AN ANALYSIS ON THE EVOLUTIONARY CHARACTERISTICS OF INDUSTRIAL DNA FROM SMART CITY PERSPECTIVES IN SOUTH KOREA

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ABSTRACT:

This study aims to analyse the evolutionary characteristics of industrial DNA from a smart city perspective. Evolutionary characteristics are the structure of industrial DNA and the relationship between industries DNA cluster. The analysis results are as follows. Firstly, the structure of the smart city industry DNA has changed. The structure of the smart city industry DNA cluster investigated in 2000 as the fusion of knowledge service and IT service with traditional service industries such as public, wholesale and retail services. On the other hand, in 2019, the structure of the smart city industry DNA showed as a fusion of ITM and traditional manufacturing such as transportation equipment, machinery, and construction. This result means that the industrial structure has changed from an industrial structure for informatization of knowledge and administration to an industrial structure for smartisation of manufacturing. Second, the relationship between the smart city industrial DNA cluster and other industrial DNA clusters changed from independent to dependent. This means a change in the location of the smart city industry DNA cluster. The smart city industry DNA cluster showed an independent relationship with the traditional industry DNA cluster in 2000. On the other hand, the relationship between the smart city industry DNA cluster and the entire industry cluster was investigated as a dependent relationship in 2019. This result means that the smart city industry DNA cluster is not easy to grow independently.

1. INTRODUCTION

Investments in the smart city industry are rapidly increasing around the world. The global smart city industry is expected to reach $2 trillion by 2027 (Frost and Sullivan, 2018).

The smart city industry market structure is expanding in its size and shifting in its structure in South Korea and abroad. The conventional industry is transforming by conversing with the smart industry. As a representative example, automobiles in the past had clustered machineries such as accelerators and engines. However, the present day shows a smart industry structure in which machines and smart technologies (contents, etc.) are merged and clustered, such as a smart car. Such examples can be found in various smart city cases, including smart buildings, smart farms, smart real estate (Airbnb), and smart mobility (Uber). As such, inter-industry convergence evolves the smart city industry structure making it more innovative (Lee et al., 2016; Jo et al., 2021).

Considering the above, the importance of the smart city industry and related industries will gradually increase and significantly impact the national policy direction for economic revitalization (Jo Sungsu et al., 2018). However, most of the previous studies are focused on the conceptual study on smart city industry taking a discursive form or the ripple effect study to measure simple economic efficiency. Therefore, various aspects of an empirical study covering the smart city industry are critical.
The study aims to analyse the evolutionary characteristics of industry DNA from a smart city perspective. Evolutionary characteristics were analysed through changes in the industry cluster DNA structure and the economic relationship between industry clusters. The study defined the convergence relationship between the smart city industry and the conventional industry as a smart city industry cluster. In addition, each industry composing the industry cluster was defined as industry DNA. Based on such definitions, the study examined how the relationship between the industry cluster and its DNA structure evolved from 2000 to 2019, when the smart city concept was introduced in South Korea.

The study was conducted in the following order. First, previous studies on industry cluster methodology were reviewed. Second, an industry cluster was established using factor analysis. The industry cluster considered the similarity of the overall economic relationship, including the purchase structure and the sales structure of the industry input-output table. Third, the evolution of the smart city industry cluster DNA structure was analysed. Fourth, the economic relationship with other industry clusters was analysed to study whether the economic properties of the smart city industry cluster were independent or dependent.

2. LITERATURE REVIEW

2.1 Smart City Industry DNA

The industry input-output table does not clearly show the classification of the smart city industry. Numerous studies were conducted to define the smart city industry as the smart city (previously named the Ubiquitous City (U-City)) project began with full momentum. Previous studies have defined the industry

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based on ubiquitous technology (Kim Wanseok (2003), Kim Jaeyoon (2003), Oh Jeongyeon (2005)) or defined smart city-related industries based on cases regarding U-City (Kim Bangryong et al. (2006), YIm Siyoung et al. (2011)). However, these studies have limitations in that it is challenging to analyse the relationship between industries as the smart city industry was not arbitrarily classified or based on the industry input-output table (Jo Sungsu et al., 2018).

