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Distinguishing Supportive Activities at Industry-Level Value Chain Analysis

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Abstract: *Although globalization gives us a more efficient product system, recent collapse of the Global Value Chain raises a severe problem for a company's sustainability. This study aimed to identify supportive activities of industry-level value chain using social network analysis. We used reported transaction data from a Korean-credit rating company in the investigation. By applying analysis of structural equivalence, we classified some companies in the transactional network. In addition, we identified the group classified as supportive activities in the industrial value chain using network parameters. This result will provide vital information to establish corporate-level strategies considering their industry-level value chain. Moreover, this result is a starting point to classify primary activities in the industry-level value chain accurately.*

Keywords: Industry-Level Value Chain; Supportive Activities; Network Analysis; Structural Equivalence

1. Introduction

A global value chain(GVC) could be said to be an integrated system or structure of business value creation that contains every activity and resource spanning multiple countries [1]. GVC, commonly led by large multinational enterprises(MNEs), deeply impacts not only the global market but also small medium-size enterprises(SMEs)'s competitiveness and their environments [2-4]. Around 70% of international trade is linked with GVC because every service, raw materials, and components across borders [5]. In recent years, building the optimal GVC has become an issue in the global society. Furthermore, it has intensified throughout the COVID-19 period.

The issue of GVC is linked with the sustainability of an enterprise, and it affects the securing of raw materials for product production, technology dependence, and appropriateness of production timing [6]. Every company wants to make the right decision to maintain a competitive position in the market and improve its profitability. In order to achieve their wishes, the company makes great efforts to establish strategic planning that reduces the costly incident from a mistake. Therefore, one of the conceptual frameworks for strategic planning, Industry-level VC analysis, can keep the company growing continuously.

Value chain analysis is a method for decomposing the firm into strategically essential activities and understanding their impact on cost behavior and differentiation [7]. It consists of a series of processes in which products are developed, produced, and sold. It includes supply chain activities such as the supply of materials, product's production, and sales. It includes various corporate activities such as firm infrastructure, human resource management, technology development, and procurement. The overall diagram is shown in Figure 1.

Since the concept of the value chain was conceived by Porter M.E [7], research about the value chain has evolved in various forms. One argument is about analyzing at what level. Firstly, the value chain analysis was applied at a firm-level to understand the internal activities of a company and to enable appropriate strategic planning. After that, the concept was extended to industry-level value chain analysis for identifying the interrelationships between suppliers and buyers in a particular industry. Porter also called it a value system [8]. In firm-level value chain analysis, cost analysis is conducted using company internal information for the efficiency of business management. On the other hand, in the industry-level, connectivity analysis is conducted between participants in the value creation process for searching the characteristics of the industry. These two concepts have been mixed and used so that the current typical value chain theory includes individual corporate and industrial units [1].

