Research on The Influence of Digital Level on Knowledge Evolution Based on Threshold Regression Model

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ABSTRACT

Manufacturing digital innovation ecosystem is an industrial organization form suitable for the digital age and an important way to realize high-quality development of manufacture. From the perspective of manufacturing digital innovation ecosystem, this paper takes the dynamic capabilities as the threshold variable, empirically testing the threshold effect of the impact of digital level on knowledge evolution based on the panel data of 28 China's manufacturing industries from 2013 to 2020. The results show that the dynamic capabilities have a significant double-threshold effect in the model of digital level on knowledge evolution. With the improvement of dynamic capabilities, the influence of digital level on knowledge inheritance presents a J-shaped relationship, while digital level and knowledge variation show a S-shaped correlation.

***Keywords**: Digital level, Manufacturing digital innovation ecosystem, Dynamic capabilities, Knowledge evolution, Threshold effect.*

1. INTRODUCTION

Benefiting from the rapid development of big data, AI, cloud computing and other technologies, the organizational boundary is gradually open, and the competition is transitioning to the innovation ecosystem. The manufacturing digital innovation ecosystem has become a strategic choice to maintain competitive advantage in a digital age.

Knowledge is an important resource for the manufacturing digital innovation ecosystem to maintain competitive advantage. According to the "cask effect", the knowledge level of manufacturing digital innovation ecosystem not only depends on the leading enterprises, but also the institutions with poor knowledge. How to improve the knowledge level of all the members is an urgent problem to be settled. Digitization transfers the traditional knowledge management activities offline and intraorganizational to online, solves the problem of cross regional knowledge exchange with the expansion of organizational size, makes knowledge interaction more frequent, and promotes the knowledge evolution.

Therefore, this paper aims to explore the influence of digital level on knowledge evolution in the scope of manufacturing digital innovation ecosystem. It will be of theoretical significance and of practical worth for promoting the knowledge level of manufacturing digital innovation ecosystem.

2. LITERATURE REVIEW

Evolution was first used in the field of biology to describe the changes of genetic traits in a population between generations. Some scholars have found that the evolution of knowledge has similar characteristics with biological evolution, so Darwin's theory of evolution is introduced into the field of knowledge management [9], and the evolution of knowledge is explained by analogy with biological evolution [17]. Therefore, knowledge evolution can be seen as a process of constantly innovating knowledge structure and forming a new knowledge system under the dual action of inheritance and variation [8]. Knowledge will retain and inherit most of the existing knowledge in the process of knowledge inheritance to maintain the coherence between new knowledge and old knowledge [3], and will search and

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incorporate relevant knowledge in the process of dissemination, and burst out new inspiration in the process of knowledge variation, resulting in a large number of brand-new and unprecedented knowledge. Knowledge inheritance and knowledge variation are mutually independent processes, but at the same time follow each other in time, coexist and interweave with each other in space [1].

With the application and popularity of digital technology, scholars pay attention to research on knowledge creation, knowledge accumulation and knowledge application under the condition of digitization, and point out that digitization can significantly promote invention patents, patent applications, patent authorization and innovation performance [4] [5] [12]. It may also be affected by the level of economic and social development, innovation ecosystem, and the intensity of intellectual property protection [2] [10], which reflects the impact of digital level on knowledge evolution to a certain extent.

Dynamic capability, an important factor dealing with environmental uncertainty and fierce market competition to bring the innovative output and obtain the advantages of sustainable competition [13], is one of the most important capabilities of manufacturing digital innovation ecosystem. Yu find that there is an inverted U-shaped relationship between digitization and innovation performance and this relation is positively moderated by dynamic capability [14]. The improvement of dynamic capabilities improves the digestion and absorption of relevant

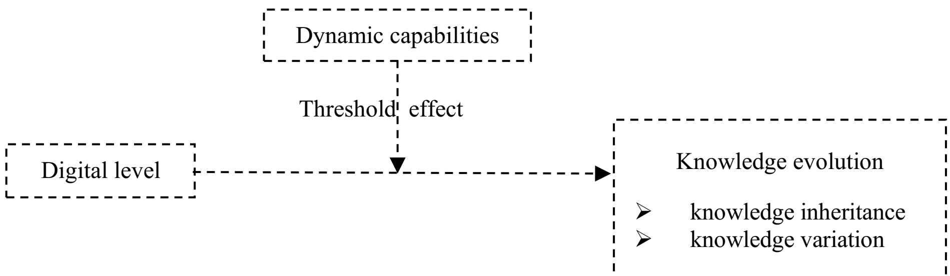

Figure 1: Conceptual Frame.

knowledge and the frequency of knowledge sharing, leading the innovation speed increase exponentially. Therefore, it can significantly affect the process of knowledge evolution.