Therefore, the study defined the smart city industry by reconstructing the industry classification of the industry input-output table based on the previous studies of smart city industry classification and technology and industry connection analysis of smart-x cases (smart car, building, farm, factory, etc.). The smart city industry was defined as IT manufacturing (ITM), IT service (ITS), and knowledge service (KS), and other miscellaneous industries were defined as conventional industries.

An industry cluster is defined as clustering of smart city and conventional industries. The clusters can be divided into a smart city and traditional industry clusters according to the industry making up the clusters. The smart city industry cluster is defined as clusters composed of ITM, ITS, and KS mentioned above. Such includes clustering between smart city industries as well as between the smart city and conventional industries. The study additionally defined each industry constituting the industry cluster as the industry cluster DNA.

2.2 Factor Analysis

Industry cluster studies include Roepke et al. (1974), Yu Wan et al. (1989), and Kim Dongju et al. (2001). Roepke et al. (1974) analysed based on the three categories of input, distribution, and synthesis using forty-four out of fifty-one sectors of the industry input-output table in Ontario, Canada. The established industry clusters were classified into thirteen inputs, sixteen distributions, and eighteen synthesis aspects.

Yu Wan et al. (1989) selected industries with significant direct and indirect effects according to input and production inducement coefficients using manufacturer pricing tables in sixty-five sectors in the 1985 industry input-output table. Factor analysis was performed afterward to classify the industry group.
Kim Dongju et al. (2001) classified the industry group by conducting factor analysis using the manufacturer pricing table for the electronics and information equipment industry among 402 basic sectors in the 1995 industry input-output table.

Most previous studies only established industry clusters and did little analysis of their changes over time. Therefore, this study establishes an industry cluster using factor analysis and examines how the smart city industry cluster structure and the economic relationship with other industries have shifted.

3. METHODOLOGY

3.1 Data

The data used in the study are 2000 and 2019 industry input-output tables issued by the Bank of Korea. Based on the literature review, the industry input-output table reclassified 168 subclassified industries into thirty-two. The industry can be divided into the smart and conventional industries. The smart industry can be split into ITM, TIS, and KS fields including twelve industries. The ITM field is divided into five industries: electrical equipment, communication/broadcasting equipment, electronic components, computers, and precision machinery. The ITS field is classified as a communication service industry. The KS field comprises six industries: professional science/technology, education, medical care, culture, broadcasting/publishing, and finance. Excluding the smart industry, twenty industries contain the primary industry of agriculture, the secondary industry including food/beverage manufacturing, wood, and metal/non-metal, and the tertiary industry such as energy generation supply, construction, wholesale/retail service, and real estate service businesses.

The analysis data period was specified because the initial concept of a South Korean smart city (the U-City) was presented in the early 2000s, and the shift of the smart city industry cluster DNA structure can be studied through to radical policy changes spanning the 2006 U-Korea Master Planning, 2008 U-City Act enactment, 2009 1st U-City Comprehensive Planning, 2014 2nd U-City Comprehensive Planning, 2017 amendment from U-City Act to Smart City Act, and 2019 3rd Smart City Comprehensive Planning.

3.2 Method

The study calculated an index representing the overall economic relationship by integrating the purchasing and sales structures in the industry input-output table to understand the industry cluster DNA structure.
In the industry input-output table, the purchasing structure can be expressed as $a_{ij} = \frac{x_{ij}}{IX_j}$, a_{ij} is the purchasing relationship between i industry and j industry. X_{ij} is a good that industry j purchases from i industry. IX_j defines the total input of j industry. a_{ij} carries identical definition to the input-output coefficient. Therefore, a_{ij} means the goods per unit which j industry purchased from i industry to produce one unit of goods.

The sales structure is expressed as $b_{ij} = \frac{x_{ij}}{OX_i}$. b_{ij} is the sales relationship between i and j industries. X_{ij} is a good that i industry sells to j industry. OX_i defines the total output of i industry. b_{ij} represents how much goods produced in each i industry are sold to other i industries, which is different from the general input-output coefficient. Therefore, b_{ij} means the goods per unit sold to j when i industry produces one unit of the goods.

