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Identification of Key Factors of Digital Transformation of Manufacturing companies Using Hybrid DEMATEL Method

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ABSTRACT

This study constructs the influencing factors system of digital transformation of manufacturing companies and determines the influencing factors of digital transformation of manufacturing companies from the technical level, the ability level, the environmental level in order to promote the process of digital transformation of manufacturing companies, consider the impact of technology, capacity and environment on digital transformation of manufacturing. To identify the most important factors and crucial factors, developed a model for identifying critical factors based on the hybrid DEMATEL (Decision-Making Trial and Evaluation Laboratory) methodology. Combined with the related data, this study carries out empirical analysis to demonstrate and verify the influencing factors system of digital transformation of manufacturing companies with the help of hybrid DEMATEL method. The empirical analysis results indicate that the investment share of digital technology, the benefit level of company of manufacturing industry and government support are the crucial factors, and the construction level of digital platform, the technical level of employees, level of construction of digitized equipment and industrial supporting capacity are the non crucial factors. The feasibility and validity of hybrid DEMATEL method are verified.

1. Introduction

The development of manufacturing companies not only reflects the level of national productivity, but also distinguishes the developing and developed countries, and its development direction and trend will have a certain impact on the national economic development. Today, the industrial 4.0 era has arrived, information technology has gradually occupied a great position in the development of industry. In the meantime, with the proposal of digital manufacturing, the application of information technology and digital technology of manufacturing companies has been greatly valued. To sum up of the related literatures [1-12], it is inevitable for the manufacturing enterprises to transform to digital, it is of practical significance to identify the crucial factors that affect the digital transformation of manufacturing companies.

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While considering the manufacturing companies, scholars pointed out the significance of the manufacturing enterprise transformation to intelligence, but also pointed out the direction and content of the manufacturing companies transformation to intelligence. Zhou et al. [1] considered that digital manufacturing is the combination of information technology and artificial intelligence technology, and runs through all the operation processes of manufacturing companies. They said that digital manufacturing will become the core force in the 4.0 era of industry. They also put forward the technological route to drive digital transformation in manufacturing. Xiao et al. [2] supposed that the popularization and application of digital technology is a key indicator to evaluate manufacturing capacity, based on this, an evaluation model is established to assess the digital transformation capabilities of manufacturing companies in different regions. Yu et al. [3] use of structural equation modeling to verify whether the supply chain can have an impact on manufacturing transformation, and defined the impact path of society and environment on manufacturing transformation. Wang and Han [4] considered the mechanism of influence of employees' psychological changes on the digital transformation of manufacturing companies from a technological change level. The final conclusion showed that the stronger employee belonging and responsibility, the more positive their attitude towards digital transformation, and the more they promote the digital transformation of manufacturing companies. Liu et al. [5] used feature extraction and SVR model in analyzing the influencing factors of promoting the digital transformation in manufacturing. The experiment result shows that capital factors and development factors are important factors to promote the promote intelligent development. Stadnicka et al. [6] considered that people are very important players in the process of digital transformation of manufacturing, and their knowledge and motivation are very important for the development of digital manufacturing companies. Zhou and Chuah [7] considered artificial intelligence as a key influencing factor of digital manufacturing, and proposed that the manufacturing concern should adopt advanced information technology and make full use of artificial intelligence technology and human resources in the process of digital transformation. Sim [8] believed that in order to realize the digital transformation of manufacturing companies, it is indispensable to improve the output and quality of products, and proposes a hierarchical factor analysis methodology, which proves that the output and quality of products will have an impact on the digital transformation of manufacturing companies. Yang et al. [9] considered that there were few researches on the impact of digital manufacturing on enterprise performance, so they used the differentiated tendency score matching method to study the impact of digital manufacturing on financial performance and innovation performance. The research results showed that digital manufacturing played an important role in improving the financial performance and innovation performance of manufacturing companies. Zhong and Fu [10] pointed out the opportunities and challenges in the process of digital transformation in manufacturing by using SWOT (strengths, weaknesses, opportunities, threats) analysis method, as well as the advantages and disadvantages of digital transformation, and based on this, put forward specific recommendations. Su and Yang [11] identified market demand, digital technology, digital equipment resources, digital interaction ability, digital service platform, digital management system, environmental change and entrepreneurship as factors affecting the upgrade of smart manufacturing transformation using grounded theory.