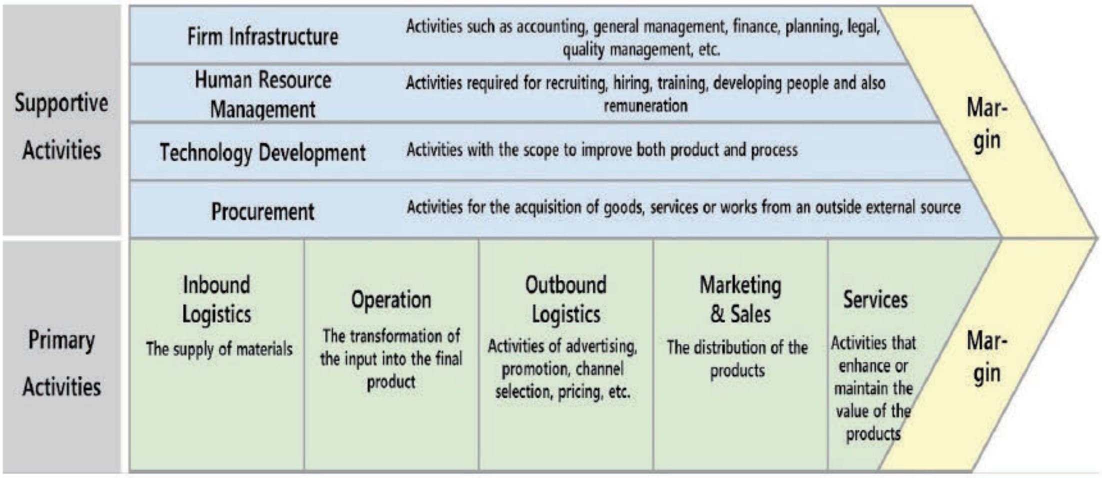

Figure 1. Typical value chain diagram excerpted from M. Porter [7]

Even if the concept of value chain theory has been mixed up and used between firm-level and industry-level, most existing value chain analysis has stayed at the firm-level due to its low utility over high cost [9]. Thus, most of the current research has been carried out by relying on cost-driven accounting data. To compose the industrial-oriented value chain, it is crucial to reserve transaction data for each company. Credit card or tax invoice information that can measure a company's transactions in real-time may be accurate. However, it is difficult to collect them since the company has secured these data to protect their business secrets. In Korea, some institutes that analyze the company credit information voluntarily offer the transaction data of the company. In this study, industry-level value chain analysis is conducted by using the data.

In current value chain analysis, distinguishing the primary activities is surely important, but it is also important to distinguish the supportive activities in advance to find out what kind of support the company is getting. Supportive activities are various activities not in the mainstream of creating value that is shown in Figure 1. It performs the role of supporting the primary activities. Although it is a part of the value chain, supportive activities are not composed of corporates in the target industry. To search the more accurate characteristics of industry, it is essential to distinguish it from the primary activities.

In recent years, the network analysis has been widely applied on value chain analysis to examine structure, participation and connectivity of the value chain [10]. With the network analysis, GVC could be simplified and conceptualized. Cerina et al. [11] used the network analysis method to study GVC as weighted directed networks by using World Input-Output Database(WIOD) and Xing et al. [12] suggested the betweenness centrality that is the parameter from network analysis as a key measurement to analyze the transfer route in GVC. The study from Ozman [13], it is identified that the network analysis and value chain analysis are in the same context.

Therefore, this study aims to apply the structure equivalence concept and network analytic method to distinguish the supportive activities at the industry-level. An algorithm for that purpose will be suggested. In addition, the result of applying the algorithm to some industries will be also presented.

In this paper, the algorithm is applied in two industries, the manufacture of flat display components and the manufacture of semiconductors. The results of algorithm and its discussion is treated at chapter 3 and 4. This paper will provide vital information to establish corporate-level strategies considering their industry-level value chain. Moreover, it will be a starting point to classify the primary activities in the industry-level value chain accurately.

2. Materials and Methods

2.1 Data

This study was conducted with the intercompany transaction data from the NICE Information Service Co., Ltd. That is a financial infrastructure service company providing corporate credit information and credit management service in Korea. The data is based on the transaction history voluntarily reported by the company as of the fiscal year, and the final mashup database was made up by adding the enterprise information data from the NICE.

In the case of the intercompany transaction data, each company directly reported high-scale sales details traded during the year. Thus, the sum of sales in the transaction data about a company often does not equal the company's total sales which are officially reported. This disparity is a potential factor that can cause severe problems in the overall analysis. Therefore, in this study, the analysis focused on the occurrence of transactions rather than sales. Also, in terms of the total revenue, we used reliable data in the company's formal accounting report.

Within the database, two industries were chosen based on a classified table from Korea Standard Industrial Classification(KSIC). One was the manufacture of flat display components industry (C2621, KSIC), and the other was the manufacture of semiconductors(C261, KSIC). The period of data for both industries was the year 2019, directly traded with the same industries. For C2621, the total number of transactions(links) used in the analysis was 4035, and the total number of actors(nodes) was 3053. For C261, the total number of transactions was 47246, and the total number of actors was 26111.

