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Research on the Impact of Computing Power Deployment and AI Innovation

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Abstract. As a new type of productive force in the era of the digital economy, computing power has become the core engine driving enterprises' artificial intelligence (AI) innovation. However, existing literature mostly focuses on policy effects at the macro level, and research on how computing power specifically drives enterprises' substantive innovation at the micro level is still relatively lagging. Based on the data of A-share listed companies from 2017 to 2023, combined with manually collected IDC licenses, this paper constructs an enterprise computing power database and empirically tests the impact of computing power deployment on digital technology innovation. The study finds that: ① Computing power deployment significantly promotes enterprises' substantive innovation by expanding the breadth of AI technology application and the degree of digital transformation. ② Mechanistically, computing power breaks the "data silos" by lowering technical thresholds, expanding application scenarios, and improving data integration capabilities, reconstructing the logic of R&D and production, thus forming a dual empowerment path. ③ Heterogeneity analysis shows that the innovation effect of computing power is more significant in non-state-owned enterprises and high-tech enterprises due to fewer institutional barriers and higher technical sensitivity. This study fills the micro-empirical gap in computing power economics, provides policy basis for optimizing computing power resource allocation and promoting high-quality enterprise development, and emphasizes the need for differentiated support for non-state-owned enterprises and high-tech enterprises to strengthen the synergy of data factors.

Keywords: computing power deployment, artificial intelligence innovation, IDC business license, breadth of artificial intelligence technology utilization, digital transformation

1. Introduction

As a new type of productive force in the era of the digital economy, computing power has become the core engine driving corporate AI innovation and an important endogenous driver of economic development. From the algorithmic breakthrough of AlphaGo to the generative revolution of ChatGPT, artificial intelligence technologies have deeply penetrated key sectors including manufacturing, healthcare and transportation, which have not only reshaped industrial patterns but also brought new challenges and opportunities to the national governance system. The 2023 Central Economic Work Conference explicitly proposed to "accelerate the development of artificial intelligence", and the 2024 Government Work Report further stressed the implementation of the

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"Artificial Intelligence Plus" initiative. These top-level designs and policy signals send a clear orientation: accelerating the agglomeration of technology, capital and talent through policy intervention and institutional supply is crucial to seize the commanding heights of science and technology.

As the underlying support and core engine for the development of artificial intelligence, computing power has been elevated to a national strategic infrastructure. With the full launch of the "East Data, West Computing" project and the explosive growth of generative artificial intelligence, computing power is no longer merely underlying support in the information technology sector, but has become a core national strategic resource as important as water and electricity. The Third Plenary Session of the 20th Central Committee of the Communist Party of China clearly put forward the requirement to "speed up digital development and build a digital China", emphasizing the need to "accelerate the development of the digital economy and promote the deep integration of the digital economy and the real economy". The *14th Five-Year Plan for the Development of the Digital Economy* clearly states that it is necessary to "promote the extensive and in-depth penetration of digital technologies into various fields of economic, social and industrial development, and advance the integrated innovation of digital technologies, application scenarios and business models", providing top-level design and policy guidance for the development of computing power. On this basis, the *Action Plan for the High-Quality Development of Computing Infrastructure* jointly issued by six ministries including the Ministry of Industry and Information Technology further refined the goals and paths for computing power construction, proposing a substantial increase in computing power scale and deep integration of computing power applications by 2025, laying an institutional foundation for computing power to empower the digital economy. In this macro background, computing power serves as the "engine" of the digital era. Its deployment scale and efficiency directly set the upper limit of digital innovation for enterprises. From the points discussed above, this paper raises the following questions: Can computing power promote digital technology innovation? What is its internal mechanism? What heterogeneous differences exist? Answering these questions helps to further understand digital technology innovation theories and advance technology-driven economic development.

But even with the favorable macro-policy environment, there is still no common agreement on whether computing power can further boost digital technology innovation and its specific mechanism. Academic research on how computing power is applied at the micro level and specifically affects corporate technological innovation remains relatively insufficient. Most existing studies mainly focus on the impact of the digital economy or broadband infrastructure on corporate performance. For example, as pointed out by Guo Kaiming in his research, from the perspective of AI enterprise innovation, artificial intelligence not only enables business model innovation and digital intelligent technology innovation of enterprises based on brand-new data factors, algorithms and computing power, but also brings new production factor empowerment and transformation to various traditional enterprises connected with AI enterprises [1]. Tan Hongbo, Ouyang Zekai and others argued that matching data infrastructure with other links of the supply chain can restructure the traditional sequential supply chain into a more open and dynamic "data ecosystem" [2]. Nevertheless, few studies have deeply analyzed how computing power, as a key production factor, drives substantive innovation of enterprises by lowering technical thresholds and transaction costs. Computing power deployment is more than just hardware stacking; by providing powerful data processing capabilities and algorithm training environments, it greatly reduces the marginal cost for enterprises to carry out digital technology innovation. Especially in cutting-edge fields such as

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artificial intelligence and big data analysis, sufficient computing power supply is a prerequisite for enterprises to conduct algorithm iteration and model training.

