# The Structure Analysis of Industrial Association Network in Digital Economy Based on Blockchain Technology

Lin Liu

sophiachina12@126.com

Taishan University. School of Management and Economics, Taian 271000, Shandong, China

**Abstract:** The digital economy, as a new driver of economic growth in China, has garnered extensive attention from various sectors. The 14th Five-Year Plan emphasizes the need to accelerate digital development and promote the deep integration of the digital economy with the real economy. In order to conduct in-depth research on the economic status, industry structure characteristics, and the main industries influenced by the digital industry in China, a network relationship management model was constructed based on blockchain technology. The maximum spanning tree algorithm, Louvain community detection algorithm, and threshold network algorithm were employed to analyze the structural characteristics of China's digital industry within the entire industry network. This analysis provides empirical support at the industry level for advancing the development of China's digital economy. The research findings indicate the following: Firstly, based on the current stage of economic development and industry structure, the digital industry is not the core or leading industry in the Chinese economy. However, it possesses significant potential and room for growth. In the future, consideration can be given to adjusting the macroeconomic structure, strengthening the application of digital technologies in core industries, promoting the adoption of digital technologies in a wider range of industries, and enhancing its overall economic status. Secondly, considering the main industries influenced by the digital industry, there exist variations in the degree of digitalization across different sectors. Therefore, differentiated policies are necessary in practice.

**Keywords:** blockchain technology, digital economy, industrial network, digital industry

## 1 INTRODUCTION

In recent years, China has faced significant downward economic pressure, and the digital economy has received widespread attention as a new driver of economic growth. With the continuous development of a new round of technological revolution and digital technologies, such as big data, the internet, cloud computing, 5G, and artificial intelligence, digital technology has been integrating and developing across various industries and sectors of the economy and society. The digital transformation of traditional industries has accelerated, giving rise to a large number of new economic forms. As the fastest-growing and most promising driver of economic growth, the digital economy has become a crucial development strategy in China, promoting industrial upgrading and digital transformation[1,2].

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After the digital economy was proposed as a major path for China's economic innovation in 2016, research surrounding it quickly gained momentum. Scholars argue that China's digital economy development presents both challenges and opportunities. Due to its unique characteristics, the focus of digital economy research should differ from that of the real economy. Building upon the analysis of digital economy characteristics, scholars have proposed potential future trends and pathways for China's digital economy[3]. China's digital economy development has its own advantages and disadvantages, thus exerting multifaceted impacts on China's high-quality economic growth. Regarding the research status of China's digital economy, scholars have employed national economic accounting methods to construct satellite account frameworks for measuring China's digital economy. Comprehensive analyses have also been conducted using econometric approaches, including the examination of the impacts of technological innovation, government subsidies, industry entry regulations, and the relationship between the digital economy and resource allocation efficiency. On an international comparative level, scholars have investigated the current status of the digital economy in Russia and Central Eastern European countries, the digital economy policies of the European Union, and comparisons of global digital economy development.

Currently, scholars' research on the digital economy primarily revolves around two aspects: firstly, the construction of an indicator system to measure the development differences of the digital economy in different regions and countries from various indicator perspectives, and secondly, the measurement of the volume of the digital economy from an accounting standpoint. These studies contribute significantly to a profound understanding of the development of China's digital economy. As a crucial development strategy in China, the digital economy also faces several urgent issues that require investigation and in-depth research. What is the position of the digital economy and its related industries in China's economic development? What are the relevant industry chains and clusters? Based on China's existing economic structure, what key areas and industries will experience synchronous growth through the promotion of digital economy development? In order to better analyze the intricate relationships between the digital industry and other industries, this study adopts an industrial network analysis method. Using industries as equal network nodes and input-output relationships between industries as network edges, the interconnected relationships between industries are transformed into a network data structure, enabling the analysis of the structured characteristics and development trends exhibited by the digital economy within it[4].

