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RESEARCH ARTICLE

The Impact of Enterprise Artificial Intelligence Capability on R&D Leaps

Jingjing Li[1] and Anan Pongtornkulpanich[1*]

[1]Chakrabongse Bhuvanarth International Institute for Interdisciplinary Studies (CBIS), Rajamangala University of Technology Tawan-OK, Bangkok, 10400, Thailand.

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***Corresponding Author:**

Anan Pongtornkulpanich

anan_po@rmutto.ac.th

ABSTRACT

In order to solve the problem of enterprises lacking the ability to quickly adapt to complex dynamic environments, the ability to create value, and the ability to continuously obtain competitive advantages, the author proposes the impact of enterprise artificial intelligence capabilities on R&D leaps. Based on a sample of Chinese manufacturing listed companies from 2012 to 2021, the author used machine learning methods to measure the artificial intelligence capabilities of enterprises, and empirically analyzed the impact of enterprise artificial intelligence capabilities on R&D leaps from the perspective of human-machine collaboration. The results showed that using the Utest test, the calculated extreme points were 15.48, 1.98, and 0.51, all of which were within the range of data values and could reject the original hypothesis at a statistical level of 6%. Through empirical research, it has been found that there is an inverted U-shaped relationship between the three dimensions of artificial intelligence capabilities and R&D leaps behavior, where too much is too little. The order of impact from high to low is artificial intelligence management ability, artificial intelligence analysis ability, and artificial intelligence basic resource ability; The dynamic nature of the environment enhances the relationship between various capabilities of enterprise artificial intelligence and R&D leaps by influencing human-machine collaboration. Conclusion: The author's research expands the measurement methods and research boundaries of enterprise artificial intelligence capabilities, and also provides some inspiration and reference for enterprises to grasp the pace of R&D leaps and seize technological opportunities.

Keywords: Artificial intelligence capability; Research and development leap; Human machine collaboration; machine learning

INTRODUCTION

We now stand at the crossroads of two decades of struggle, facing opportunities and challenges. The 14th Five-Year Plan has provided a good direction for the country's bicentennial campaign (Hutchinson, 2020). The 14th Five Year Plan clearly stated that we should take China's overall transformation as a priority, follow innovation, Internet integration, big data , intelligence and other industries, and complete many construction projects. of strategies to create sectors with added value and appropriate standards. In the current period of change in the development pattern of the country, from rapid growth to positive growth, from the construction of energy buildings to the construction of energy innovation, from innovation to independent innovation, from technology to technological superiority. It has become an important path for China's future development. Business strategy is the key to achieve new independence, become a new country, and complete the "catch-up" task. At the same time, their level of technological development reflects the level of technological development of the technology companies in the country (Abdelfattah et al., 2024).

We now stand at the crossroads of two decades of struggle, facing opportunities and challenges. The 14th Five Year Plan provided a good direction for the country's bicentennial campaign . The 14th Five-Year Plan clearly states that we must prioritize China's overall transformation, follow innovation, Internet integration, big data, technological intelligence and other fields and complete many developments. and strategies to create value-added industries with appropriate standards. Nowadays, the country's development pattern is changing, from rapid growth to positive development, from energy construction to innovation power, from innovation to freedom, from technology to technological advantage. It has become an important path for China's future development. Business strategy is the key to achieving new independence, becoming a new country, and completing the "delivery". At the same time, their technological development level reflects the technological development level of domestic technology companies. From the significant difference between these two lists, it can be concluded that for the R&D innovation behavior of enterprises, more R&D investment is not better, but effective R&D strategies need to be matched with it (Zhao et al., 2022; Chen, 2023). Especially in the field of strategic emerging technologies, the dynamic transformation of R&D trajectory is a key action for enterprises and countries to capture opportunities in emerging technologies, achieve breakthroughs in key core technologies, shift from single innovation to comprehensive innovation, and shift from product competition to industry chain competition (Wang et al., 2023). As shown in Figure 1:

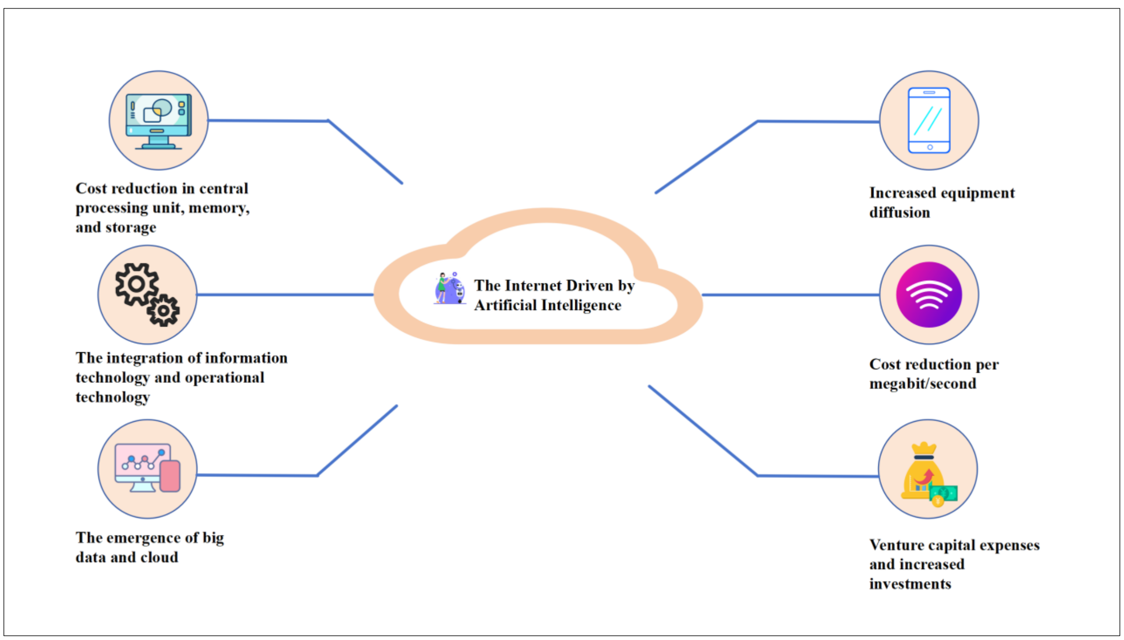


Figure 1 Artificial Intelligence

LITERATURE REVIEW

Researchers at home and abroad have tried to explore the R & D leaps from different perspectives. Some researchers have studied the impact of R & D leaps mainly on their impact on firm performance and performance. The transfer of R & D capital can improve the economic return of the business and the effective management of R & D capital and resource allocation (Reshetnikova & Mikhaylov, 2023).

