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Original Paper

Sci-tech Finance and Technological Innovation of AI Computing Power Enterprises: Based on the Perspective of Financial Regulation

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Abstract

As the new round of technological revolution continues to evolve, computing power is progressively emerging as the "new qualitative productive force" in the era of digital economy; AI computing power, being the core component of computing power, has consequently garnered extensive attention. This study examines the impact of sci-tech finance on the technological innovation of AI computing power enterprises, the mechanism of action, and the role of financial regulation, using data from Chinese A-share listed AI computing power enterprises from 2014 to 2022. The findings are as follows: Firstly, the development of sci-tech finance significantly enhances the technological innovation capacity of AI computing power enterprises. Secondly, the alleviation of financing constraints partially mediates this effect. Thirdly, overall financial regulation exerts a negative regulatory effect on the relationship between sci-tech finance and technological innovation; specifically, financial regulation in the eastern region has a negative regulatory role, whereas in the non-eastern regions, it exhibits a positive regulatory role. These research conclusions hold certain implications and reference value for enhancing the sci-tech finance system, fostering the development of the computing power industry, and reforming the regulatory system.

Keywords

sci-tech finance, AI computing power enterprises, technological innovation, financing constraints, financial regulation

1. Introduction

In 2023, amidst the emergence of new quality productivity and the ongoing advancement of industrial upgrading, the computing power industry has been accorded a prominent status in China's development agenda. The world is presently in the convergence period of the fourth industrial revolution and the scientific and technological revolution, with this revolution, centered around computing power, propelling productivity towards increasingly intelligent and digital directions.

Liu (2024) discovered that with each 1% increase in the computing power index, the level of the digital economy will rise by 3.3‰, and GDP will increase by 1.8‰. As the core component of the computing power industry, AI computing power is not only emerging as a pivotal force in shaping the future socio-economic landscape but also, through its interplay and integration with data and algorithms, is giving rise to new forms of digital, intelligent, and ecological quality productivity (Mi et al., 2024). In contemporary society, information technology and artificial intelligence have become significant indicators of national competitiveness. Possessing robust AI computing power enables more efficient processing and analysis of vast data, thereby fostering technological innovation and industrial upgrading. Consequently, the development of the AI computing power industry contributes to enhancing a country's global competitiveness. As the core driving force behind digital transformation, AI computing power provides intelligent decision support for enterprises, aids in optimizing production processes, and improves service quality. By advancing the AI computing power industry, the digital transformation and intelligent upgrading of various industries can be expedited. AI computing power has become the pivotal force in promoting national development. Therefore, technological innovation in the AI computing power industry is essential for enhancing the country's overall strength. In the context of strengthening enterprises as the main market players in technological innovation, improving the technological innovation level of AI computing power enterprises is of paramount importance for achieving high-quality economic development and enhancing total factor productivity.

The technological innovation activities of AI computing power enterprises are typically characterized by high investment and high risk, making it challenging to support these activities solely with internal funds. Consequently, enterprises require sufficient external financing to sustain the development of innovation activities and to effectively prevent and mitigate potential risks under scientific supervision mechanisms. However, the nature of R&D renders it particularly susceptible to financing constraints under the traditional financial model (Brown et al., 2012). As a unique institutional arrangement in China, sci-tech finance can channel substantial financial resources into technological innovation activities by deeply integrating the technology chain with the financial chain under scientific financial supervision. This integration allows the three elements to influence each other, disperse risks, and foster integrated development. Nevertheless, there is a scarcity of research examining the relationship between sci-tech finance and the technological innovation of AI computing power enterprises from the perspective of financial regulation. Therefore, this paper poses three questions: (1) Can the development of sci-tech finance enhance the technological innovation capabilities of AI computing power enterprises? (2) If sci-tech finance can indeed promote the technological innovation of AI computing power enterprises, what intermediary variables are utilized to achieve this? (3) What is the regulatory role of financial regulation in the relationship between sci-tech finance and the technological innovation of AI computing enterprises?

2. Literature Review

Sci-tech finance encompasses a series of systematic institutional arrangements implemented by the government, financial institutions, capital markets, and social intermediaries, primarily aimed at fostering technological innovation and supporting the development of high-tech industries. AI computing power denotes the computational capacity utilized to execute artificial intelligence tasks. Financial regulation involves a suite of measures undertaken by regulatory agencies to oversee the flow and utilization of financial resources, with the objective of mitigating the likelihood of systemic risks. Presently, research on sci-tech finance, AI computing power, and financial regulation predominantly concentrates on the following aspects.