2.2 Used environment for analysis

The data analysis was carried out by the Python version 3.8.5 with the Jupyter Notebook through the virtual environment of Anaconda. For the database and data cleansing, Pandas version 1.4.2 was used, and Scikit-learn version 1.0.2 which is a popular machine learning package, was also used for conducting agglomerative clustering and calculating silhouette scores. Agglomerative clustering is the method to conduct modularization based on structural equivalence as a matrix form input and silhouette score is one of the popular methods to determine optimal parameter 'k' for the clustering that finally affects to determine the number of modules. For the network analysis, NetworkX version 2.7.1 which is for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks was imported.

2.3 Network analysis

Network analysis is a well-known methodology, especially in social science. By the network analysis, researchers can analyze the related structures that appear from the recurrence of these relations and display relations between actors [14].

Ozman suggested a cyclic causal model of network research, which was presented in a literature study on inter-corporate networks [13]. By the study, it is verified that the theoretical background of Porter's value chain analysis and network analysis between companies are in line as the following list and Figure 2 shows its circular structure.

- An emphasis on identifying the source of sustainable competitive advantage.
- An insistence on the importance of complex linkage and interrelationship.
- The identification of generic strategies which must be pursued consciously and coherently in the different value-creating activities.

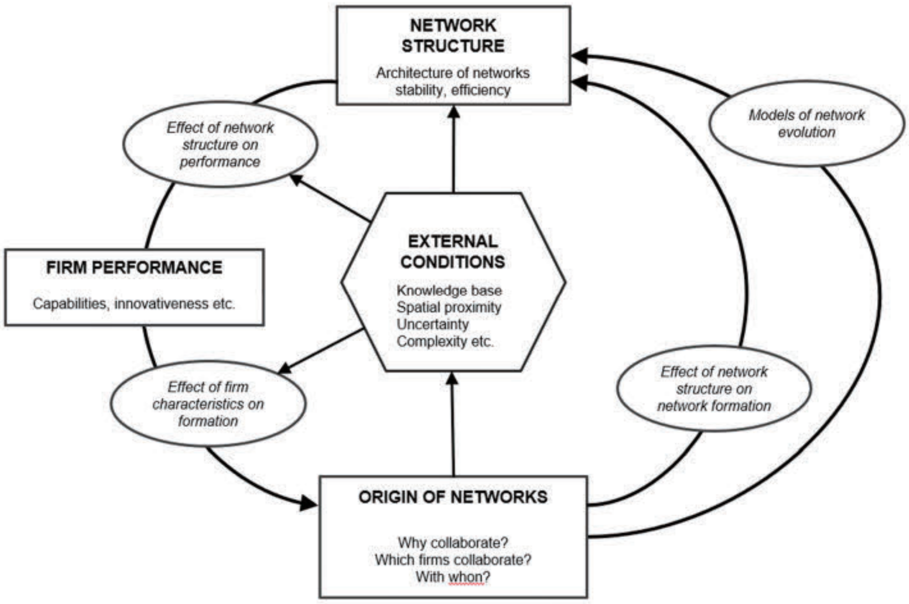

Figure 2. Circular flow diagram of network research adapted from Ozman M. [13]

The network graph was created based on the transaction data, and network parameters were obtained from the graph. In this study, the following three network parameters were mainly used, in-degree centrality, out-degree centrality, and betweenness centrality.

