Asia Pacific Journal of Information Systems
Vol. 31 No. 3 (September 2021), 358-377

ISSN 2288-5404 (Print) / ISSN 2288-6818 (Online)
https://doi.org/10.14329/apjis.2021.31.3.358

A Comparison of Structural Position and Exploitative Innovation Based on a Patent Citation Network of the Top 100 Digital Companies

Hyun Mo Kang[a], Il Young Choi[b], Jae Kyeong Kim[c], Hyun Joo Shin[d,*]

[a] *Researcher, AI Management Research Center, Kyung Hee University, Korea*
[b] *Lecturer, Graduate School of Business Administration, Kyung Hee University, Korea*
[c] *Professor, School of Management, Kyung Hee University, Korea*
[d] *Ph.D. Candidate, Department of Business Administration, Graduate School, Kyung Hee University, Korea*

A B S T R A C T

Knowledge drives business innovation. However, even if companies have the same knowledge element in the business ecosystem, innovation performance varies depending on the structural position of the technical knowledge network. This study investigated whether there is a difference in exploitative innovation according to the structural position of the AI technical knowledge network. We collected patents from the top 100 digital companies registered with the US Patent Office from 2015 to 2019 and classified the companies into knowledge producer-based brokers, knowledge absorber-based brokers, knowledge absorbers, and knowledge producers from the perspective of knowledge creation and flow. The analysis results are as follows. First, a few of the top 100 digital companies disseminate, absorb, and mediate knowledge, while the majority do not. Second, exploitative innovation is the largest, in the order of knowledge producer, knowledge absorber-based broker, knowledge absorber, and knowledge producer-based broker. Finally, patents for industrial intelligence occupy a large proportion, and knowledge producers are leading exploitative innovation. Therefore, latecomers need to expand their resources and capabilities by citing patents owned by leading companies and converge with existing industries into AI-based industries.

Keywords: Artificial Intelligence, Exploitative Innovation, Knowledge Network, Knowledge Flow, Patent Citation Network

Ⅰ. Introduction

As the development of the global economy is driven by the use, production, and diffusion of knowledge (Powell and Snellman, 2004), companies are acquiring, transmitting, and generating knowledge by form-

*Corresponding Author. E-mail: nayarexia@nate.com

ing networks through social relationships (Phelps et al., 2012). More specifically, in an environment in which existing competitive advantages are destroyed and boundaries between industries are broken, the high-tech industry is making efforts to create new markets and acquire knowledge through strategic alliances such as R&D consortiums, patent licenses, and patent cross licenses (Grigoriou and Rothaermel, 2017). In fact, more recently, the high-tech industry has led digital technology innovation through technology convergence such as artificial intelligence (AI) and big data.

AI technology during the introductory stage has evolved from the level of laboratory research to the commercialization stage, a stage that includes manufacturing robots, smart assistants, proactive health care management, automated financial investing, virtual travel booking agents, social media monitoring, conversational marketing bots, and natural language processing (NLP) tools. This has led to explosive market growth and intelligent convergence of other industries. In other words, by evolving from machine learning to deep learning, AI systems can help predict and infer problems through self-learning using data collected through audio, video, and sensors in various applications, such as safety, medical care, defense, finance, and welfare. In particular, global AI companies are building an AI business ecosystem by expanding business partners based on the complementarity or substitution of technical knowledge such as patents (Quan and Sanderson, 2018).

Various organizational forms, large-scale innovation organizations, and mechanisms of cross-realm transposition are key success factors in developing a knowledge ecosystem (Powell et al., 2010), and as a result, networks are an important means for knowledge transfer and dissemination (Boschma and Ter Wal, 2007). Therefore, the spread of technical knowledge through the knowledge network in the business ecosystem is a key factor determining the competitiveness of a company. In other words, companies drive not only their own innovation but also the innovation of other companies by creating strong technical knowledge through competition in the business ecosystem. Hence, many researchers have studied the spread of knowledge based on social network analysis using patent data in various domain ecosystems, such as technology diffusion exploration (Chang et al., 2009), nanotechnology analysis (Li et al., 2007), promising technology prediction (Bruck et al., 2016; Cho and Shih, 2011; Erdi et al., 2013), organic internal knowledge flow of solar cells (Choe et al., 2016), patent value analysis (Yang et al., 2015), printed electronics technology (Kim et al., 2014), IoT (Kim et al., 2017; Takano et al., 2016), nd mobile ecosystems (Lee et al., 2016; Lee and Kim, 2017).