In the domain of sci-tech finance, extant research predominantly centers on the quantification of sci-tech finance and its effects on various industries. Guo et al. (2023) have delineated sci-tech finance into funding index, environment index, and output index, based on an evaluation framework that considers both inputs and outputs, thereby constructing a comprehensive evaluation system for the development level of regional sci-tech finance. Lu et al. (2023) have selected indicators from diverse dimensions including government, money markets, and capital markets, and applied the entropy method to quantify the development level of sci-tech finance across provinces in China. Building upon this quantification, scholars have conducted empirical studies to assess the impact of sci-tech finance on industrial development. Cui (2024) utilized a VAR model to examine the relationship between sci-tech finance and the high-quality development of China's manufacturing sector, revealing that sci-tech finance exerts a significant influence on the high-quality development of manufacturing. In the context of a burgeoning marine economy, Xu et al. (2021) have adopted this as a focal point and discovered that government financial investments in sci-tech finance notably enhance the innovation efficiency of the marine industry.

In the realm of AI computing power, scholars predominantly engage in discussions regarding the current state of AI computing power development and network construction. Guo et al. (2022) have delved into the subject from the perspective of heterogeneous AI computing power, elucidating the formation mechanism and technical architecture of its operational platform. Amidst the growing proliferation of AI applications, Zheng (2021) highlighted the continuous emergence of new-generation supercomputers tailored for AI applications, and emphasized the necessity of infrastructure construction for AI computing power systems. Furthermore, the utilization of AI computing power necessitates a stable and mature computing power network system. Wang et al. (2021) have developed a superior-performing computing power network framework known as Net-in-AI, aimed at addressing the issue of uneven resource distribution within computing power networks.

In the domain of financial regulation, the conclusions concerning its impact on technological innovation are not uniform. Li et al. (2021), utilizing data from Chinese A-share listed companies spanning from 2011 to 2018, discovered that an increase in the intensity of financial regulation aids in elevating corporate technological innovation levels. Nonetheless, owing to the differing requirements of financial regulation across various industries, the impact of financial regulation can vary substantially. Li and Zhang (2022) undertook a study on New Third Board enterprises from 2012 to 2019, and their findings indicated that under stringent financial regulation, corporate technological innovation output has diminished. Influenced by variations in both internal and external characteristics of the enterprises, the impact of financial regulation on corporate technological innovation manifests strong heterogeneity.

3. Theoretical Analysis and Research Hypothesis

3.1 The Promotion Effect of Sci-tech Finance

As a product of the profound integration of technology and finance, sci-tech finance channels financial resources towards nationally-supported high-tech projects and industries, empowering high-tech enterprises with increased funding and a heightened inclination to innovate (Liu et al., 2022). In the contemporary era of digital transformation, computing power has emerged as a critical cornerstone supporting the development of industries such as telecommunications and finance. From the standpoint of industrial development theory, sci-tech finance can propel technological innovation in AI computing power enterprises by optimizing resource allocation and adjusting industrial policies. The development of sci-tech finance facilitates the optimization of resource allocation by directing capital towards AI computing power enterprises with innovative potential and market prospects, thereby achieving optimal resource allocation and fostering the growth of the entire industry. Additionally, the theory of industrial convergence also provides theoretical backing for this promotion effect. As sci-tech finance and the AI computing power industry integrate deeply, their boundaries become increasingly indistinct, resulting in a mutually reinforcing and co-developing dynamic. Sci-tech finance offers AI computing power enterprises more precise and efficient financial services, while AI computing power enterprises drive the upgrade and optimization of sci-tech finance products through technological innovation. Therefore, this paper proposes Hypothesis 1:

H1: Sci-tech finance exerts a significant positive impact on the technological innovation of AI computing power enterprises.

