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# Research on the Impact of Digital Transformation on Innovation Performance in Manufacturing Enterprises

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**Abstract:** A key route for manufacturing organizations to reach innovation is using digital transformation. This essay performs regional heterogeneity analysis and empirically tests the degree of digital transformation of manufacturing companies on innovation performance using about 2,000 listed manufacturing companies in China's A-shares from 2008 to 2023. The study revealed that the performance of innovation in manufacturing companies is much improved by digital transformation, rather favorably. The eastern and southern parts of China have more notable positive influence than the center area. At last, depending on the findings of the studies, pertinent suggestions are offered by the government as well as the business.

**Keywords:** Digital transformation, Enterprise innovation performance, Manufacturing.

## 1. Introduction

In the digital age, the digital system built on the basis of information technology has generated great application value in all walks of life. At the same time, driven by national policies and industrial development, manufacturing enterprises are facing a new wave of digital development and innovation. Introducing information technology and digital technology into the manufacturing production chain to upgrade the technical system and innovate the management model can create new benefits for enterprises, and also produce the new concept of digital performance. The digital technology has broken through the traditional development model, and the performance management of enterprises has also shown new development trends. Based on this, clarifying the impact of digital transformation on innovation performance, actively responding, and formulating scientific optimization paths can provide assistance for the development of manufacturing enterprises.

## 2. Literature Review and Research Hypothesis

### 2.1. Literature Review

Theoretical research and quantitative research define the two main divisions of current debates on "digital transformation and innovation". From the perspective of theoretical research, existing research roughly divides the types of enterprise innovation promoted by digital transformation into three types: management, product, and business model. In terms of product innovation, Ji et al. believe that the digital technology has a strong driving effect on user participation in the product innovation process [1]. Xiao et al. pointed out that big data resources have a positive effect on the product innovation performance [2]. In terms of management innovation, Qi and Xiao pointed out that the internal management model is constantly changing under the background of digital economy [3]. Xu et al., analyzed the impact of AI on the management objects, management characteristics, decision-making process and management ethics of enterprises [4]. In terms of business model innovation, Luo believes that digital technology has high penetration and can subvert traditional business models, thereby accelerating the formation of new ways to drive economic growth and promote economic development [5]. Li et al. stated out that digital empowerment can promote business model innovation in manufacturing companies [6]. On the one hand, Wu et al. developed an indicator for measuring the extent of enterprise digital transformation in the annual reports of listed companies by analyzing the frequency of digital-related keywords. This indicator is based on quantitative research [7]. For the measurement of enterprise innovation, Zhang and Long used the number of enterprise patent authorizations as an indicator to measure enterprise innovation [8, 9].

### 2.2. Research Hypothesis

#### 2.2.1. The Impact of Digital Transformation on Innovation

The in-depth promotion of digital transformation by manufacturing enterprises can promote their own innovation level, which is specifically demonstrated in the subsequent three aspects: First, identify innovation opportunities. Under the digital economy, manufacturing enterprises are facing a complex and ever-changing organizational innovation environment. The influx of a large amount of information often catches enterprises off guard, resulting in the inability to respond in time. By introducing digital tools such as cloud computing and AI, enterprises can quickly scan, capture, and identify innovation opportunities; Second, reduce innovation costs. Enterprise innovation is not easy and requires a lot of manpower, material resources, and financial investment. Digital tools can accomplish many tasks, such as achieving precise marketing and customer service, SCM systems optimizing inventory management and logistics transportation, etc., to reduce costs for enterprises; Third, shorten the innovation cycle. Generally speaking, innovation often has the features of long cycles, high risks, and strong uncertainties. By introducing PLM systems and cloud computing technologies, enterprises can quickly realize the rational allocation of various resources across regions and departments, achieve the effect of collaborative innovation, shorten the innovation cycle, and reduce innovation risks. There, the following hypothesis is put forth:

H1: The innovation performance of manufacturing enterprises is positively impacted by digital transformation.