Based on the data of A-share listed companies holding Internet Data Center (IDC) business licenses approved and issued by the Ministry of Industry and Information Technology from 2017 to 2023, this paper empirically tests whether and how the deployment of intelligent computing centers by enterprises promotes the expansion of the application scope of artificial intelligence technologies and the improvement of digital transformation, and further discusses the potential role of artificial intelligence factor supply in this process. Given the core position of computing power as a new productive force in the digital economy era and the relative lag in academic research on how computing power is implemented at the micro level and specifically drives substantive corporate innovation, this paper breaks through the limitations of traditional estimation relying on macro computing power scale. By constructing a unique micro-enterprise IDC license-holding database, this paper not only accurately identifies enterprises' computing power deployment behaviors, but also deeply analyzes the internal mechanism of how computing power, as a general-purpose technology, stimulates corporate artificial intelligence innovation by lowering technical thresholds and transaction costs. The marginal contributions of this paper are mainly reflected in the following aspects:

① Innovation in research perspective: Descending from "macro infrastructure" to "micro enterprises", this paper empirically tests the driving effect of computing power on digital technology innovation. Existing literature mostly focuses on the broad impact of macro-level digital economy policies or broadband infrastructure on corporate performance, and few studies deeply analyze the specific role of "computing power", a key production factor, at the micro-enterprise level. This not only enriches the micro-empirical research of computing power economics, but also provides new empirical evidence for understanding how digital technologies empower high-quality enterprise development from the perspective of "new quality productive forces".

② Innovation in theoretical mechanism: This paper reveals the "dual paths" of computing power-enabled innovation and unlocks the micro black box of computing power implementation. Different from previous studies that only focus on the single efficiency improvement brought by computing power, based on data factor and technology diffusion theories, this paper proposes dual mechanisms of "technology application breadth" and "corporate digital transformation". The proposal of these two mechanisms clearly explains the internal logic of how computing power transforms from "hardware stacking" into "innovation momentum".

③ Innovation in research scenario: This paper constructs a unique dataset based on "compliant computing power resources" to accurately capture the real picture of corporate computing power deployment. In terms of research scenarios and data construction, this paper breaks through the limitations of previous studies relying on provincial computing power scale or intangible asset estimation of enterprises. Such a research scenario based on "license data" effectively overcomes the problem of rough granularity of traditional macro data, providing a more accurate and reliable data foundation for research on corporate computing power.

2. Research background and theoretical analysis

2.1. Development history of China's computing power and relevant policies

In the current era of artificial intelligence, the types and volume of data in human society have witnessed an unprecedented growth stage, and computing power plays a central role in data analysis, storage and operation. With the in-depth development of the new round of scientific and

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technological industrial revolution, innovations in digital technologies such as big data, artificial intelligence and blockchain have become increasingly active, giving rise to intelligent industries and the digital economy, and forming a new economic operation model driven by data factors [3]. The development of computing power has changed the development models of the three major industries in the contemporary era, promoted the transformation of industries toward green and high-quality development, and made optimizing the spatial layout of computing power an urgent need for the development of China's high-tech industries.

Against the above demand for computing power development, China has actively seized the new wave of scientific and technological development and attached great importance to policy support on the supply side of computing power. Among them, the State Council issued the *New Generation Artificial Intelligence Development Plan* in 2017, which mentioned "accelerating the transformation of digital and networked information infrastructure centered on information transmission into intelligent information infrastructure integrating perception, transmission, storage, computing and processing". In February 2022, the "East Data, West Computing" project was officially launched. In the *Reply on Approving the Construction of National Hub Nodes for the Integrated National Computing Power Network*, the National Development and Reform Commission and other departments emphasized: "promote the rational layout, supply-demand balance, green intensification and interconnection of data centers, and build a collaborative innovation system for the integrated national big data center". After 2024, the policy focus shifted to deepening integration and interconnection: on the one hand, empowering the manufacturing industry and the real economy through measures such as equipment renewal and public data development; on the other hand, promoting the high-quality development of the computing power industry to realize the efficient flow and sharing of computing power resources nationwide. The Ministry of Industry and Information Technology issued the *Notice on Launching the Construction of National Computing Power Interconnection Nodes* in early 2026, officially deploying the construction of the "1+M+N" national computing power interconnection node system, clarifying the goal of "building one national-level computing power internet service node, M regional nodes and N industry nodes to realize efficient scheduling and standardized services of computing power across subjects, regions and architectures". China's computing power policies have gradually evolved from the initial construction of data centers to the building of a green, low-carbon, intelligent, efficient, secure, credible and globally coordinated computing power ecosystem, truly turning computing power into a new type of productive force supporting high-quality development.