To sum up, the literatures considering on digital manufacturing are mostly about digital product, digital equipment, digital process and digital management, which mainly focus on the research in the fields of technology, engineering and industrial production policies and strategies [1-42]. The research results thinking about the factors influencing the digital transformation of manufacturing industry are relatively scattered, and there is no systematic discuss on the affecting factors of manufacturing digital transformation. According to existing literatures, we will systematically analyze the affecting factors of digital transformation of manufacturing companies, identify key factors, to offer the theoretical foundation for manufacturing digital transformation. First of all, this study constructs the influencing factor evaluation system of digital transformation of manufacturing companies and determines the influencing factors of digital transformation of manufacturing companies from the technical level, the ability level, the environmental level. Based on the construction of affecting factors system of digital transformation of manufacturing companies, combined with the related data, this study carries out empirical analysis to demonstrate and verify the affecting factors system of digital transformation of manufacturing companies with the help of hybrid DEMATEL method.

2. Construction of Influencing Factors System

2.1 Technical Level

With the arrival of digital manufacturing technology, the level of technological research and development and technological innovation of manufacturing companies has been improved. As the foundation of digital development of manufacturing companies, information technology plays an extremely important role in the process of digital transformation of manufacturing companies [12]. Now, we have entered the era of industry 4.0. Countries around the world are accelerating a study of digital transformation in manufacturing companies. Key technologies in the period of industry 4.0, such as Internet of things, artificial intelligence, big data and cloud computing, have been fully applied in the manufacturing companies. These technologies promote the development of traditional manufacturing companies towards digital and gradually enhance industrial competitiveness. Kalyaev [13] believed that manufacturing companies could accelerate the digital transformation by increasing the investment in digital manufacturing technology, so as to realize the intellectualization earlier. Li et al. [14] indicated that with the development of the manufacturing companies, digital service platforms such as big data platform, cloud service platform and Internet platform based on information technology are more and more widely used in the manufacturing companies, which has an impact on the digital transformation of the manufacturing companies. He and Bai [15] proposed the application of digital twin technology in digital manufacturing, indicating that the application of this technology can enhance the sustainability of digital manufacturing development, and also proposed the impact of digital manufacturing services and systems on the digital transformation for manufacturing companies. To sum up, the digital transformation of the manufacturing companies will be affected by the technology level. Therefore, this study takes the share of digital technology investment and the level of digital platform construction as the influencing factors of technology level.

2.2 Ability Level

During the digital transformation of the manufacturing industry, the core competence of manufacturing enterprises is the infrastructure of digital transformation in manufacturing. Some scholars had pointed out in their literatures that digital manufacturing technology was an important prerequisite and guarantee for digital development and digital transformation of manufacturing companies [16-17]. Lai et al. [18] analyzed digital manufacturing capability from four aspects: Personnel, resources, technology and manufacturing. Personnel aspects include personnel training and personnel technical level, resources aspects include smart devices and network performance, technology aspects include information security, technology research and development, manufacturing aspects include detailed workflow and warehouse management. Chen et al. [19] constructed 15 indexes to evaluate digital manufacturing capability based on manufacturing scale and efficiency, the ability to innovate in the manufacturing industry, product flow capacity and information development capability. The 15 indexes to evaluate digital manufacturing capability are further used to evaluate the digital manufacturing capacity of 31 cities in China. The evaluation results show that business benefits, innovation input, infrastructure construction and information technology capabilities are very important to the smart development of manufacturing companies. Stadnicka et al. [6] indicated that digital manufacturing systems could be built and optimized by motivating employees to use advanced information technologies such as big data and artificial intelligence. To sum up, the benefit level of manufacturing companies, the technical level of employees and the construction level of digital equipment are taken as the influencing factors of capacity level.

2.3 Environmental Level

As an important driving force of national development, the transformation to digital manufacturing and the realization of digital manufacturing can not only improve the level of industrial development, but also promote national economic development and enhance national comprehensive competitiveness. Therefore, in the transformation of manufacturing, the government, as the guarantee and backing of the development of the manufacturing companies, should ensure the stability of the overall environment for the development of the manufacturing companies. The government should also ensure the high-quality development under the support of the overall environment, manage and restrict the participation of individuals or organizations in the activities of the manufacturing companies through the corresponding economic and social systems. Moreover, the government should supervise and control the product price and product quality according to the regulations in order to promote the digital transformation process of manufacturing companies [20]. The digital transformation of manufacturing companies is not only affected by the government, but also by the industrial innovation ability and industrial support ability. Grodach and Gibson [21] believed that the construction of relevant products, human resources, technical resources and other supporting industries in the region could facilitate the digital transformation of the manufacturing companies. Zhao [22] pointed out in a recent study that the manufacturing companies can minimize the production cost and improve the industrial performance by improving the supporting capacity of the industry. Meanwhile, it can improve the supporting capacity of the industry through the market operation of the government, so as to speed up the digital transformation of the manufacturing companies. In short, government support and industrial support capacity are the influencing factors of capacity level.