As a distinctive data structure, scholars both domestically and internationally have employed various methods for analyzing the structure of industrial networks. These include social network analysis, network degree and centrality methods, complex network centrality methods, GLW analysis model, knowledge network methods, and others. The application of these methods provides valuable references for the research conducted in this paper. Simultaneously, some scholars have analyzed industrial networks based on input-output tables. An and Sun[5], for instance, studied the dominant characteristics of the energy industry in economic development from the perspective of energy and material flows in industrial networks. Wang et al[6]. investigated the transfer paths of rare earth resources in industrial networks, highlighting industries with the strongest intermediate effects and flow-constraint key nodes in the industrial network. However, there is a scarcity of literature that utilizes industrial network analysis to examine the development characteristics of the digital economy industry[7].

In this study, we constructed a network relationship management model based on blockchain technology. The structural characteristics of China's digital industry were analyzed within the entire industrial network using the maximum spanning tree algorithm, Louvain community detection algorithm, and threshold network algorithm. This analysis provides empirical support at the industry level for promoting the development of China's digital economy and presents two specific findings.

## 2 THE OVERALL ARCHITECTURE OF NETWORK RELATIONSHIP MANAGEMENT BASED ON BLOCKCHAIN

This paper provides a decentralized solution based on blockchain for the network relationship management model, aiming to achieve a balance between security, trustworthiness, and cost-effectiveness. It can offer unified management for diverse network relationships and also verify privacy data without revealing the data itself. The network relationship management model is built on the P2P Kademlia distributed peer-to-peer network. It stores and verifies relationship data while providing user data query services. Additionally, it ensures the integrity of data transmitted within the Fabric network and verifies the integrity of transactions, thus preventing data tampering. The network relationship management model operates without centralized servers and responds to users' data upload and query requests at the node level[8]. The hierarchical architecture is illustrated in Figure 1.

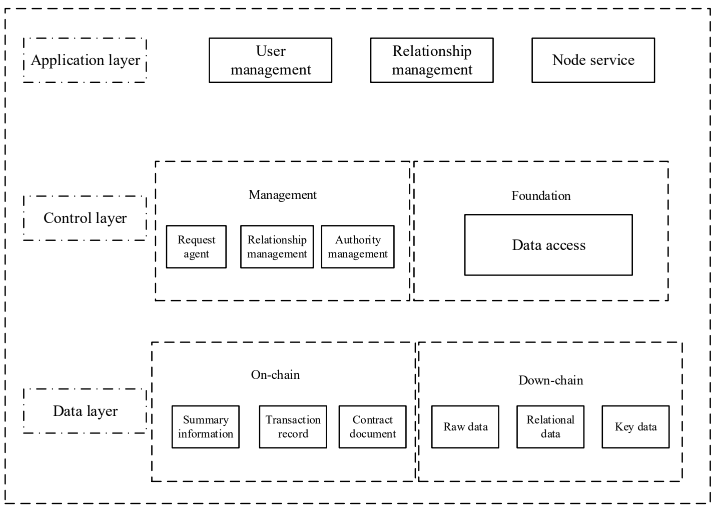


Figure 1. System hierarchy diagram

The core logic of the entire system prototype is illustrated in Figure 1 and can be divided into three layers: the application layer, control layer, and data layer, which are independent yet work collaboratively. The application layer's main function is to facilitate user interaction with the blockchain network through the web frontend application. Users can engage in asset transactions in the external environment, establish network relationships with counterparties regarding assets, and also revoke or view corresponding asset relationships. The Node service plays a specific role in handling user requests[9]. The control layer's primary function is to execute asset transactions through smart contracts, establish network relationships between transacting parties, and define preconditions for relationship establishment, as well as the data state after establishment. The data layer employs a combination of on-chain and off-chain storage. The blockchain's timestamp technology and consensus mechanism ensure the uniqueness of data on the blockchain. Off-chain, Neo4j is used to store raw data, actual transaction data, and historical relationship data, ensuring data uniqueness[10].