The overall economic relationship (c_{ij}) that integrates the purchasing and sales aspects used in the study is expressed as $c_{ij} = a_{ij} + b_{ij}$. Factor analysis was conducted based on the index (c_{ij}) created in such a way to derive an industry cluster based on the similarity of the overall economic relationship.

Next, the economic relationship with other industry clusters was analysed to confirm whether the smart city industry cluster's economic properties are independent or dependent on other industry clusters. The analysis method created an input-output table between the established clusters. The diagonal matrix value being more significant than other matrix values in the input-output table between industry clusters indicates that goods transactions between industries in its own industry cluster are greater than goods transactions with industries belonging to other clusters. Therefore, an industry cluster with a

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large diagonal matrix value carries a high economic independence locatable without relations to other industry clusters. However, the diagonal matrix value being smaller than other matrix values indicates an economically dependent industry cluster that must be located in relation to others.

4. RESULT AND DISCUSSION

4.1 The Characteristic Analysis Result of the Smart City Industry Cluster DNA Structure

The characteristic analysis result on the smart city industry cluster DNA structure is as follows. The industry cluster was set according to the economic relationship similarities between industries.

The 2000 industry cluster comprises ten sectors accounting for 88.0% of the total variance. The smart city industry cluster, including the smart city industry DNA, has six sectors accounting for 61.230% of the total variance. Additionally, the cluster with only the smart city industry DNA accounts for 18.064% of the total variance in three sectors (⑤ITM; computer, precision machinery manufacturing, and ⑦KS; social service) among six smart city industry clusters sectors (Table 1).

Industries Cluster	2000		
	Total	%Var	% Cumulative
① KS- business support services	5.516	17.237	17.237
② KS- textile manufacturing industry	4.417	13.804	31.041
③ Chemical manufacturing	4.060	12.687	43.728
④ ITM- heavy equipment manufacturing	3.880	12.125	55.853
⑤ ITM- computer, precision machinery manufacturing	2.810	8.780	64.633
⑥ Commercial	1.782	5.568	70.201
⑦ KS- social service	1.523	4.760	74.961
⑧ KS- broadcast and publishing	1.447	4.523	79.484
⑨ Real estate service	1.424	4.450	83.935
⑩ Food and beverage manufacturing	1.304	4.076	88.011

Table 1. Factor loading (2000 year)

The 2000 smart city industry cluster was set up as follows. ①An industry cluster that includes the DNA of business support services such as wholesale/retail, public administration/ defence, telecommunications, and miscellaneous industries focused on KS (cultural sports and financial insurance) DNA. ② An industry cluster that includes the DNA of the textile manufacturing industry, such as textile/leather product manufacturing, transportation service, mining, wood/paper manufacturing, and printing industry, focused on KS (medical health) DNA. ④An industry cluster that includes the DNA of heavy equipment manufacturing, such as machinery, transportation equipment, construction industry, and miscellaneous manufacturing focused on ITM (electrical equipment and electronic parts) DNA. ⑤ITM (computer and precision machinery manufacturing) industry cluster. ⑦KS (social service) industry cluster (Table 2).

Industries Cluster	2000		
	Industries DNA	Factor loading	Characteristics of cluster
① KS- business support services	Business support services	0.938	Smart City Industries Cluster
	KS_ cultural service	0.934	
	KS_ finance and insurance	0.905	
	Wholesale and retail trade services	0.895	
		0.802	
	Other service	0.648	
	Public administration and defence services	0.622	
	ITS_ communication service		
② KS- textile manufacturing industry	KS_ medical and human health service	0.902	Smart City Industries Cluster
	Textile manufacturing industry	0.862	
	Transport services	0.851	
	Mining	0.791	
	Wood and paper	0.751	
③ Chemical manufacturing	Metal equipment manufacturing	0.997	Traditional Industries Cluster
	Energy generation and supply	0.993	
	Chemical manufacturing	0.992	
	Metal and non-metal	0.991	
④ ITM- heavy equipment manufacturing	Machine manufacturing	0.935	Smart City Industries Cluster
	Transport equipment manufacturing	0.833	
	ITM_ electronic signal equipment	0.823	
	ITM_ electronic component	0.747	
	Other manufacturing	0.615	
	Construction	0.598	
⑤ ITM- computer, precision machinery manufacturing	ITM_ computer	0.963	Smart City Industries Cluster
	ITM_ communication and media equipment	0.910	
	ITM_ precision instrument	0.874	
⑥ Commercial	Accommodation and food services	0.950	Traditional Industries Cluster
	Agriculture and Fishing	0.857	
⑦ KS- social service	KS_ professional, scientific, and technical services	0.800	Smart City Industries Cluster
	KS_ Education	0.621	
⑧ KS- broadcast and publishing	KS_ broadcast and publishing	0.972	Smart City Industries Cluster
⑨ Real estate service	Real estate service	0.894	Traditional Industries Cluster
⑩ Food and beverage manufacturing	Food and beverage manufacturing	0.955	Traditional Industries Cluster