Based on research results from related literatures [1-42], we can summarize the influencing factors of digital transformation of manufacturing companies, the influencing factors and descriptions are shown in Table 1.

Table 1
Influencing factors and descriptions

Influencing Factors	Descriptions
Investment share of digital technology F1	Proportion of capital invested in digital technology by manufacturing companies in total investment amount
Construction level of digital platform F2	Business scope and perfection covered by digital service platform
Benefit level of manufacturing companies F3	Total profit of manufacturing
Technical level of employees F4	Information technology application level and R & D level of employees
Construction level of digital equipment F5	Operation process and operation level covered by digital equipment

Influencing Factors	Descriptions
Government support F6	The development of manufacturing enterprises is supported by the government, including financial resources and policies
Industrial supporting capacity F7	Support of relevant industries, products, human resources, technical resources and other factors in the region

2.4 Influencing Factors System

Through the technical level, capability level and environmental level, the relevant influencing factors are obtained in Table 1. The influencing factors system is formed by the relevant influencing factors.

3. Methodology

3.1 Hybrid DEMATEL Method

Decision-making Trial and Evaluation Laboratory (DEMATEL) is a methodology of system science, a method of using of graph theoretic and matrix tools to determine the importance of group elements [23-26]. Based on DEMATEL method, hybrid DEMATEL method uses of graph theoretic and matrix facilities to determine the importance of group elements. Hybrid DEMATEL method expounds the combination of expert evaluation information, expert preferences, interval fuzzy numbers and binary semantics, makes full use of the knowledge mastered by experts, and obtains the interrelationship between influencing factors of system through expert language evaluation, the direct influence matrix. Hybrid DEMATEL method uses matrix and related mathematical theories to calculate the extent of influence, extent of impact, extent of centrality and extent of causality of each influencing factor, determine the bond among influencing factors and identify the critical influencing factors, so as to solve complex social problems.

Si et al. [23] pointed out that DEMATEL is a common decision-making method that can make decisions on problems with incomplete information and limited data. Sun et al. [24] believed that DEMATEL method is an effective tool to analyze the relationship between system factors, it has obvious advantages in solving non-linear and complex social problems, and has become a hot research method of key factors in recent years. Zhou et al. [25] identified 5 key factors from 20 influencing factors of emergency management by using DEMATEL method. Li et al. [26] proposed the mixed decision-making method of DEMATEL method and DS evidence theory, and identified 5 key factors of urban safety management. Although DEMATEL method has many applications in identifying key factors, the semantic transformation mode of experts' original evaluation in this method is insufficient, ignoring the differences caused by different semantic preferences of experts, which makes it impossible to carry out in-depth decision analysis. With the improvement and development of DEMATEL method, considering that experts may have different preferences for the semantic transformation of original evaluation, the hybrid DEMATEL method is proposed, that is, different evaluation matrices are established according to different preferences of experts, the evaluation information is processed by binary semantics, and then processed by DEMATEL method, finally, the key factors are identified with the hybrid ideas, the hybrid ideas lie in the combination of expert evaluation information, expert preferences, interval fuzzy numbers and binary semantics. To sum up, we will use the hybrid DEMATEL method to identify the key factors affecting the digital transformation in manufacturing companies. The key factors for digital transformation of manufacturing companies put emphasis on the importance, significance and criticality of influencing factors of digital transformation of manufacturing companies. The non key factors of digital transformation of manufacturing companies put emphasis on the auxiliary and secondary function of influencing factors of digital transformation of manufacturing companies.

At present, there are some semantic transformation methods in DEMATEL method, like estimation transformation and fuzzy transformation, among which real number, interval number and triangular fuzzy number are more common. If the invited experts have different preferences for semantic transformation, the initial matrix established according to semantic transformation will also be different. We refer to the existing literatures [27-29], three semantic transformation sets of real numbers, interval numbers and triangular fuzzy numbers are given.

i. Real numbers semantic transformation set, using 0, 1, 2, 3, 4 to represent the language evaluation information of no, weaker, weak, strong, stronger.
ii. Interval numbers semantic transformation set, using (0,0), (0,0.25), (0.25,0.5), (0.5,0.75), (0.75,1) to represent the language evaluation information of no (N), weaker (VL), weak (L), strong (H) and stronger (VH).
iii. Triangular fuzzy numbers semantic transformation set, using (0,0,0.25), (0,0.25,0.5), (0.25,0.5,0.75), (0.5,0.75,1.00), (0.75,1.00,1.00) to represent the language evaluation information of no (SN), weaker (SVL), weak (SL), strong (SH) and stronger (SVH).

3.2 Identification Step and Process

To facilitate the construction of the model, we identify the crucial factors for intelligent transformation of manufacturing companies with the following symbols and concepts. The following symbols and concepts are shown in Table 2.

