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Convergence between Green Technology and Building Construction in the Republic of Korea

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Abstract: This study examines the convergence between green technology and building construction in Korea using both input-output and network analysis from 1990 to 2015. The industry type of the input-output tables used in the Bank of Korea is reclassified into 20 categories. The analytical results are summarized as follows: First, the construction industry is expanding its production area by adopting green technologies (KRW 2245 billion → KRW 7842 billion). Second, the impact of green technologies on the growth rate of the construction industry is greater than that of traditional construction technologies (technical coefficient 0.5410 → 0.5831). Third, the results of the analysis show that smart green technology enhances efficiency in the construction industry (multiplier coefficient 2.3673 → 2.4972). Our input-output model reveals that the smart green technology coefficient input to construction is relatively small, but the output is bigger in effects. Also, the results of the input-output analysis show that both hardware and software smart technologies continuously increase energy demand. Finally, the network analysis demonstrates the rapid convergence of smart technologies in the construction industry (pathway 13 → 22). These results demonstrate that smart green technology leads to a high value-added output in the construction industry.

Keywords: construction; smart green technologies; green building; industrial convergence; input-output model; network analysis

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1. Introduction

Traditional industry is currently on the evolutionary path of digitizing. For a long time, digitization has been an important issue for the construction of buildings and infrastructure [1]. Digitalization, as well as sustainable energy use and management, has long been an issue in our society [2]. Nowadays, more than half of the world's population live in urban areas. Human activities are under pressure from this high population density and buildings and require sustainable development [3]. Sustainable economic development based on a city-centered philosophy resulted in greenhouse gas emissions. The progressive emission of greenhouse gasses has made global warming a worrisome environmental problem. In this context, there is a debate on how to minimize the impact on the environment and increase energy efficiency through the use of intelligent systems in smart buildings [4] In general, a smart building can be defined as the convergence of information and communication technology for building management and green technology for energy efficiency.

Studies on smart buildings have focused on innovative technologies for air conditioning and heating, lighting, and solar thermal energy efficiency [5]. Empirical studies have been conducted on how to reduce energy consumption through innovative technologies in buildings [6,7]. There have also been studies on industrial and economic aspects [8]. These studies have predicted that the high value added in construction, service, and information and communication technology (ICT) will lead to a large demand in construction.

Accordingly, there have been many studies on the application of smart green technologies in construction. However, the existing studies do not provide a clear understanding of the convergence of smart green technologies in the construction industry. Therefore, this study examines the relationship between smart green technologies and construction as a technological convergence toward smart buildings.

This study undertakes several steps to determine how smart green technology converges within the construction industry. First, a literature survey defining the industrial segments of smart technology and green technology. Second, we estimated how much the smart green industry is purchased in the construction industry. The study also examined the multiplier effects of smart green technologies on the overall construction industry. The IO model is used to estimate technical coefficients and production-inducing coefficients. Finally, this study examined convergence changes between smart green technologies and the construction industry. The study used the centrality and network analysis.

The remaining chapters of this study are organized as follows: Section 2 examines the theoretical background of smart and green technologies, offering an in-depth exploration of the existing research concerning inter-industry convergence. In Section 3, the study elucidates the input-output model and network analysis as the analytical model utilized and describes the data sources in the analysis. Section 4 systematically examines the integration of smart and green technologies within the construction industry, with a specific focus on input-output analysis and network analysis. Lastly, Section 5 summarizes the study's findings, outlines its limitations, and suggests directions for future research.

2. Literature Review

Since the smart and green technologies used in the construction industry can be defined very broadly depending on the field, it is necessary to examine the fields related to this study in detail. Accordingly, in this chapter, we looked at the theoretical background of what smart and green technologies are and explained the concept of the convergence of smart and green technologies and construction. In addition, existing research related to industrial convergence was reviewed.

2.1. Theoretical Background: Smart and Green Technilogies

What is an intelligent building? The intelligent building is a topic that has been discussed for a long time. Before the intelligent building, there was the concept of the smart building. This has been discussed since 1990. Wong's study states that smart buildings should minimize human interaction. In other words, a smart building is a control system that minimizes mutual interference [9]. This means that building management requires the integration of various systems [9,10]. The smart building requires more smart devices, materials, and sensors for building automation [11].

There are some studies that have discussed the importance of smart technologies or green buildings from the ICT perspective, separately from system integration. Zero-energy buildings, which maximize energy efficiency and limit carbon emissions, or green buildings, which are inextricably linked to performance, have been the subject of several studies [12]. Putting these together, essentially linked green buildings have been the subject of various studies. The green building is a balanced approach when it comes to infrastructure and energy conservation, including building infrastructure, information and communication technologies (ICTs), and energy savings [13].

Smart buildings are driven by climate change and integrate the aspects of energy conservation and management with smart technology systems that optimize services and operations. The concept of smart buildings began to change with intelligent buildings that take into account all aspects [14,15]. Putting these together, it can be said that a smart building is an ICT which includes a separate green technology for sustainable energy efficiency.

What are smart technologies? Existing studies state that smart technologies simply extend beyond ICT and require technology that adds an intelligence function to things [8,16].

These technologies are sensing, processing, networking, and interfacing [17]. Intelligent technology for intelligence manages humans' five senses (e.g., cognitive function). For example, they consist of a smell sensor, an auditory sensor, a visual sensor, and a vibration sensor. The collected data (content) that the user needs require a suitable algorithm for processing knowledge content. For example, if the collected data are smoke, then fire creates smoke. Knowing that the smoke is from a fire is the knowledge algorithm. The delivery of the data here is an act of network technologies (e.g., Wi-Fi, 5G, and broadband). The interface is a technology that converts information from processed data into information and makes it available to the user by outputting it to the display.

These technologies can be divided into three industry sectors. Sensor and interface technologies are close to the manufacturing industry's IT. Processing technology is related to the knowledge-based service industry. Network technology is close to the IT service industry. This is evident in the smart car, smart farm, smart factory, and smart building cases. Through these cases, studies have examined the questions of what a required technology is and how it is related to the related industry [8,16]. On the other hand, smart technologies change over time and the categorization of the industry changes, so it is difficult to create a strong framework based on these limited aspects.

In particular, the OECD introduced a definition of the ICT industry that breaks down the dichotomy of traditional manufacturing and services in the economy [18–20]. The OECD definition of ICTs and knowledge services industries is a useful taxonomy, although it may not cover the full range of related activities. The OECD industry classification method is the most appropriate classification in terms of economic quantification and we can conduct comparative studies between countries in terms of economics [21]. This study classified smart technology as IT manufacturing, IT services, and knowledge services based on the above OECD method.