Degree centrality is one of the basic parameters from a network [15]. The degree centrality of an actor(node) can be easily expressed as the number of links(edges) that the actor has. In that context, in-degree centrality is the number of links from other nodes to the corresponding node and out-degree centrality is the number of links from the corresponding node to other nodes. In-degree centrality(inDCi) and out-degree centrality(outDCi) are given by,

$$inDC_i = \frac{in\_d_i}{g-1} \tag{1}$$

$$outDC_i = \frac{out\_d_i}{g-1} \tag{2}$$

Betweenness centrality is the degree which one node is located in the shortest path between the other nodes [12], and betweenness centrality(BCi) is given by,

$$BC_i = \frac{\sum_{j<k} g_{jk}(n_i)/g_{jk}}{(g-1)(g-2)} \tag{3}$$

2.4 Structural equivalence

In the network analysis, the layers of nodes that are similarly located in the network say the position. The criterion for dividing the layers is equivalence, and structural equivalence means that the two nodes have completely the same connection relationship for all other nodes [16, 17]. Figure 3 shows well about the idea of structural equivalence. So, based on the homogeneity assumption, structural equivalence is estimated that nodes with similar sources and destinations play the same role. By the homogeneity assumption, actors which have the same structural equivalence also share other similarities such as attitude, behavior, and outcome. It means that they have similar reactions when they are in similar environments.

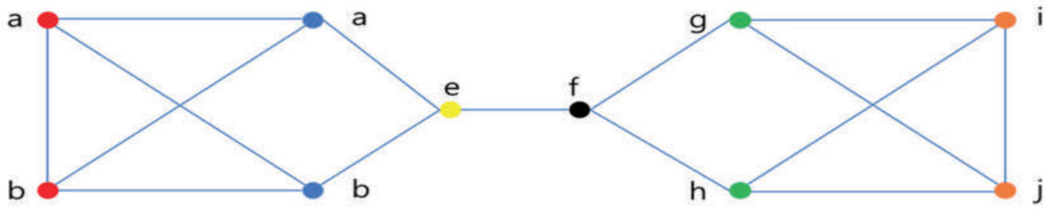

Figure 3. Example of structural equivalence adapted from Lorrain F. and White H. [16]

In the network, two equivalent nodes are usually distinguished by the degree of connection, same centrality, and label, and they have features to replace each other perfectly. Accordingly, it is often used as a data reduction tool because it can build a simplified network model without sacrificing the essential characteristics of the network [18]. Nevertheless, the definition of structural equivalence is an ideal mathematical model, and it is a rare phenomenon in reality. Therefore, researchers try to measure the degree to which actors are structurally equivalent to each other in actual analysis.

There are some noted ways to measure the degree of structural equivalence, but in this study, hierarchical clustering with the input data formed as a matrix was used. Hierarchical clustering analysis modularizes(clusters) all nodes by identifying the structural equivalence of each node with the advantage of higher speed than the others. In the Python library, Scikit-learn, provides the agglomerative clustering method as a type of hierarchical clustering.

2.5 Algorithm

The algorithm is operated with the modularized data and the network parameters. Each module(cluster) has network parameter information and company information that belongs to a module, including the revenue. At first, users input some parameters such as target year and target industry codes, and the database is composed based on the input values. The first clustering(modularizing) is carried out, and module data is generated. After the algorithm brings a module data in turns, it judges in-node bias which means that the nodes belonging to the target industry must not exceed 5%.

Next, the algorithm conducts by checking the betweenness centrality. If the module has a low betweenness centrality value, the nodes gathered in the module have a high possibility that they do not have an essential role in the network. It means that the module should be divided into supportive activities.

Finally, it checks whether the module has quite high out-degree centrality value and low in-degree centrality value. High out-degree centrality and low in-degree centrality mean that transaction of the nodes in the module mainly does not purchase any product from these industries.

Through these processes, the algorithm lastly determines whether the modules are supportive activities or not. The whole process is shown in Figure 4.