3.2 The Mediating Effect of Financial Constraints

From the perspective of the information asymmetry theory, technological innovation of AI computing power enterprises is characterized by high investment and high risk. Moreover, certain projects and operations within these enterprises involve state secrets, rendering corporate information incomplete and non-transparent, which complicates the acquisition of financing under the traditional financial system. According to a World Bank report, approximately 80% of enterprises in China encounter difficulties in accessing financial resources. In the traditional credit market, information asymmetry results in elevated external financing costs for enterprises, subsequently becoming a hindrance to their development (Ma & Guo, 2021). Sci-tech finance possesses the functions of information transmission and evaluation, which can effectively mitigate information asymmetry and alleviate the challenges and high costs associated with financing for AI computing power enterprises, thereby fostering technological innovation. From the perspective of the MM theory, due to market imperfections, capital structure serves as a tool for enterprises to minimize capital costs and risks. Sci-tech finance, with its flexible financing channels, assists enterprises in optimizing their capital structure and reducing capital costs, thereby enhancing their technological innovation capabilities. Based on this, this paper proposes Hypothesis 2:

H2: Sci-tech finance can significantly alleviate the financing constraints faced by AI computing power enterprises, thereby promoting their technological innovation.

3.3 The Regulatory Effect of Financial Regulation

From the risk-return trade-off theory, financial regulation is designed to manage systemic risk and safeguard investors from undue losses. However, this risk-averse regulatory environment can impede the execution of high-risk, high-reward projects, which are frequently the primary drivers of significant technological innovations. For high-tech emerging industries characterized by high costs and high risk, excessive risk control may induce investors and financial institutions to adopt a cautious stance towards the investment and financing of such enterprises, resulting in a contraction in the innovation output of enterprises under stringent financial regulation. Furthermore, shifts in regulatory policies often impose stricter compliance requirements. To satisfy these requirements, AI computing enterprises must allocate more resources and energy to compliance management rather than concentrating on technological innovation. This misallocation of resources will diminish the innovation efficiency of enterprises. Therefore, Hypothesis 3 is proposed:

H3: Financial regulation plays a negative moderating role between sci-tech finance and technological innovation of AI computing power enterprises.

4. Research Design

4.1 Model Construction

To validate Hypothesis 1, the fixed effects model emerges as the optimal selection based on the results of the Hausman test. Consequently, this paper constructs the following benchmark regression model:

$$Innovation_{it} = \alpha_0 + \alpha_1 STF_t + \alpha_2 Controls_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

Where $Innovation_{it}$ represents the technological innovation level of AI computing power enterprise *i* in year *t*, STF represents the sci-tech finance development level in year *t*, and $Controls$ represents the control variables. To absorb the impact of fixed effects, by referring to the study of Clement and Xavier (2020), but since the development level of sci-tech finance in this paper only changes with time, not with enterprises, this paper adopts the individual fixed effect model, μ_i represents the fixed effect of enterprises and ε_{it} is the random error term.

To verify Hypothesis 2, this paper constructs the following mediating effect model:

$$SA_{it} = \alpha_0 + \alpha_1 STF_t + \alpha_2 Controls_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$Innovation_{it} = \gamma_0 + \gamma_1 STF_t + \gamma_2 Controls_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

Where SA_{it} is the financing constraints faced by AI computing power enterprise *i* in year *t*, and the meanings of other variables are consistent with those in (1).

To verify Hypothesis 3, this paper constructs the following moderating effect model:

$$Innovation_{it} = \varphi_0 + \varphi_1 STF_t + \varphi_2 FRI_{it} + \varphi_3 STF_t \times FRI_{it} + \varphi_4 Controls_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

Where FRI_{it} represents the level of financial regulation that AI computing power enterprise *i* is subject to in year *t*, and the meanings of other variables are consistent with (1).

4.2 Variable Description

4.2.1 Dependent Variable: Technological Innovation Level of AI Computing Power Enterprises

Owing to the time lag inherent in patent authorization, this paper employs the number of patent applications filed by AI computing power enterprises in the current year as a proxy for the level of scientific and technological innovation. To mitigate the impact of heteroscedasticity, this paper applies the natural logarithm transformation to the data.

4.2.2 Independent Variable: Sci-tech Finance

To more comprehensively quantify sci-tech finance, it is further divided into two dimensions: government sci-tech finance and market sci-tech finance. The quantitative index for government sci-tech finance is represented by government R&D investment. Market sci-tech finance is comprehensively assessed using indicators such as technology loans from financial institutions, enterprise R&D expenditure, and venture capital support. To derive a comprehensive indicator reflecting the development level of sci-tech finance, the entropy weight method is employed for the calculation. The calculation methods and attributes of each indicator are shown in Table 1.