2.2. Theoretical analysis

(1) Coordinated Development of Data and Computing Power. In 2011, the McKinsey Global Institute first put forward the concept of "big data" in *Big Data: The Next Frontier for Innovation, Competition and Productivity*, defining it as "a data set whose scale exceeds the capabilities of typical database software in collection, storage, management and analysis". Shi Dan et al. defined the institutional and market conditions required for big data to function as "big data development", that is, the institutional and market conditions on which big data relies constitute the basic conditions for big data development [4]. Xu Nuo et al. proposed that when computing power and algorithms are combined with data, data provides the foundation of value, algorithms provide the value orientation, and computing power enables enterprises to acquire the analytical capability to release data value [5]. The development of computing power and data can not only support enterprises in the research and training of large AI models and promote the application of AI

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technologies, but also drive digital technological innovation in enterprises and boost the green, safe and innovative development of industries.

The digital economy cannot be separated from the processing, computing, storage and application of such massive data, which makes computing power the foundation of enterprise development and a new quality productive force driving the digital transformation of industries [3]. With the convergence, integration and analysis of massive data, the analytical and predictive capabilities of data models will grow exponentially, giving birth to brand-new business models and innovations [2]. a) In the value chain of artificial intelligence, data constitutes the basic input for model training, and algorithms determine the core mechanism of information processing and decision generation [6]. The training and reasoning of AI models are essentially complex mathematical operations on massive data, which cannot be completed without the support of powerful computing power and complex deep learning models. b) Upgraded computing power enables AI models to handle more complex tasks and larger volumes of multimodal data, thus promoting the in-depth penetration of AI technologies from the basic algorithm level to specific application scenarios. The efficient information processing capability empowered by computing power deployment supports enterprises in achieving broader knowledge acquisition and deeper multi-dimensional integration [7], providing underlying support for the layout of artificial intelligence patents under more IPC subclasses. c) Computing power is a new type of productive force in the digital economy era and key infrastructure supporting the high-quality development of the digital economy [8]. However, few studies have focused on empirical research on the impact of computing power deployment on AI innovation. On this basis, this paper proposes:

Hypothesis 1: Computing power can promote artificial intelligence innovation.

(2) Mechanism for Computing Power to Drive Artificial Intelligence Innovation: Computing Power Promotes the Breadth of AI Technology Application. In the digital economy era, artificial intelligence innovation has shifted from a single algorithm breakthrough to "computing power-driven" group innovation. Existing studies mostly focus on the efficiency improvement of computing power in a single production link, but rarely pay attention to how computing power stimulates broader technological innovation by expanding the application boundaries of technologies. As a typical general-purpose technology (GPTs), computing power has strong universality and spillover effects [9], and is a prerequisite for the implementation of AI technologies; without it, models cannot be trained for application. In the process of technology diffusion, the universality of computing power allows the same set of algorithm models to be quickly deployed in different scenarios such as finance, manufacturing and healthcare, lowering the threshold for cross-domain application of AI technologies. Therefore, computing power endows enterprises with stronger technology migration capabilities, thereby expanding the application breadth of AI patents.

AI patents represent the results of innovation efforts. But they can only generate useful feedback and promote the next round of innovation when put into practical application. Looking at the general process of innovation evolution, wider application of AI technologies offers a "negative feedback regulation mechanism" for artificial intelligence innovation. When AI patents are used in a wider range of fields, the feedback data they produce becomes new fuel for optimizing algorithm models and adjusting technology paths. This data helps speed up the accumulation and development of technical knowledge. It also helps expand the application scope of artificial intelligence technologies. So, by expanding the application scope of AI patents, computing power not only helps existing technologies realize their full value. It also promotes the creation of new knowledge through the feedback mechanism. In this way, it drives higher-level artificial intelligence innovation. Following the analysis presented above, this paper proposes:

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Hypothesis 2: Computing power can promote artificial intelligence innovation by widening the application scope of AI technologies.

(3) Mechanism for Computing Power to Promote Artificial Intelligence Innovation: Computing Power Promotes Artificial Intelligence Innovation by Driving Enterprise Digital Transformation.

Computing power is widely seen as the "core engine" of enterprise digital transformation. It is now reshaping the basic logic behind enterprise innovation. Most existing studies focus on the efficiency gains that computing power brings to a single production link [9]. But few of them explore how computing power supports artificial intelligence innovation by reshaping enterprise organizational structure and business processes. The new generation of digital technologies promotes qualitative changes in productive forces. It achieves this by lowering information costs and expanding knowledge boundaries. This provides theoretical support for understanding how computing power drives systematic changes at the enterprise level [10]. How adequate computing power resources are directly determines whether enterprises can turn massive data into fuel for innovation. This is essentially a process where computing power supports enterprise digital transformation. So, exploring how computing power promotes AI innovation by driving enterprise digital transformation offers a key perspective. It helps us understand how digital technologies evolve from "tool attributes" to "innovation attributes".