Previous studies focused on the impacts of digital level and dynamic capabilities on knowledge evolution respectively, but ignored the threshold effect of dynamic capabilities between digital level and knowledge evolution. Based on the panel data of 28 China's manufacturing industries from 2013 to 2020, this paper introduces dynamic capabilities as threshold variable to test whether there is a threshold effect on the impact of digital level on knowledge evolution and analyzes its mechanism to provide a theoretical basis for the improvement of knowledge level of manufacturing digital innovation ecosystem.

3. RESEARCH DESIGN

3.1 Variable Selection

The interpreted variables are knowledge inheritance (KI) and knowledge variation (KV). Invention patents refer to unprecedented, original, novel and practical patented technologies or methods, which fundamentally break through the existing technologies and establish new concepts and technical standards, resulting in new products or services. The utility model and design patents are more the extension of existing products and technologies, or the transformation of existing technology platforms and products which have the characteristics of gradual progress. This paper adopts the annual growth of invention patent applications and utility model and design patent applications to describe knowledge inheritance and knowledge variation respectively in line with the works of Zhang and Kang et al. [6] [15].

The explanatory variable of this study is the digital level described by the number of computers used of manufacturing industry, the number of websites and the number of enterprises with e-commerce trading activities in each sub industry, which is the same as Zhou et al. and Li et al. [7] [16]

The threshold variable is the dynamic capabilities described by R&D investment intensity, the proportion of high-tech talents and profit margin in line with the works of Wang et al. and Yin et al. R&D investment intensity reflects the importance attached to innovation by the manufacturing digital innovation ecosystem, which is expressed by the ratio of R&D expenditure to main business income. The proportion of high-tech talents reflects the quality of workers and has an important impact on the dynamic capabilities, which is expressed by the ratio of the number of master's and doctor's personnel to the number of R&D personnel. Profit margin is an intuitive embodiment of dynamic capabilities, which is expressed by the ratio of profit to main business income.

Technology introduction is put in this model as control variable. There are different views on the impact of technology introduction on the innovation output. Technology introduction is an important channel to realize technology catch-up, however, excessive dependence on foreign technology will hinder the increase of internal knowledge stock.

Table 1: Variable description.

Variable Type	Symbol	Variable Name	Indicator
Explained variable	KI	knowledge inheritance	Annual growth of patent applications for utility models and designs
	KV	knowledge variation	Annual growth of invention patent applications
Explanatory variable	D	digital level	Number of computers used (0.439), number of websites owned (0.268), number of enterprises with e-commerce transactions (0.293)
Threshold variable	DC	dynamic capabilities	R&D investment intensity (0.563), proportion of high-tech talents (0.328), profit margin (0.109)
Control variable	TI	technology introduction	Technology introduction expenditure

3.2 Data Source

Considered that a balanced data panel is needed in the panel threshold model, the data involved in this study span from 2013 to 2020, and up to 28 manufacturing industries not including other manufacture, utilization of waste resources, and repair service of metal products, machinery and equipment. The data come from the China Science and Technology Statistical Yearbook and the China Statistical Yearbook. Table 1 provides the list. The weight of the measurement index is in brackets. In order to eliminate the influence of different dimensions of statistical data in various industries, the data used in the model are standardized by using the deviation method before empirical research.

3.3 Second Section

Taking the dynamic capabilities as the threshold variable, the threshold effect regression model of the impact of digital level on knowledge evolution is established as follows.

Single-threshold model:

$$\begin{aligned} KI_{it}(\text{or } KV_{it}) = \eta_1 D_{it} I(DC_{it} \le \varphi) + \eta_2 D_{it} I(DC_{it} > \varphi) \\ + \xi TI_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{1}$$

Multiple-threshold model (taking double-threshold as an example):

$$\begin{aligned} KI_{it}(\text{or } KV_{it}) = \eta_1 D_{it} I(DC_{it} \le \varphi_1) + \eta_2 D_{it} I(\varphi_1 < DC_{it} \le \varphi_2) \\ + \eta_3 D_{it} I(DC_{it} > \varphi_2) + \xi TI_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Here, KI is knowledge inheritance, KV is knowledge variation, D is digital level, I(.)is the indicator function, DC is the threshold variable standing for dynamic capabilities, TI is technology introduction.

4. EMPIRICAL RESULTS

4.1 Threshold Effect Regression Results and Analysis

As shown in table 2, there are significant double threshold of dynamic capabilities both on knowledge inheritance and knowledge variation. Table 3 shows the threshold estimates and confidence interval. Within the 99% confidence interval, the threshold estimates are 0.314 and 0.463 respectively for knowledge inheritance. Within the 95% confidence interval, the threshold estimates are 0.441 and 0.492 respectively for knowledge variation.

Table 2: Results of panel threshold testing.

Model	Threshold	F value	P value	Bootstrap	F critical value		
					1%	5%	10%
KI	Single threshold	47.41***	0.001	1000	37.801	26.816	22.304
	Double threshold	40.35***	0.004	1000	34.602	24.897	20.156
	Triple threshold	31.113	0.832	1000	72.516	81.684	111.691
KV	Single threshold	40.89**	0.038	1000	55.655	38.851	31.865

	Double threshold	60.27**	0.046	1000	94.331	56.831	42.248
	Triple threshold	15.74	0.506	1000	137.026	95.179	71.799

Table 3: Results of threshold estimates.