What is green technology? The demand for green buildings is increasing due to climate change worldwide [22]. According to this trend, many countries and international organizations have developed sustainable green building rating systems. The most representative ones are the Leadership in Energy and Environmental Design (LEED) of the USA, Building Research Establishment Environmental Assessment Method (BREEAM) of the UK, LEED of Canada, Deutsche Gesellschaft für Nachhaltiges Bauen (DGNB) of Germany, Green Star of Australia and New Zealand, and Indian Green Building Council (IGBC) of India.

The important function of these assessment systems and green technology focuses on energy consumption and the recycling of resources. In addition, there have been studies on planning green buildings or green cities. The elements associated with green technology are recycling resources (e.g., the use of heavy water, rain collectors, recycling, and minimizing waste), maximizing carbon absorption (e.g., solid green), and maximizing the use of renewable energy such as active solar systems, passive solar systems, geothermal energy, and wind energy [23]. From this point of view, green technology can be divided into energy generation, energy use and supply, resource recycling, and manufacturing industries. Recent studies have shown solar, heat pump, and heat storage technologies for efficient energy management in buildings [24–26]. These studies manifest that the green-technology-related industries are the energy generation industry (e.g., solar, thermal, and wind energy), energy supply industry (e.g., electric, gas, and water), and energy recycling and process industry (e.g., rain recycling and waste processing). Categorizing the green technology industry is about utilizing and applying smart technology for energy efficiency [4].

This study defines an integrated technology that uses a knowledge algorithm to control smart buildings, using smart technologies such as sensors, green technologies to save carbon, and renewable and recycled energy as key components (Figure 1).

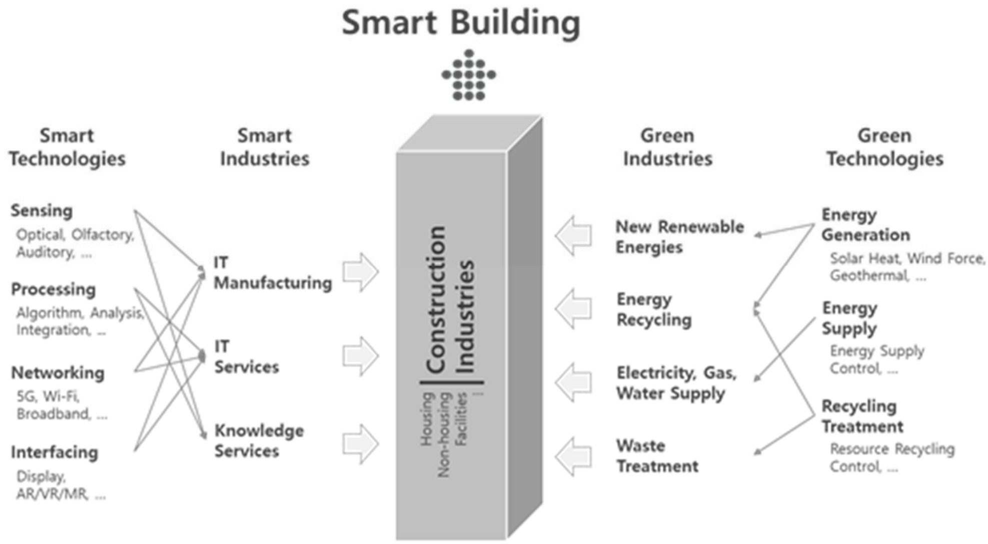

Figure 1. The conceptual framework of a smart building analysis.

2.2. Related Research

In a research study on convergence industries, Leontief used various methods such as a commitment-output model based on input-output tables, structural path analysis, and network analysis. Lee and Kim analyzed the changes in the structure of the construction industry using the 1980 and 1990 input-output tables. The structure of the construction industry changed based on services and telecommunications. These changes resulted in the active development of intelligent buildings, office automation, and so on. This change was the basis for the revival of the construction industry at that time. At the same time, construction is becoming a high value-added industry, reflecting the trend of services and information [27]. The study by Lee and Leem confirmed that the structure of the telecommunications industry leads to innovation as a tool for knowledge sharing. The study found that the telecommunications industry plays an important role in innovation in the knowledge economy [28].

The studies by Jo and Lee and Jo et al. examined the smart industry and construction from a smart city perspective, different from previous studies. They also analyzed the relationships between the smart city industry and other industries. In Jo and Lee's study, the changes in industry structure between the smart city industry and the construction industry were analyzed using the 1980 and 2014 input-output tables. They defined that the smart city industry consists of IT manufacturing, IT services, and knowledge services. In particular, the study showed that IT manufacturing and IT services are very important in the relationship with the construction industry. The study also explains that the smart city industry has a comprehensive influence on other industries, such as smart farms, smart buildings, and smart grids [9]. Jo et al.'s study investigated the industrial ecosystem from the Korean information era to the current smart city period. They used four tables of data every 15 years from the 1960 input-output tables to 2015 (1960, 1975, 2000, and 2015). The study results confirmed that the smart city industry replaced other industries and is making new value chains in all industries. However, their final conclusion was that this impact is not big, and they emphasized that smart city year has not come yet [16].

Most of the industrial analyses in the existing studies used an input-output model, a structural path analysis model, and a network analysis model. The input-output model can calculate the structure and ripple effect of the industry, but it is difficult to grasp the detailed path and value chain of the ripple effect of the industry. The structural path analysis model can identify the ripple effect of an industry as a detailed path, but since it is an analysis based on production-inducing effects, it has limitations in identifying the input structure of the industry.

Other research areas that integrate methods such as the input-output model and structural pathway analysis include research related to energy pathway extraction [29] and carbon emissions [30]. Lenze extracted pathways related to energy use, water use, and air emissions for all industries in Australia [31]. Butnar et al. studied the flows of 11 air pollutants along the economic supply chain of Spain [32]. There are also studies that have experimented with the applicability of structural pathway analysis to measuring flows in economic and environmental networks. More recently, research has been conducted to analyze and interpret economic, industrial, and social phenomena using network analysis.

Hidalgo et al. analyzed the evolution of the production structures of continents and countries using network analysis [33]. In the study by McNerney et al., who argued that the network methodology is excellent for studying the relationships between industries, a network of the money flows of 45 countries was applied and analyzed using the OECD international input-output tables [34]. Liu and Zhang's study examined the flow of urban ecological networks in Beijing by combining a monetary input-output table and a physical input-output table to analyze the urban ecosystem [35]. Stamopoulos et al. used network analysis to quantify the economic impact of the ICT industry on the Greek economy. The ICT industry contributed significantly to the Greek economy. He found that ICT services (i.e., a subdivision of the ICT industry) are closely linked to transactions between industries [21]. Li et al. developed an integrated assessment model based on network analysis for industrial structure changes in China and Japan [36]. Wang and Chen used the network analysis method to study the energy and water flow between the Beijing, Tiajin, and Hebei regions. They analyzed the energy dependence, impact, and recycling rate in the three cities [37]. In addition, according to recent research, green technology products are expected to have a significant impact on the economic, environmental, and social aspects of the construction supply chain [38].