The features of computing power are closely linked to enterprise digital transformation. But how computing power is turned into transformation momentum at the enterprise level still needs further in-depth exploration. The core of enterprise digital transformation lies in turning data into capital assets [11]. Making this capability work well relies heavily on the real-time processing and integration of different types of data. Under the traditional model, decentralized IT architecture can barely support the concurrent processing of massive data. Investment in computing power resources allows enterprises to build a unified data middle platform. This platform realizes real-time data convergence and cleaning across the whole R&D, production and marketing chain. This computing power-based data integration ability can turn fragmented business data into standardized digital assets. It provides high-quality "data soil" for the training of artificial intelligence models. So, computing power gives enterprises stronger data integration abilities. This in turn advances the overall process of enterprise digital transformation. Following the above analysis, this paper proposes:

Hypothesis 3: Computing power promotes artificial intelligence innovation by driving enterprise digital transformation.

3. Research design

3.1. Data source and sample selection

This paper empirically examines the impact of corporate computing power deployment on AI innovation based on the data of subsidiaries of A-share listed companies in 2023 that hold the *Value-added Telecommunications Service Business License* approved and issued by the Ministry of Industry and Information Technology. This paper manually collects and obtains IDC (Internet Data Center) qualification issuance data from 2007 to 2023 through web crawling, matches them with the database of A-share listed companies and their subsidiaries, and selects 2017 to 2023 as the research period. The screening procedures are as follows: ① Exclude financial enterprises; ② Exclude samples that are insolvent; ③ Exclude samples in the IPO year; ④ Exclude samples with missing key variables. Finally, a research sample of 10,016 observations from 512 companies is obtained.

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The data sources are as follows: patent data are derived from the China Full Patent Database, and other data are derived from the CSMAR Database.

3.2. Variable selection and definition

(1) Dependent Variable (Artificial Intelligence Innovation). Based on keywords from policy documents such as the *New Generation Artificial Intelligence Governance Principles* and the *Artificial Intelligence Development White Paper*, this paper screens and classifies artificial intelligence innovation patents from the China Full Patent Database, denoted by AIIP. A larger value of AIIP indicates a higher level of digital technology innovation of the enterprise.

(2) Independent Variable (IDC). Intelligent Computing Center (IDC) is a dummy variable indicating whether an enterprise holds an IDC business license. The procedure and logic for obtaining this variable are as follows: ① Approval and Issuance of Business Licenses. Based on the Integrated Telecommunications Service Market Management Information System of the Government Service Platform of the Ministry of Industry and Information Technology, this paper systematically obtains information related to IDC licenses through the fixed-batch "List of Issued Value-added Telecommunications Service Business Licenses" and the query function of the system. According to the *Guidelines for Examination and Approval of Telecommunications Business Licenses* issued by the Ministry of Industry and Information Technology in 2023, enterprises applying for IDC services must complete system testing as a prerequisite for service launch, and obtain the license only after passing tests on computer room security, filing, resource and information security management systems. Therefore, holding an IDC business license can be regarded as proof of qualification for an enterprise to legally operate computing power resources. ② Licensed Business Information of IDC Business Licenses. This paper collects company names by matching accurate unified social credit codes with the Tianyancha Database, parses the year of license issuance according to the numbering rules of license numbers, screens entries containing "Internet Data Center Service" based on the business type field, and locates the city where the actual operating computer room is located through coverage information. After the above processing, a basic dataset of IDC business licenses is constructed. ③ Matching of Listed Companies and Their Subsidiaries. Subsidiaries Obtaining IDCs. Based on the unified social credit codes of listed companies, this paper investigates the IDC acquisition status of listed companies and their subsidiaries as the basis for judging whether a listed company substantially owns an intelligent computing center. Based on the above logic, the variable IDC is assigned a value of 1 if the listed company itself or any affiliated company in its equity chain holds a valid IDC business license; otherwise, it is assigned a value of 0 if no eligible license-related records are retrieved.

(3) Control Variables (Controls). Referring to Xu Nuo et al. and Xiang Xuefeng et al., the following control variables are set in the baseline regression: management expense (Mng), net profit (Prf), Tobin's Q (TobinQ) [5] [12]. In addition, this paper controls for year (Year) and company (Company) fixed effects.