#### 2.2.2. Regional Heterogeneity

The innovation performance in manufacturing enterprises is influenced by regional distinctions in the impact of digital transformation, which is mainly due to differences in economic development levels, policy support, talent reserves and other factors in different regions. From the economic development level, Wang Jun et al. stated that the development of the digital economy shows a decreasing trend from "east-middle-west" in horizontal space [10]. The digital economy will largely lead to differences in the level of regional digital transformation. From the perspective of policy support, different regions have different preferential policies for digital transformation, and thus the success rate of digital transformation of local enterprises is also different. Digital transformation requires technical and management talents. From the perspective of talent reserves, economically developed regions generally have more sufficient talent reserves, including high-level technical personnel and managers, which makes it easier for enterprises in these regions to achieve digital transformation and promote innovation. Regions with a shortage of talent will face greater transformation difficulties and innovation challenges. There, the following hypothesis is put forth:

H2: The innovation performance of manufacturing enterprises in eastern, southern, and central China is affected differently by their digital transformation.

# 3. Methodology

## 3.1. Data Collection and Sample Selection

The manufacturing companies that were listed on the A-share market in China from 2008 to 2023 make up the initial data sample. The initial data processing process is as follows: First, remove *ST, and delisted companies from the sample; Second, remove samples with serious data missing; Finally, all continuous variables are shrinked, and the shrinking objects are 1% of the observations above and below. After the above processing, 2000 observations are finally obtained. This essay uses annual reports of listed corporations as well as CSMAR database data. This essay uses SPSS to do the following data analysis.

## 3.2. Variables

#### 3.2.1. Explained variables

This essay draws on the practice of Zhang and Long [8] and uses the total number of patent authorizations to measure corporate innovation performance, and then adds 1 to the total number and takes the natural logarithm as the explained variable.

#### 3.2.2. Explanatory variables

This essay uses the practice of Wu et al. [7] and the frequency of keywords related to digital transformation such as big data, AI, etc. in the annual reports of listed manufacturing companies as a measurement indicator for constructing corporate digital transformation, then adds 1 to the frequency of digital transformation words and takes the natural logarithm as the explanatory variable.

#### 3.2.3. Control variables

This essay uses the return on total assets of enterprises, the debt-to-asset ratio of enterprises, as control variables, the shareholding ratio of the main shareholder of enterprises, and dual-position holding. The variable definitions are shown in Table 1.

**Table 1.** Variables Definition

| Variable Types | Variable Name | Variable Symbols | Variable Definition |
|---|---|---|---|
| Explained variable | Innovation Performance | PA | Ln (the number of patents in the current year + 1) |
| Explanatory variables | Digital Transformation | DT | Ln (digital word frequency in that year + 1) |
| Control variables | Debt-to-asset Ratio | LEV | Total Liabilities/Total Assets |
| | Return on Total Assets | ROA | Net profit/total assets |
| | Shareholding ratio of the largest shareholder | TOPI | Number of shares held by the largest shareholder/total number of shares |
| | Two jobs at the same time | DUAL | 1 if the chairman is also the CEO, 0 otherwise |

## 3.3. Model Building

The subsequent model is established in this essay to evaluate the research hypothesis:

$$PA_{i,t} = \alpha + \alpha_1 DT_{i,t} + \sum \alpha_k Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (1)$$

The enterprise is represented by i in the aforementioned paradigm, while t represents time. The enterprise's innovation performance is represented by PA, and digital transformation is represented by DT. The control variable is control. Σ Year is the time fixed effect, Σ Industry is the industry fixed effect, and ε is the random error term. The empirical equation known as Model (1) is intended to evaluate the hypothesis H1.

# 4. Empirical Analysis

## 4.1. Descriptive Statistical Analysis

Result is shown in Table 2. The minimum value PA is 1.100, the maximum value is 7.451, and the standard deviation is 1.177, indicating that the innovation level among manufacturing enterprises is uneven. The minimum value of DT is 0.693, the maximum value is 5.343, and the standard deviation is 1.054, indicating that the current degree of digitalization varies greatly.

**Table 2.** Descriptive Statistical Analysis

| Variable | Sample Size | Average | Median | Standard Deviation | Min | Max |
|---|---|---|---|---|---|---|
| PA | 2 000 | 3.620 | 3.556 | 1.177 | 1.100 | 7.451 |
| DT | 2 000 | 2.034 | 1.947 | 1.054 | 0.694 | 5.343 |
| LEV | 2 000 | 0.374 | 0.361 | 0.188 | 0.021 | 1.112 |
| ROA | 2000 | 0.051 | 0.048 | 0.067 | -0.839 | 0.787 |
| TOPI | 2000 | 33.651 | 31.691 | 14.461 | 2.9 | 81.89 |
| DUAL | 2000 | 0.336 | 0 | 0.473 | 0 | 1 |

## 4.2. Correlation Analysis

Table 3 presents the correlation coefficients among the factors discussed in this essay. The Pearson correlation coefficient between DT and PA is 0.206, above the 1% significance level test, signifying a positive association between DT and PA. H1 was initially verified.