Table 1. Sci-tech Finance Index System

Variable Names	Calculation Methods	Weight	Attribute
Government R&D investment	Government funds in internal R&D expenditure /GDP	0.266	+
technology loans from financial institutions	Other funds in internal R&D expenditure /GDP	0.390	+
enterprise R&D expenditure	Corporate capital in internal R&D expenditure /GDP	0.199	+
venture capital support	Venture capital /GDP	0.145	+

4.2.3 Mediating Variable

In the extant research literature, the KZ, WW, and SA indexes are commonly employed to assess the degree of corporate financing constraints. However, given that the computation of the KZ and WW indexes predominantly relies on corporate financial variables, there may be mutual interference among these variables, potentially leading to endogeneity issues. Drawing upon the research of Ju Xiaosheng et al. (2013), this paper opts to utilize the SA index to evaluate the degree of financing constraints faced by AI computing power enterprises. The calculation formula is as follows:

$$SA_{it} = 0.043 \times (\ln size_{it})^2 - 0.737 \times \ln size_{it} - 0.04 \times age_{it} \tag{5}$$

Where $size_{it}$ denotes the asset scale of enterprise *i* in year *t*, and age_{it} denotes the establishment time of enterprise *i* in year *t*.

4.2.4 Moderating Variable

This paper employs the intensity of financial regulation as the moderator variable. The development of sci-tech finance may also introduce certain risks, which should be monitored by financial regulators. Consequently, in the empirical study of this paper, financial regulation is incorporated within the scope of investigation as a crucial moderating variable. To accurately gauge the intensity of financial regulation, the ratio of financial regulation expenditure to the added value of the financial industry is adopted as the calculation method (Tang et al., 2020).

4.2.5 Control Variables

Acknowledging that the technological innovation of AI computing power enterprises is influenced not only by sci-tech finance but also by a range of internal company factors, to ensure the accuracy and reliability of empirical research, this paper selects six variables as control variables. The names, symbols, and calculation methods of these control variables are detailed in Table 2.

Table 2. Control Variables

Variable Names	Variable Symbols	Calculation Methods
enterprise size	*scale*	ln (Total assets of the enterprise)
return on total assets	*ROA*	Net profit/Total assets
asset-liability ratio	*Lev*	Total liabilities/Total assets
corporate cash flow	*Cash*	Cash flow from operating activities/Total assets
corporate capital intensity	*Capital*	ln（Fixed assets/Number of employees）
ownership concentration	*OC*	Number of shares held by top 10 shareholders/Total number of shares

4.3 Data Sources and Descriptive Statistics

The enterprise data utilized in this paper are primarily sourced from the Wind database, whereas the data pertaining to sci-tech finance are chiefly derived from reports such as the National Economic Statistical Bulletin, China Science and Technology Statistical Yearbook, and China Venture Capital Development Report issued by the National Bureau of Statistics. The study sample comprises AI computing power enterprises listed on the A-share market between 2014 and 2022. To ensure the robustness of the data, all continuous variables underwent a 1% and 99% truncation at the tails. Consequently, 347 observed values from 50 listed companies were selected as research samples after excluding enterprises with missing key variables.

Table 3 presents the descriptive statistics of the empirical data utilized in the study. The substantial disparity between the maximum and minimum values of enterprise innovation indicates a significant variation in the innovation capabilities among the sampled enterprises. Additionally, the financing constraints are uniformly negative, suggesting that all enterprises in the sample have experienced external financing difficulties during their development process.

Table 3. Descriptive Statistics of Variables

Variables	Observations	Mean	Std. dev	Min	Max
Innovation	347	2.745	1.832	0.000	8.306
STF	347	0.494	0.209	0.189	0.761
SA	347	-3.799	0.267	-4.544	-2.708
FRI	347	0.007	0.007	0.001	0.039
Scale	347	22.146	1.206	20.279	26.049
ROA	347	0.020	0.087	-0.389	0.146
Lev	347	0.389	0.200	0.081	0.867
Cash	347	0.031	0.064	-0.230	0.180
Capital	347	11.94	1.211	9.066	15.148
OC	347	0.521	0.147	0.179	0.871

5. Empirical Results Analysis

5.1 Baseline Regression Results

Table 4 details the benchmark regression results regarding the impact of sci-tech finance on the technological innovation of AI computing power enterprises. Column (4) presents the regression results corresponding to Equation (1). After accounting for the influence of fixed effects and control variables, the regression coefficient of sci-tech finance on the innovation level is significantly positive at the 5% significance level. This finding robustly demonstrates that sci-tech finance significantly enhances the technological innovation capability of AI computing power enterprises, thereby verifying Hypothesis 1(H1).