Even if the same knowledge element is already owned in the business ecosystem, innovation performance varies depending on the structural position of the technical knowledge network (Zaheer and Bell, 2005), as more innovative and performant companies are located in the center of a network, where access to new knowledge is easier (Tsai, 2001). In particular, not only companies with the ability to identify and utilize knowledge resources but also innovative companies that bridge structural gaps are performing well (Zaheer and Bell, 2005).

Previous studies have focused on factors that influence innovation from a network perspective, such as centrality and density (Guan and Liu, 2016; Ma et al., 2020; Wen et al., 2021). However, as the roles of companies in the knowledge network, such as dissemination, absorption, and mediation of knowledge, are diverse (Choe et al., 2016), our study aims to classify companies into knowledge producers, knowledge absorber-based brokers, knowledge absorbers, and knowledge producer-based brokers according to their structural position in the patent citation network and to discover whether there are differences in exploitative innovation for each group. To achieve this purpose, AI-related US patents of the top 100 digital companies selected by Forbes in 2019 were collected, and a nonparametric statistical test was performed to determine whether there was a difference in exploitative innovation.

Ⅱ. Related Works

2.1. Artificial Intelligence

AI, which is a term first used by computer scientist John McCarthy at the Dartmouth Conferences in 1956, refers to the intelligence of computers used to solve complex problems (Strong, 2016). AI technology is widely used in cognitive computing, machine learning, deep learning, natural language processing, data mining, speech recognition, pattern recognition, computer vision, image recognition, and virtual reality. Accordingly, the size of the AI technology market is expected to reach $190.6 billion in 2025 from $21.5 billion in 2018 (Marketsandmarkets, 2018).

To date, AI has transcended human information processing capabilities by processing vast amounts of data through various deep learning models, and as a result, AI is useful for discovering various ideas and opportunities (Haefner et al., 2020). Accordingly, research on AI is being actively conducted in various fields, such as medicine (Holzinger et al., 2019; Yu and Kohane, 2019), education (Holmes et al., 2019; Timms, 2016), health care (Davenport and Kalakota, 2019; Maddox et al., 2019), marketing (De Bruyn et al., 2020; Huang and Rust, 2020), agriculture (Patrício and Rieder, 2018; Smith, 2020), and manufacturing (Lee et al., 2018).

2.2. Innovation

Innovation refers to a new idea or method (Rogers, 2010; Van de Ven, 1986; Zaltman et al., 1973), and thus, when people perceive an idea or method as new, it becomes an innovation (Van de Ven, 1986). Since innovation affects corporate performance by, for example, increasing market share and increasing corporate value (Rousseau et al., 2016), it is important for companies to constantly innovate to be sustainable.

In general, innovation is divided into explorative innovation and exploitative innovation. Explorative innovation is an innovation activity that seeks new competencies or opportunities by using new knowledge, whereas exploitative innovation refers to an innovative activity that refines and improves existing competencies with resources or knowledge already possessed by a company.

Greve (2007) found that when the performance of the aspiration level in product innovation decreases, the rate of initiating explorative and exploitative innovation increases and that explorative and exploitative innovation increases when absorbed or unabsorbed free resources increase. It was also argued that the rate of initiating also increased. Lai and Weng (2016) argued that in the technological discontinuity stage, companies perform both utilitarian and explorative innovation activities, but they put more effort into explorative innovation than exploitative innovation for capacity building. Bernal et al. (2019) found that the innovation performance of companies implementing explorative innovation strategies is high in an environment with rapid technological development, but that this has no significant impact on exploitative innovation strategy or innovation performance. Lee et al. (2019) revealed that in the high-tech industry, the enterprise's search orientation has a positive effect on radical product-innovation activities, but that in the low-tech industry, the enterprise's use orientation negatively affects radical product-innovation activity.

