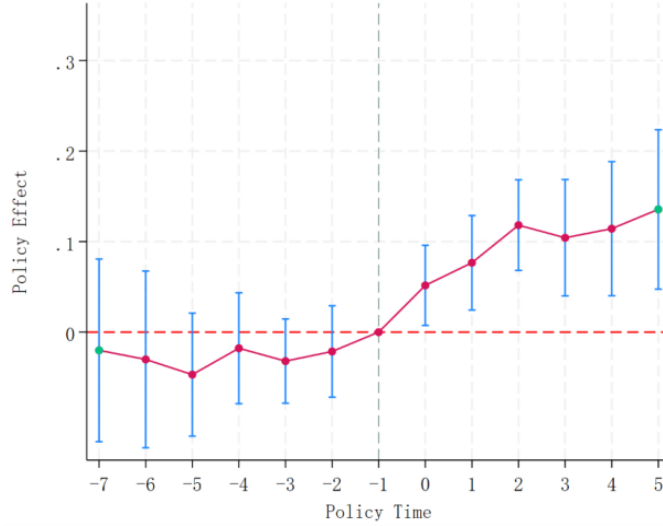


Figure 1. Parallel Trend Test in Empirical Research

3.3. Placebo Test

Placebo tests are another important robustness tool to remove estimation bias in DID models. They dismiss spurious policy effects, caused by missing variables or random noise and confirm the causal plausibility of baseline results. We use the three categories of placebo tests based on Chen et al. (2025)^[18]: individual placebo test, unconstrained mixed placebo test, and constrained mixed placebo test. In the case of the individual placebo test we simply randomize pseudo-treated firms among the entire sample and, with the others being pseudo-controls, we again re-estimate the baseline model on this random sample. In the unconstrained mixed placebo test, we generate pseudo treatment and control groups at random, and we stop the implementation of pseudo policy randomly by random process (before we re-run regressions). In constrained mixed placebo test, that is we keep the real batch structure of pilot zone firms, but randomly reassign pseudo treated firms and pseudo policy time points. The distribution patterns of the coefficients in all three placebo tests are similar; as all the virtual policy coefficients are normally distributed around zero. Our actual baseline regression policy coefficient is in the far right tail of this distribution, with a clear deviation of a placebo generated coefficient. The presence of placebo effects is corroborated by the consistent positive effect of AI pilot policies on the critically important digital innovation, thus, confirming the strength of our key findings.

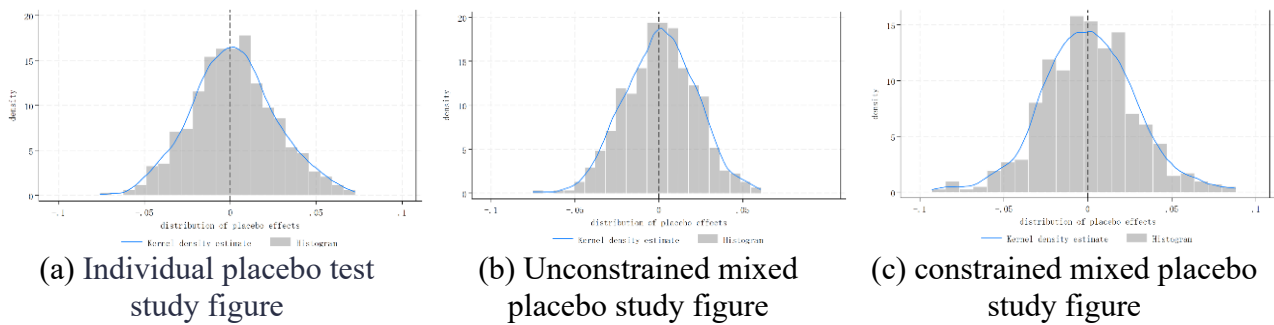


Figure 2. Placebo Test Results

4. Heterogeneity Analysis

4.1. Industry Competition Intensity

The innovation push by AI pilot policies is nuanced by the incentives and R&D motivation of firms within the industry dependent on the competition in the industry. In accordance with Ma and Jin (2026)^[21], we determine the Herfindahl-Hirschman Index (HHI) to assess the competition in the industry. We divide the sample into low competition and high competition subgroup and use the annual HHI median as a split and run the regression separately. Table 3 reports results of subgroup estimation in The columns (1) and (2). The p-value of the cross-group difference test is 0.072, which indicates that the two coefficients are significantly different at the 10% level of confidence.

This is heterogeneity brought about by different competitive incentives in various industries. The companies in highly competitive markets depend on technological advancements to maintain and increase market shares (Zhang and Guo, 2026)^[19]. On the one hand, AI pilot policies offer these computer infrastructure and financial subsidies that reduce the costs of intelligent transformation costs among firms and encourage them to allocate more resources to essential digital research. On the other hand, the harsh competition on the market raises long-term returns related to the independent development of technology. This is because firms are actively exploiting policy dividends to more aggressively drive internal R&D, and they are producing more powerful policy-induced innovation returns. Conversely, companies in industries with low competition are not threatened by market pressure and innovation, and, thus, the marginal increase in digital innovation due to the policy is low.

4.2. Industrial Entity Attribute

The classification of manufacturing or non-manufacturing defines the demands of digital transformation and the situations of technology use in firms, which moderate the conversion of policy dividend into innovations outputs. The sample was divided into manufacturing and non-manufacturing listed companies based on the CSRC industrial classification standard and we perform grouped regressions. The results are in columns (3) and (4) of Table 3. The p-value of the cross-group difference test is 0.076, which means that there is significant divergence of the coefficients at the 10 percent level.