As such, previous studies using the network analysis method have had excellent results in analyzing economic, industrial, and social phenomena and estimating their ripple effect paths. However, the studies that used network analysis focused on macroeconomics such as continents, nations, and entire industries. The most studied topics were carbon emissions and knowledge cities as the current trends of industrialization and urbanization. This study combines the input-output model with the network analysis method to fill the gaps and overcome the limitations of previous studies. The study investigated the hot topic of the convergence between smart green technology and construction.

3. Research Model and Data

3.1. The Input-Output Model for Industry Analysis

This study used an input-output model and network analysis method as analysis tools. An input-output model is a tool for the quantitative analysis of the production and interactions between industries through trade activities. In particular, the model captures the interdependencies between industries step by step, and this analysis examines the multiple impacts for each industry in an input-output analysis [39].

The basic structure of the input-output model is a matrix consisting of an endogenous sector and an exogenous sector. The endogenous sector shows the intermediate input and demand between industries. It has the form of a square matrix. The column of the square matrix shows the input of each industry and indicates the quantity of goods to be purchased. The row indicates the extent to which each industry's products are sold as demand from other industries. Thus, the quadratic matrix, which consists of intermediate inputs and intermediate demand, represents the relationship between the purchase of intermediate inputs and the sale of demand products between industries and has the greatest importance in the input-output model.

The exogenous sector consists of primary inputs and final demand. The primary input includes the value added and the final demand includes household consumption and information consumption. In an input-output table, the total output of the total of the row and the total of the column is consistent. The basic structure of an input-output table (industry associations) is shown in Figure 2.

Output(j) Input(i)		Intermediate Demand						Final Demand	Total Supply
		1	2	…	j	…	n		
Intermediate Input	1	X_{11}	X_{12}	…	X_{1j}	…	X_{1n}	y_1	X_1
	2	X_{21}	X_{22}	…	X_{2j}	…	X_{2n}	y_2	X_2
		⋮	⋮		⋮		⋮	⋮	⋮
	i	X_{i1}	X_{i2}	…	X_{ij}	…	X_{in}	y_i	X_i
		⋮	⋮		⋮		⋮	⋮	⋮
	n	X_{n1}	X_{n2}	…	X_{nj}	…	X_{nn}	y_n	X_n
Value Added		V_1	V_2	…	V_j	…	V_n		
Total Inputs		X_1	X_2	…	X_j	…	X_n		

Figure 2. Concept of an input-output model.

The input-output model (industry association analysis) is based on the input coefficient (technical coefficient) calculated from the input-output table. The technical coefficient (a_{ij}) is based on the median input for each sector divided by the total input. This means the amount of input of industry i that industry j needs to produce one unit of output. The technical coefficient can be calculated using Equation (1):

$$a_{ij} = x_{ij}/X_j \tag{1}$$

where a_{ij} is the (i, j)th technical coefficient and x_{ij} is intermediate input of the (i, j)th industry. X_j represents the total input of industry j. This study analyzed the input of the smart green industry needed when the construction industry produces one unit of output.

The multiplier coefficient (b_{ij}) can be calculated through the technical coefficient. It means when the final demand of industry j increases production by one unit, what industry $i's$ direct and indirect impact would be. The multiplier coefficient can be calculated using Equation (2).

$$B_{ij} = [I - A]^{-1} \tag{2}$$

where B_{ij} is the production-inducing coefficient matrix and consists of b_{ij}. I is the unit matrix and A is a matrix of technical coefficients. This study defines the production-inducing coefficient as the direct and indirect effects of the smart green industry and the traditional industry when the construction industry increases its output by one unit.

3.2. Network Analysis Model

The network analysis model uses social network analysis, degree centrality, and eigenvector centrality. Degree centrality is the simplest and most intuitive indicator. It is measured by default as the number of links to a given node. Degree centrality indicates the direct impact or activity between industry i and industry j. For example, the more links associated with a particular node, the higher the value of the link degree centrality. Industries with a high degree of centrality can create new opportunities through other industries. Many industries are directly linked, so we can explore a number of alternatives to industry growth.

Degree centrality is divided into in-degree centrality and out-degree centrality when there is a directionality of the connection. This study started from the production-inducing coefficient, in which directionality exists, and network centrality was analyzed. The analysis results of this study were derived from in-degree centrality ($DC^{in}(i)$) and out-degree centrality ($DC^{out}(i)$) using the following Equation (3):

$$DC^{in}(i) = \frac{1}{n-1}\sum_{j=1}^{n} f_{ij} \tag{3}$$

where $DC^{in}(i)$ is the in-degree centrality of i industrial nodes. n is the total number of industries in the entire network. f_{ij} represents the direct and indirect effect of industry j on industry i when industry j increases its output by one unit of production (Equation (4)).

$$DC^{out}(i) = \frac{1}{n-1}\sum_{j=1}^{n} f_{ji} \quad (4)$$

where $DC^{out}(i)$ is the out-degree centrality of i industrial nodes. n is the total number of industries in the entire network. f_{ji} is the production-inducing coefficient as industry $j's$ direct and indirect impact when industry i increases its production by one unit.

The in-degree centrality is similar to the forward linkage effect, and the out-degree centrality has a similar meaning to the backward linkage effect.

Having a large number of connected nodes does not necessarily make a node an important node. If degree centrality is critical to the number of directly connected nodes, then eigenvector centrality is a connected node that can weigh the importance of other nodes. For example, the influence is greater if it is connected to a strong person than if it is connected to a large number of weaker people. In other words, a node connected to important nodes is the more critical node. A large value of eigenvector centrality means that the node itself is connected to a large number of nodes with a high score, as expressed in Equation (5).

$$EV_i = \sum_{j=1}^{n} C_j Z_{ij} \quad (5)$$

where EV_i is an eigenvector and n is the number of industries in the whole network. C_j is of importance and industry j, Z_{ij} means a connection from industry i to industry j. Vector C is the eigen equation of $\lambda C = ZCC$. The eigenvector centrality can be derived from vectors corresponding to the largest eigenvalue (λ).

3.3. Research Data

The study uses data for Korea from the 1990 and 2015 input-output tables issued by the Bank of Korea. The reason for choosing these two years is that they clearly show the changes in Korea's smart green industry.

The input-output table published by the Bank of Korea produces a data sheet every five years. The 2015 input-output table is the most recent. Accordingly, this study used the 2015 input-output table as the most current data at the time the study was conducted. The study used the 2015-based GDP deflator for changes and comparative analysis. A total of 164 industries were reclassified into 20 sub-classified industries for the purposes of this study, taking into account the basic sectors of industry (Table 1).

IT manufacturing focuses on functions such as storing computational measurement data using the movement of electrons and includes wired and wireless communication devices capable of transmitting voice and data information. These industries are classified as representative industries that collect, transmit, and output data from intelligent buildings. The IT service industry has five software parts: portal, online information, database, online content, and online information process. These industries have functions such as data analysis, processing, and use and monitoring in intelligent buildings.