There are many determinants of this innovation. Love and Roper (1999) argued that technology transfer and networking can replace R&D, which is a determinant of the innovation process, while Romijn and Albaladejo (2002) argued that the number of university-trained engineers that reflect the skill of the workforce, the total R&D expenditure per employee that reflects the technological effort, the interactions with R&D institutions and suppliers, the international market orientation, etc., are all important determinants. Bhattacharya and Bloch (2004) argued that company size is an important determinant of innovation but that R&D intensity, market concentration, and export intensity are important in the high-tech industry, while profitability is a determinant of innovation in the low-tech industry. Further, Le and Lei (2019) argued that transformational leadership and knowledge sharing are important factors in product innovation and innovation processes and that the higher the perceived organizational support is, the higher the transformational leadership for innovation.

Patents are a driver of innovation through new technologies inasmuch as they give exclusive rights to innovative technologies, and companies create new technologies and innovations through patents. Thus, as patented knowledge flows by citation, it potentially provides extensive information on knowledge flow and spread. Therefore, patent

citation network analysis makes it possible to analyze the flow and spread of technical knowledge among companies.

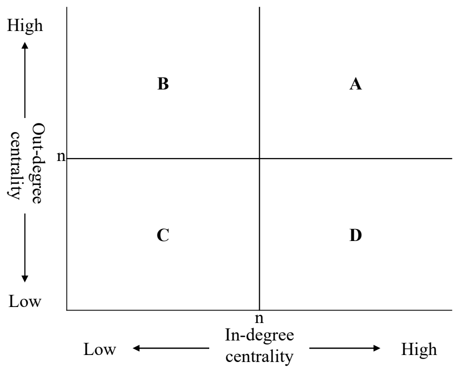
2.3. Patent Citation Network Analysis

A patent is an administrative act that gives an invention or its legitimate successor an exclusive right for a certain period of time in exchange for making the invention public. Accordingly, patent citation analysis is useful for understanding the flow of technical information.

In general, social network analysis is used for patent citation analysis. Social network analysis is a technique that quantitatively analyzes the connection relationships between entities (Wasserman and Faust, 1994) and is used in various business fields, such as vision and strategy, products and services, marketing and selling, delivery, customer service, human capital, information technology, external relationships, and knowledge management (Bonchi et al., 2011).

Indices that are frequently used for social network analysis include degree centrality and betweenness centrality. Degree centrality is an index that measures the degree of connection with other nodes. In degree centrality, the centrality that measures the degree of connection from a link to the inside is called the in-degree centrality, whereas the centrality that measures the degree of the link toward the outside is called the out-degree centrality. Betweenness centrality is an index that measures the degree of mediator role played by a node. Therefore, in the patent citation network, the in-degree centrality indicates the degree of absorption of technical knowledge, the out-degree centrality indicates the degree of production of technical knowledge, and the betweenness centrality indicates the degree of convergence of technical knowledge.

To classify companies according to the flow of knowledge in a patent citation network, a method of displaying in-degree centrality and out-degree centrality in a two-dimensional space is widely used, as shown in <Figure 1> (Lee and Kim, 2017). Here, the in-degree centrality is indicated on the *X*-axis, while the out-degree centrality is indicated on the *Y*-axis. Group *A* is a knowledge producer and absorber group, group *B* is a knowledge absorber group, group *C* is a small knowledge production and absorption group, and group *D* is a knowledge producer group.