As a visual analysis, Li and Wang (2021) examine the impact of R&D leaps on firm performance. The results of the study show that the actual and relative R & D investment can affect the performance of the company. However, whether R&D leaps can improve firm performance depends on whether R&D leaps can be managed and used effectively. Based on the attentional view, the impact of R&D leaps on enterprise performance. The research results show that both the absolute and relative amount of R&D investment will have an impact on enterprise performance, but whether the R&D leaps can actually improve enterprise performance depends on whether the R&D leaps can be effectively managed and utilized. It is concluded that only when R & D leaps improves the dual innovation attention of management decision-makers, enterprises can promote performance only by R & D leaps, and it proves the inevitable relationship between manager attention and R & D strategy transformation (Li et al., 2023). As research deepens, some researchers have researched the direction of R & D leapfrogging. First distinguish between R&D leaps and divide them into R&D forward leaps and R&D negative leaps. The successful leap in research and development refers to the transformation of enterprises from the search for innovation to the discovery of new technologies; the negative leaps in research and development is due to the transformation of the economy from research innovation to innovation (Lv et al., 2022). The effect of R&D leaps on firm failure and finds that both positive and negative R&D leaps affect failure, while negative R&D leaps do not impact on security (Shen et al., 2022).

The manufacturing sector has always been important in supporting the development and sustainable development of the country. In recent years, due to the development of information technology, the emergence of digital marketing has created many uncertainties in the manufacturing sector and created many new businesses, products, needs and trends. Faced with this problem, how can manufacturers turn this uncertainty into an opportunity for the company? Knowledge is an important factor in changing and developing business development, and it is important for enterprises to maintain knowledge capabilities. Please share your thoughts below.

H1a: There is an inverted U-shaped relationship between a company's AI resources and R&D leaps.

H1b: There is an inverted U-shaped relationship between a company's AI analysis capabilities and R&D leapfrogging.

H1c: There is an inverted U-shaped relationship between company AI management and R&D leaps.

H2a: Environmental dynamism positively moderates the U-shaped relationship between business AI capital stock and R&D leaps.

H2b: Environmental dynamism positively moderates the U-shaped relationship between business AI analysis capabilities and R&D leapfrogging.

H2c: Environmental dynamism positively moderates the U-shaped relationship between business AI management capabilities and R&D leapfrogging.

H3a: Trust management positively moderates the U-shaped relationship between a firm's AI resource capacity and R&D leapfrogging.

H3b: Overconfidence moderates the U-shaped relationship between a firm's AI analysis capability and R&D leapfrogging.

H3c: Executive overconfidence positively moderates the inverted U-shaped relationship between a firm's AI management capabilities and R&D leap frogging (How & Cheah, 2023; Bui & Nguyen, 2023).

RESEARCH METHOD

Sample Selection and Data Sources

The data sources for this study are three parts. Firstly, the data for text analysis comes from the annual reports of enterprises downloaded from Juchao Information Network, which are captured using Python. Secondly, patent data comes from patent search engines (Incopat and Soopat); Due to the fact that the appearance design only changes the appearance and is not related to technical changes, the patent data used by the author only includes invention patents and utility model patents (Kang & Kim, 2020). Thirdly, the financial data for adjusting and controlling variables comes from the CSMAR database, which has been manually processed and calculated. The sample observation year was selected from 2012 to 2021. Due to some companies not disclosing or missing patent data, after excluding * ST, ST class companies, and data missing companies, the final sample data was 600 companies.

Variable Design

Dependent variable: Development Leap (LEAP)

Divide the patent application data of enterprises from 2012 to 2021 into four quarters per year, and measure it using the GARCH model's student residuals. The specific measurement steps are:

Firstly, the GARCH model is used to predict the patents for each year and quarter of a company's patent application. The GARCH model can identify unpredictable changes in the number of patent applications that deviate from historical trends, while trend based model residuals measure the R&D leaps of the company, resulting in residuals $\mathrm{e_{itn}}$ and leveraged residuals $\mathrm{h_{itn}}$ (König et al., 2022).

Secondly, the student residuals of the GARCH model for the number of patents of the i-th enterprise in the i-th quarter of the t-th year were calculated by standardizing the residuals, and the student residuals $e_{itn}(stud)$ were calculated using the following formula (1).

$$e_{itn}(stud) = \frac{e_{itn}}{s_i\sqrt{(1-h_{itn})}} \tag{1}$$

Among them, $\mathrm{s_i}$ is the standard deviation of $\mathrm{e_{itn}}$, and leveraged residual $\mathrm{h_{itn}}$ is the leverage effect generated by adjusting for $\mathrm{s_i}$, used to measure the difference between leaving and leaving the sample.

Thirdly, by comparing the student residuals of each enterprise in each quarter of the year, the maximum value $e_{it}(Max)$ is found to be the binary innovation switching of the i-th enterprise in the t-th year (Leung & Sharma, 2021). $e_{it}(Max)$ measures the maximum degree of unexpected fluctuations in a company's R&D investment in a certain year. If R&D investment is relatively stable, the value of $e_{it}(Max)$ is relatively small, and a significant increase or decrease in R&D investment will lead to a larger value of $e_{it}(Max)$.

Independent variable: Artificial Intelligence (AI)

The author measured the ability of artificial intelligence and made some changes based on this, using the same text analysis method as the author's research. Among them, questionnaire survey method is the most commonly used method in research, but it takes a long time and has strong subjectivity. Some scholars in the literature also use the number of enterprise intelligent devices (such as robots) or the application of artificial intelligence software as proxy variables to measure artificial intelligence, but this measurement method cannot accurately reflect the size of artificial intelligence capabilities (Lembrechts et al., 2020). Text analysis method is a widely used method in information technology research in recent years, which can objectively demonstrate the size of artificial intelligence capabilities. However, there are also certain shortcomings in accuracy. The initial data is based on the annual report of the enterprise, and the specific processing process is divided into the following steps:

The first step is to prepare and organize the work. Firstly, convert the downloaded annual report into text format and encode it accordingly to unify it into a fixed format. Secondly, define the mother word, which serves as a target for localization, identifying which text content is highly relevant to artificial intelligence, and then extracting these contents through Python programs to reorganize the text (Hou et al., 2021). The author conducted text analysis on 600 annual reports with high relevance to artificial intelligence using the TF-IDF algorithm. 7143 words were identified as valid (TF-IDF value>0) in the analysis, and 175 mother words related to artificial intelligence were selected by the author. Through parameter tuning, the author compared 15 groups of mother words selected from 10 to 150 (with a step size of 10) and confirmed that using 100 or more mother words can effectively eliminate the centrality brought by the method itself.