# 3 DIGITAL ECONOMY INDUSTRIAL NETWORK ANALYSIS METHOD

## 3.1 Industrial network construction

An industry network refers to a network data structure constructed based on industries as nodes and the connections between industries as edges. In an industry network, each industry serves as an analytical entity within the network, while the relationship between industries highlights their relative importance and the overall network structure. Assuming there are n industrial sectors in an economy, the input-output relationship between industry sectors is represented by matrix $X_{ij}$, indicating the value of products from industry $i$ used as inputs by industry $j$. Since each industry sector can be connected to others, the interdependence among the $n$ industrial sectors can be represented by an $n*n$ matrix.

From a network perspective, the input-output relationship among n industrial sectors can be represented as a network structure, where the industrial sectors serve as vertices and the input-output relationships between sectors serve as edges. This network structure can be denoted as $G = (V, Arc, W)$, where $V$, $Arc$, and $W$ are represented as Equation (1).

$$\begin{cases} V = \{v_1, v_2, v_3, ..., v_n\} \\ Arc = \{arc_1(v_1, v_2), arc_2(v_2, v_3), ...\} \\ W = \{w_1(v_1, v_2), w_2(v_2, v_3), ...\} \end{cases} \quad (1)$$

The vertex set V represents the n industrial sectors, and the weighted directed edge set Arc represents the input-output relationships between the industrial sectors. If there exists an input-output relationship between two industrial sectors, the arc value is set to 1; otherwise, it is set to 0. W denotes the specific weights of the directed edges.

## 3.2 Industrial network feature extraction algorithm

### 3.2.1 Industrial backbone network extraction-Maximum spanning tree algorithm

If the actual network has a large number of edges and a dense structure, it becomes difficult to visually analyze the main relationships within the network. Therefore, it is necessary to retain the strongest industrial connections in the network, and here a spanning tree algorithm is used to extract the backbone network. Classical spanning tree algorithms include the Minimum

Spanning Tree (Prim's algorithm) and Kruskal's algorithm, both of which compute the minimum connected path in an undirected graph. However, in this study, the actual network is a directed weighted graph, where the input and output relationships between industries have a direction, indicating the inputs required by industries in their production and the products consumed by industries in their output. The goal of extracting a spanning tree here is to retain the strongest structural relationships in the network, so the connecting edges are selected based on their maximum weights[12]. This approach is inspired by the basic idea of Kruskal's algorithm but with modifications to the weight part, resulting in the Maximal Spanning Tree algorithm used in this study. The calculation steps are as follows.

Let's assume that *G = (V, Arc, W)* is a weighted directed connected graph with N nodes, and TreeA = (TV, TA, TW) is a subgraph of G. The process of computing the maximum spanning tree, maxTreeA, of graph G can be divided into four steps.

Step 1: Arrange the weights w of all directed edges Arc in graph G in descending order as w1, w2, ..., wn.

Step 2: Select the edge arci1 with the maximum weight and the two nodes corresponding to that edge, and include them in the graph TreeA = (TV, TA, TW).

Step 3: Continue selecting edges in descending order. If the nodes at both ends of the selected edge are not already included in the spanning tree structure, include that edge and the new corresponding nodes in the graph TreeA = (TV, TA, TW). Repeat this step until all nodes in graph G are included in TreeA, that is, V = TV.

Step 4: Check if the number of edges in the graph TreeA is equal to N-1. If the number of edges is less than N-1, then the graph is not connected. In this case, further select edges to include in TreeA, following the same method of selecting edges in descending order while avoiding the formation of cycles, until TreeA becomes a fully connected graph. This will yield the maximum spanning tree of graph G.