The knowledge services industry consists of areas such as knowledge-based artificial intelligence decision-making algorithms. Knowledge services include areas that have the overall control over content in smart buildings [40,41]. The green industry consists of new renewable energy technologies that minimize carbon emissions while recycling energy generation and supply to buildings. The green industry is very relevant to green technologies. Solar panels that generate new renewable energy and smart grids that manage and operate energy are examples of the convergence of IT and the green industry [16].

Table 1. Classification of smart green industries and traditional industries.

No.	Industries of Classification	
1	IT Manufacturing (ITM)	Smart and Green
2	IT Services (ITS)	
3	Knowledge Services (KS)	
4	New Renewable and Recycle Energy (NRRE)	
5	Construction (C)	
6	Agriculture and Fishing (AF)	Traditional
7	Mining (M)	
8	Light (L)	
9	Chemical (CH)	
10	Metal and Non-metal (MNM)	
11	Machinery Manufacturing (MM)	
12	Transport Equipment Manufacturing (TEM)	
13	Other Manufacturing (OM)	
14	Wholesale and Retail Trade Services (WRTS)	
15	Accommodation and Food Services (AFS)	
16	Transport Services (TS)	
17	Real Estate Services (RES)	
18	Business Support Services (BSS)	
19	Public Administration and Defense Services (PADS)	
20	Other Services (OS)	

Smart green systems minimize energy consumption through new technological innovations while promoting energy conservation and the reuse of materials to support the environmental aspects of sustainability [42]. Specifically, the green industry includes nuclear energy and waste from buildings users, as well as aspects of energy generation such as new renewables and hydropower; and it includes the recycling of resources [43].

Construction is an industry about buildings, including residential real estate and dormitories, and all structural facilities, including buildings such as commercial public educational facilities. It also includes architectural renovation and civil engineering. Buildings that are smart and capable of generating and delivering sustainable energy are classified as smart green industries in this study.

4. Analysis Results

4.1. Changes in the Amount of Production That the Construction Industry Purchases for Smart Green Industries

How much does the construction industry need green technologies? To answer this first question, this study used an input-output model to determine the construction industry's consumption level of green technologies (Table 2). This study examined the purchases of green technologies by the construction industry.

In 1990, the construction industry bought a total of KRW 10,088 billion (Korean currency unit) of technologies from other industries. In 2015, it bought KRW 130,695 billion of technologies, an increase of KRW 120,606 billion in 25 years. In 1990, the construction industry bought KRW 2245 billion (22.26%) from smart green industries and KRW 7842 billion (77.74%) from traditional industries. In 2015, the construction industry purchased KRW 33,376 billion from smart green industries, an increase of KRW 31,130 billion compared to 1990. The construction industry purchased KRW 97,319 billion from traditional industries, an increased of KRW 89,476 billion. As a result, the rate of traditional industrial purchases in the construction industry is decreasing (−3.28%), while the rate smart green industry purchases is increasing (+3.28%).

Table 2. Purchase activities of the construction industry in 1990 and 2015 (unit: KRW million, %).

Industries		Construction in 1990	Construction in 2015	Amount of Growth	Rate of Growth
Smart and Green	ITM	71,552 (7.09)	9,356,875 (7.16)	8,641,348	1207.7
	ITS	50,964 (0.51)	714,920 (0.55)	663,956	1302.8
	KS	1,433,508 (14.21)	22,368,220 (17.11)	20,934,712	1460.4
	NRRE	45,835 (0.45)	935,993 (0.72)	890,158	1942.1
	SUM	2,245,834 (22.26)	33,376,008 (25.53)	31,130,174	-
Traditional	AF	21,193 (0.21)	500,720 (0.38)	479,527	2262.7
	M	170,735 (1.69)	264,933 (0.20)	94,198	55.2
	L	643,065 (6.37)	5,194,992 (3.97)	4,551,927	707.8
	CH	524,754 (5.20)	10,594,875 (8.11)	10,070,121	1919.0
	MNM	4,466,853 (44.28)	52,532,440 (40.19)	48,065,587	1076.1
	MM	615,237 (6.10)	5,606,611 (4.29)	4,991,374	811.3
	TEM	54,734 (0.54)	84,515 (0.06)	29,781	54.4
	OM	20,582 (0.20)	5,082,660 (3.89)	5,062,078	24,594.5
	C	48,661 (0.48)	64,588 (0.05)	15,927	32.7
	WRTS	580,979 (5.76)	7,388,364 (5.65)	6,807,385	1171.7
	AFS	-	783,447 (0.60)	783,447	-
	TS	335,452 (3.32)	1,886,276 (1.44)	1,550,824	462.3
	RES	94,607 (0.94)	592,447 (0.45)	497,840	526.2
	BSS	253,120 (2.51)	6,329,772 (4.84)	6,076,652	2400.7
	PADS	-	-	-	-
	OS	13,009 (0.13)	413,035 (0.32)	400,026	3075.1
	SUM	7,842,979 (77.74)	97,319,675 (74.46)	89,476,696	-
Total SUM		10,088,814 (100.0)	130,695,683 (100.0)	120,606,869	-

Purchases green technologies by construction services are evolving into a knowledge service, with new renewables showing the largest percentage increase. The result is a reduction in carbon dioxide emissions from construction and increased energy efficiency, reflecting the focus on using new renewable energies [44]. The reason the construction industry buys more from smart green industries than traditional industries is because the industry is buying new technologies and applying them to construction as green technologies emerge and grow [45].

In other words, there is a shift from red concrete buildings (e.g., brick) to smart buildings that combine information and communication technology with green technology. The fact that more green technologies are being purchased by the construction industry supports the argument that buildings now have more facilities and equipment such as computers using energy.

4.2. Changes in Smart Green Industries' Input in the Construction Industry

The results of the technical coefficient analysis are presented in Table 3. The technical coefficient of the whole construction industry increased from 0.541 in 1995 to 0.5831 in 2015, which means that the input cost of technical materials increased to KRW 42.1 to construct a building worth KRW 1000. The technology coefficient of smart green industries increased from 0.1204 in 1990 to 0.1475 in 2015 (+0.0271). On the other hand, the technical coefficient of traditional industries going into construction was 0.0151 in 2015, which is lower than the coefficient for smart green industries.

Table 3. Changes in the input of smart green industry into construction, 1990 to 2015 (unit: technical coefficient).