Table 2
Symbols and concepts

Symbols	Concepts
$A_k = \left(a_{ij}^k\right)_{n\times n}$	a_{ij}^k means that the semantic transformation value of the k-th expert's the i-th influencing factor to the j-th influencing factor is a real value, 1 ≤ k ≤ K, A_k represents the initial direct correlation matrix of real numbers established by the k-th expert after semantic transformation.
$B_v = \left(b_{ij}^v\right)_{n\times n}$	b_{ij}^v means that the semantic transformation value of the v-th expert's the i-th influencing factor to the j-th influencing factor is an interval value, 1 ≤ v ≤ V, B_v represents the initial direct correlation matrix of interval numbers established by the v-th expert after semantic transformation.
$C_m = \left(c_{ij}^m\right)_{n\times n}$	c_{ij}^m means that the semantic transformation value of the m-th expert's the i-th influencing factor to the j-th influencing factor is a triangular fuzzy value, 1 ≤ m ≤ M, C_m represents the initial direct correlation matrix of triangular fuzzy numbers established by the m-th expert after semantic transformation.
$AA_k = \left(aa_{ij}^k\right)_{n\times n}$	aa_{ij}^k is the value of evaluation information obtained from the linear transformation of real number information values, 0 ≤ aa_{ij}^k ≤ 1. AA_k is the real number initial direct correlation matrix transformed into A_k.

Make the set of influencing factors is $X = \{x_1, x_2, \cdots, x_n\}$, $S = (s_0, s_1, \cdots, s_{l-1})$ is the bivariate semantic language evaluation set and l is the number of elements in the language evaluation set S. Based on the influence of DEMATEL on scaling, chooses l =5, which can be simply described as $S = (s_0, s_1, s_2, s_3, s_4)$. As shown in Figure 1, $\mu(x)$ is a membership function of the fuzzy number x.

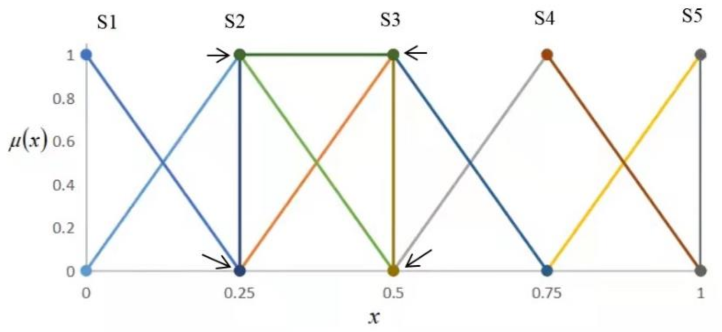

Fig. 1. The relationship between interval fuzzy numbers and binary semantics

Note. The values indicated by the arrows in the figure are binary semantic transformation values of interval or triangular fuzzy numbers.

The main steps and processes of identifying the key influencing factors of digital transformation of manufacturing companies based on hybrid DEMATEL method are as follows:

(1) We invite K+V+M experts to establish the initial direct correlation matrix of influencing factor languages, among which K experts prefer real number semantic transformation, V experts prefer interval number semantic transformation, and M experts prefer triangular fuzzy number semantic transformation.

(2) We linearize real number initial direct correlation matrix with Eq. (1), converts real number initial $A_k = \left(a_{ij}^k\right)_{n\times n}$ to $AA_k = \left(aa_{ij}^k\right)_{n\times n}$, cause $a \le aa_{kij} \le 1$.

$$aa_{ij}^k = a_{ij}^k / \sum_{j=1}^{n} a_{ij}^k \tag{1}$$

We convert $AA_k = \left(aa_{ij}^k\right)_{n\times n}$, $B_v = \left(b_{ij}^v\right)_{n\times n}$, $C_m = \left(c_{ij}^m\right)_{n\times n}$ to binary set matrix $\tau\left(AA_k\right) = \left(s_{qij}^k, \alpha_{qij}^k\right)_{n\times n}$, $\tau\left(B_v\right) = \left(s_{qij}^v, \alpha_{qij}^v\right)_{n\times n}$, $\tau\left(C_m\right) = \left(s_{qij}^m, \alpha_{qij}^m\right)_{n\times n}$, inside q=0, 1, 2, 3, 4.

