Digital Transformation of Manufacturing Enterprises, Dual Network Embedding, and Innovation Efficiency

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Abstract. How digital transformation allocates resources in manufacturing enterprises and ensures the enhancement of innovation efficiency has become an important issue in this cutting-edge research topic. Using unbalanced panel data from A-share listed manufacturing enterprises in China from 2013 to 2021, this paper introduces dual network embedding as a mediating variable to construct a theoretical model that clarifies the impact mechanism between digital transformation of manufacturing enterprises and innovation efficiency. The results indicate that digital transformation in manufacturing enterprises significantly enhances innovation efficiency, and dual network embedding plays a mediating role between digital transformation and innovation efficiency. Ultimately, this paper provides feasible suggestions for manufacturing enterprises to strengthen dual network embedding through digital transformation with a focus on innovation efficiency.

Keywords: Digital transformation, Dual network embedding, Innovation efficiency.

1 Introduction

The real economy is the foundation of a country's economy, and high-quality development of manufacturing enterprises is key to supporting high-quality macroeconomic development in China. However, currently, China's manufacturing industry has weak core technologies and innovation capabilities, urgently needing to enhance innovation efficiency. The outline of China's 2035 vision proposes that digitalization drives the strengthening of cooperation between network entities, supports the transformation and application of scientific and technological achievements, and promotes innovation integration among large, medium, and small enterprises.

Based on this, this paper uses unbalanced panel data from A-share listed manufacturing enterprises in China from 2013 to 2021 to construct a model of "digital transformation of manufacturing enterprises - dual network embedding - innovation efficiency," revealing the mechanism of the impact of digital transformation on innovation efficiency.

K. Zhang et al. (eds.), *Proceedings of the 5th International Conference on Economic Management and Big Data Application (ICEMBDA 2024)*, Advances in Economics, Business and Management Research 313,
https://doi.org/10.2991/978-94-6463-638-3_56

2 Theoretical Analysis Framework and Model Hypotheses

2.1 Impact of Digital Transformation on Innovation Efficiency

Gamache (2019) found that digital transformation is significantly positively correlated with enterprise innovation efficiency [1]. Wang Hui et al. (2021) studied the relationship between digital transformation, organizational resilience, and innovation efficiency in small and medium-sized enterprises using empirical sampling methods [2].

Using digital information technology, manufacturing enterprises can more effectively integrate information and other resources, optimize the innovation process and management Based on this, the following hypothesis is proposed:

H1: Digital transformation of manufacturing enterprises has a significant positive impact on innovation efficiency.

2.2 Mediating Role of Dual Network Embedding

Granovetter (1985) was the first to divide network embedding into structural embedding and relational embedding [3], where structural embedding refers to the network position of each node member, generally measured by centrality and structural holes. This paper primarily measures based on the above. Wang et al. (2014) decomposed collaborative networks and knowledge networks [4]. Subsequently, Yao Yanhong and Gong Yu (2022) explain the impact mechanism of collaborative network embedding and knowledge network embedding [5].

2.2.1. Mediating Role of Collaborative Network Embedding.

Research by Caner et al. (2015) indicates that collaborative networks can enhance product novelty, thereby affecting the innovation process of enterprises [6]. Cao Xia and Song Qi (2016) found that collaborative networks promote innovation efficiency [7].

Digital transformation significantly deepens the direct or indirect relationships among different entities within the network, facilitating manufacturing enterprises to enhance product novelty. Based on this, the following hypotheses are proposed:

H2: Collaborative network embedding plays a mediating role between digital transformation of manufacturing enterprises and innovation efficiency;

2.2.2. Mediating Role of Knowledge Network Embedding.

Guan and Liu (2016) believe that the "path dependency" caused by knowledge networks promotes enterprise innovation performance [8]. Xin Lin (2022) illustrated how knowledge network centrality can enhance enterprise innovation performance through financing constraints [9].

Digital transformation stimulates the fusion output of internal knowledge elements related to innovation by quickly integrating and filling knowledge gaps in technology and management, thus assisting enterprises in achieving continuous iteration of innovative products and enhancing innovation efficiency. Based on this, the following hypothesis is proposed:

H3: Knowledge network embedding plays a mediating role between digital transformation of manufacturing enterprises and innovation efficiency.