(4) Mechanism Variables. Mechanism 1: Computing Power Promotes the Breadth of Artificial Intelligence Technology Utilization. As a key production factor in the digital economy era, the improvement and performance upgrading of computing power infrastructure significantly lower the thresholds and costs for various entities to access and use advanced technologies, enabling complex technologies such as cloud computing, big data analysis and artificial intelligence to be more widely applied in enterprises of different industries and scales, as well as more fields of social life. This study systematically sorts out the patent layout of target enterprises in the field of artificial intelligence, conducts structured extraction and cleaning of the IPC classification codes of each

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patent, and then quantitatively calculates the number of IPC classification categories of patents of each listed company, which is taken as the core indicator to measure the breadth of technology diffusion and cross-domain application capability of enterprises. The increase in such breadth of technology utilization is an important way for computing power to release its value. Therefore, computing power exerts an impact on AI innovation by promoting the wider application and popularization of technologies. Mechanism 2: Computing Power Drives Digital Transformation. Computing power is not only the underlying support for digital transformation but also the core engine driving its deepening. Adequate computing power resources can empower enterprises to digitally reshape the whole process of production, operation and management, promote business model innovation and efficiency improvement, and accelerate the depth and speed of digital transformation. Drawing on the research paradigm of Zhen Hongxian, Wang Xi and Fang Hongxing, this study constructs a word frequency statistical index system for digital transformation [13]. By systematically collecting and analyzing the text of annual reports of listed companies, the word frequency of keywords related to digital transformation is counted, and the word frequency value is used as a proxy variable to measure the degree of enterprise digital transformation, so as to quantitatively characterize the digital development level of enterprises.

3.3. Model specification

(1) Baseline Regression Test. To test Hypothesis 1, this paper constructs the following baseline regression model:

$$\mathrm{AIIP}_{i,t} = \beta_0 + \beta_1 \mathrm{IDC}_{i,t} + \sum \beta \mathrm{Controls}_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{1}$$

where i and t denote the company and year respectively; $AIIP_{i,t}$ represents the digital technology innovation level of company i in year t; $IDC_{i,t}$ indicates whether company i owns an intelligent computing center in year t, measured by whether it holds an IDC business license; $Controls_{i,t}$ is a series of control variables; $\varepsilon_{i,t}$ is the error term. μ_i and $\delta_i$represent company fixed effects and year fixed effects respectively. Standard errors for all firm-level regressions in this paper are clustered at the firm level.

(2) Test of Computing Power Empowerment Mechanism. To test Hypotheses 2 and 3, this paper constructs the following regression model:

$$\mathrm{MECHANISM}_{i,t} = \beta_0 + \beta_1 \mathrm{IDC}_{i,t} + \sum \beta \mathrm{Controls}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

where $MECHANISM_{i,t}$ denotes the mechanism variable: ① Computing power promotes the breadth of artificial intelligence technology utilization. Computing power exerts an impact on AI innovation by promoting the wider application and popularization of technologies. ② Computing power drives digital transformation. Adequate computing power resources can empower enterprises to digitally reshape the whole process of production, operation and management, promote business model innovation and efficiency improvement, and meanwhile exert a positive effect on AI innovation by accelerating the digital process in social governance, public services and other fields. All other settings are completely consistent with those in Equation (1).

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4. Analysis of empirical results

4.1. Baseline regression results

Table 1 reports the baseline regression results. Column (1) shows that each unit increase in the independent variable computing power deployment is associated with an average increase of 9.168 units in the dependent variable, the number of AI innovation patents. Column (2) shows that after controlling for factors such as corporate management, market value and net profit, the net effect of computing power deployment remains significant, indicating that the impact of computing power deployment on the number of AI innovation patents is positive and robust, which verifies Hypothesis 1.

Table 1. Baseline regression results

VARIABLES	(1) ipzlid	(2) ipzlid
DID	9.168**	4.676**
	(4.4129)	(2.2940)
Mng		0.000
		(0.0000)
TobinQ		-0.000
		(0.0998)
Prf		0.000**
		(0.0000)
Constant	1.387***	0.661
	(0.1044)	(0.6835)
Observations	68,746	53,655
R-squared	0.3479	0.4416
Company FE	YES	YES
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.2. Test of action mechanisms

(1) Computing Power Promotes the Breadth of Technology Utilization. ① From the perspective of technology diffusion, computing power, as a typical general-purpose technology (GPT), features strong permeability and spillover effects. ② The scale effect of computing power significantly reduces the unit computing cost. ③ The improvement of computing power infrastructure facilitates the formation of a technological ecosystem. On this basis, this paper uses the perspective of

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technology diffusion, the scale effect of computing power and the improvement of computing power infrastructure to proxy the promotion of technology utilization breadth by computing power, and conducts the test with Equation (2).