(3) We convert the binary set matrix values by mapping $\xi : F(S) \to [0, l-1]$ to real values represented by binary semantics.

$$\xi\left(\tau\left(AA_k\right)\right) = \xi\left(F(S)\right) = \xi\left(s_{qij}^k, \alpha_{qij}^k\right) = \sum_{q=0}^{4}\left(q^* \alpha_{qij}^k\right) / \sum_{q=0}^{4}\left(\alpha_{qij}^k\right) = \beta_{qij}^k \tag{2}$$

$$\xi\left(\tau\left(B_v\right)\right) = \xi\left(F(S)\right) = \xi\left(s_{qij}^v, \alpha_{qij}^v\right) = \sum_{q=0}^{4}\left(q^* \alpha_{qij}^v\right) / \sum_{q=0}^{4}\left(\alpha_{qij}^v\right) = \beta_{qij}^v \tag{3}$$

$$\xi\left(\tau\left(C_m\right)\right) = \xi\left(F(S)\right) = \xi\left(s_{qij}^m, \alpha_{qij}^m\right) = \sum_{q=0}^{4}\left(q^* \alpha_{qij}^m\right) / \sum_{q=0}^{4}\left(\alpha_{qij}^m\right) = \beta_{qij}^m \tag{4}$$

(4) We make out the initial direct correlation matrix of binary semantics by different experts, the formula is as follows, where round is the rounded integer operator [28].

$$\Delta : [0, l] \to S \times [-0.5, 0.5)$$

$$d_{ij}^k = \begin{cases} s_{qij}^k = q, q = round\left(\beta_{qij}^k\right) \\ \eta_{qij}^k = \beta_{qij}^k - q, \eta_{qij}^k \in [-0.5, 0.5) \end{cases} \tag{5}$$

$$d_{ij}^v = \begin{cases} s_{qij}^v = q, q = round\left(\beta_{qij}^v\right) \\ \eta_{qij}^v = \beta_{qij}^v - q, \eta_{qij}^v \in [-0.5, 0.5) \end{cases} \tag{6}$$

$$d_{ij}^m = \begin{cases} s_{qij}^m = q, q = round\left(\beta_{qij}^m\right) \\ \eta_{qij}^m = \beta_{qij}^m - q, \eta_{qij}^m \in [-0.5, 0.5) \end{cases} \tag{7}$$

(5) We compute the initial direct correlation matrix of binary semantics after weighted averaging, in Eq. (8).

(6) We normalize the direct correlation matrix to get the normalized direct correlation matrix $G=\left[g_{ij}\right]_{n\times n}$.

(7) We compute the composite influence correlation matrix T, I is Unit Matrix, q is the power of the direct correlation matrix.

$$\left(\overline{s_{ij}},\overline{\eta_{ij}}\right)=\Delta\left[\left(\frac{1}{k}\sum_{i=1}^{k}\Delta^{-1}\left(\overline{s_{qij}},\overline{\eta_{qij}}\right)+\frac{1}{v}\sum_{i=1}^{v}\Delta^{-1}\left(\overline{s_{qij}},\overline{\eta_{qij}}\right)+\frac{1}{m}\sum_{i=1}^{m}\Delta^{-1}\left(\overline{s_{qij}},\overline{\eta_{qij}}\right)\right)1/3\right] \tag{8}$$

$$g_{ij}=\Delta^{-1}\left(\overline{s_{ij}},\overline{\eta_{ij}}\right)/\left(\max_{1\le i\le n}\sum_{i=1}^{n}\Delta^{-1}\left(\overline{s_{ij}},\overline{\eta_{ij}}\right)\right),i,\ j=1,2,\cdots,n \tag{9}$$

$$T=\lim_{q\to\infty}\left(G+G^2+\cdots+G^q\right)=G\left(1-G\right)^{-1} \tag{10}$$

(8) We calculate influence degree R_i , affected degree D_i and center degree P_i , cause degree H_i.

$$R_i=\sum_{j=1}^{n}T_{ij},i=1,2,\cdots n \tag{11}$$

$$D_i=\sum_{i=1}^{n}T_{ij},\ j=1,2,\cdots n \tag{12}$$

$$P_i=R_i+D_i,i=1,2,\cdots n \tag{13}$$

$$H_i=R_i\text{-}D_i,i=1,2,\cdots n \tag{14}$$

(9) We combine influence extent, affected extent, center extent and cause degree to identify the key factors of digital transformation of manufacturing companies.

3.3 Data Description and Interpretation

Based on the construction of the influencing factors system of the digital transformation of manufacturing companies, we carry out analysis of experience of the identification of the key factors of digital transformation of manufacturing companies. First of all, 65 top managers (master degree, more than 15 years of work experience) from large-sized manufacturing companies were invited to rate and score the influencing factors by questionnaires with the help of email. The recovery rate and effective rate of the questionnaires are both 100%. The scoring results of 65 top managers were processed comprehensively and uniformly, and the scoring results of 65 top managers could be summarized into seven types according to the average processing treatment, the comparison of scoring results and the choice of top managers' different semantic transformation preferences. The values of k, v, m, preferences and comprehensive scoring results of seven types are shown in Tables 3-9.