Model	Threshold	Threshold estimate	95% conf. interval of threshold
KI	Single threshold	0.314	[0.311,0.320]
	Double threshold	0.463	[0.413,0.466]
KV	Single threshold	0.441	[0.440,0.447]
	Double threshold	0.492	[0.477,0.503]

With the improvement of dynamic capabilities, the coefficients of digital level on knowledge inheritance are 0.756, 1.233 and 1.894 respectively. The influence of digital level on knowledge inheritance is increasing and thus present a J-shaped relationship. The coefficients of digital level on knowledge inheritance are 0.434, 0.969 and 0.106 respectively. The influence of digital level on knowledge variation has marginal decreasing effect and as a result of S-shaped correlation. On the whole, the coefficients of digital level on knowledge inheritance are greater than that of digital level on knowledge variation, which indicates that digital level plays a more significant role in promoting knowledge inheritance. It may be that knowledge variation require more subjective initiative compared with knowledge inheritance, and the knowledge flow and sharing in the process of knowledge inheritance is more obviously affected by the digital level. In addition, no matter what stage the dynamic capabilities are in, the coefficients of digital level on knowledge evolution is positive, indicating that digital level has a significant positive role in promoting knowledge evolution.

Table 4: Results of panel threshold regression.

Model	Variable	Coef.	P value
KI	TI	-0.548***	0.002
	I(DC≦0.314)	0.756***	0.002
	I(0.314<DC≦0.463)	1.233***	0.000
	I(DC>0.463)	1.894***	0.000
	cons	0.138*	0.056
KV	TI	-0.063	0.601
	I(DC≦0.441)	0.434***	0.007
	I(0.441<DC≦0.492)	0.969***	0.000
	I(DC>0.492)	0.106	0.504
	cons	0.691*	0.065

As for technology introduction, there is a significant negative impact on knowledge inheritance. It shows that with the improvement of dynamic capabilities, over reliance on technology introduction will inhibit the knowledge inheritance. The innovation ecosystem should gradually get rid of the dependence on external technology and pay more attention to independent innovation.

4.2 Industry Distributions Heterogeneity Analysis

Due to the significant differences among manufacturing industries, the figure 2 shows industry distributions with different dynamic capabilities thresholds.

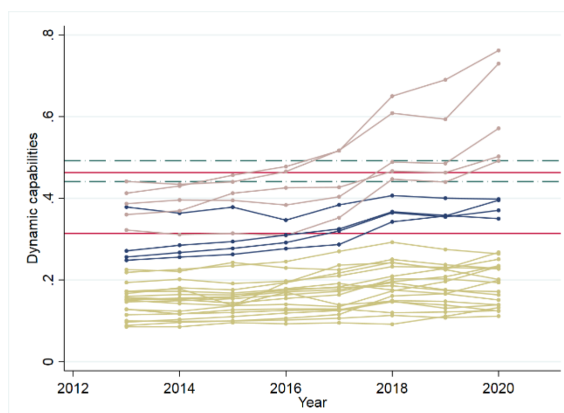

Figure 2: Industry distributions with different dynamic capabilities thresholds.

The dynamic capabilities of most industries are still at a lower edge while are steadily improving. The number of industries with dynamic capabilities less than 0.314 decreased from 22 in 2013 to 19 in 2020, and the number of industries with dynamic capacity greater than 0.492 increased from 2 in 2013 to 5 in 2020. These five industries are manufacture of medicines, manufacture of special purpose machinery, manufacture of railway, ship Aerospace and other transport equipments, manufacture of computer, communication and other electronic equipment and manufacture of measuring instrument and machinery highly coincide with the China's high-tech industries, which shows that China's high-tech industries have developed rapidly and the industrial ecological mechanism is relatively sound, which is the key direction of manufacturing development in the future.

5. CONCLUSION

This study incorporates digital level, knowledge evolution and dynamic capabilities into a unified framework and analyzes the threshold effect of dynamic capabilities on knowledge evolution. After considering dynamic capabilities' influence on knowledge evolution, digital level and knowledge inheritance present a J-shaped relationship, while digital level and knowledge variation show a S-shaped correlation. In recent years, the number of industries in the range of medium and high dynamic capabilities has gradually increased, and the trend of manufacturing digital innovation ecosystem is developing in a good direction.

The manufacturing digital innovation ecosystem is the current trend, which is also the key strategy of high-quality development. Building a collaborative, efficient and sustainable manufacturing digital innovation ecosystem is conducive to knowledge share and innovation so as to promote knowledge evolution. Additionally, promoting the integration of digitalization and manufacturing also plays a significant role in knowledge evolution, which the policy makers should increase the investment of digital infrastructure to make sure the application of digital technology can be deepen.

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