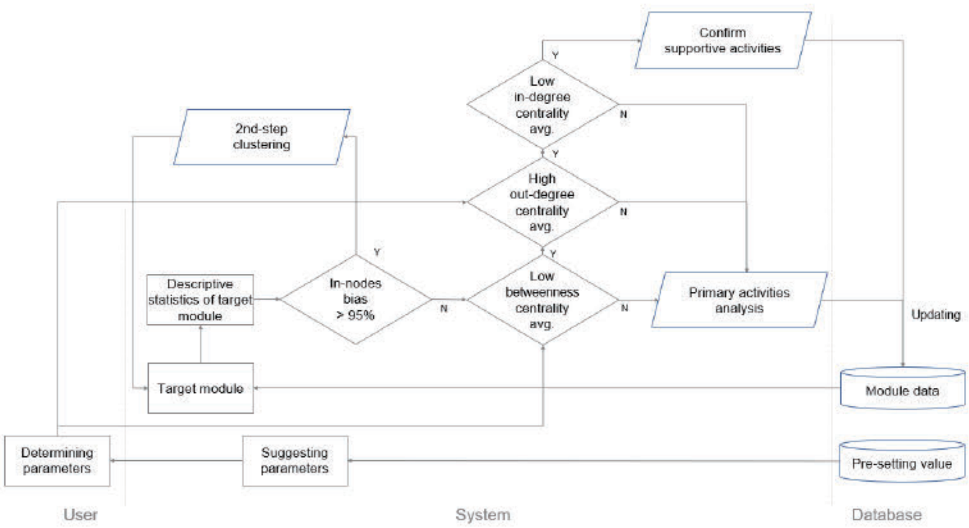

Figure 4. Algorithm for determining the supportive activities

3. Results

3.1 Case 1: Manufacture of flat display components industry(C2621)

Table 1 and 2 are the result of applying the algorithm to the C2621 industry. As shown in Table 1, module 4 consists only of nodes in the target industry (representing 'in nodes' in the table), C2621. While module 4 has zero betweenness centrality and in-degree centrality, out-degree centrality is clearly of high value. Thus, the algorithm determined module 4 as supportive activities.

Table 2 shows compositional companies of module 4. Most industry codes consist of information and communication industry starting with J and the others are technology service industry and retail industry starting with M and G respectively. Their representative products are software development, enterprise solution, E-commerce-related authentication service, import and export cargo information, machine parts retailing, and certification service. With this information, it is proper to determine module 4 as supportive activities.

Table 1. The result value of network parameter by applying algorithm to the C2621 industry

Module number	Number of all nodes	Number of in nodes	Representative company	Bet. avg.[1]	OD avg.[2]	ID avg.[3]
0	1953	389	E-MART Inc., Coupang Corp., HANWHA Corp.	0.000009	0.000219	0.000392
1	370	17	LG Electronics Inc., LG Uplus Corp., SK Telecom Co., Ltd.	0.000336	0.000742	0.0002
2	507	58	HYUNDAI GLOVIS Co., Ltd., HYUNDAI WIA Corp., HYUNDAI TRANSYS Inc.	0.000173	0.000587	0.000403
3	4	4	Samsung Display Co., Ltd., LG Display Co., Ltd., OVERDIGM, Inc.	0.014822	0.004587	0.05824
4	6	0	DOUZONE BIZON Co., Ltd., MISUMI Corp., KTNET	0	0.018676	0
5	212	3	LS Cable & System Asia Ltd., LX Pantos Co., Ltd., LS ELECTRIC Co., Ltd.	0.000071	0.000634	0.000087
6	1	1	EROSDISPLAY Corp.	0.036113	0.057012	0.027195

[1] Average of betweenness centrality

[2] Average of out-degree centrality

[3] Average of in-degree centrality

Table 2. The information of companies belonging to module 4, C2621

Company	Industry code	Scale	Product	Transaction freq.
ECOUNT Inc.	J58222	Small	Software development	46
DOUZONE BIZON Co., Ltd.	J62010	Middle	Enterprise solution	46
CROSSCERT: Korea Electronic Certification Authority	J58221	Small	E-commerce-related authentication service	65
KTNET	J63111	Middle	Provision of import and export cargo information	104