Table 3
Evaluation information from top manager 1

	F_1	F_2	F_3	F_4	F_5	F_6	F_7
F_1	0	2	3	2	4	3	2
F_2	3	0	2	3	2	1	4
F_3	2	2	0	2	3	4	1
F_4	1	3	4	0	2	2	3
F_5	2	1	2	4	0	3	2
F_6	3	4	2	2	1	0	3
F_7	4	2	3	1	2	3	0

Table 4
Evaluation information from top manager 2

	F1	F2	F3	F4	F5	F6	F7
F1	N	L	VL	VH	VH	L	H
F2	L	N	H	L	VL	L	L
F3	VH	L	N	H	L	VH	H
F4	H	L	H	N	VL	L	H
F5	H	H	L	L	N	H	H
F6	L	H	H	VL	L	N	L
F7	L	H	H	L	H	H	N

Table 5
Evaluation information from top manager 3

	F1	F2	F3	F4	F5	F6	F7
F1	SN	SVH	SH	SH	SVH	SH	SH
F2	SVL	SN	SL	SH	SL	SH	SH
F3	SL	SL	SN	SH	SH	SH	SVH
F4	SVH	SH	SH	SN	SL	SVL	SL
F5	SL	SL	SH	SL	SN	SVL	SVH
F6	SVH	SVH	SL	SL	SH	SN	SL
F7	SL	SL	SH	SVL	SL	SVL	SN

Table 6
Evaluation information from top manager 4

	F1	F2	F3	F4	F5	F6	F7
F1	SN	SH	SL	SH	SH	SL	SH
F2	SH	SN	SVH	SH	SL	SH	SH
F3	SVL	SH	SN	SH	SL	SL	SL
F4	SVH	SH	SH	SN	SH	SH	SH
F5	SH	SH	SL	SH	SN	SH	SL
F6	SH	SL	SL	SH	SH	SN	SH
F7	SH	SH	SL	SL	SL	SL	SN

Table 7
Evaluation information from top manager 5

	F1	F2	F3	F4	F5	F6	F7
F1	0	1	2	2	1	3	3
F2	2	0	2	3	1	2	3
F3	1	4	0	3	3	2	2
F4	2	2	3	0	2	1	2
F5	3	3	3	3	0	2	3
F6	2	2	4	1	2	1	2
F7	1	2	3	2	2	4	0

Table 8
Evaluation information from top manager 6

	F1	F2	F3	F4	F5	F6	F7
F1	N	L	H	L	H	L	L
F2	L	N	L	L	L	H	H
F3	VH	H	N	VH	H	H	H
F4	L	L	H	N	L	L	VH
F5	L	L	L	L	N	H	H
F6	L	L	H	L	VH	N	VH
F7	H	H	H	H	VH	VH	N

Table 9
Evaluation information from top manager 7

	F1	F2	F3	F4	F5	F6	F7
F1	0	3	2	3	3	2	3
F2	3	0	4	3	2	3	3
F3	1	3	0	3	2	2	2
F4	4	3	3	0	3	3	3
F5	3	3	2	3	0	3	2
F6	3	2	2	3	3	0	3
F7	3	3	2	2	2	2	0

3.4 Empirical Analysis Processes and Results

Based on the initial direct correlation matrix given by three experts after semantic transformation, the normalized direct correlation matrix G is obtained by calculating step (1)-step (6). Then, we according to step (7), the comprehensive influence correlation matrix T is obtained.

$$G = \begin{bmatrix} 0.0000 & 0.1713 & 0.1213 & 0.1999 & 0.2427 & 0.1499 & 0.1713 \\ 0.0942 & 0.0000 & 0.1437 & 0.1513 & 0.0866 & 0.1361 & 0.1589 \\ 0.1734 & 0.1163 & 0.0000 & 0.1734 & 0.1530 & 0.2184 & 0.1937 \\ 0.1932 & 0.1513 & 0.1875 & 0.0000 & 0.0866 & 0.0866 & 0.1513 \\ 0.1448 & 0.1366 & 0.1448 & 0.1328 & 0.0000 & 0.1244 & 0.2019 \\ 0.1799 & 0.2160 & 0.1437 & 0.0866 & 0.1361 & 0.0000 & 0.1228 \\ 0.1304 & 0.1437 & 0.1799 & 0.0790 & 0.1437 & 0.1228 & 0.0000 \end{bmatrix}$$