Table 2. Structure of smart city industry cluster DNA (2000 year)

The 2019 industry cluster carries ten sectors, accounting for 82.6% of the total variance. Among them, the smart city industry cluster, including smart city industry DNA, was set up in five sectors which accounts for 45.1% of the total variance. Out of the five sectors, the industry cluster containing just the smart city industry DNA was in two sectors (③KS- social service and ⑥ ITM- computer and precision machinery manufacturing), accounting for 18.563% of the total variance (Table 3).

Industries Cluster	2019		
	Total	%Var	% Cumulative
① ITM- heavy equipment manufacturing	4.175	13.046	13.046
② Chemical manufacturing	4.015	12.547	25.594
③ KS- social service	3.356	10.487	36.081
④ KS-other service	2.848	8.900	44.980
⑤ Business support services	2.824	8.826	53.807
⑥ ITM- computer and precision machinery manufacturing	2.584	8.076	61.882
⑦ Commercial	2.055	6.422	68.304
⑧ Real estate and public service	1.741	5.441	73.746
⑨ KS-Other manufacturing	1.480	4.624	78.370
⑩ Food / beverage and textile manufacturing	1.368	4.274	82.644

Table 3. Factor loading (2019 year)

The 2019 smart city industry DNA community was set up as follows. ①An industry cluster that includes the DNA of heavy equipment manufacturing that includes machinery manufacturing, transportation equipment manufacturing, and construction industry, focused on ITM (electrical equipment and electronic parts) DNA. ③An industry cluster that includes ITS (telecommunications) DNA focused on KS (professional science/technology, education, culture/sports, and financial insurance) DNA. ④An industry cluster that includes other services such as KS (medical health) DNA and miscellaneous service industry DNA. ⑥An industry cluster that includes DNA from miscellaneous manufacturing industries focused on KS (broadcasting, publishing) DNA. ⑨An industry cluster that includes KS (broadcasting, publishing service) DNA, and miscellaneous manufacturing (Table 4).

Industries Cluster	2019		
	Industries DNA	**Factor loading**	**Characteristics of cluster**
① ITM- heavy equipment manufacturing	Machinery manufacturing	0.952	Smart City Industries Cluster
	Transportation equipment manufacturing	0.915	
	ITM_ electrical equipment	0.894	
	ITM_ electronic parts	0.737	
	Construction industry	0.571	
② Chemical manufacturing	Metal equipment manufacturing	0.991	Traditional Industries Cluster
	Metal and non-metal	0.990	
	Energy generation and supply	0.989	
	Chemical manufacturing	0.989	
③ KS- social service	KS_ professional science/technology	0.823	Smart City Industries Cluster
	KS_ education	0.777	
	KS_ culture/sports	0.754	
	KS_ financial insurance	0.737	
	ITS_ telecommunications	0.388	
④ KS- other service	KS_ medical health	0.793	Smart City Industries Cluster
	Other services	0.735	
	Transport service	0.731	
⑤ Business support service	Mining	0.843	Traditional Industries Cluster
	Wholesale and retail trade services	0.788	
	Business support service	0.674	
	Wood and paper, publishing	0.545	
⑥ ITM- computer and precision instrument	ITM_ Computer	0.978	Smart City Industries Cluster
	ITM_ Precision instrument	0.845	
	ITM_ Communication and media equipment	0.750	
⑦ Commercial	Accommodation and food services	0.944	Traditional Industries Cluster
	Agriculture and Fishing	0.925	
⑧ Real estate and public service	Real estate service	0.859	Traditional Industries Cluster
	Public administration and defence services	0.623	
⑨ KS- other manufacturing	KS_ broadcasting and publishing service	0.732	Smart City Industries Cluster
	Other manufacturing	0.546	
⑩ Food / beverage and textile manufacturing	Food and beverage manufacturing	0.874	Traditional Industries Cluster
	Textile manufacturing	0.411	