The second step is to perform text extraction work. After the mother word is determined, the extraction work can be carried out, but it is also necessary to determine the window for text extraction. This concept in information science represents the number of words to be extracted from the mother word as the center of text extraction, and the amount of information can ensure the integrity of the sentence without losing the meaning of extraction due to being too large (Shi et al., 2021). Propose the desired text window through this workflow. The specific process is to use Python to search the annual reports of 600 manufacturing related enterprises in the past 10 years using the sorted keywords. The windows of 50 words before and after the keywords (a total of 100 words) are extracted, and these contents are put into a file to form our text library to be analyzed. The purpose of this step is to extract the part of the annual reports that focuses on artificial intelligence, but in order to prevent excessive centralization or focusing on specific vocabulary in subsequent analysis, we have expanded the number of mother words to avoid the above situation.

Step three, co-occurrence analysis. Using Text Rank (a Markov chain algorithm developed based on the mathematical concept of co-occurrence rate, which is a supervised biased semi supervised machine learning algorithm widely used in text analysis) algorithm to analyze text libraries using co-occurrence rate analysis (if two words appear close in position, they are considered to be mutually recommended, and each co-occurrence is considered as one vote for each other. Finally, all votes are counted and normalized to form a co-occurrence rate), this can form a pairwise co-occurrence relationship (referred to as word vector relationship) between all vocabulary in the text, and draw a network diagram based on this relationship (Mgbemena, 2020). Finally, the weight of each parent word in the total text is obtained, which is the importance of that word, and the distance matrix between words is obtained through the pair wise co-occurrence relationship between words.

Step 4, cluster analysis and result calculation. Using the co-occurrence network mentioned above for clustering analysis, the author hopes to divide the elements in these grid graphs into dimensions based on the grid graphs. Due to the fact that the only available data is the word vector matrix, the author has chosen a unique clustering method that can handle the distance matrix: Hierarchical clustering is the clustering of existing data. Artificial intelligence capabilities are divided into three dimensions, namely Artificial Intelligence Infrastructure Capability (AISC), Artificial Intelligence Analysis Capability (AIAC), and Artificial Intelligence Management Capability (AIMC), as shown in Table 1. Finally, the corresponding artificial intelligence capabilities of each manufacturing enterprise for each year are calculated by combining the weights generated in the previous step with the word frequency of relevant artificial intelligence vocabulary in the annual report (Nardo et al., 2020).

Table 1 Classification and Keyword of Artificial Intelligence Capability Dimensions in Enterprises

Dimension	keyword
Artificial Intelligence Basic Resource Capability (AISC)	Management system, components, digitalization, integration, chip, e-commerce, system, intelligence, terminal, production line, Internet, informatization, software, patent, robot, information system
Artificial Intelligence Analysis Capability (AIAC)	Data center, operations and maintenance, interconnection, data processing, IoT, CNC systems, e-commerce, modules, information technology, computers, system integration, artificial intelligence, business models, recognition, data mining, websites, commerce, modularity
Artificial Intelligence Management Capability (AIMC)	Intelligent manufacturing, office automation, business intelligence, data management, management software, microelectronics, perception, components, terminal products, systematization, databases, algorithms, integration, visualization, information management, networking, IoT, CNC machine tools

Adjusting Variables

1. Environmental dynamism (EU)

The author measures environmental dynamism by using the fluctuation of abnormal sales revenue of enterprises, and measures environmental dynamism by using the coefficient of variation of operating revenue of sample enterprises over 5 years. The author calculates the ratio of standard deviation and mean of main business revenue of sample enterprises over the past 5 years and represents it logarithmically.

2. Executive overconfidence (OC)

Domestic scholars have proposed various measurement indicators to measure executive overconfidence, among which the most commonly used measurement methods are the following four: Firstly, due to the comprehensive implementation of the "salary limit" policy by the Chinese government on executives of state-owned enterprises, the salary data lacks accuracy; Secondly, considering the similarity between performance forecasts and actual performance can lead to measurement bias; Finally, considering that the industry prosperity index is relatively macro, there is a significant gap between the expectations of managers themselves, and there is a certain deficiency in reflecting individual differences among managers. Therefore, the author's approach is to measure the proportion of executive shareholding in the total share capital of listed companies.

Control Variables

To minimize the impact of other potential variables on the study design, the author integrated other studies to control for the following variables. ① Return on equity (ROE) is expressed as the ratio of income to assets. ② R & D intensity (RDI) is expressed as the ratio of the company's research and development investment to total assets. ③ A company's Tobin Q value (TQ) is used to measure the price. ④ Business size (SIZE) is measured by the global logarithm of total capital and business income of the main business, the latter is used as a proxy for analysis the strong. ⑤ Equity concentration (TOP) is expressed as the ratio of ownership of the largest shareholder (Li et al., 2021). ⑥ Asset-liability ratio (ALR), expressed as the ratio of the company's total debt to total assets. ⑦ The number of patents (NP) is expressed as the number of patents applied for by a company every year. In addition, the author uses years as a control variable because the new trends in the economy can change over time. In summary, the association of each variable in this study is shown in Table 2.

Table 2 Measurement of Main Variables

Variable category	The name of the variable	Variable code	Variable measurement
dependent variable	R&D leaps	LEAP	Using the Student Residual of GARCH Model to Measure
argument	artificial intelligence	AI	Using Python for text analysis, capture statements containing the keyword "artificial intelligence" in the company's annual report, and perform data cleaning
Adjusting variables	Environmental dynamism	Tc	Using abnormal sales revenue fluctuations in enterprises to measure the dynamic nature of the moderating variable environment
	Executive overconfidence	EU	Measuring the proportion of executive shareholding in the total share capital of a listed company
	Asset return rate	ROE	Return on equity=Net profit/Net assets
	R&D intensity	RDI	R&D intensity=R&D investment/total assets
	Tobin's Q	TQ	Tobin Q=market value/asset replacement cost
control variable	Enterprise scale	SIZE	Enterprise size=In (total assets)
	Equity concentration	TOP	Equity concentration=shareholding ratio of the largest shareholder
	Equity concentration	ALR	Asset liability ratio=total liabilities/total assets
	Number of patents	NP	Number of patents applied by enterprises
	Year	YEAR	Year dummy variable, year of event occurrence

Data Analysis Methods

Firstly, the author used analysis software Python to capture the data, selected 600 listed companies as research samples, downloaded the annual report information of each company, and then extracted keywords related to artificial intelligence and 50 related vocabulary before and after the keywords in the annual report for co-occurrence and clustering analysis, obtaining the core variable - artificial intelligence capability. Secondly, the author used the GARCH model function in the data analysis software Stata to process and analyze the panel data of patent applications of enterprises from 2012 to 2021, and obtained data on the variable of R&D leaps (Ansari et al., 2020). Finally, the author used Stata to conduct overall descriptive statistical analysis and correlation analysis on the collected panel data of listed companies, and used multiple regression econometric methods to conduct regression analysis on the sample data to empirically test the hypotheses previously proposed and draw the author's research conclusions.