$$T = \begin{bmatrix} 1.3078 & 1.4823 & 1.4337 & 1.3660 & 1.4357 & 1.3506 & 1.5710 \\ 1.0828 & 1.0158 & 1.1337 & 1.0405 & 1.0189 & 1.0506 & 1.2176 \\ 1.4410 & 1.4261 & 1.3062 & 1.3277 & 1.3551 & 1.3895 & 1.5653 \\ 1.2735 & 1.2637 & 1.2823 & 1.0222 & 1.1354 & 1.1239 & 1.3406 \\ 1.2517 & 1.2698 & 1.2671 & 1.1476 & 1.0661 & 1.1649 & 1.3955 \\ 1.2784 & 1.3349 & 1.2655 & 1.1189 & 1.1889 & 1.0588 & 1.3384 \\ 1.1532 & 1.1857 & 1.2035 & 1.0286 & 1.1100 & 1.0861 & 1.1322 \end{bmatrix}$$

The influence extent, affected extent, center extent and cause degree are obtained from step (8), Tables 10 and 11 show the results

Table 10
Influence degree and affected degree

Influence factors	F1	F2	F3	F4	F5	F6	F7
Influence degree	9.9470	7.5598	9.8109	8.4416	8.5627	8.5838	7.8993
Affected degree	8.7885	8.9784	8.8919	8.0513	8.3101	8.2244	9.5605

Table 11
Center degree and cause degree

Influence factors	F1	F2	F3	F4	F5	F6	F7
Center degree	18.7355	16.5382	18.7028	16.4929	16.8728	16.8082	17.4598
Cause degree	1.1585	-1.4186	0.9190	0.3904	0.2526	0.3593	-1.6611

From Table 11, we can see that the center degree is F_1, F_3, F_7, F_5, F_6, F_2, F_4 from large to small, and the cause degree is F_1, F_3, F_4, F_6, F_5, F_2, F_7 from large to small. The scores of degrees of centrality and causality of F1 and F3 are higher.

From the point of view of the degree of rationality, the influencing factors can be divided into two categories. The scores of F_1, F_3, F_4, F_6 and F_5 are greater than zero, belonging to the attribute of reason. The scores of F_2 and F_7 are less than zero, belonging to the attribute of result.

The cause score of F_1 is the highest, manifesting that F_1 is the factor that has the biggest impact for other factors, and the center score ranks first, so F_1 is identified as a key factor. The cause degree score of F_2 was negative, indicating that it is vulnerable to other factors, and its center degree ranked sixth, so it is identified as non-critical factors. The cause degree and center degree of F_3 ranked second, and the influence degree of F_3 also ranked second, indicating that F_3 is the key factor. The cause degree score of F_4 is in the third place, but the center degree score is in the end, indicating that the importance of F_4 is not high, and its influence ranking is low, so F_4 is identified as non-critical factors. F5 has the middle ranking of cause degree, cause degree, influence degree and affected degree, which indicates that F5 has little influence on the digital transformation of manufacturing companies, so it is identified as a non-critical influencing factor.F6 has the cause degree ranked in the front, which is a cause attribute, but the center degree is ranked in the back, and then analyze the influence degree and affected degree.F6 has the third highest influence degree and the sixth highest affected degree, so it can be identified as F6 as a F7 has the lowest score for cause and the highest score for influence, and is ranked sixth in influence, indicating that it is more influenced by other factors, so it is determined to be a non-critical factor.

In summary, the key factors influencing the digital transformation for manufacturing companies are F_1, F_3, F_6, the non-key factors are F_2, F_4, F_5, F_7.

For the purpose of test, the practicability and validity of the improved method, we use the traditional DEMATEL method to identification of key factors again. Tables 12 and 13 show the identification results.

Table 12
Influence degree and affected degree

Influence factors	F1	F2	F3	F4	F5	F6	F7
Influence degree	7.5947	6.1641	7.2462	6.6112	6.5752	6.7094	6.3562
Affected degree	6.8415	6.8287	6.9685	6.3019	6.4767	6.6112	7.2284

Table 13
Center degree and cause degree

Influence factors	F1	F2	F3	F4	F5	F6	F7
Center degree	14.4362	12.9928	14.2147	12.9131	13.0519	13.3206	13.5846
Cause degree	0.7532	-0.6646	0.2777	0.3093	0.0985	0.0982	-0.8722

From Table 12 and Table 13, we can see that the center degree by traditional DEMATEL method is F_1, F_3, F_7, F_6, F_5, F_4, F_2 from large to small, and the cause degree is F_1, F_4, F_3, F_5, F_6, F_2, F_7 from large too small. The most important influencing factor is still F_1. The difference between the traditional methods and the improved methods is that F_5 and F_6 are switched in centrality and causality ranking, but the results of key factors identification are not changed. The small differences do not affect the results of decision making. Compared with the principles, operation mechanism, execution procedures of other DEMATEM methods [30-33], the hybrid DEMATEL method can deal with centrality and causality ranking problems effectively, the hybrid DEMATEL method puts emphasis on the combination of expert evaluation information, expert preferences, interval fuzzy numbers and binary semantics, the feasibility, effectiveness and accuracy of the hybrid DEMATEL method are verified.