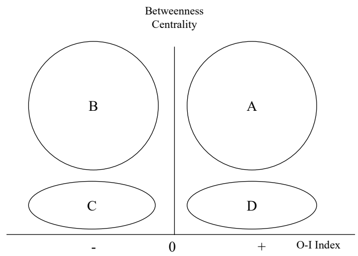


<Figure 1> Classification Using in-degree Centrality and Out-degree Centrality

However, there is no information on the mediating role of knowledge because this method indicates the in-degree centrality and out-degree centrality in a two-dimensional space. Therefore, Choe et al. (2016) developed the O-I index, as presented in Equation (1), to classify companies according to the flow of knowledge in the patent citation network.

$$\text{O} - \text{I Index} = \frac{(Out\!-\!degree\ centrality - In\!-\!degree\ centrality)}{(Out\!-\!degree\ centrality + In\!-\!degree\ centrality)} \quad (1)$$

Choe et al. (2016) classified companies into four groups, as displayed in <Figure 2>, using the O-I index and betweenness centrality. Group *A* was termed a knowledge producer-based broker, Group *B* a knowledge absorber-based broker, Group *C* a knowledge absorber, and Group *D* a knowledge producer.



<Figure 2> Company Classification Using O-I Index and Betweenness Centrality

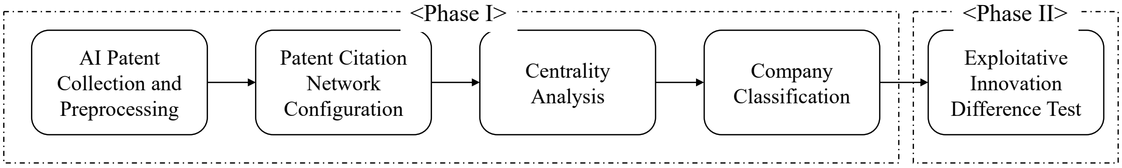
This study attempts to analyze the differences in innovation by group by classifying the 100 digital companies using the O-I index and betweenness centrality.

Ⅲ. Research Method

3.1. Research Process

The purpose of this study is to classify companies into four groups according to the structural position in the AI ecosystem and to determine whether the groups differ in exploitative innovation. To achieve these goals, we perform a two-phase analysis process, as shown in <Figure 3>. The first is to classify companies into four groups according to the structural location of the patent citation network, and the second is to test whether there is a difference in the exploitative innovation of each group.

Company classification using AI patent citation network analysis is composed of four steps: AI patent collection and preprocessing, patent citation network configuration, centrality analysis, and company classification. First, in the data-collection step, AI-re-



<Figure 3> Research Framework

lated IP codes are searched using the US patent search service of KIPRIS (www.kipris.or.kr) provided by the Korean Intellectual Property Office based on International Patent Classification (IPC). In this study, data are collected using the AI-related IPCs described in Tseng and Ting (2013). The field of AI can be divided into four subfields: problem reasoning and solving, machine learning, network structure, and knowledge processing systems. The IPCs related to problem reasoning and solving are G06E1/00, G06E3/00, G06F15/00, G06F15/18, G06F17/00, G06F17/20, G06G7/00, and G06N99/00; those related to machine learning are G05B13/02, G06E1/00, G06E3/00, G06F15/18, G06G7/00, G06N3/00, G06N3/08, G06N3/02, and G06N3/12; those related to network structure are G06E1/00, G06E3/00, 06F15/00, G06F15/18, G06F17/00, G06J1/00, G06N3/00, G06N3/04, and G06N3/10; and those related to knowledge processing system are G06F15/00, G06F15/18, G06F17/00, G06F9/44, G06N5/00, G06N5/02, G06N5/04, G06N7/00, G06N7/02, G06N7/04, G06N7/06, and G06N7/08. Second, in the step of configuring a patent-citation network, a patent-citation network including the top 100 digital companies is configured. The third step is to compute in-degree centrality, out-degree centrality, and betweenness centrality. The final step is to classify the companies into knowledge producers, knowledge absorber-based brokers, knowledge absorbers, and knowledge producer-based brokers using these centralities.

To test whether each group differs from the other groups with respect to exploitative innovation, innovation is calculated using patent family size. Patent family size is an indicator of the national scope of patent protection and is used to measure innovation (Lanjouw and Schankerman, 1999). In this study, a difference test was performed using nonparametric statistics.