Industries		Construction in 1990	Construction in 2015	Amount of Growth	Rate of Growth
Smart and Green	ITM	0.0383 (7.09)	0.0400 (6.87)	0.0017	4.5%
	ITS	0.0027 (0.5)	0.0031 (0.54)	0.0004	15.9%
	KS	0.0768 (14.2)	0.1001 (17.16)	0.0232	30.2%
	NRRE	0.0024 (0.45)	0.0041 (0.71)	0.0017	70.4%
	SUM	0.1204 (22.26)	0.1475 (23.30)	0.0271	-
Traditional	AF	0.0011 (0.21)	0.0022 (0.38)	0.0011	97.2%
	M	0.0091 (1.69)	0.0011 (0.2)	−0.0080	−87.0%
	L	0.0344 (6.37)	0.0232 (3.98)	−0.0112	−32.6%
	CH	0.0281 (5.2)	0.0474 (8.13)	0.0193	68.5%
	MNM	0.2395 (44.27)	0.2351 (40.32)	−0.0044	−1.8%
	MM	0.0329 (6.09)	0.0250 (4.3)	−0.0079	−23.9%
	TEM	0.0029 (0.54)	0.0003 (0.06)	−0.0026	−87.1%
	OM	0.0011 (0.2)	0.0227 (3.9)	0.0216	1961.1%
	C	0.0026 (0.48)	0.0002 (0.04)	−0.0023	−88.9%
	WRTS	0.0311 (5.75)	0.0330 (5.67)	0.0019	6.1%
	AFS	-	0.0035 (0.6)	0.0035	-
	TS	0.0179 (3.32)	0.0084 (1.44)	−0.0095	−53.1%
	RES	0.0050 (0.93)	0.0026 (0.45)	−0.0024	−47.7%
	BSS	0.0135 (2.5)	0.0283 (4.85)	0.0148	108.7%
	PADS	-	-	-	-
	OS	0.0006 (0.12)	0.0018 (0.31)	0.0012	165.0%
	SUM	0.4205 (77.74)	0.4356 (74.70)	0.0151	-
Total SUM		0.5410 (100.0)	0.5831 (100.0)	0.0421	-

The inputs of construction technology materials are IT manufacturing, the intelligent green industry of knowledge-based services, and traditional industries such as the metal industry, non-metal light industry, and machinery and chemical industry, which were the mainstays. However, in terms of the growth rate of technology application from 1990 to 2015, intelligent green industries increased greatly, such as new renewable energy (70.4%), knowledge-based services (30.2%), IT services (15.9%), and IT manufacturing (4.5%).

The technical coefficients of the intelligent green industry were applied to the construction industry in 1990 in the order of knowledge, IT manufacturing, IT services, and new renewable energy. Notably, the technical coefficients increased in 2015, with new renewable energy showing the largest rate of increase (70.4%).

To sum up, the input of IT manufacturing technology (e.g., sensing technology to see, hear, and smell), knowledge services (e.g., data processing algorithms), IT service technology (e.g., software, information networking), and green technology (e.g., energy efficiency, new renewable energy, and energy recycling) into construction has been increasing, leading to buildings becoming smarter over time.

New renewable energy recycling has increased its input to construction. The results of this analysis show that the use of technology in construction has changed over time. The merging of knowledge, infrastructure, information services, and green technology in construction is evident.

4.3. Changes in the Ripple Effect of Construction on Smart Green Industries

The production-enhancing effect of construction on other sectors of the economy increased from 2.3673 in 1990 to 2.4972 in 2015, an increase of 0.1299 (Table 4). In 1990, when the construction of KRW 1000 was carried out, it generated a total effect of KRW 2367. In 2015, this effect was KRW 2497. The production-enhancing effect of construction affecting smart green industries was an increase of 0.0952. The production-enhancing effect of construction on traditional industry was an increase of 0.0425.

Table 4. Changes in the ripple effect of construction on smart green industries, 1990 to 2015 (unit: multiplier coefficient, %).

Industries		Construction in 1990	Construction in 2015	Amount of Growth	Rate of Growth
Smart and Green	ITM	0.0806 (3.4)	0.0943 (3.77)	0.0137	17.0
	ITS	0.0121 (0.51)	0.0188 (0.75)	0.0068	55.8
	KS	0.1361 (5.74)	0.1892 (7.57)	0.0531	39.0
	NRRE	0.0318 (1.34)	0.0534 (2.14)	0.0216	68.0
	SUM	0.2607 (11.01)	0.3559 (14.25)	0.0952	-
Traditional	AF	0.0255 (1.08)	0.0177 (0.71)	−0.0078	−30.5
	M	0.0757 (3.19)	0.0804 (3.22)	0.0047	6.2
	L	0.0849 (3.58)	0.0740 (2.96)	−0.0109	−12.9
	CH	0.1723 (7.27)	0.1775 (7.11)	0.0052	3.0
	MNM	0.4975 (21.01)	0.4079 (16.33)	−0.0896	−18.0
	MM	0.0626 (2.64)	0.0507 (2.03)	−0.0119	−18.9
	TEM	0.0171 (0.72)	0.0116 (0.46)	−0.0055	−32.2
	OM	0.0038 (0.16)	0.0669 (2.68)	0.0631	1621.1
	C	1.0114 (42.72)	1.0027 (40.15)	−0.0087	−0.9
	WRTS	0.0674 (2.84)	0.0794 (3.18)	0.0120	17.8
	AFS	-	0.0243 (0.97)	-	-
	TS	0.0427 (1.8)	0.0668 (2.67)	0.0241	56.3
	RES	0.0200 (0.84)	0.0177 (0.71)	−0.0023	−11.5
	BSS	0.0225 (0.95)	0.0554 (2.22)	0.0329	145.9
	PADS	-	-	-	-
	OS	0.0025 (0.1)	0.0077(0.31)	0.0052	207.1
	SUM	2.081 (88.99)	2.1235 (85.75)	0.0425	-
Total SUM		2.3673 (100.0)	2.4972 (100.0)	0.1299	-

In terms of the smart green industry, knowledge services and new renewables were analyzed as the most affected industries. As already indicated, the results are consistent with the results of the analysis on the purchasing side and the analysis on the technical input side. Of particular note is IT services. Although the IT service industry showed that its technical input (0.0031) was the smallest and its rate of increase (15.9%) was not large, the analysis of production-inducing coefficients found that the rate of increase was the second-largest at 55.8%. This means that IT services is a low-cost, high-efficiency industry, which has a large effect compared to its low technology input.

In the smart green industry, the production-inducing effect increased; the ramifications were large as a result of the analysis of the technical coefficients of knowledge (0.1892), IT manufacturing (0.0943), new renewable energy (0.0534), and IT services (0. 0188). As for traditional industries, most of them, with the exception of a few industries, were found to be less conducive to production. This means that construction has transferred these impacts to smart green industries and certain traditional industries such as other manufacturing and business support services. The construction industry benefits more from smart green industries than any other industry.

4.4. Changes in the Network Relationship between Smart Green Industries and Construction

4.4.1. Changes in the Network Structure of Inter-Industries

The results of the basic analysis of the entire network structure are shown in Table 5. The network links connecting industry and commerce were 381 in 1990 and 400 in 2015, and the density of the network diagram showed an increase of 0.05 from 1.003 to 1.053. This means that, as the number of links increases, the network's connectivity is strengthened. A network built on the production-inducing factors of the input-output table is a complete network in which all industries are linked.