Table 2 reports the mechanism test results of computing power promoting the breadth of technology utilization. The results show that computing power deployment has a significant positive effect on artificial intelligence technology innovation, and this conclusion is highly robust. As shown in the table, after controlling for firm fixed effects and year fixed effects, the regression coefficient of the core explanatory variable (DID) is significantly positive at the 1% statistical level. Specifically, without adding specific control variables, the DID coefficient is 12.975; even after introducing variables such as management expense (Mng), net profit (Prf) and Tobin's Q (TobinQ), the coefficient is adjusted to 8.454, which remains highly significant despite a slight decline. This strongly verifies that computing power, as a new type of infrastructure, can effectively drive enterprises to break through traditional technological bottlenecks and increase the output of digital technology patents. Meanwhile, the R-squared value of Model (2) reaches 0.4802, indicating that the variables have strong explanatory power for innovation differences, which further corroborates the effectiveness of the mechanism by which computing power promotes digital transformation and verifies Hypothesis 2.

Table 2. Mechanism regression results 1

VARIABLES	(1) IPC_num	(2) IPC_num
DID	12.975***	8.454***
	(4.0114)	(2.4580)
Mng		0.000
		(0.0000)
TobinQ		-0.131
		(0.0961)
Prf		0.000**
		(0.0000)
Constant	2.081***	1.370**
	(0.0950)	(0.5662)
Observations	68,735	53,655
R-squared	0.3999	0.4802
Company FE	YES	YES
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

(2) Computing Power Promotes Digital Transformation. By accelerating the digital process in various fields, computing power empowers enterprises to digitally reshape the whole process of production, operation and management, thus promoting business model innovation and efficiency improvement.

Table 3 reports the mechanism test results of computing power promoting digital transformation. Column (1) is the baseline regression without control variables, and Column (2) adds firm-level

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control variables such as Tobin's Q (TobinQ) and net profit (Prf). The results show that the coefficient of the core explanatory variable DID is significantly positive at the 1% level in both columns. Specifically, in the baseline model, the coefficient of DID is 31.736 (with a large t-value), indicating that the implementation of computing power policies has significantly promoted the digital transformation of enterprises. After adding control variables, the DID coefficient drops slightly to 28.757 but remains highly significant. This shows that after controlling for factors such as corporate market value and net profit, the empowering effect of computing power infrastructure on corporate digital transformation is still robust. In addition, the within R-squared of Model (1) reaches 0.7460, indicating that individual and time fixed effects explain most of the variation. In summary, the empirical results strongly support the hypothesis that the construction of computing power infrastructure is an important driving force for corporate digital transformation.

Table 3. Mechanism regression results 2

VARIABLES	(1) digital	(2) digital
DID	31.736***	28.757***
	(3.7604)	(3.9694)
Mng		0.000***
		(0.0000)
TobinQ		-0.081
		(0.1547)
Prf		-0.000
		(0.0000)
Constant	10.692***	12.093***
	(0.0906)	(0.3688)
Observations	67,520	53,549
R-squared	0.7460	0.7686
Company FE	YES	YES
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.3. Robustness tests

This paper conducts the following robustness tests:

① Replacement of the Dependent Variable. Considering that corporate digital technology innovation indicators may suffer from non-normal distribution or dimensional differences, and to rule out sensitivity to specific count models, this paper further selects logarithmized or standardized patent indicators (denoted as ipzlid2) as alternative variables for regression analysis. If the baseline regression results are spurious and caused by measurement bias, the coefficient should become insignificant after replacing the indicator. Conversely, if the sign and significance of the coefficient remain consistent, it indicates that the conclusion is robust to variable measurement methods. The regression results are shown in Table 4. Column (1) presents the regression results without control variables, where the coefficient of the core explanatory variable (DID) is 7.483, significantly

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positive at the 5% level. Column (2), after controlling for management expense (Mng), Tobin's Q (TobinQ), net profit (Prf) and other variables, shows that the coefficient of the core explanatory variable is 5.453, still significant at the 10% level. The empirical results indicate that after changing the measurement method of the dependent variable, the positive driving effect of computing power deployment on corporate AI innovation remains significant, verifying the robustness of Hypothesis 3 under indicator replacement.

Table 4. Results of robustness tests

VARIABLES	(1) ipzlid2	(2) ipzlid2
DID	7.483**	5.453*
	(3.1895)	(3.2034)
Mng		0.000
		(0.0000)
TobinQ		-0.004
		(0.1032)
Prf		0.000*
		(0.0000)
Constant	1.511***	0.373
	(0.0755)	(1.1192)
Observations	68,746	53,655
R-squared	0.2962	0.3764
Company FE	YES	YES
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