**Table 3.** Correlation Analysis

| Variable | PA | DT | LEV | ROA | TOPI | DUAL |
|---|---|---|---|---|---|---|
| PA | 1 | | | | | |
| DT | 0.206 *** | 1 | | | | |
| LEV | 0 .349*** | - 0.004 | 1 | | | |
| ROA | - 0.047** | - 0.061*** | - 0.295*** | 1 | | |
| TOPI | 0.054 ** | - 0.054** | 0.042 * | 0.102 *** | 1 | |
| DUAL | - 0.088*** | 0.046 ** | - 0.195*** | 0.039 * | 0.029 | 1 |

Note: ***, **, and * represent that the coefficient is significant at the 1%, 5%, and 10% levels respectively.

Then by evaluating the variance inflation factor (VIF), as shown in Table 4, the maximum value of the explanatory variable and control variable VIF is 1.14, which is far less than the critical value 10. The multicollinearity isse is eliminated, multiple regression analysis can be performed, and the empirical results are credible.

**Table 4.** Collinearity Diagnosis

| Variable | VIF | 1/VIF |
|---|---|---|
| DT | 1.15 | 0.874358 |
| LEV | 1.12 | 0.897201 |
| ROA | 1.05 | 0.958662 |
| TOPI | 1.03 | 0.980760 |
| DUAL | 1.02 | 0.991812 |
| Mean VIF | 1.08 | |

## 4.3. Multiple Regression Analysis

This essay uses the Hausman test to determine model selection. The result of the Hausman test is "prob>chi2 = 0", which significantly rejects the null hypothesis. Therefore, this essay chooses fixed effects model for multiple regression analysis.

Table 5 shows model (1), the fundamental model with all control variables. Model (2) brings digital transformation (DT) into (1), and the output reveals that the regression coefficient of digital transformation is 0. 162, which is relevant at the 1% statistical level. All things considered, hypothesis H1 has been confirmed and DT improves the PA in manufacturing companies.

**Table 5.** Regression Analysis Results

| | Model (1) | Model (2) |
|---|---|---|
| Variables | PA | PA |
| DT | | 0.162*** |
| | | (6.95) |
| LEV | 2.181*** | 2.151*** |
| | (16.80) | (16.75) |
| ROA | 1.286*** | 1.378*** |
| | (3.57) | (3.86) |
| TOPI | 0.006*** | 0.007*** |
| | (3.47) | (3.53) |
| DUAL | -0.057 | -0.062 |
| | (-1.17) | (-1.29) |
| Constant Term | 2.579*** | 2.257*** |
| | (32.37) | (24.70) |
| Year | Yes | Yes |
| Industry | Yes | Yes |
| Sample Size | 2,000 | 2,000 |
| $R^2$ | 0.262 | 0.279 |
| F-statistic | 80.92 | 75.80 |

## 4.4. Heterogeneity Analysis

For further ensure the authenticity of the conclusion, this essay will do a heterogeneity analysis based on regional characteristics [11]. It can be observed from the heterogeneity analysis results in Table 6 that the regression coefficients of DT in eastern China and southern China are 0. 148 and 0. 200 respectively, both of which are significant at the 1% statistical level, indicating that DT has a significant positive effect on PA. However, the positive effect of DT on the PA of manufacturing enterprises in the central region is not significant. The reason may be that the eastern and southern regions are more economically developed than the central region, with sound infrastructure and a higher concentration of high-end talents, which is favourable for the advancement of digital transformation and the implementation of innovative activities. Therefore, hypothesis H2 is tested, and there are differences in the innovation performance in eastern, southern, and central China that are affected by their digital transformation.