Table 5. Fundamental analysis of network structure (unit: number of).

Year	Node	Link	Graph Density	Threshold (Average of Leontief Multiplier)	Link of Threshold Application (%)	Graph Density of Threshold Application
1990	20	381	1.003	0.0833	65 (18.06)	0.171
2015	20	400	1.053	0.0951	85 (22.37)	0.224

In this complete network, it is not easy to find cross-sector connections. In other words, the raw network built by the input-output table is very dense because the value of the production-inducing coefficient is very small, since most inter-industry linkages have only significant associations above a certain level that must be used for the analysis.

Accordingly, in this study, the average value of the production-inducing coefficient was used as a threshold to find the optimal number of connections in the industrial network. A value higher than the average of the production-inducing coefficient is represented in the network. In 1990 and 2015, the threshold values were 0.0833 and 0.0951, respectively. The number of connections to which the threshold value applied was 65 in 1990 and 85 in 2015. The density of the network was given as 0.171 and 0.224, respectively. The number of these connections corresponds to 18.06% and 22.37% of the total network, respectively.

The results of the basic analysis of the network structure look as displayed in Figure 3. The blue and green nodes represent the intelligent green industry, the red color represents the construction industry, and the gray node represents the traditional industry. The sizes of the nodes in the network were expressed in terms of the centrality of the connection. Networks with thresholds applied could confirm that, in 1995, the size of the nodes in traditional industries was large when the nodes of the smart green industry were shown to be small.

IT servicee and business support servicee have been identified as isolated nodes. On the other hand, in 2015, the network confirms that the nodes of the intelligent green industry are larger than those in 1990. All of them seemed to be interconnected, with no isolated nodes. This means that the influence of the intelligent green industry is increasing.

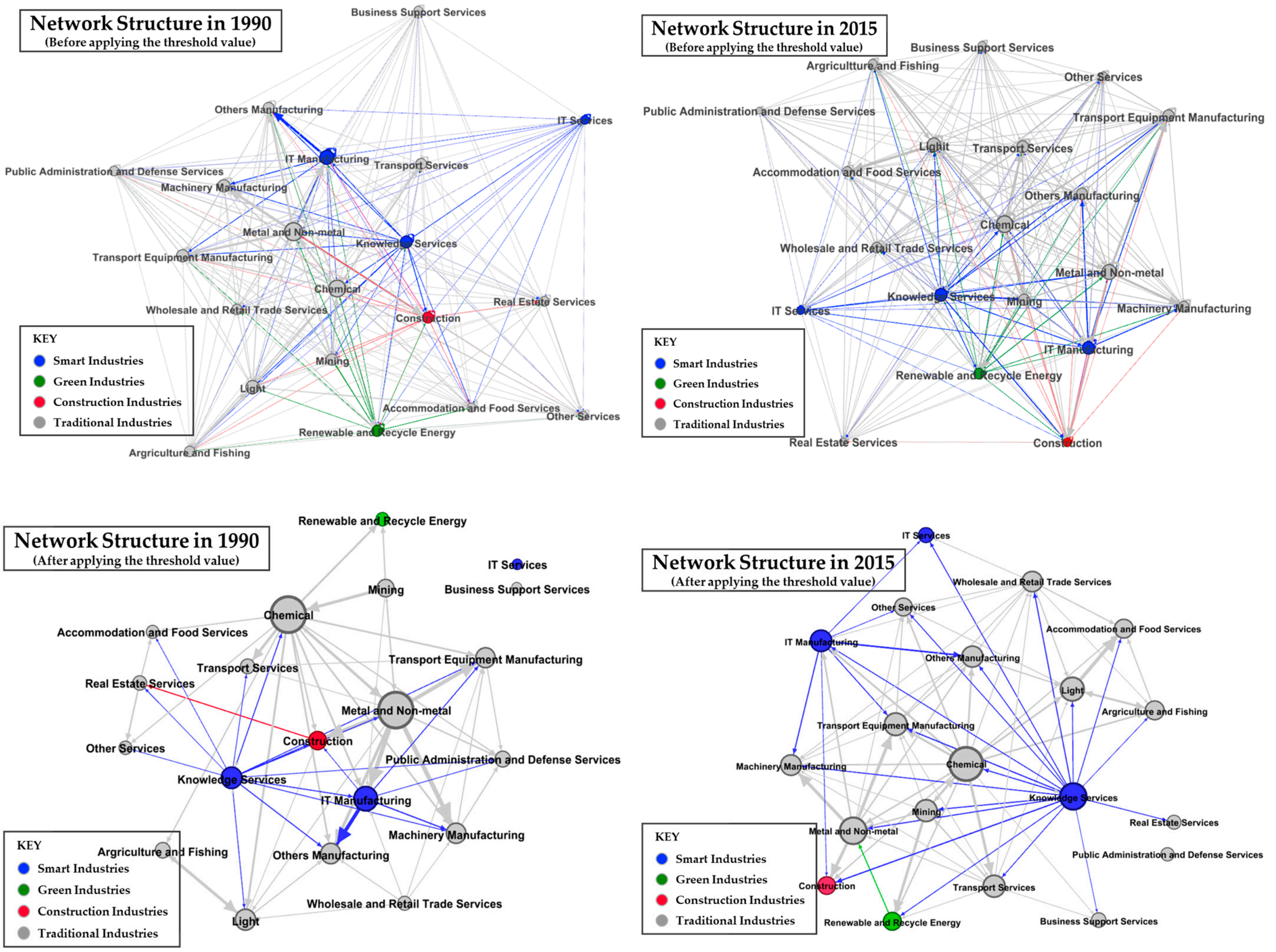

Figure 3. Network structure before and after applying the threshold.

4.4.2. Changes in the Network Centrality of Industries

Table 6 shows the results of the analysis of the in-degree and out-degree centrality and eigenvector centrality. The value of in-degree centrality shows that traditional industries are mainly at the top, and that the smart green industry has a low centrality value for the most part. The smart green industry accounted for about 15% of the total of in-degree centrality in 1990. The in-degree centrality of IT manufacturing (1.08) had the highest value, accounting for 9.34% of the total in 1990. In 1990, IT services had a value of 0, because the production-inducing effect of IT services has a below-average value. In 2015, the in-degree centrality of the smart green industry accounted for about 15% of the total, similar to 1990. However, IT manufacturing (0.8) and new renewable energy (0.78) appeared to be higher-than-average industries.

The out-degree centrality of the smart green industry was about 19.8% in 1990 and 18.4% in 2015 in the entire network. It should be noted that, in both 1990 and 2015, the analysis found that IT services had no impact on other industries. This means that the production-enhancing effect of IT services is minimal and that it has industry-dependent rather than independent characteristics.