Table 4. Baseline Regression Results

	(1)	(2)	(3)	(4)
Variables	*Innovation*	*Innovation*	*Innovation*	*Innovation*
STF	0.791*	-0.252	1.190***	0.830**
	(0.463)	(0.383)	(0.247)	(0.374)
scale		1.009***		0.518***
		(0.069)		(0.137)
ROA		1.672		-0.711
		(1.079)		(0.843)
Lev		-0.696		-1.617**
		(0.440)		(0.655)
Cash		-0.920		-0.370
		(1.270)		(0.921)
Capital		0.225***		0.130
		(0.062)		(0.086)
OC		0.007		0.013
		(0.005)		(0.011)
Constant	2.348***	-22.278***	2.157***	-10.729***
	(0.248)	(1.586)	(0.130)	(3.249)
Fixed effect	NO	NO	YES	YES
N	347	347	347	347
R^2	0.008	0.447	0.810	0.834

Standard errors in parentheses.

*p<0.1, ** p<0.5, *** p<0.01.

5.2 Robustness Test

5.2.1 Change the Clustering Standard Error

Although this paper controls for relevant macro-level factors in the empirical analysis to mitigate the potential interference of time trends on the estimation results, the influence of the time effect cannot be entirely eliminated. To evaluate the impact of sci-tech finance more comprehensively, a cluster analysis on the benchmark regression results over the time dimension was conducted. The corresponding regression results are presented in Column (1) of Table 5, where the regression coefficient of sci-tech finance is positive and significant at the 5% level. This further corroborates the positive impact of sci-tech finance on the technological innovation of AI computing power enterprises.

5.2.2 Change the Data Processing Method

In this analysis, the data are winsorized at a stricter 2.5% quantile. Following this adjustment, the regression analysis is re-conducted, and the results are presented in Column (2) of Table 5. The findings indicate that the regression coefficient of sci-tech finance remains positive and significant at the 1% level, with no substantial change in the coefficient value. This further validates the robustness of our previous research results.

5.2.3 Change the Measurement of Variables

In accordance with the regulations of the National Bureau of Statistics on industrial classification and the primary sources of business income for AI computing power enterprises, this paper classifies AI computing power enterprises as industrial manufacturing enterprises. The development level of sci-tech finance is measured by replacing the original index of the entropy weight method with the annual increment of medium and long-term loans. As shown in Column (3) of Table 5, after altering the measurement method of sci-tech finance, the results remain significantly positive, thereby confirming the robustness of the previous findings.

Table 5. Robustness Test Results

	(1)	（2）	(3)
Variables	*Innovation*	*Innovation*	*Innovation*
STF	0.830**	0.847***	0.583**
	(0.433)	(0.376)	(0.172)
Control Variables	YES	YES	YES
Fixed effect	YES	YES	YES
N	347	347	347
R^2	0.834	0.822	0.441

Standard errors in parentheses.

*p<0.1, ** p<0.5, *** p<0.01.

6. Further Discussion

6.1 Mediating Effect Test

Based on the previous theoretical discussion, this paper selects financial constraints as the mediating variable. To more clearly reveal the influence mechanism of the development of sci-tech finance on the technological innovation of AI computing power enterprises, a mediating effect model is employed for empirical analysis, the model setting is shown in Equation (2) and (3) above. The mediating effect test results in Table 6 indicate that the coefficient of sci-tech finance on financing constraints is negative and significant at the 1% level, demonstrating that the development of sci-tech finance can significantly alleviate the financing constraints faced by AI computing enterprises. Additionally, the coefficient of financial constraints on technological innovation is significantly positive at the 5% level. Therefore, Hypothesis 2 (H2) is confirmed.

Table 6. Mediating Effect Test Results

	(1)	(2)
Variables	*SA*	*Innovation*
STF	-0.268***	0.830**
	(0.025)	(0.374)
SA		0.754**
		（0.495）
Control Variables	YES	YES
Fixed effect	YES	YES
N	347	347
R^2	0.834	0.973

Standard errors in parentheses.

*p<0.1, ** p<0.5, *** p<0.01.

6.2 Moderating Effect Test

Based on the previous analysis, this paper tests the moderating effect from the perspective of financial regulation, as outlined in Equation (4). Column (1) in Table 7 presents the test results of the moderating effect. The results indicate that overall financial supervision has a positive but not significant impact on technological innovation. However, the interaction coefficient between sci-tech finance and financial supervision is significantly negative, suggesting that overall financial supervision has a negative moderating effect on the impact of sci-tech finance development on the technological innovation of AI computing enterprises. Thus, Hypothesis 3 (H3) is confirmed.