**Table 6.** Heterogeneity Analysis

| | Easy | South | Central |
|---|---|---|---|
| Variables | P A | P A | P A |
| DT | 0.148 *** | 0.200 *** | 0.109 |
| | (5.61) | (2.87) | (1.05) |
| LEV | 2.164 *** | 1.959 *** | 2.573 *** |
| | (14.48) | (5.35) | (4.97) |
| ROA | 1.282*** | 0.776 | 2.407 |
| | (3.37) | (0.57) | (1.20) |
| TOPI | 0.006** | 0.021*** | 0.002 |
| | (2.58) | (4.17) | (0.29) |
| DUAL | -0.110** | 0.201 | -0.502* |
| | (-2.05) | (1.36) | (-1.81) |
| Constant term | 2.371*** | 1.847*** | 2.008*** |
| | (22.27) | (6.97) | (5.70) |
| Year | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes |
| Sample Size | 1,593 | 2 87 | 2 30 |
| $R^2$ | 0.281 | 0.396 | 0.331 |
| F-statistic | 5 6.66 | 1 2.15 | 8.232 |

# 5. Conclusion and Recommendations

## 5.1. Conclusion

How does digital transformation affect manufacturing organizations' performance of innovation? Based on data of Chinese listed manufacturing businesses between 2008 and 2023, this paper experimentally investigates this problem and subsequently derives findings: First, Chinese manufacturing enterprises' innovation is affected by digital transformation. Performance has a major beneficial impact; second, digital transformation has a major positive influence on the innovation performance of manufacturing companies in the eastern and southern areas of China, but it is not significant in the less developed central regions.

## 5.2. Recommendations

This essay will offer pertinent recommendations from two levels: businesses and governments, thereby accelerating the speed of digital transformation, improving corporate innovation performance, and supporting high-quality growth of China's manufacturing sector.

For enterprises, first, to accelerate the pace of digital transformation, enterprises should deeply analyze the current innovation environment they are facing, and fully evaluate their internal and external resources, and use this as a basis to promote a digital transformation strategy that meets the characteristics of the enterprise; second, promote organizational change. Digital transformation not only revolutionizes the technical tools and business models of enterprises, but also reshapes the organizational structure and management methods of enterprises. Therefore, in order to promote this change, enterprises must redesign the organizational structure, business processes and job classifications that match them, build a digital organizational structure, and cultivate a digital corporate culture; third, train and improve employees' digital literacy, and master digital tools and related platforms.

For the government, first, strengthen the construction of digital infrastructure. As the cornerstone of the digital economy, digital infrastructure provides indispensable support for the vigorous digital economy. For example, we will promote the expansion and acceleration of fiber optic networks, accelerate the deep coverage of 5G networks, carry out IPv6 transformation and application of network facilities, and accelerate the upgrading of space information infrastructure; build a regional coordinated development mechanism among the eastern, southern and central regions to promote common prosperity and progress among all regions, such as jointly building regional industrial cooperation bases and resource deep processing base.

# References


[1] Gu Anwei, Jiang Huihui, Lu Xifeng, et al. Research on the configuration effect of user participation in product innovation under digital context—fsQCA analysis based on TOE framework [J]. Science and Technology Progress and Countermeasures, 2022, 39(22): 72-81.

[2] Xie Kang, Xia Zhenghao, Xiao Jinghua. Enterprise implementation mechanism of big data becoming a real production factor: product innovation perspective [J]. China Industrial Economy, 2020(5): 42-60.

[3] Qi Yudong, Xiao Xu. Enterprise management transformation in the digital economy era [J]. Management World, 2020, 36(6): 135-152, 250.

[4] Xu Peng, Xu Xiangyi. The logic and analytical framework of enterprise management transformation in the era of artificial intelligence [J]. Management World, 2020, 36(1):122-129, 238.

[5] Luo Zhenli. Three basic attributes of the development of my country's digital economy [J]. People's Forum·Academic Frontier, 2020(17): 6-12.

[6] Li Panpan, Qiao Han, Guo Tao. Research on the cross-level effect of digitalization level on business model innovation of manufacturing enterprises [J]. Research Management, 2022, 43(11): 11-20.

[7] Wu Fei, Hu Huizhi, Lin Huiyan, et al. Enterprise digital transformation and capital market performance: empirical evidence from stock liquidity [J]. Management World, 2021, 37(7): 130-144, 10.

[8] Zhang Jichang, Long Jing. Digital transformation, dynamic capabilities and corporate innovation performance: empirical evidence from high-tech listed companies [J]. Economics and Management, 2022, 36(3): 74-83.

[9] Gao Xia, Cao Jieqiong, Bao Lingling. The impact of heterogeneity of openness of industry-university-research cooperation on enterprise innovation performance [J]. Research Management, 2021, 42(9): 112-119.

[10] Wang Jun, Zhu Jie, Luo Qian. Measurement of the development level and evolution of China's digital economy [J]. Journal of Quantitative and Technical Economics, 2021, 38(7): 26-42.