MISUMI Corp.	G46599	Middle	Machine parts wholesale and retail	58
ICR Corp.	M72919	Small	Certification service of technical test and inspection	23

3.2 Case 2: Manufacture of semiconductors industry(C261)

The result of analyzing the C261 industry is shown in Table 3 and 4. Module 13, 14, 15, and 16 were classified as supportive activities by the algorithm. These modules only have the in-nodes, which means all the nodes in the modules belong to the target industry. Also, they are composed with low betweenness centrality and in-degree centrality, and high out-degree centrality.

Table 4 shows compositional companies of modules that are determined as supportive activities. As in case 1, the most are belonging to industry code starting with J, and starting with H and O are also in it. Representative products are almost the same with case 1, and it seems enough to judge as supportive activities.

Table 3. The result value of network parameter by applying algorithm to the C261 industry

Module number	Number of all nodes	Number of in nodes	Representative company	Bet. avg.	OD avg.	ID avg.
0	3	1	SK hynix Inc., KEPCO, KT Corp.	0.020583	0.002349036	0.003192
1	5	2	LX Semicon Co., Ltd., SFA Semicon Co., Ltd., COMUNICATION WEAVER Co., Ltd.	0.0001	3.83E-05	0.000835
2	108	75	LS ELECTRIC Co., Ltd., DB HiTek Co., Ltd.	0.002782	0.000876278	0.002067
3	3	2	KITECH, KOSTAT Inc., I&C Technology Co., Ltd.	0.025286	0.003778884	0.01103
4	36	34	Amkor Technology Inc., STATS ChipPAC Korea Ltd., Lumens Co., Ltd.	0.00605	0.002136261	0.006052
5	115	48	KOREA ELECTRIC TERMINAL Co., Ltd., Sungho electronic Co., Ltd., ODTech Co., Ltd.	0.001457	0.000481242	0.000379
6	14	7	Chung Ho Nais Co., Ltd., DOUZONE BIZON Co., Ltd., SGS Korea Co., Ltd.	0.00611	0.008863599	0.002068
7	2	1	MISUMI Corp., CP&T Corp.	0.02257	0.02541172	0.004596
8	67	25	HiMsolutek Corp., Barom Korea Co., Ltd., SEOIL ELECTRONICS Co., Ltd.	0.000402	0.001712045	0.000159
9	991	622	Hanwha Systems Co., Ltd., Humax Co., Ltd., SK Hynix System IC Inc.	0.000236	0.000180251	0.000363
10	221	144	ON Semiconductor Corp., ITM Semiconductor Co., Ltd., Signetics Corp.	1.19E-06	3.47E-07	0.000456
11	8996	1208	SAMSUNG ELECTRO-MECHANICS Co., Ltd., Samsung Engineering Co., Ltd., HANWHA Corp.	2.55E-08	7.66E-08	5.40E-05
12	15495	1659	SAMSUNG SDS Co., Ltd., Renault Korea Motors Co., Ltd., NAVER Corp.	8.21E-06	6.43E-05	1.80E-05
13	1	0	KOREAN AIRLINES Co., Ltd.	0.000874	0.004825737	3.83E-05

14	2	0	LG Uplus Corp., SK Telecom Co., Ltd.	0.002178	0.001780927	3.83E-05
15	4	0	KTNET, CROSSCERT: Korea Electronic Certification Authority, ECOUNT Inc.	0	0.021447721	0
16	1	0	Incheon Regional Customs	0.006352	0.002221371	3.83E-05
17	1	0	Samsung Electronics Co., Ltd.	0	0	0.000421
18	1	0	HYUNDAI MOTOR COMPANY	0.003195	0.000191498	7.66E-05
19	1	0	LG Electronics Inc.	0.003819	0.000191498	0.000345
20	3	0	Samsung Display Co., Ltd., LG CHEM. Ltd., Hyundai Oilbank Co., Ltd.	0.000192	3.83E-05	6.38E-05
21	12	0	KIA Corp., POSCO, HYUNDAI MOBIS	0	0	7.66E-05
22	9	0	HYUNDAI GLOVIS Co., Ltd., E-MART Inc., SK Networks Co., Ltd.	0.000206	0.00020852	8.94E-05