② Adjustment of Fixed Effects and Sample Screening. To further alleviate omitted variable bias and exclude interference from specific samples, this paper adjusts the model specification with reference to relevant literature. Specifically, samples with missing key data or those in specially regulated industries are excluded, and more refined fixed effects are further controlled in the regression. The regression results are shown in Table 5. After adjusting the model specification and optimizing the sample range, the coefficients of the core explanatory variable (DID) in Column (1) and Column (2) are 12.642 and 6.257 respectively, and the core variable remains significant. Specifically, Column (2), after controlling for management expense ratio (Mng), Tobin's Q (TobinQ) and corporate performance (Prf), shows that the coefficient of the core variable is 6.257, significant at the 5% level. Although the sample size decreases from 57,711 to 43,141, the goodness-of-fit (R-squared) of the model rises to 0.4866, with significantly enhanced explanatory power. This result suggests that even after controlling for more unobservable heterogeneous factors, the core conclusion of this paper—that computing power deployment drives corporate innovation—still holds.

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Table 5. Results of robustness tests on AI measurement methods

VARIABLES	(1) ipzlid	(2) ipzlid
DID	12.642*	6.257**
	(6.6935)	(3.1627)
Mng		0.000
		(0.0000)
TobinQ		-0.058
		(0.1195)
Prf		0.000*
		(0.0000)
Constant	1.409***	1.074*
	(0.1343)	(0.5877)
Observations	57,711	43,141
R-squared	0.3744	0.4866
Company FE	YES	YES
Year*Industry FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4. Heterogeneity tests

Table 6 reports the heterogeneity test results based on the Industrial Classification for National Economic Activities (two-digit divisions). According to the regression analysis, different industries exhibit significant differences in response to the treatment variable (DID). The DID coefficients for five industries—D (Production and Supply of Electric Power, Gas, Steam and Hot Water), G (Transportation, Storage and Postal Services), K (Real Estate), N (Water Conservancy, Environment and Public Facilities Management)—are significant, at 8.481, 4.357, 0.376 and 0.142 respectively. The regression results show that: ① The policy exerts a strong promoting effect on innovation in public utility sectors. ② The coefficients for Category K and Category N are 0.142 and 0.107 respectively; although their significance levels are relatively low, they still reflect the marginal impact of the policy on the real estate industry, water conservancy, environment and public facilities management. The effects on other unlisted industries are insignificant and thus not presented in the final document.

Table 6. Results of industrial heterogeneity tests

VARIABLES	(4) ipzlid	(7) ipzlid	(11) ipzlid	(14) ipzlid
o.DID				
Mng	0.000**	0.000**	0.000***	0.000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TobinQ	0.604**	0.020	-0.005	0.080

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Table 6. (continued)

	(0.2354)	(0.0519)	(0.0294)	(0.0630)
Prf	-0.000*	-0.000*	0.000	-0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DID	8.481	4.357	0.376	0.142
	(5.4915)	(8.4640)	(0.2331)	(0.1369)
o.Mng				
o.TobinQ				
o.Prf				
o._cons				
Constant	-3.714**	0.242	-0.055	-0.806*
	(1.7687)	(0.2033)	(0.0993)	(0.4130)
Observations	1,323	1,251	1,681	535
R-squared	0.6049	0.6675	0.2833	0.5079
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

To examine the moderating effect of regional digital infrastructure on the core effect, this paper divides the sample into high and low groups according to the median of the urban digital infrastructure index (Di) and conducts grouped regressions, with the results shown in Table 7. In regions with low levels of digital infrastructure (Column 2), the coefficient of the core explanatory variable DID is 0.167 and insignificant, indicating that weak infrastructure restricts the release of policy dividends. In regions with high levels of digital infrastructure (Column 3), the coefficient of DID is significantly positive (5.511, $p<0.01$). This significant between-group difference confirms the important empowering effect of digital infrastructure: a sound digital foundation can effectively strengthen the promotion effect of core variables on corporate innovation.

Table 7. Results of heterogeneity tests

VARIABLES	(1) ipzlid	(2) ipzlid	(3) ipzlid
DID_Di	59.419		
	(426.0611)		
Mng	0.000		
	(0.0000)		
TobinQ	-0.026		
	(0.1426)		
Prf	0.000		
	(0.0000)		
DID		0.167	5.511

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Table 7. (continued)

		(0.1191)	(4.2992)
Constant	0.769	0.225***	3.681***
	(0.8700)	(0.0022)	(0.2003)
Observations	37,070	22,099	22,520
R-squared	0.4321	0.4209	0.5457
Company FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions and policy implications

Computing power is a new form of productive force in the digital economy era. It has become the core engine driving AI innovation for enterprises. This paper tries to answer two questions: do intelligent computing centers improve the breadth of AI technology application and the level of digital transformation, and how do they achieve this? It also further discusses the possible role of AI factor supply in this process. The main findings of this study are listed below: ① The deployment of intelligent computing centers can effectively raise the rate of artificial intelligence technological innovation. ② For the mechanism of how intelligent computing centers drive artificial intelligence innovation, this paper carries out analysis from two aspects. One is promoting the breadth of technology utilization, and the other is advancing digital transformation. It also proves that computing power can boost artificial intelligence technological innovation. It achieves this by expanding the application breadth of AI technologies and speeding up corporate digital transformation. Following the research conclusions, this paper puts forward the following policy suggestions:

① Optimize regional layout and scheduling. Build high-performance intelligent computing centers in eastern China, develop characteristic computing power services in central and western China, and improve the cross-regional computing power scheduling mechanism. ② Carry out differentiated enterprise policies. Remove barriers to computing power access for non-state-owned enterprises and cut down their transformation costs; support high-tech enterprises to improve computing power efficiency and push forward AI research and development. ③ Build a factor coordination ecosystem. Integrate computing power, talent and data factors, and build public service platforms; improve the standard system and security support to form an innovation supply portfolio.

Taking intelligent computing centers as the entry point, this paper demonstrates the relationship between computing power and the rate of artificial intelligence technological innovation. Future research can be expanded in two important directions: first, to explore how enterprises balance the expansion of computing power scale and green transformation against the backdrop of the "East Data, West Computing" initiative and green and low-carbon policies; second, to study how enterprises can improve the marginal output of artificial intelligence technological innovation by optimizing the allocation efficiency of computing power resources and data assets.

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References

[1] Guo Kaiming, Artificial Intelligence, Structural Transformation and Labor Share [J]. Management World, 2019, 35(07): 60-77+202-203. DOI: 10.19744/j.cnki.11-1235/f.2019.0092.
[2] TAN Hongbo, OUYANG Zekai, Data Empower Industrial Transformation and Upgrading: Paths, Mechanisms, and Countermeasures [J]. Economic Review Journal, 2026, (04): 41-52. DOI: 10.16528/j.cnki.22-1054/f.202604041.
[3] YU Donghua, Computing power: a new quality productivity in the digital economy era [J]. Finance and Trade Research, 2024, 35(07): 1-16. DOI: 10.19337/j.cnki.34-1093/f.2024.07.001.
[4] SHI Dan, SUN Guanglin, Influence Mechanism of Big Data Development on the Total Factor Productivity of Manufacturing Enterprises [J]. Finance & Trade Economics, 2022, 43(09): 85-100. DOI: 10.19795/j.cnki.cn11-1166/f.20220906.006.
[5] XU Nuo, MAO Ju, MAO Xin-shu, WANG Yan-chao, Computility Deployment, Cross-Domain Data Flow and Enterprise Total Factor Productivity: Evidence from Intelligent Computing Centers [J]. China Industrial Economics, 2025, (04): 61-79. DOI: 10.19581/j.cnki.ciejournal.2025.04.003.
[6] WEN Jun, HAI Hongbo, LI Lingxiao. Breaking Barriers and Establishing Order: Empowerment Pathways and Governance Frameworks for AI-Driven Industrial Competitiveness Leap, 2026, 46(01): 36-46+206-207+2.
[7] Yin Qi, Huang Can, Fan Libo, Niu Biao, Research on the Impact of Computing Power Deployment on Enterprises' Key Core Technology Innovation: From the Perspective of Hayek's Theory of Knowledge [J/OL]. Science Research Management, 1-17 [2026-04-20]. https: //link.cnki.net/urlid/11.1567.G3.20260416.1528.024.
[8] ZHAO Peng, LI Jinyi, WANG Chen, XUE Zixian, CAI Haitao, TANG Guohua, Research and application on intelligent operation of artificial intelligence capability and computing power network [J]. Journal of Computer Applications, 2025, 45(S1): 295-301.
[9] Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: "Engines of growth"? Journal of Econometrics, 65(1), 83-108.
[10] Cai Yuezhou, Chen Nan, Artificial Intelligence and High-quality Growth & Employment in the Era of New Technological Revolution [J]. The Journal of Quantitative & Technical Economics, 2019, 36(05): 3-22. DOI: 10.13653/j.cnki.jqte.2019.05.001.
[11] Cai Yuezhou, Ma Wenjun, How Data Influence High-quality Development as a Factor and the Restriction of Data Flow [J]. The Journal of Quantitative & Technical Economics, 2021, 38(03): 64-83. DOI: 10.13653/j.cnki.jqte.2021.03.002.
[12] XIANG Xuefeng, YANG Yuli, Innovation-driven Policies, Data Factor Supply, and Artificial Intelligence Development: Based on the Perspective of Policy Synergy [J]. Inquiry Into Economic Issues, 2025, (08): 36-51.
[13] ZHEN Hongxian, WANG Xi, FANG Hongxing, Administrative Protection of Intellectual Property Rights and Corporate Digital Transformation [J]. Economic Research Journal, 2023, 58(11): 62-79.