In terms of eigenvector centrality, in 1990 and 2015, IT manufacturing had above average values, while the rest of the smart green industry was found to be below average. This suggests that there are few direct or indirect links to industries (e.g., traditional industries at the top) that are important in the network, with the exception of IT manufacturing.

Table 6. Changes in the network centrality, 1990 to 2015 (unit: centrality coefficient, %).

Rank	In-Degree		Out-Degree		Eigenvector	
	1990	2015	1990	2015	1990	2015
1	OM (1.45, 12.53)	TEM (1.61, 11.36)	MNM (3.08, 26.63)	CH (3.35, 23.65)	PADS (1, 11.56)	TEM (1, 12.57)
2	TEM (1.15, 9.96)	MM (1.35, 9.52)	CH (3.01, 26.0)	**KS (2.50, 17.6)**	TEM (0.75, 8.72)	OS (0.84, 10.6)
3	MM (1.13, 9.77)	AFS (1.09, 7.73)	**KS (1.38, 11.9)**	MNM (1.86, 13.1)	OM (0.73, 8.51)	MM (0.78, 9.92)
4	**ITM (1.08, 9.34)**	L (1.05, 7.41)	**ITM (0.92, 7.95)**	M (1.16, 8.22)	C (0.73, 8.47)	OM (0.58, 7.35)
5	C (0.97, 8.39)	OM (1.01, 7.14)	M (0.77, 6.73)	WRTS (1.02, 7.24)	TEM (0.64, 7.46)	L (0.57, 7.23)
6	L (0.93, 8.09)	OS (0.92, 6.50)	L (0.57, 4.98)	L (1.01, 7.13)	MM (0.56, 6.54)	TEM (0.49, 6.18)
7	PADS (0.76, 6.59)	C (0.86, 6.12)	WRTS (0.48, 4.22)	TEM (0.94, 6.68)	L (0.51, 5.90)	**ITM (0.46, 5.81)**
8	CH (0.71, 6.20)	MNM (0.81, 5.74)	AF (0.37, 3.22)	**ITM (0.82, 5.83)**	CH (0.49, 5.75)	AFS (0.44, 5.54)
9	MNM (0.62, 5.42)	**ITM (0.80, 5.67)**	RES (0.31, 2.75)	OM (0.53, 3.76)	**ITM (0.49, 5.72)**	MNM (0.41, 5.18)
10	TEM (0.59, 5.13)	**NRRE (0.78, 5.55)**	MM (0.27, 2.39)	AF (0.39, 2.78)	OS (0.38, 4.47)	C (0.36, 4.53)
11	**NRRE (0.40, 3.50)**	TEM (0.77, 5.48)	TEM (0.21, 1.89)	TEM (0.23, 1.66)	AFS (0.38, 4.47)	AF (0.34, 4.35)
12	OS (0.39, 3.45)	AF (0.71, 5.00)	C (0.14, 1.21)	**NRRE (0.12, 0.86)**	MNM (0.36, 4.27)	CH (0.34, 4.30)
13	AFS (0.35, 3.02)	CH (0.66, 4.70)	OM (0, 0)	MM (0.09, 0.67)	RES (0.34, 4.04)	**NRRE (0.32, 4.06)**
14	AF (0.33, 2.89)	M (0.53, 3.78)	PADS (0, 0)	BSS (0.08, 0.62)	**KS (0.33, 3.86)**	M (0.25, 3.18)
15	RES (0.23, 1.99)	WRTS (0.39, 2.76)	TEM (0, 0)	AFS (0, 0)	AF (0.33, 3.86)	WRTS (0.25, 3.18)
16	M (0.22, 1.92)	**ITS (0.33, 2.37)**	**NRRE (0, 0)**	OS (0, 0)	M (0.28, 3.31)	**ITS (0.22, 2.80)**
17	**KS (0.20, 1.75)**	BSS (0.17, 1.20)	OS (0, 0)	C (0, 0)	**NRRE (0.25, 2.99)**	BSS (0.12, 1.53)
18	**ITS (0, 0)**	**KS (0.14, 1.00)**	AFS (0, 0)	**ITS (0, 0)**	WRTS (0, 0)	**KS (0.09, 1.18)**
19	WRTS (0, 0)	RES (0.12, 0.89)	**ITS (0, 0)**	RES (0, 0)	**ITS (0, 0)**	RES (0.02, 0.34)
20	BSS (0, 0)	PADS (0, 0)	BSS (0, 0)	PADS (0, 0)	BSS (0, 0)	PADS (0, 0)
Total SUM	11.5, 100	14.1, 100	11.5, 100	14.1, 100	8.64, 100	7.95, 100
AVG	0.58	0.71	0.58	0.71	0.43	0.40

Note: Bold characters are smart and green industries. See the abbreviation. You can check the Abbreviation.

In both 1990 and 2015, the in-degree and out-degree centrality of IT manufacturing had above-average values. This is because IT manufacturing has a very close relationship with traditional industries [16]. The results of the analysis showed that the smart green industry has a reciprocal relationship with other industries, and its influence is also increasing. In particular, for new renewable energy, its value and share are increasing in all centralities. This is likely caused by the increasing use of carbon credits and the response to climate change.

4.4.3. Changes in the Network Industry Path between Smart Green Industries and the Construction Industry

The ramifications of the multiplier coefficient describe the relationship between industry and industry as a ripple effect. However, the network industry path can analyze all delivery systems of the production-inducing coefficient. In other words, we can find out how strong the ripple effect of the intelligent green industry is on which path to construction. In this study, the network industry path was extracted from a network created so that only those above the threshold could be represented.

The results of the network industrial pathway analysis of the smart green industry to the construction industry are shown in Table 7. The analysis of the industrial network showed an increase of 9 from 13 in 1990 to 22 in 2015, which means that the link is strengthened, and a new value chain is created between the intelligent green industry and the construction industry. If we look at them in detail, they are as follows: it was shown that IT manufacturing has a tangential link to construction. The weights were increased by 0.014 from 0.080 to 0.094. This means that IT manufacturing does not run through other industries, but mediates its ramifications through a direct relationship with construction. IT services did not appear in the industry path of the 1990 and 2015 network, which means that IT services above the threshold have no effect on construction. This means that its ramifications are very small in absolute terms.

Table 7. Changes in the industrial network path from 1990 to 2015.