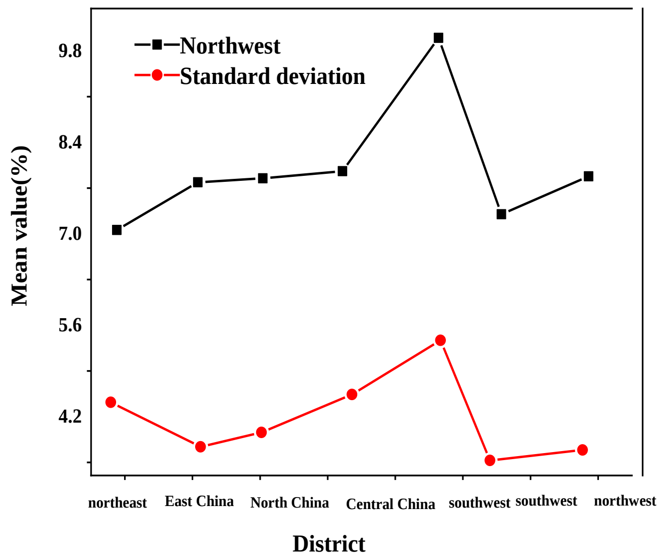
RESULT ANALYSIS

Descriptive Statistics

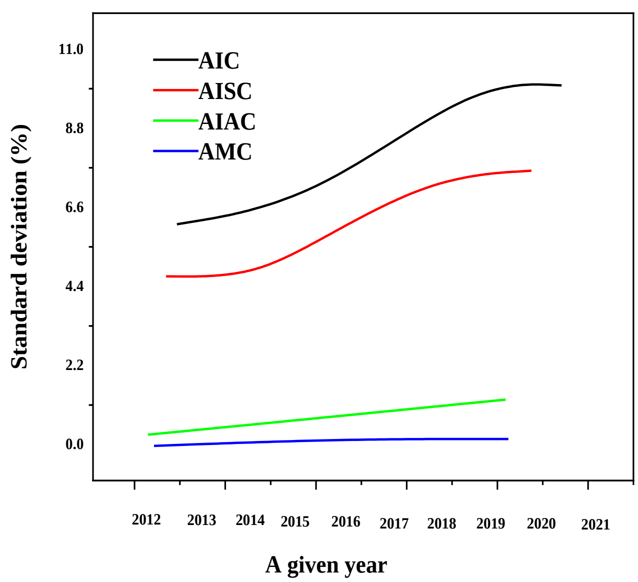
Table 3 presents the statistical analysis of the total AI ability of the main variables. According to the results of the study, compared to state-owned enterprises, non-state-owned enterprises have higher content and different forms of intellectual capital.As shown in Figure 2 (a) (b), overall, the AI level in the manufacturing industry has been increasing year by year. Compared to the artificial intelligence capabilities in different regions, the artificial intelligence capabilities in South China are the highest, mainly due to the better development of AI in Guangdong Province, secondly, the development of artificial intelligence capabilities in North China, Central China, and East China follows closely behind. Among them, the development of artificial intelligence in Zhejiang and Beijing is relatively good. In contrast, the artificial intelligence capabilities in Southwest China are the lowest, and the level of artificial intelligence in provincial manufacturing enterprises generally decreases from the southeast coast to the inland, which is also consistent with China's geographical and economic context (Ren et al., 2023).

Table 3 Descriptive statistical analysis of artificial intelligence capabilities

	mean value	standard deviation	minimum value	maximum value
Total sample	8.0388	4.407	1.940	23.821
state-run	7.175	4.002	1.940	23.821
Non State Owned	8.484	4.486	1.940	23.821
high-tech	8.844	4.745	1.940	23.821
Non high-tech	6.842	3.47	1.940	23.821
Northeast China	7.056	4.650	1.940	23.821
East China	7.77	4.214	1.940	23.821
North China	7.976	4.074	1.940	23.821
Central China	7.844	4.577	1.940	23.821
South China	10.177	5.238	1.940	23.821
southwest China	6.909	3.164	1.940	23.556
northwest China	7.563	3.436	1.987	18.090



2(a)



2(b)

Figure 2 Comparison of mean and standard deviation of AI capabilities in different regions (left) and AI levels in different years (right)

Second, a summary of the results for the various elements of the sample is presented in Table 4, which usually shows the mean, standard deviation, and other factors of the fabric sample (Zeadally et al., 2020). Table 5 shows the level of correlation coefficients between variables. There is a negative correlation between AI infrastructure investment and R&D leaps ($r=-0.027$, $p<0.06$); There is a negative correlation between AI analysis capability and R&D leaps ($r=-0.043$, $p<0.06$); There is a negative correlation between AI management capabilities and R&D leaps ($r=-0.035$, $p<0.02$); This proves the validity of the author's research to a certain extent, but there is no control to control the influence of other variables, so their special relationship needs to be further investigated.

Table 4 Descriptive statistics of the variables

variable	N	M	SD	MIN	MAX
LEAP	8044	11.96	25.73	0.22	185.54
AISC	8044	6.33	3.66	0	35.29
AIAC	8044	0.88	0.63	0	3.28
AIMC	8044	0.19	0.19	0	0.96
EU	8044	0.27	0.18	0.02	1
OC	8044	0.66	1.03	0	2.46
ROE	8044	0.07	0.12	-0.5	0.32
ALR	8044	0.42	0.3	0.04	0.8
TOP	8044	33.08	13.8	8.78	71.44
TQ	8044	1.92	1.16	0	7.05
SIZE	8044	22.25	1.17	20.14	25.74
RDI	8044	0.01	0.01	0	0.08
NP	8044	15.38	42.37	0	315

Table 5 Correlation coefficient matrix

	LEAP	AISC	AIAC	AIMC	EU	OC	ROE	ALR	TOP	TQ	SIZE	RDI	NP
LEAP	1												
AISC	-0.025*	1											
AIAC	-0.045***	0.708***	1										
AIMC	-0.035***	0.581***	0.505***	1									
EU	-0.011	0.112***	0.113***	0.094***	1								
OC	0.042***	0.175***	0.074***	0.094***	0.054***	1							
ROE	-0.007	0.002	-0.026***	-0.003	0.114***	0.036***	1						