### 3.2.2 Industrial network Cluster partition -Louvain algorithm

Industrial clusters refer to a group of industries that naturally form due to interactive relationships such as competition and cooperation. From the perspective of industrial networks, the relationships between industries can vary in terms of density[13]. These distinct relationships are reflected in the network structure, forming various network communities that can be identified using relevant algorithms. In this study, we employ the Louvain algorithm for network community detection, focusing on the exploration of communities in complex networks. The basic idea is to establish a modularity function with a measurement value ranging from -1 to 1, which quantifies the density of internal connections within network communities. The mathematical expression of the modularity function is defined as shown in Equation (2).

$$Q = \frac{1}{2l}\sum_{i,j}[w_{ij} - \frac{w_i w_j}{2l}]\varphi(c_i, c_j) \qquad (2)$$

Here, $Q$ represents modularity, $l$ denotes the total number of edges in the graph. When there is an edge between node $i$ and node $j$, $l$ equals 1; otherwise, $l$ equals 0. $wij$ represents the weight of the edge between node $i$ and node $j$, $wi$ represents the sum of weights of all edges connected to node $i$, $wj$ represents the sum of weights of all edges connected to node $j$, and $ci$ represents the community that includes node $i$. $\varphi(ci, cj)$ is a function where $\varphi(ci, cj)$ equals 1 when $ci$ equals $cj$; otherwise, $\varphi(ci, cj)$ equals 0.

Let's assume the entire network has N nodes, where each node is initially considered as an independent community, resulting in N initial communities. We will consider the impact on the community modularity by incorporating node i into the communities of all its neighboring nodes j. This impact can be divided into two aspects: first, the effect of node i leaving its original community on its community modularity, and second, the effect of node i joining the community of node j on the modularity of the new community. By calculating the impact values generated by all such changes, we can determine the node movement that maximizes the positive influence on the modularity of the two communities. Assuming the independent node i is moved to community C, the increase in modularity resulting from this node movement can be represented by Equation (3).

$$\Delta Q=[\frac{\sum_{in}+2_{W_i,in}}{2l}-(\frac{\sum_{tot}+w_i}{2l})^2]-[\frac{\sum_{in}}{2l}-(\frac{\sum_{tot}}{2l})^2-(\frac{w_i}{2l})^2] \qquad (3)$$

Here, ∑in represents the sum of edge weights within community $C$, ∑tot represents the sum of weights of all connections from nodes in the entire network to nodes in community $C$, $wi$ represents the sum of weights of all edges connected to node $i$, $wi,m$ represents the sum of weights of edges connecting node $i$ to nodes in community $C$, and $w$ represents the sum of weights of all edges in the entire network. The algorithm for partitioning industrial cluster networks into small industrial communities reflects economic clustering behavior.

#### 3.2.3 Industrial network Cluster partition -Louvain algorithm

In order to separately discuss the digital industry and its main supporting industries, it is necessary to extract the industries closely related to the digital industry from the original industrial network for analysis. From a practical computation perspective, this involves taking the nodes in the digital industry network as the center and setting a threshold for their surrounding connection relationships. Nodes with strong connection relationships are retained, while nodes with weak connection relationships are discarded, resulting in the main driving group centered around the digital industry[14].

### 3.3 Data source and data processing

In order to provide a comprehensive and complete reflection of China's industrial economic structure, this study utilizes data from China's Input-Output (I-O) tables as the foundation for constructing the industrial network. The Chinese I-O tables, published by the National Bureau of Statistics, are a set of authoritative data that describe the input-output relationships among industries in China. The intermediate flow matrix in the I-O tables describes the supply and demand relationships of goods and services between industries, thus effectively capturing the interdependencies among industries[15].

The intermediate flow matrix in the Input-Output (I-O) tables is denoted as $X$, where $xij$ represents the element in the *i-th* row and *j-th* column. It quantifies the value of products produced by industry $i$ that are inputted to industry $j$. The magnitude of $xij$ directly measures the strength of the input-output relationship between industry $i$ and industry $j$. In the subsequent construction of the network relationships, the element $xij$ in the intermediate flow matrix represents a directed edge from industry node $i$ to industry node $j$ with a weight of $xij$. Similarly, the element $xji$ in the intermediate flow matrix represents a directed edge from industry node $j$ to industry node $i$ with a weight of $xji$. Although both $xij$ and $xji$ measure the connection between industry $i$ and industry $j$, they differ in terms of the direction and numerical value in the network relationships.