The rationality behind this discontinuity is manufacturers financing frictions. Manufacturing companies need huge expenditures in upfront research and development, but the asymmetry of information reduces their levels of disclosure of research and development and increases external funding costs, generating extreme financing shortages (Xue, 2022)^[20]. Consequently, AI pilot policies provide less powerful innovation benefits to manufacturers. Entering R&D in non-manufacturing firms is less challenging. They quickly use the computing facilities and policy-supported R&D subsidies to undertake digital R&D in algorithms and software to achieve greater gains in critical digital innovation with the same policy backing.

4.3. Industrial Technology Attribute

The endowment of digital R&D resources and the capacity to absorb AI policy support by firms is mediated by high-tech or non-high-tech classification, which influences their endowment of resources and potential absorption capacity. In line with Bai (2022)^[22], we align industry codes with the Classification of High-Technology Industries (2013) published by the National Bureau of Statistics and classify the sample into high-tech and non-high-tech. In Table 3, grouped regression results are given in columns (5) and (6). The cross-group difference test p-value stands at 0.092 demonstrating statistically significant differences in the coefficients at the level of 10 percent.

Non-high-tech firms start with weaker digital technology foundations. AI pilot policies supply public computing power, R&D subsidies and industry-university-research platforms that compensate for internal technical shortages, generating large marginal innovation improvements and stronger incremental policy incentives. High-tech firms maintain long-term digital R&D layouts with mature

R&D teams and equipment. Their baseline innovation investment stays at a high level, so AI pilot policies deliver smaller additional innovation gains and smaller regression coefficients.

Table 3. Heterogeneity Analysis Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Industry Competition Intensity	Physical Attribute of Industry	Technology Intensity	Attribute of Industry		
	Low	High	Low	High	Low	High
AIPZ	0.067**	0.120***	0.166***	0.059***	0.143***	0.071***
	-0.026	-0.025	-0.026	-0.021	-0.022	-0.023
Standard Error	p-value=0.072*		p-value=0.076*		p-value=0.092*	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12684	12500	10578	18975	13294	16250
Adjusted R2	0.751	0.735	0.711	0.757	0.665	0.754

5. Conclusions and Policy Implications

This paper uses the National New-Generation AI Innovation Development Zone pilot policy as a quasi-natural experiment. Based on 2014–2024 panel data of China’s A-share listed firms, we adopt a staggered DID model to systematically examine the causal effects, transmission features and heterogeneous patterns of AI pilot policies on critical digital technology innovation. Parallel trend tests and three types of placebo tests jointly confirm the robustness and causal validity of our core results. Two primary conclusions emerge. First, AI pilot policies significantly promote firms’ critical digital technology innovation, acting as an important institutional tool to advance corporate breakthroughs in core digital technologies. Second, policy innovation gains exhibit substantial industrial heterogeneity. Compared with low-competition, manufacturing and high-tech industries, AI pilot policies generate stronger innovation incentives for high-competition, non-manufacturing and non-high-tech firms. Marginal policy innovation dividends are more fully released in sectors with weak innovation foundations and heavy digital transformation pressure, reflecting the policy’s targeted strengths of bridging capability gaps and activating market innovation vitality.

Our empirical evidence confirms the positive enabling role of AI pilot policies in corporate critical digital innovation, while highlighting uneven policy effectiveness across industries. To amplify the overall efficiency of AI pilot zone policies, mitigate cross-industry implementation gaps and advance core digital innovation across all industrial sectors, we propose three targeted policy recommendations based on our empirical findings.

First, local governments should build tiered innovation incentive mechanisms and upgrade the cross-industry innovation business environment. AI pilot zones need to continuously improve regional innovation infrastructure and sustain healthy market competition ecosystems. Local authorities should coordinate the open supply of public innovation resources including shared computing power, digital research databases and industry-university-research cooperation channels. These resources lower firms’ R&D costs and trial-and-error risks for core digital technologies, guiding firms to prioritize original and critical digital innovation. Local governments can also roll out inclusive innovation incentives and innovation tolerance mechanisms, alongside special digital innovation subsidies and achievement rewards. These measures fully mobilize R&D enthusiasm among market entities, break rigid industrial development barriers and steadily lift overall industrial innovation capacity.

Second, regulators should implement differentiated, targeted industrial support to improve policy dividend conversion efficiency for all firm types. On one hand, authorities should expand financial support for digital innovation, simplify application procedures for innovation projects and accelerate policy implementation. These measures encourage all market participants to conduct R&D in algorithm optimization, digital platform construction and scenario application upgrades. On the other hand, policymakers need to complete supporting digital innovation systems for the real economy. Governments can set up special funds for critical digital technology breakthroughs, build matching

platforms for intelligent manufacturing supply and demand, and establish collaborative industry-university-research innovation carriers. These institutions focus on core fields including industrial software, industrial internet and intelligent production technologies to ease manufacturers' long R&D cycles, capital shortages and financing constraints. Such actions deepen the integration of digital technologies and the real economy and consolidate the industrial foundation of digital transformation.

Third, pilot zones should optimize the precise allocation of innovation resources and build a cross-industry collaborative digital innovation ecosystem. Local authorities should coordinate high-quality innovation resources to deliver integrated public services including policy subsidies, technical guidance, talent recruitment and open innovation platforms for all market participants. These services help firms overcome shortages in digital technology reserves and incomplete R&D systems. Meanwhile, governments should dynamically adjust policy support priorities. After consolidating basic innovation capacity, authorities should concentrate premium resources on breakthrough research in cutting-edge core technologies. They should guide leading innovation entities to conduct deep R&D on underlying architectures, high-end chips and frontier information technologies. Policymakers should facilitate cross-industry technology exchange, achievement sharing and experience learning, leverage leading firms' technological spillover effects, and cultivate an industrial digital innovation ecosystem featuring coordinated growth and universal capability upgrading across all firm types.

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