ALR	-0.012	0.004	0.057***	-0.018*	0.065***	-0.258***	-0.224***	1					
TOP	-0.067***	-0.132***	-0.135***	-0.131***	0.025**	-0.169***	0.122***	0.048***	1				
TQ	-0.025*	-0.017*	-0.003	0.037***	0.036***	0.038***	0.157***	-0.293***	-0.025**	1			
SIZE	-0.045***	0.123***	0.191***	0.037***	0.085***	-0.261***	0.107***	0.503***	0.177***	-0.317***	1		
RDI	0.032***	0.333***	0.246***	0.232***	0	0.163***	0.104***	-0.141***	-0.05***	0.135***	-0.067***	1	
NP	-0.002	0.192***	0.168***	0.143***	-0.015	-0.003	0.085***	0.152***	0.045*	-0.064***	0.392***	0.206***	1

Data Analysis of Artificial Intelligence Capabilities and R&D Leaps

Hypothesis testing

The sample data used by the author is the same data from 2012 to 2021. The data was first pre-regression to ensure that the data itself does not influence the findings. Among them, all constant variables are cut off at the 2% level to avoid the influence of the significance of the empirical results. Second, because the panel data used by the authors may have problems such as heteroskedasticity, order correlation, and correlation, the use general assumptions may lead to biased results. Therefore, the model was estimated using statistical software Stata16.0 and Driscoll Kraay's standard error (Nahr et al., 2021). Meanwhile, the results of Hausman rejected the null hypothesis, thus confirming the model's working stability. The year is also controlled to avoid the possibility of a negative change in the repetition pattern.

Table 6 shows the regression results of the relationship between the three dimensions of business intelligence capabilities and R&D leaps, with R&D leaps as the dependent variable. Model 1 shows a simple model including only control variables, while Model 2 represents the relationship between intellectual property investment and R&D leaps. It was shown that the coefficient of cognitive ability has a positive effect ($r = 0.159$, $p < 0.02$), the coefficient of the squared regression term is negative ($r = - 0.006$, $p < 0.06$), like an inverted U. -. the relationship between intellectual property capital stock and leaps in research and economic development; The regression coefficient for big data analysis ability in Model 3 is significantly positive ($r = 0.536$, $p < 0.2$), while the squared regression coefficient is significantly negative ($r = -0.135$, $p < 0.2$), indicating an inverted U-. the relationship between intellectual property analysis and business R & D leaps; According to Model 4, the coefficient of cognitive control is positive ($r = 1.114$, $p < 0.02$), the coefficient of the squared regression term is negative ($r = -1.118$, $p < 0.02$), and U- is also present. modeled relationship between intellectual property management and business R & D leaps (Gregory et al., 2021).

Table 6 Regression Results of Artificial Intelligence Capability and R&D Leaps

Model

variable	(1)	(2)	(3)	(4)
AISC		0.159***		
		-2.75		
$AISC^2$		-0.006**		
		(-2.04)		
AIAC			0.536*	
			-1.82	
$AIAC^2$			-0.135*	
			(-1.76)	
AIMC				1.114***
				-3.39
$AIMC^2$				-1.118***
				(-2.97)
ROE	1.045***	1.039***	1.032***	1.037***
	(4.33)	(4.63)	(4.57)	(4.27)
RDI	15.300**	14.457*	15.188**	15.072**
	(3.00)	(1.88)	(3.00)	(1.97)
TQ	-0.024	-0.022	-0.024	-0.025
	(-0.98)	(-1.08)	(-1.04)	(-1.03)
SIZE	0.506**	0.449**	0.494**	0.495**
	(2.41)	(2.09)	(2.33)	(2.25)
TOP	0.004	0.003	0.003	0.0032
	(0.67)	(0.54)	(0.62)	(0.55)
ALR	0.555	0.642	0.578	0.576
	(1.24)	(1.38)	(1.25)	(1.28)
NP	0.015***	0.015***	0.015***	0.016***
	(9.77)	(10.66)	(10.43)	(9.94)
Constant	-0.088	0.537	-0.015	0.125
	(-0.03)	(0.12)	(-0.01)	(0.04)
Observations	8,038	8,038	8,038	8,038
N	600	600	600	600
R^2	0.0295	0.0305	0.0278	0.0297
F	693.77***	1396.18***	1256***	299.8***

When verifying the moderating effect of corporate environmental dynamism and executive overconfidence on AI capabilities and R&D leaps, the author conducted a centralized treatment of environmental dynamism, executive overconfidence, as well as artificial intelligence basic resource capabilities, analytical capabilities, and management capabilities, in order to examine the moderating effect of regenerated transaction cross-terms.

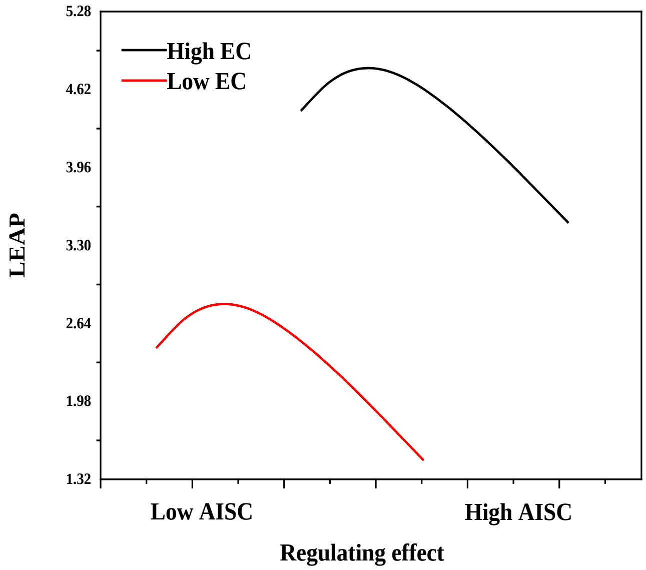
Table7 shows the moderating effects of environmental dynamism and executive overconfidence on the three dimensions of artificial intelligence capability and R&D leaps. Firstly, models 5, 6, and 7 examine the moderating effect of environmental dynamism on artificial intelligence capabilities and R&D leaps(Wu et al., 2020).

Model 5 introduces the primary term of artificial intelligence basic resource capability and the interaction term of environmental dynamics (AISC × EU), the secondary term of artificial intelligence basic resource capability and the interaction term of environmental dynamics (AISC2 × EU) into the regression model. in order to more intuitively determine the role of environmental dynamism, Figures 3 (a), (b), and (c) show the regulatory effect of environmental dynamism on artificial intelligence capabilities and R&D leaps. It can be seen that environmental dynamism positively regulates the inverted U-shaped relationship between artificial intelligence basic resource capabilities and R&D leaps. Hypothesis 2a is supported.The regression coefficients of the interaction term between artificial intelligence management capability and environmental dynamism (AIMC x EU) and the interaction term between square term and environmental dynamism (AIMC2 x EU) in Model 7 are significant ($r=3.134$, $p<0.02$; $r=-4.510$, $p<0.02$). Together with Figure 2 , it can be seen that environmental dynamism positively moderates the U-shaped relationship between intellectual property management capabilities and R&D leaps. Hypothesis 2c was supported.