Table 4. Structure of smart city industry cluster DNA (2019year)

The analysis results are summarized as follows. First, the explanatory power of smart city industry clusters was analysed to be lower in 2019 than in 2000. Specifically, in 2000, KS DNA was divided into four industry clusters while paired with other conventional industries, showing the high explanatory power of the smart city industry clusters. On the other hand, the overall explanatory power for the 2019 KS DNA, which was separated into several clusters, was lowered as it was clustered into three factors. However, the explanatory power of the industry cluster with just the smart city industry DNA was higher in 2019 than in 2000. The ITM-heavy equipment manufacturing industry, for instance, which carried four factors in 2000, was analysed to have one factor with high explanatory power in 2019. Such results can be taken as that the smart city industry DNA in the overall industry structure is transforming into a central from auxiliary industry characteristics of other conventional industries.

Second, the 2000 smart city industry cluster was a conversing of the smart city industry DNA such as KS and ITS as well as the conventional service industry DNA such as public and wholesale services. However, 2019 saw a shift in the convergence between ITM, the smart city industry DNA, and the conventional manufacturing DNA such as transportation equipment, machinery, and construction. Such results indicate that the smart city industry structure went from a form for informatization of knowledge and administration to smartification of manufacturing.

4.2 Analysis of Economic Relations of Smart City Industry Cluster

The economic relationship analysis results of the smart city industry cluster are as follows. The economic relationship was analysed based on the input-output table between industry clusters.

In 2000, four industry clusters, including ①KS-Business Support Service, ② KS- textile manufacturing, ③ Heavy Chemical Manufacturing, and ④ITM- heavy equipment manufacturing, were found to be economically independent of other industries. On the other hand, there are six industry clusters economically dependent on other industries, including ⑤ITM- computer and precision machinery manufacturing, ⑥Commercial related, ⑦ KS- social service, ⑧KS- broadcasting /publishing service, ⑨ Real estate service, and ⑩Food and beverage manufacturing (Table 5). Meanwhile, it was analysed that all industry clusters in 2019 except for ②Heavy chemical manufacturing had a dependent relationship with one another. For example, the ④ ITM-heavy equipment manufacturing smart city industry cluster that commonly appeared in 2000 and 2019 was economically independent in 2000 but was found to be economically dependent on almost all industry clusters in 2019 (Table 6).

The results indicate that the economic influence of the smart city industry cluster is expanding to more diverse clusters than in 2000. Such also indicates the challenges in independent growth of the smart city industry cluster; hence it grows through connection with other industries.

5. CONCLUSIONS

The study aims to analyse the evolutionary characteristics of industry DNA from a smart city perspective. Evolutionary characteristics were analysed through changes in the industry cluster DNA structure and the economic relationship between clusters. The industry input-output tables for 2000 and 2019 issued by the Bank of Korea were used as the analysis data. The GDP deflator was applied to the tables based on the manufacturer pricing for comparative analysis between the two years.

The major results are as follows. First, the explanatory power of the smart city industry cluster was higher in 2000, but the explanatory power with only the smart city industry DNA was higher in 2019. These results indicate that the smart city industry DNA in the overall industry structure is shifting from auxiliary to central industry nature of other conventional industries.