No.	Industrial Path in 1990						Weight	Industrial Path in 2015							Weight	Changes
1	ITM	C					0.080	ITM	C						0.094	0.014
2	ITS						N/A	ITS							N/A	N/A
3	KS	C					0.136	KS	C						0.189	0.053
4	KS	ITM	C				0.204				-					Extinct
5	KS	L	C				0.187				-					Extinct
6	KS	L	CH	C			0.274				-					Extinct
7	KS	L	CH	M	MNM	C	0.994				-					Extinct
8	KS	L	CH	MNM	C		1.024				-					Extinct
9	KS	CH	C				0.297	KS	CH	C					0.333	0.036
10	KS	CH	MNM	C			0.959	KS	CH	MNM	C				0.770	−0.189
11	KS	CH	M	MNM	C		0.929	KS	CH	M	MNM	C			0.946	0.017
12				-				KS	CH	M	NRRE	MNM	C		1.247	New
13				-				KS	CH	M	TS	MNM	C		0.967	New
14				-				KS	CH	M	TS	NRRE	MNM	C	1.057	New
15				-				KS	CH	TS	MNM	C			1.069	New
16				-				KS	CH	TS	NRRE	MNM	C		1.159	New
17				-				KS	CH	TS	M	NRRE	MNM	C	1.627	New
18	KS	MNM	C				0.611	KS	MNM	C					0.564	−0.047
19	KS	MNM	CH	C			0.754				-					Extinct
20	KS	MNM	M	CH	C		0.738				-					Extinct
21				-				KS	M	MNM	C				0.764	New
22				-				KS	M	NRRE	MNM	C			0.817	New
23				-				KS	M	TS	MNM	C			0.785	New
24				-				KS	M	TS	NRRE	MNM	C		0.875	New
25				-				KS	M	TS	M	NRRE	MNM	C	1.343	New
26				-				KS	TS	MNM	C				0.689	New
27				-				KS	TS	NRRE	MNM	C			0.752	New
28				-				KS	TS	M	NRRE	MNM	C		1.220	New
29				-				KS	NRRE	MNM	C				0.657	New
30	NRRE						N/A	NRRE							N/A	N/A
31				-				NRRE	MNM	C					0.530	New

New renewables did not emerge as a pathway for the grid industry in the construction industry in 1990. However, in 2015, a pathway emerged that went through the metal and nonmetal industries and influenced the construction industry. Most network industries were analyzed in the knowledge service industry. The number of network industries in knowledge services increased from 12 in 1990 to 20 in 2015. This means that, among the intelligent green industries, the construction industry has been greatly influenced by knowledge services.

In particular, the network industrial path from knowledge services to the construction industry was confirmed, with 7 disappearing and 15 being newly created. The missing network path is the path that started with the knowledge service industry and then gave rise to the light industry and the metal–nonmetal industry. The path "KS → MNM → C" did not disappear, but its branching weights were analyzed to decrease (−0.047). This means that the path of the network industry is weakened by the light industry and the metal–base metal industry.

On the other hand, network industry routes related to chemical mining and transportation services may have newly emerged, or their weights were partially increased. In particular, the newly emerged network industrial route is the intelligent green industrial route, which includes new renewable energy and accounts for 67% of the total. This means that new renewable energy affects the construction industry, and issues such as new renewable energy and carbon dioxide emissions have probably been transferred to the construction industry.

If we look at this path of the network industry, we can see that the demand for smart green technology is spilling over into the construction industry. This shows that we are beyond the initial stage of the informatization of the construction industry [16]. These results mean entering into the smart era. In addition, the smart green industry has more than a direct relationship with the construction industry; it was analyzed to establish indirect associations through different industries.

5. Conclusions

This study analyzed how smart green technology and construction have been changed by the convergence of smart buildings from the industrial side. The analysis data in this study are the input-output tables for 1990 and 2015 issued by the Bank of Korea, and the industry category of the input-output table was reclassified into 20 industries. In this study, the analytical model was used, which consists of the input-output model and network analysis.

The construction industry still performs important production activities through the purchase of traditional technology (industries). It was studied that the scale of production activities is gradually expanding through the purchase of intelligent green technology. In particular, the new renewable energy sector recorded the largest percentage increase in purchases. This is due to the dramatic increase in the demand for carbon emission reduction and energy-efficient new renewable energy in buildings. As a result, the growth rate of smart green technology deployment in the construction industry is greater than that of technology in traditional industries. This has been a sharp increase and further increases in H/W, S/W, and energy-related equipment and facilities, indicating that somatization is proceeding rapidly. As for its impact on construction, the smart green industry has been studied as a low-cost, high-efficiency industry that uses less technology and has a great impact. The intelligent green industry is a must for the sustainable operation of the construction industry and shows that it is an industry that leads the high value-added construction industry.

In the network analysis, it was found that the influence of the smart green industry is increasing and turning into an interdependent relationship with construction and other industries. This was also reflected in the results of the network industry pathways. The number of network industries increased by nine between 1990 and 2015. The connection between the smart green industry and the construction industry has intensified. This means that the construction industry is increasing the demand for the smart green industry. This indicates that the impact of the intelligent green industry is relatively new and innovative. It was analyzed that the smart green industry prefers to establish indirect links through other industries than a direct relationship with the construction industry. In particular, it was found that the value and proportion of new renewable energy hace increased the most. This is due to the problem of carbon emissions and the response to climate change.

These results stem from Korea's smart-related policies. Since 1990, Korea has established various policies such as the policy on e-Korea (2002), broadband Korea (2003), U-Korea (2006), U-City Law (2008), and 1st and 2nd U-city master plans (1990 and 2015). These policies hafe promoted the convergence of smart green and traditional industries. In this regard, smart technologies related to IT manufacturing, IT services, and knowledge services are expected to be widely used in buildings and cities (urban areas).

However, the classification of the smart green industry is still a problem. As technology advances, the boundaries of the industry blur, as the lines between service and production are unclear. This study was developed based on existing studies, including the content of the papers published by the OECD, and we derived a smart green industry, but it cannot be said that this is accurate. This study made a new classification of the industry and identified the link between smart green technology and construction based on the various aspects of the proposed classification, which provides useful experimental results.

The limitations of this study and the future research direction are as follows: The input-output tables of the Republic of Korea are updated once every five years. For this reason, there is a limitation that the most recent data cannot be used to analyze the current time frame, which is affected by COVID-19. Future research should be conducted not only on Korea, but also on high-GDP countries such as China, Germany, Japan, and the United States. This will provide a better understanding of how experience in Korea differs from or is similar to other countries and provide better insights. Also, in addition to research at the national level, it is also necessary for specific aspects to analyze how smart green industries are changing across regions. Industry input-output tables can be used to analyze what convergence relationship green technology has with construction in the real-world urban context of building.

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Abbreviations

ITM	IT Manufacturing
ITS	IT Services
KS	Knowledge Services
NRRE	New Renewable and Recycle Energy
C	Construction
AF	Agriculture and Fishing
M	Mining
L	Light
CH	Chemical
MNM	Metal and Non-Metal
MM	Machinery Manufacturing
TEM	Transport Equipment Manufacturing
OM	Others Manufacturing
WRTS	Wholesale and Retail Trade Services
AFS	Accommodation and Food Services
TS	Transport Services
RES	Real Estate Services
BSS	Business Support Services
PADS	Public Administration and Defense Services
OS	Other Services

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