Table 7 Regression results of the moderating effect of environmental dynamism and executive overconfidence

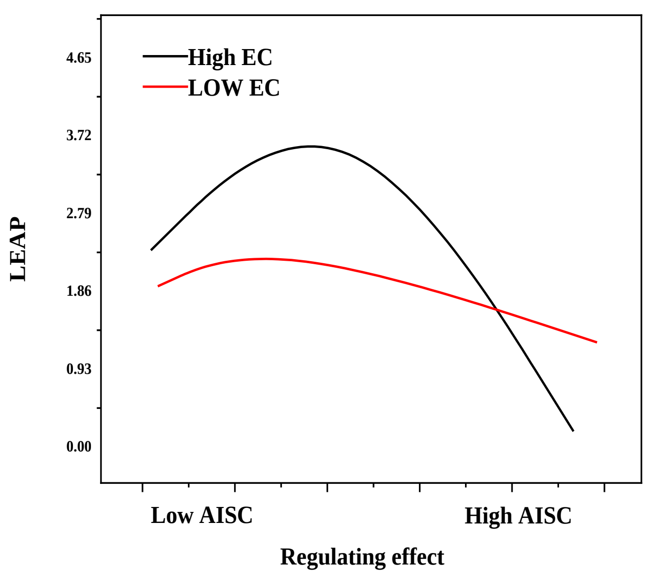
	model					
variable	(5)	(6)	(7)	(8)	(9)	(10)
AISC	0.148***			0.148**		
	(2.85)			(2.32)		
$AISC^2$	-0.006**			-0.006*		
	(-2.06)			(-1.68)		
AIAC		0.438*			0.508	
		(1.75)			(1.58)	
$AIAC^2$		-0.099			-0.129*	
		(-1.54)			(-1.74)	
AIMC			1.019***			1.178***
			(2.97)			(2.68)
$AIMC^2$			-0.886**			-1.078**
			(-2.12)			(-2.29)
EU	0.678**	0.748**	0.666*			
	(1.97)	(2.32)	(1.78)			
AISC×EU	0.204***					
	-2.73					
$AISC^2$×EU	-0.009*					
	(-1.88)					

AIAC×EU		3.634***				
		-3.91				
$AIAC^2$×EU		-1.119***				
		(-4.03)				
AIMC×EU			3.134***			
			-4.56			
$AIMC^2$×EU			-4.510***			
			(-4.22)			
OC				0.088**	0.126**	0.107**
				(2.18)	(2.32)	(2.28)
AISC×OC				0.168**		
				-2.35		
$AISC^2$×OC				-0.009***		
				(-2.65)		
AIAC×OC					0.498	
					(-1.28)	
$AIAC^2$×OC					-0.122	
					(-1.17)	
AIMC×OC						1.402***
						(-2.64)
$AIMC^2$×OC						-1.318***
						(-2.72)
control variable	control	control	control	control	control	control
Constant	2.741	3.122	1.836	0.336	0.284	0.117
	(0.64)	(0.78)	(0.44)	(0.09)	(0.08)	(0.07)
Observations	8,038	8,038	8,038	8,038	8,038	8,037
N	600	600	600	600	600	600
R^2	0.0314	0.0317	0.0305	0.0314	0.0298	0.0296
F	302***	27.96***	100.7***	49.18***	412.5***	245.0***



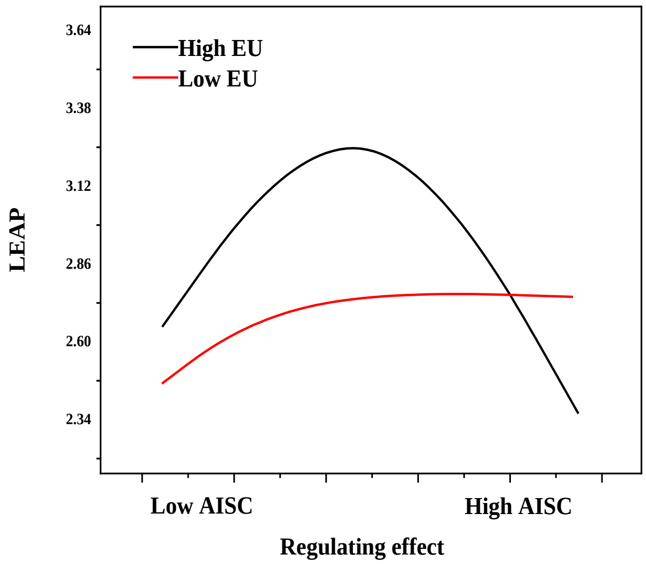
High EC
Low EC
5.28
4.62
3.96
3.30
2.64
1.98
1.32
LEAP
Low AISC
High AISC
Regulating effect

3(a)



High EC
LOW EC
4.65
3.72
2.79
1.86
0.93
0.00
LEAP
Low AISC
High AISC
Regulating effect

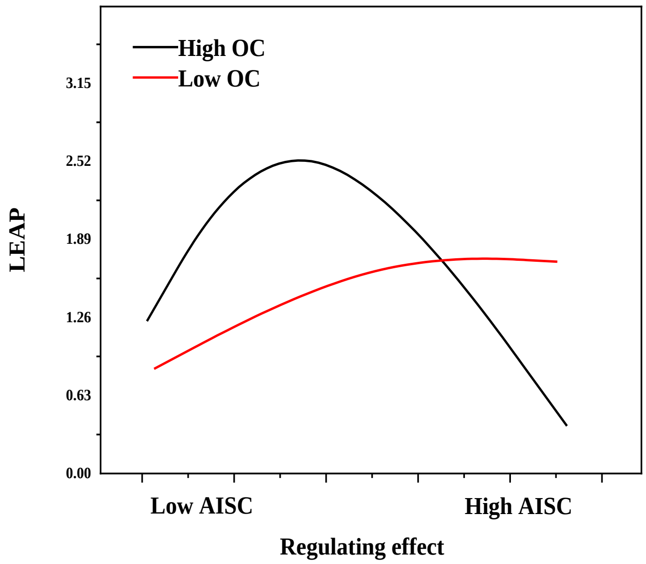
3(b)