Second, the smart city industry cluster in 2000 appeared as the conversion of the smart city industry DNA with KS and ITS and the conventional service industry DNA with public, wholesale and retail services. On the other hand, 2019 saw a change in the conversion to the form of the smart city industry DNA such as ITM and conventional manufacturing DNA such as transportation equipment, machinery, and construction. Such results mean that the smart city industry structure has shifted from a form for informatization of knowledge and administration to a form for smartification of manufacturing.

Third, the smart city industry cluster changed from an economically independent relationship to a dependent relationship with other industry clusters. In 2000, the smart city industry cluster was majorly independent of other industry clusters. However, in 2019, it changed to having an economically dependent relationship with almost all clusters. Such indicates the trend of economic influence of the smart city industry cluster expanding to diverse industry clusters than in 2000. It is also challenging for the smart city industry cluster to grow independently. Therefore, it is now growing through connections to other industries.

Industrial Cluster	①	②	③	④	⑤	⑥	⑦	⑧	⑨	⑩
①	0.101	0.052	0.082	0.058	0.035	0.050	0.103	0.142	0.110	0.171
②	0.013	0.163	0.319	0.027	0.006	0.016	0.023	0.210	0.002	0.087
③	0.028	0.135	0.797	0.205	0.042	0.075	0.074	0.066	0.031	0.217
④	0.023	0.016	0.036	0.250	0.169	0.012	0.027	0.014	0.106	0.018
⑤	0.004	0.002	0.002	0.011	0.125	0.001	0.022	0.005	0.001	0.001
⑥	0.000	0.008	0.003	0.001	0.000	0.047	0.001	0.000	0.000	1.258
⑦	0.029	0.014	0.048	0.045	0.033	0.017	0.124	0.063	0.008	0.086
⑧	0.006	0.002	0.003	0.001	0.001	0.001	0.130	0.092	0.001	0.005
⑨	0.041	0.013	0.006	0.005	0.001	0.030	0.067	0.014	0.015	0.012
⑩	0.000	0.004	0.003	0.000	0.000	0.186	0.000	0.000	0.000	0.419

*Note: ① KS- business support services cluster, ② KS- textile manufacturing industry cluster, ③ Chemical manufacturing cluster, ④ ITM- heavy equipment manufacturing cluster, ⑤ ITM- computer, precision machinery manufacturing cluster, ⑥ Commercial cluster, ⑦ KS- social service cluster, ⑧ KS- broadcast and publishing cluster, ⑨ Real estate service cluster, ⑩ Food and beverage manufacturing cluster

Table 5. Technical coefficient matrix of inter-industrial cluster in 2000

Industrial Cluster	①	②	③	④	⑤	⑥	⑦	⑧	⑨	⑩
①	0.101	0.036	0.197	0.522	0.785	0.406	0.056	0.190	0.076	0.181
②	0.265	0.249	1.569	2.469	0.617	1.060	0.201	0.638	0.503	0.234
③	0.802	0.204	0.276	0.399	0.129	0.340	0.133	0.843	0.832	0.516
④	0.281	0.047	0.367	0.249	0.059	0.077	0.045	0.190	0.171	0.112
⑤	0.453	0.195	0.944	1.403	0.176	0.319	0.257	0.457	0.556	0.430
⑥	0.037	0.044	0.023	0.067	0.050	0.434	0.106	0.177	0.066	0.010
⑦	0.227	0.068	0.065	0.065	0.022	0.021	0.164	0.369	0.522	0.674
⑧	0.234	0.037	0.033	0.012	0.007	0.010	0.158	0.170	0.155	0.146
⑨	0.122	0.117	0.118	0.208	0.215	0.123	0.060	0.335	0.618	0.106
⑩	0.081	0.133	0.033	0.043	0.030	0.006	0.689	0.308	0.052	0.462

*Note: ① ITM- heavy equipment manufacturing cluster, ② Chemical manufacturing cluster, ③ KS- social service, ④ KS-other service, ⑤ Business support service cluster, ⑥ ITM- computer and precision instrument cluster, ⑦ Commercial cluster, ⑧ Real estate and public service cluster, ⑨ KS- other manufacturing cluster, ⑩ Food / beverage and textile manufacturing cluster

Table 6. Technical coefficient matrix of inter-industrial cluster in 2019

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