3 Empirical Analysis

3.1 Data Selection and Processing

This paper uses A-share manufacturing companies listed on the Shanghai and Shen

Zhen stock exchanges in China from 2013 to 2021 as the research sample. The data sources include the Guo Taian database, the Wan Fang database and the National Patent Search Service platform. To reduce the interference of outliers, the data was organized and filtered as follows: (1) Exclude data with individual patent holders; (2) Remove samples labeled as ST and *ST; (3) Delete samples with significant missing observations. Based on these principles, a final dataset of 1,610 listed companies with 7,775 observations was compiled, resulting in unbalanced panel data.

3.2 Measurement of Variables

3.2.1. Explained Variable: Innovation Efficiency (IE).

This paper adopts an improved dynamic two-stage DEA model based on Kao (2009) [10] and Han et al. (2018) [11] to regard R&D expenditures and R&D personnel as initial inputs, while the number of patent applications and total intangible assets are seen as intermediate outputs. Operating income and net profit are defined as final outputs, and efficiency values for each stage and overall efficiency were measured using Max DEA Ultra 7.9 software.

3.2.2. Explanatory Variable: Digital Transformation (DT).

The digital transformation index of enterprises is calculated using six indicators weighted according to the data published by Guo Taian in 2022.

3.2.3. Mediating Variable: Dual Network Embedding.

Referencing the research methods of Wang et al. [12], this paper constructs cooperation and knowledge networks using the patent application information of listed manufacturing companies in UCINET 6.0. The software is then used to calculate the centrality and structural hole values for each node in these networks, specifically as follows:

1. Centrality: The centrality metric quantifies the degree to which a node occupies a core position in the network. The calculation formula is as follows:

$$C_i = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{1}$$

where C_i is the closeness centrality of node i, d_{ij} is the shortcut distance from node i to node j, and n is the network size. Following prior research, relative degree centrality is used to measure the centrality characteristics of the knowledge network. The calculation formula is as follows:

$$RC_i = \frac{\sum_j x_{ij}}{n-1} \tag{2}$$

where RC_i is the relative degree centrality of node i, $\sum_j X_{ij}$ represents the absolute centrality of the node; when there is a connection between nodes i and j, $X_{ij} = 1$, otherwise, $X_{ij} = 0$. n reflects the total number of nodes, indicating the overall scale of the network.

2. Structural Holes: Existing literature primarily measures structural holes using a negative indicator called constraint. Given that the computed range of constraint values from the sample is between 0.047 and 2, this paper adopts the "2-constraint indicator C_i" to characterize the value of structural holes at the node.

$$C_{ij} = \left(P_{ij} + \sum_{k \neq i,j} P_{ik} P_{kj}\right)^2 \tag{3}$$

$$C_i = \sum_j C_{ij} \tag{4}$$

In equation (4), C_i is the constraint indicator, and in equation (3), C_{ij} indicates the extent to which knowledge element i is constrained by j. In the knowledge network, a direct connection exists between knowledge elements i and j, with k being a third-party knowledge element connected to both i and j. P_{ij} denotes the strength of the direct relationship from i to j, P_{ik} indicates the strength of the relationship from k to i, and P_{kj} reflects the strength of the relationship from k to j.

3.2.4. Control Variable.

1. Firm Size (SIZE): Natural logarithm of total assets
2. Firm Age (AGE): $t - \text{year of establishment} + 1$ (5)
3. Debt-to-Asset Ratio (LEV): $Total\ liabilities/Total\ assets$ (6)
4. Ownership Type (STATE): State-owned enterprises take "1", non-state-owned enterprises take "0"
5. Industry (IND): Industry code

4 Empirical Tests

4.1 The Impact of Digital Transformation on Innovation Efficiency

Using innovation efficiency as the dependent variable, and five factors—firm age, firm size, firm nature, debt-to-asset ratio, and industry type—as control variables, we introduced digital transformation as the independent variable. The regression results of the impact of digital transformation on innovation efficiency are shown in Table 1.

Table 1. Regression Results of Digital Transformation on Innovation Efficiency.

	(1)	(2)
Variable	IE	IE
DT		0.023***
		(5.56)
Contral	Yes	Yes
Constant	6.034***	6.295***
	(6.81)	(7.11)
Observations	7,775	7,775
R-squared	0.024	0.028

In column (1) of Table 1, which includes only the control variables, the regression results show that firm size and age are negatively correlated with innovation efficiency at the 1% significance level. Upon adding the variable digital transformation (DT) in column (2), with the coefficient of digital transformation being 0.023 and significant at the 1% level. This indicates that digital transformation in manufacturing firms can significantly enhance their innovation efficiency, thereby supporting hypothesis H1.