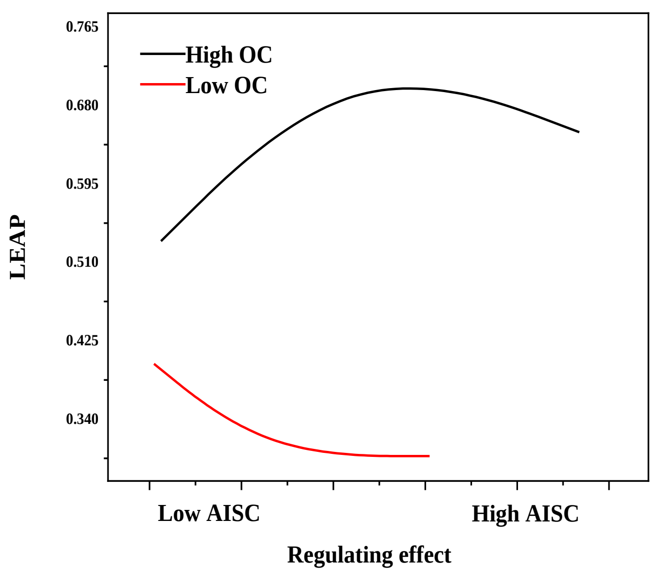
3(c)

Figure 3 Inverted U-shaped regulatory effect on environmental dynamics

Secondly, models 8, 9, and 10 examine the moderating effect of executive overconfidence on artificial intelligence capabilities and R&D leaps. Model 8 introduces the primary term of artificial intelligence basic resource capability and the interaction term of executive overconfidence (AISC × OC), the secondary term of artificial intelligence basic resource capability, and the interaction term of executive overconfidence ($AISC^2$ × OC) into the regression model, the results showed that the regression coefficients of the interaction term between artificial intelligence basic resource capability and executive overconfidence, as well as the square term and executive overconfidence, were significant ($r=0.168$, $p<0.06$; $r=-0.009$, $p<0.02$). From Figure 3 (a, b and c), it can be seen that executive overconfidence positively regulates the inverted U-shaped relationship between artificial intelligence basic resource capability and R&D leaps, and hypothesis 3a is supported. Hypothesis 3b is not supported. The regression coefficients of the interaction term (AIMC × OC) between artificial intelligence management ability and executive overconfidence, as well as the interaction term ($AIMC^2$ × OC) between square term and executive overconfidence in Model 10, are significant ($r=1.402$, $p<0.02$; $r=-1.318$, $p<0.02$). From Figure 4 (a) (b), it can be seen that executive overconfidence positively regulates the inverted U-shaped relationship between artificial intelligence management ability and R&D leaps, and hypothesis 3c is supported.



4(a)



4(b)

Figure 4: The inverted U-shaped moderating effect of executive overconfidence

Robustness Testing

The high scores including Utest are 15.48, 1.98, and 0.51. As shown in Table 8, the cloud content is all within the range of data values and can reject the initial hypothesis at the 6% statistical level. At the same time, the slope of the total profit has a negative sign over time, so we can think of this as a U-shaped relationship.

Table 8 Main Effect Utest Test Results

Utest	AISC	AIAC	AIMC
Value range	[0, 36.29]	[0, 3.28]	[0, 0.98]
Slope	[0.17,-0.21]	[0.50,-0.36]	[1.12,-1.05]
extreme point	15.48	1.98	0.51
t-value	1.66	1.57	2.31
P>Itl	0.06	0.07	0.02

Secondly, in order to verify the reliability of the overall model conclusions mentioned above, the author also adopts various methods for robustness testing, including: Replacing the measurement method for controlling variable enterprise size.

According to Table 9, it can be seen that the basic resource capacity, analysis ability, and management ability of artificial intelligence all exhibit an inverted U-shaped relationship with R&D leaps; The dynamic nature of the environment positively regulates the relationship between artificial intelligence capabilities and R&D leaps; Executive overconfidence positively moderates the relationship between artificial intelligence basic resource capabilities, artificial intelligence management capabilities, and R&D leaps, while the moderation of artificial intelligence analysis capabilities and R&D leaps is not significant (Enholm et al., 2022).

Table 9 Robustness Test Analysis Results 1

	Model									
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AISC		0.168***			0.159***			0.158**		
		(2.85)			(2.93)			(2.38)		
$AISC^2$		-0.006**			-0.006**			-0.006*		
		(-2.07)			(-2.08)			(-1.68)		
AIAC			0.575*			0.453*			0.542*	
			(1.91)			(1.82)			(1.67)	
$AIAC^2$			-0.123*			-0.088			-0.121	
			(-1.64)			(-1.37)			(-1.65)	
AIMC				1.218***			1.118***			1.283***
				(3.68)			(3.31)			(2.89)

$AIMC^2$	-1.148***			-0.912**			-1.068**
	(-2.82)			(-2.15)			(-2.23)
EU		0.791**	0.865**	0.763*			
		(2.05)	(2.32)	(1.85)			
AISC×EU		0.232***					
		-2.68					
$AISC^2$ ×EU		-0.008**					
		(-1.98)					
AIAC×EU			3.872***				
			-3.64				
$AIAC^2$ ×EU			-1.168***				
			(-3.83)				
AIMC×EU				3.025***			
				-4.15			
$AIMC^2$ ×EU				-4.239***			
				(-3.56)			
OC					0.083**	0.123**	0.104**
					(2.13)	(2.28)	(2.32)
AISC×OC					0.168**		
					-2.35		
$AISC^2$ ×OC					-0.009***		
					(-2.63)		
AIAC×OC						0.505	

									(-1.32)	
$AIAC^2$ ×OC									-0.126	
									(-1.22)	
AIMC×OC										1.368***
										-2.48
$AIMC^2$ ×OC										-1.320***
										(-2.72)
control variable	control	control	control	Control	control	control	control	control	control	control
Constant	4.840	5.088	4.774	4.935	8.029***	8.568***	7.198***	7.198***	5.892***	5.628***
	(1.58)	(1.62)	(1.51)	(1.57)	(3.32)	(3.28)	(3.02)	(3.18)	(3.59)	(3.23)
Observations	8,038	8,036	8,036	8,036	8,038	8,038	8,038	8,038	8,038	8,048
N	600	600	600	600	600	600	600	600	600	600
R2	0.0290	0.0295	0.0295	0.0288	0.0308	0.0311	0.0295	0.0302	0.0285	0.0273
F	1950.41	5038	1645	231.68	825.6	18.15	104.8	80.84	284.2	123.5

Change the measurement method to correct the difference

Deviance from the center was estimated using least-squares regression of the last 5 years of revenue and annual deviation of the main business, and the residual was used as abnormal sales revenue business. The variance of business abnormal returns is used to measure the uncertainty of the center of variance. The results in Table 10 show that the positive environmental variable moderates the U-shaped relationship between the three dimensions of intellectual ability and R&D leaps, which is positive as in the old results.