4. Conclusion and Managerial Implications

We first analyze the factors that affect the digital transformation of manufacturing companies, then identification of key factors through hybrid DEMATEL method, and finally validate the results using the traditional DEMATEL method. The results of the empirical analysis and empirical tests show that the investment share of numerical technique, the benefit level of manufacturing enterprises and government support are the crucial factors, the construction level of digital platform, the technical level of employees, the construction level of digital equipment and industrial supporting capacity are non-key factors. The order of the importance of the key factors from high to low is the investment share of digital technology, the benefit level of manufacturing companies and government support. Meanwhile, it also verifies that the hybrid DEMATEL method for identifying key factors.

In conclusion, in the process of digital transformation of manufacturing, relevant national departments and industry personnel should recognize the significance of digital transformation in manufacturing and do following to ensure smooth progress of digital transformation of manufacturing.

i. Digital technology is the key factor in the transition from manufacturing to intelligence. Digital technology not only determines the level of building digital platform, but also affects the speed of forming digital production system, and then affects the speed of digital transformation of manufacturing. In sum, the manufacturing companies should focus more on digital technology, increase investment in digital technology study and progress and application, promote the digital transformation of manufacturing companies, and further improve the level of manufacturing intelligence.

ii. The benefit level of manufacturing companies as the basis for the operation activities and self-development of manufacturing companies. Its benefit level not only explains the current development status of manufacturing companies, but also the future development prospects of manufacturing companies. The manufacturing companies formulate the digital transformation plan based on its efficiency level. If the efficiency level is high, it can ensure the investment in digital technology and the construction of digital devices, and accelerate the digital transformation of manufacturing companies. Conversely, failed to successfully drive the transformation of manufacturing companies to intelligence, or even affect the current level of intellectualization development. In a word, the manufacturing companies should ensure its efficiency level and provide economic guarantee for its intellectualized transformation.

iii. With the development of science and technology, the government not only formulation of a digital development strategy, information and intelligence for the manufacturing companies, but also provided a better development environment and development policies for the development of the manufacturing companies, which promoted the digital transformation and development of the manufacturing companies. The government is in favor of policies for the manufacturing companies to facilitate the digital development of the manufacturing companies. In a word, the government should play its guiding and supporting role, provide convenience for the development of manufacturing companies, and increase the training of talents to speed up the digital transformation for manufacturing companies.

On the basis of the existing literatures on digital transformation of manufacturing companies, we construct a more systematic influencing factors system of digital transformation of manufacturing companies from technology level, capacity level and environment level, and identify the key and non-key factors. In summary, the study provides the direction of development and theoretical basis for digital transformation of manufacturing companies. When identifying the crucial factors, we use the hybrid DEMATEL method to transform the evaluation information in a specific way, which reduces the errors in the process of transformation and makes the recognition results more accurate. The feasibility and validity of this method are also verified. Compared with the principles, operation mechanism, execution procedures of other DEMATEM methods [30-33], the hybrid DEMATEL method can deal with centrality and causality ranking problems effectively, the hybrid DEMATEL method puts emphasis on the combination of expert evaluation information, expert preferences, interval fuzzy numbers and binary semantics, the feasibility, effectiveness and accuracy of the hybrid DEMATEL method are verified.

In summary, the hybrid DEMATEL method can identify the essential and key factors with higher accuracy, we can provide reference for the consider on the digital transformation of manufacturing companies.

This study is tentative, which fuses hybrid DEMATEL method to identify the crucial factors of digital transformation of manufacturing companies. The influencing factors of digital transformation of manufacturing companies are relatively few, which do not form the systematic framework. Moreover, this study is lack of objective data and large sample data. In the future, we will add more influencing factors to form the systematic framework of influencing factors of digital transformation of manufacturing companies. We will use objective data and large sample data to carry out empirical analysis to increase the universality of research results, reduce the negative impacts caused by multicollinearity.

Author Contributions

Conceptualization, M.C. and B.L.; methodology, M.C.; software, X.Y.; validation, M.C., B.L. and X.Y.; formal analysis, M.C.; investigation, M.C.; resources, M.C.; data curation, M.C.; writing—original draft preparation, M.C.; writing—review and editing, M.C.; visualization, M.C.; supervision, M.C.; project administration, M.C.; funding acquisition, B.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data used to support the findings of this study are available to anyone.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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