However, due to the varying levels of development in the AI computing power industry and financial sectors across different regions in China, the effect of overall financial regulation may not accurately reflect the situation nationwide. Columns (2) and (3) in Table 7 show that financial regulation exerts a negative moderating effect in the eastern region, whereas it plays a positive regulatory role in non-eastern regions of China.

This phenomenon is primarily driven by the function and cyclical characteristics of financial regulation. AI computing power enterprises in non-eastern regions are in the early stages of development, with various compliance procedures and processes still being imperfect. If the intensity of financial regulation increases, their innovation capabilities will be significantly reduced. In the early stages of industrial development, financial regulation is relatively loose to provide more space for enterprise innovation. Conversely, the development of AI computing power enterprises in the eastern region is relatively mature, with more established compliance processes. Therefore, even if the intensity of financial supervision increases, their innovation capabilities are not greatly affected. When the industry is in the mature stage, enterprises may engage in boundary-crossing behaviors to gain more market advantages. Consequently, during this period, financial regulation is relatively strict, which significantly inhibits innovation.

Table 7. Moderating Effect Test Results

Variables	(1) *Innovation*	(2) *Innovation*	(3) *Innovation*
STF	0.552*	0.193**	0.692*
	(0.491)	(0.559)	(1.448)
FRI	31.739	27.032*	-143.926*
	(19.374)	(30.583)	(80.040)
*STF*FRI*	-110.768**	-43.655*	154.987*
	(36.843)	(57.016)	(120.699)
Control Variables	YES	YES	YES
Fixed effect	YES	YES	YES
N	343	292	51
R^2	0.842	0.445	0.775

Standard errors in parentheses.

*p<0.1, ** p<0.5, *** p<0.01.

7. Conclusions and Policy Suggestions

7.1 Research Conclusions

In the context of the rapid development of new quality productivity in China, the importance of technological innovation for the country is self-evident. With the accelerated development of the digital economy, technological innovation in the computing power industry has become even more critical. Based on the annual data of Chinese A-share listed AI computing enterprises from 2014 to 2022, this paper empirically analyzes the impact of sci-tech finance on the technological innovation of AI computing enterprises, the mediating mechanism of financing constraints, and the moderating role of financial regulation. The study draws the following conclusions:

(1) The development of sci-tech finance significantly promotes the technological innovation of AI computing power enterprises. (2) The alleviation of financing constraints serves as a key mediating factor in the process by which sci-tech finance promotes technological innovation in AI computing power enterprises. (3) Overall financial regulation negatively moderates the impact of sci-tech finance on the technological innovation of AI computing power enterprises. Regionally, financial regulation in eastern China negatively moderates the impact of sci-tech finance on technological innovation in AI computing power enterprises, while in non-eastern regions of China, it positively moderates this impact.

7.2 Policy Suggestions

Based on the above conclusions, policy suggestions are put forward as follows:

(1) Strengthen the deep integration of sci-tech finance and AI computing power. Given the significant role of sci-tech finance in promoting technological innovation among AI computing power enterprises, the government should actively innovate sci-tech finance products and services to better meet the needs of these enterprises. Additionally, the government should further increase investment in sci-tech finance and encourage financial institutions to direct more credit resources towards AI computing power enterprises through policy guidance and tax incentives. This will further stimulate the innovation vitality of AI computing power enterprises.

(2) Optimize the financing environment and alleviate financing constraints. Optimizing the financing environment and alleviating financing constraints are essential for the technological innovation of AI computing enterprises. By improving the capital market structure, the government can provide diversified financing channels for AI computing power enterprises, such as developing equity financing and bond financing. This will reduce the financing difficulties faced by these enterprises, thereby enhancing their ability and willingness to engage in scientific and technological innovation.

(3) Balance financial regulation and innovative development. Regulators should properly coordinate the relationship between financial regulation and innovative development when performing their duties. In the era of the digital economy, leveraging technologies such as big data, it is essential to establish a flexible regulatory framework and a scientific and technological regulatory system that can quickly adapt to market dynamics. This approach will enable financial regulation to fully promote innovation.

(4) Implement differentiated regulatory strategies. In the eastern region of China, financial regulation should be appropriately adjusted to create a more favorable environment for AI computing enterprises to innovate. In the non-eastern regions, the guiding role of financial regulation should be strengthened to continue playing a positive regulatory role.

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