Table 10 Results of Robustness Test Analysis II

	model		
variable	(1)	(2)	(3)
AISC	0.127***		
	(-3.95)		
$AISC^2$	-0.005**		
	(-2.02)		
AIAC		0.405***	

		(4.05)	
$AIAC^2$		-0.102***	
		(-3.25)	
AIMC			1.207***
			(-4.56)
$AIMC^2$			-1.341***
			(-2.63)
EU	0.118**	0.105***	0.113**
	(2.54)	(2.71)	(2.34)
AISC×EU	0.024**		
	-2.33		
$AISC^2$×EU	-0.002*		
	(-1.94)		
AIAC×EU		0.490***	
		-2.76	
$AIAC^2$×EU		-0.168***	
		(-3.98)	
AIMC×EU			0.408
			-0.83
$AIMC^2$×EU			-1.266*
			(-1.75)
control variable	Control	control	control
Constant	-1.187	-1.907	-1.364
	(-0.25)	(-0.45)	(-0.33)
Observations	6,765	6,765	6,757
N	878	878	878
R2	0.0294	0.0291	0.02865
F	2576	7.238	1809

Delete Sensitive Years

On December 7, 2017, the Ministry of Industry and Information Technology of China released the "13th Five Year Plan for China's Intelligent Manufacturing", which identified two key periods and ten key tasks for the five-year development of industrial intelligence in China. This policy dividend injects a "booster" into the intelligent manufacturing industry, which can promote the concept stocks of related intelligent equipment industries such as robotics and automation, intelligent logistics equipment, etc. to benefit in the medium and long term. Due to the fact that the author's research sample is manufacturing enterprises, this plan is highly relevant to the author's research. Therefore, we removed the 2018 sample for re regression. Table 11 shows.

Table 11 Results of Robustness Test Analysis III

	model									
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AISC		0.188***			0.181***			0.184***		
		(3.02)			(3.17)			(2.73)		
$AISC^2$		-0.008***			-0.007***			-0.008***		
		(-2.91)			(-3.24)			(-2.37)		
AIAC			0.662**			0.545**			0.593*	
			(2.03)			(2.03)			(1.74)	
$AIAC^2$			-0.192**			-0.153**			-0.176**	
			(-2.21)			(-2.13)			(-2.13)	
AIMC				1.038***			0.945***			0.998***
				(3.61)			(2.91)			(2.79)
$AIMC^2$				-1.075***			-0.848**			-0.911**
				(-3.83)			(-2.17)			(-2.45)
EU					0.688**	0.805***	0.672*			
					(2.16)	(2.67)	(1.89)			
AISC×EU					0.208**					
					(2.28)					

$AISC^2$×EU					-0.008					
					(-1.58)					
AIAC×EU						4.208***				
						(-3.62)				
$AIAC^2$×EU						-1.259***				
						(-3.58)				
AIMC×EU							2.854**			
							(-2.43)			
$AIMC^2$×EU							-4.433**			
							(-2.54)			
OC								0.123***	0.160***	0.145**
								(2.77)	(2.66)	(2.53)
AISC×OC								0.175**		
								(-2.26)		
$AISC^2$×OC								-0.008**		
								(-2.44)		
AIAC×OC									0.580	
									(-1.36)	
$AIAC^2$×OC									-0.140	
									(-1.30)	
AIMC×OC										1.337***
										(-2.77)
$AIMC^2$×OC										-1.278***
										(-3.12)
control variable	control	control	control	Control	control	control	control	control	control	control
Constant	-0.733	-0.234	-0.942	-0.578	1.948	2.313	1.028	-0.465	-0.555	-0.471

	(-0.15)	(-0.04)	(-0.26)	(-0.14)	(0.48)	(0.63)	(0.27)	(-0.13)	(-0.14)	(-0.12)
Observations	7,146	7,146	7,146	7,146	7,146	7,146	7,146	7,146	7,146	7,146
N	600	600	600	600	600	600	600	600	600	600
R^2	0.0287	0.0315	0.0306	0.0302	0.0335	0.0318	0.0312	0.0323	0.0305	0.0285
F	1246.79	404.45	331.54	16.29	948.7	146.3	185.7	16.42	145.7	37.92

Note: * represents p<0.10. * ** represents p<0.06. *** represents p<0.02

Based on the above regression analysis, Table 12 summarizes all hypothesis testing results proposed by the author.

Table 12 Summary of Hypothesis Testing

Assume	Inspection results
H1a: There is an inverted U-shaped relationship between the basic resource capability of artificial intelligence and the leap in enterprise research and development	support
H1b: There is an inverted U-shaped relationship between artificial intelligence analysis capability and enterprise R&D leap	support
H1c: There is an inverted U-shaped relationship between artificial intelligence management capability and enterprise R&D leap	support
H2a: The inverted U-shaped relationship between the ability of artificial intelligence basic resources and R&D leaps in the positive regulation of environmental dynamics	support
H2b: The positive impact of environmental dynamics on the inverted U-shaped relationship between artificial intelligence analysis ability and R&D leaps	support
H2c: The inverted U-shaped relationship between the positive regulation of environmental dynamics and artificial intelligence management capabilities and R&D leaps	support
H3a: Executive overconfidence positively regulates the inverted U-shaped relationship between artificial intelligence basic resource capabilities and R&D leaps	support
H3b: Executive overconfidence positively affects the inverted U-shaped relationship between artificial intelligence analysis ability and R&D leaps	not supported
H3c: Executive overconfidence positively regulates the inverted U-shaped relationship between artificial intelligence management ability and R&D leaps	support

CONCLUSION

We use Stata statistical analysis software and drawing software to systematically analyze the sample data. Firstly, a descriptive statistical analysis was conducted on the main variable of artificial intelligence capability, observing the overall development trend of the data, including the distribution of manufacturing enterprises, different regional development levels, and the overall situation of different types of enterprises. At the same time, basic characteristics such as sample size, mean, variance, and maximum and minimum values of the overall variables were analyzed. In addition, the multiple regression method was determined through relevant tests, and the D-K standard error was applied to the data for regression testing. The test results showed that the hypotheses proposed by the author in the study were mostly validated. Finally, in order to verify the robustness of the results, we first conducted a Utest test on the existence of the inverted U-shaped main effect. Secondly, we conducted robustness tests on the entire model using three methods, including replacing control variable measurement, adjusting variable measurement, and deleting sensitive years. The results showed that both the significance and direction of the regression results were consistent with the original regression, which can prove that the author's conclusion has good robustness and credibility.

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