The official Chinese Input-Output (I-O) tables for the years 2007, 2012, and 2017 are based on actual survey data and provide detailed industry classifications. For other years such as 2010 and 2015, the I-O tables are estimated based on the results of the previous surveys, with industry classification consisting of 42 sectors. Therefore, in this study, the 2007, 2012, and 2017 Chinese I-O tables serve as the foundational data, and they are standardized to a common classification system with 130 industry categories to construct the industrial network for computational analysis.

# 4 ANALYSIS OF INDUSTRIAL NETWORK STRUCTURE OF DIGITAL ECONOMY

## 4.1 Construction of industrial network of digital economy

Based on the formulas and the data from the 2007, 2012, and 2017 Chinese Input-Output (I-O) tables, the industrial networks for each of these three years can be constructed. The visual results are shown in Figure 1.

Due to the intricate relationships between industries, the visual effects of the network are not prominent, requiring further quantification and structural analysis. The industrial networks for these three years all consist of 130 nodes, including 12 nodes related to digital hardware manufacturing, 2 nodes related to digital software and services, and 2 nodes related to digital data.

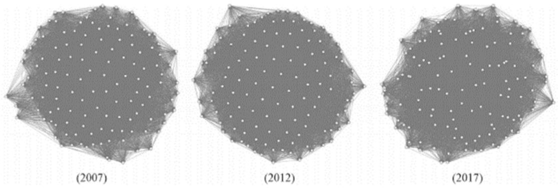


Figure 2. Industrial network time sequence diagram based on input-output table data

The number of network edges in the Input-Output (I-O) table networks is shown in Table 1. Looking at the annual changes in the number of directed edges in the I-O table networks, from 2007 to 2012, the number of connected edges increased from 13,121 to 13,404, indicating a wider and more pervasive inter-industry relationship. In 2017, the number of connected edges in the I-O network decreased to 12,638, suggesting a weakening of the mutual interdependence in input-output relationships between industries. This indicates a more intensive and endogenous production relationship, with intermediate inputs being "purer" than before, and production processes becoming clearer and more specialized.

Table. 1. Number of directed edges in input-output network

| Network edge number | 2007 | 2012 | 2017 |
|---|---|---|---|
| Global network | 13121 | 13404 | 12638 |
| Digital hardware manufacturing class | 2335 | 2496 | 2495 |
| Digital software and services | 406 | 424 | 432 |
| Digital data class | 428 | 434 | 426 |

The trends in the number of network edges in the digital industry exhibit different characteristics. For the digital hardware manufacturing network, the number of connected edges increased from 2,335 in 2007 to 2,496 in 2012, remaining relatively stable at 2,495 in 2017. The digital software and services network consistently showed a growth trend, with the number of connected edges increasing from 406 in 2007 to 428 in 2012, and further rising to 432 edges in 2017. The digital data network saw an increase in connected edges from 425 in 2007 to 434 in 2012, followed by a decrease to 426 edges in 2017. Overall, the trends in the number of network edges in the digital industry are higher than the average level of the overall network, with the digital software and services industry exhibiting the most active growth.

### 4.2 Analysis on radiation effect of industrial network in digital economy

Although the digital industry does not hold a central position in the overall economic structure of China and has yet to establish a strong leading industry effect, it is still possible to identify the main radiating scope of the digital industry based on China's current digital economic development strategy and existing industry structure. From the perspective of industrial networks, the 16 industry classifications within the digital industry interact with each other, and each refined industry classification can interact and associate with other non-digital industries. This interactive relationship can be filtered through a threshold network to extract the main radiating effects of the digital industry.