Table 4. The information of companies belonging to module 13, 14, 15, and 16, C261

Company	Industry code	Scale	Product	Transaction freq.
KOREAN AIRLINES Co., Ltd.	H51100	Large	Air transport	127
LG Uplus Corp.	J61220	Large	Communication, voice, and data service	61
SK Telecom Co., Ltd.	J61220	Large	Communication, voice, and data service	34
KTNET	J63111	Middle	Provision of import and export cargo information	724
CROSSCERT: Korea Electronic Certification Authority	J58221	Small	E-commerce-related authentication service	577
ECOUNT Inc.	J58222	Small	Software development	425
BusinessOn Communication Co., Ltd.	J58222	Small	Electronic tax invoice issuance service	514
Incheon Regional Customs	O84114	Gov.	Customs duty	59

4. Discussion

The algorithm developed through the study sorted the supportive activities to a certain extent. It is reasonable to judge like that because the nodes in modules of supportive activities are famous companies in Korea servicing authentication, cargo, invoice, and so on.

However, it is also true that some nodes that should be judged as supportive activities are in general modules. For example, 'DOUZONE BIZON Co., Ltd.' sorted as supportive activities in case 1 is in module 6 of case 2 which are primary activities. Because the algorithm modularized the network by the concept of structural equivalence, actors(nodes) that play similar roles within the network structure have been bound together even if the actors are not in the target industry. To overcome the problem, stepwise clustering could be the way known to be helpful in complex networks [19].

In this study, the algorithm classifies the modules by the network parameters such as betweenness centrality, in-degree centrality, and out-degree centrality. Low betweenness and in-degree centrality and high out-degree centrality are keys for determining supportive activities. Still, there are some modules that are not distinguished as supportive activities despite fulfilling the conditions. It happens due to in-nodes (belonging target industry) and out-nodes (not belonging target industry) mixed. As mentioned before, there is a difficulty occurring to the characteristic that structural equivalence is an ideal mathematical model. It is complicated to distinguish the supportive activities thoroughly, but it should be somewhat surmountable by advancing the algorithm.

Lastly, comparing case 1 and case 2, the algorithm seems to be more well operated in small-size networks. Also, as the network becomes more extensive, there is a problem that the required computational power increases exponentially when computing the structurally equivalent degree and the network parameters. For the appropriate compromise, a moderate threshold for the number of transactions needs to be set. If the limit is exceeded, there is room for upgrading the algorithm in a way that uses other features.

5. Conclusions

This paper proposed an algorithm to distinguish the supportive activities within the industry-level value chain analysis using the network parameters. Distinguishing the supportive activities is the first step to conducting value chain analysis at industry-level. The proposed algorithm performed well in the C2621 industry as well as in the C261 industry. Separating the supportive activities for accurate industry-level value chain analysis plays a significant role in corporate business strategies such as risk management, stock management, and future planning.

However, it also has limitations. Due to the algorithm just tested for two cases in the manufacturing industry, it did not reflect the inherent diversity of various industries. Although the algorithm worked well, it does not perfectly distinguish the supportive activities. Also, this study exposed the weaknesses in a large size network.

So, the future study will conduct the test and develop the algorithm by applying it in various industries. It will help to find optimized parameters to be preset, and it makes the algorithm more robust. The utility of stepwise clustering shall also be verified. It is expected that stepwise clustering will work to overcome the disclosed weak point. Indeed, a way to properly position the modules in primary activities has to be studied.

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Conflicts of Interest: The authors declare no conflict of interest.

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