4.2 Testing the Mediating Effect of Cooperative Networks

Table 2. Regression Results of Cooperative Network Mediating Effect.

	(1)	(2)	(3)	(4)
Variable	Co-CEN	Co-STR	IE	IE
DT	0.169***	0.073***		
	(18.77)	(6.94)		
Co-CEN			0.040***	
			(7.82)	
Co-STR				0.019***
				(4.15)
Contral	Yes	Yes	Yes	Yes
Constant	-76.283***	-2.455***	9.190***	0.106
	(-40.14)	(-109.5)	(9.47)	(7.51)
Observations	7,775	7,775	7,775	7,775
R-squared	0.278	0.151	0.032	0.027

This paper will employ the sequential testing method proposed by Professor Wen Zhonglin[13] to verify. The specific regression results are shown in Table 2.

The first two columns of Table 2 validate the relationship between digital transformation in manufacturing firms and cooperative network embedding. The results in columns (1) and (2) demonstrate that digital transformation in manufacturing firms significantly positively influences embedding in cooperative networks. The results in columns (3) and (4) demonstrate that embedding in cooperative networks significantly positively influences innovation efficiency. Overall, confirming hypothesis H2.

4.3 Testing the Mediating Effect of Knowledge Networks

This paper will again utilize the sequential testing method to verify. The specific regression results are shown in Table 3.

Table 3. Regression Results of Knowledge Network Mediating Effect.

	(1)	(2)	(3)	(4)
Variable	Kn-CEN	Kn-STR	IE	IE
DT	0.085***	0.029***		
	(12.12)	(8.01)		
Kn-CEN			0.040***	
			(5.98)	
Kn-STR				0.026**
				(2.05)
Contral	Yes	Yes	Yes	Yes
Constant	0.023	0.481***	0.059***	0.059***
	(1.61)	(6.16)	(6.76)	(6.66)
Observations	7,775	7,775	7,775	7,775
R-squared	0.163	0.074	0.029	0.025

The first two columns of Table 3 validate the relationship between digital transformation in manufacturing firms and knowledge network embedding. The results in columns (1) and (2) reveal that digital transformation in manufacturing firms has a significant positive impact on embedding in knowledge networks. The results in columns (3) and (4) reveal that embedding in knowledge networks has a significant positive impact on innovation efficiency. In summary, supporting hypothesis H3.

4.4 Robustness and Endogeneity Analysis

Table 4. Robustness and endogeneity analysis

	(1)		(3)	(4)
Variable	IE (Initial)	IE (Deleted)	IE	IE
DT	0.023***	0.028***	0.023***	
	(5.56)	(5.28)	(5.56)	
L. DT				0.093***
				(5.78)
Contral	Yes	Yes	Yes	Yes
Constant	6.295***	7.407***	6.295***	3.877***
	(7.11)	(7.19)	(7.11)	(4.04)
Observations	7,775	6667	7,775	7775
R-squared	0.028	0.027	0.028	0.029

Other electronic equipment manufacturing industries such as computers may make their digital transformation degree much higher than other industries, so the samples of related industries are deleted, and the robustness test results are shown in columns (1) and (2) in Table 4. The empirical results show that the digital transformation of manufacturing enterprises still positively and significantly affects the innovation efficiency.

In order to prevent endogenous problems, this paper intends to use the instrumental variable method to test the above conclusions. In this paper, the lag phase of enterprise digital transformation (L. DT) is used as a tool variable to replace the original independent variable to regress the main effect. As shown in column (3) and (4) in Table 4, the regression coefficient of innovation efficiency on the lag phase of the digital transformation level of enterprises is still significant, indicating that there is no causal relationship.

5 Conclusion

The main line of this research is "Digital Transformation - Dual Network Embedding - Innovation Efficiency." Based on the empirical results, the following conclusions can be drawn: Digital transformation in manufacturing firms can significantly enhance innovation efficiency. Cooperative network and knowledge network embedding plays a mediating role between digital transformation and innovation efficiency in manufacturing firms.

Especially in the current context of domestic economic transformation and increasing international uncertainty, strengthening organizational resilience and enhancing the adaptability of manufacturing firms to this emerging strategy of digital transformation is becoming increasingly important. Managers in manufacturing firms should adopt a series of measures to ensure that all departments maintain stable operations during the transformation process and have the capability to respond rapidly to external changes, helping to mitigate the fluctuations and shocks of the digital transformation process, and providing assurance for the long-term development of the firms.

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