Based on the input-output coefficient matrices of 2007, 2012, and 2017, the directly constructed industry network relationship is highly dense and difficult to discern, as shown in Figure 1. In order to better identify the industry relationships that are significantly associated with the digital industry within the network, cumulative distribution graphs of the weighted associations between the digital industry and other industries in 2007, 2012, and 2017 were separately plotted, as shown in Figure 3-5. It can be observed that the strength of associations between industries falls within the range of [0, 0.472]. Among them, the industry connections with values in the range of [0, 0.01] account for approximately 90% of all connections, while the industry connections with values in the range of [0.01, 0.472] make up 10%. These industry associations represent the main radiating effects that this study aims to analyze. From the perspective of associations with the digital industry, if the threshold value is too small, it fails to highlight the main relationships within the network, resulting in poor discernibility and visualization effects.

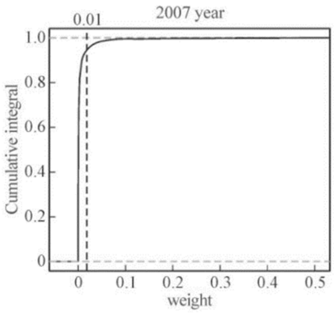


Figure 3. Digital Industry Network weight cumulative Distribution Map (2007)

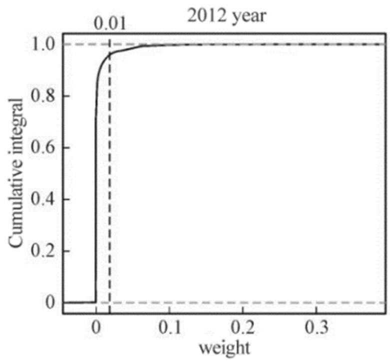


Figure 4. Digital Industry Network weight cumulative Distribution Map (2012)

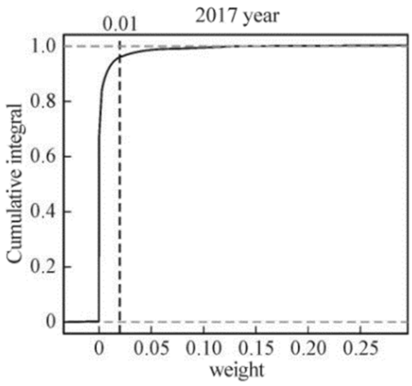


Figure 5. Digital Industry Network weight cumulative Distribution Map (2017)

In order to provide a clearer and quantitative description of the main associations between the digital industry and non-digital industries, a table format is adopted here to present the primary associated industries and their respective association weights with the digital industry. Due to the numerous subcategories within the digital industry, this study analyzes representative industry classifications from three major domains: digital hardware manufacturing, digital software and services, and digital data. The selected industries are computer manufacturing, software and information technology services, and news and publishing. Based on the threshold network calculations for 2007, 2012, and 2017, the main associated industry types for these three representative digital industries are displayed in Table 2.

Table 2. Typical digital industry related industry type and correlation intensity

| Related industry | Correlation weight |
|---|---|
| Business service | 0.0823 |
| Professional technical service | 0.0725 |
| Finance industry | 0.0428 |
| Wholesale and retail trade | 0.0128 |
| Business service | 0.0117 |
| Insurance | 0.0102 |
| Construction industry | 0.0114 |

## 5 CONCLUSION

This paper builds a network relationship management model based on blockchain technology, aiming to deeply study the economic status quo, industrial structure characteristics and major industries affected by China's digital industry. By using maximum spanning tree algorithm, Louvain community detection algorithm and threshold network algorithm, we analyze the entire industrial network and reveal the structural characteristics of Chinese digital industry. This study provides empirical support for promoting the development of China's digital economy and provides reference for relevant decision-makers at the industry level. The results show that from the perspective of economic development stage and industrial structure, digital industry is not the core industry or the leading industry in China's economy. However, the digital industry has huge potential and room for growth. Therefore, the future development can consider adjusting the macro-economic structure, strengthening the application of digital technology in core industries, promoting the application of digital technology in a wider range of industries, so as to improve the status of digital industry in the overall economy.

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