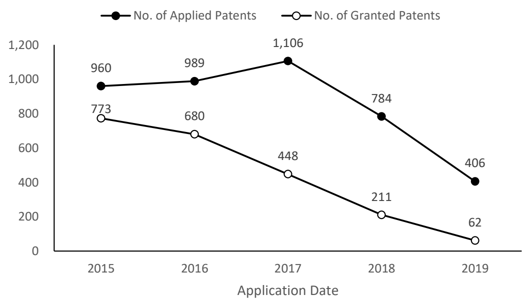
3.2. Sample and Data

AI patents were collected from Forbes' Top 100 Digital Companies of 2019 (see the <Appendix>). When examining the top 100 digital companies by continent, it is found that there are 43 companies in North America, 37 in Asia, 18 in Europe, 1 in Oceania, and 1 in Africa. Additionally, looking at the data by industry, there are 4 companies in the field of broadcasting and cable, 5 in the business and personal services field, 1 in the business products and supplies field, 4 in the communications equipment field, 7 in the computer hardware field, 11 in the computer services field, 1 in the enterprise and consumer financial services field, 2 in the electrical equipment field, 5 in the electronics field, 1 in the health care equipment and services field, 6 in the internet and catalog retail field, 1 in the oil and gas operations field, 2 in the recreational products field, 15 in the semiconductor field, 7 in the software and programming field, 26 in the telecommunications services field, and 2 in other fields.

Ⅳ. Experimental Results

4.1. Frequency Analysis

The patents collected for analysis are shown in <Figure 4>. The number of patents applied for was 960 in 2015, 989 in 2016, 1,106 in 2017, 784 in 2018, and 406 in 2019. It can be concluded that companies have established patent strategies to improve the quality of their products rather than achieve quantitative growth. In addition, the number of patent registrations continues to decline, with 773 cases in 2015, 680 cases in 2016, 448 cases in 2017, 211 cases in 2018, and 62 cases in 2019. This occurs not only because the number of registrations decreases when the number of applications decreases but also because there were many applications for the quantitative growth of AI patents in the early days, and thus new and inventive patent requirements are not being met. In addition, as AI evolves into industrial intelligence, it is believed that the number of patents representing AI in the main IPC has decreased due to the various applications of AI.



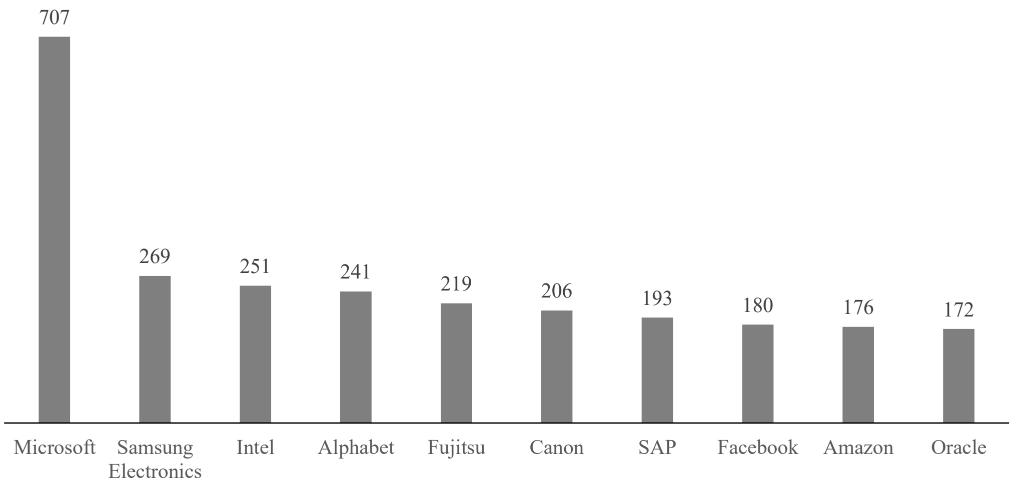
<Figure 4> Number of Patents by Years

<Table 1> shows the patents collected for analysis by the AI field. The patents applied for and registered include problem reasoning and solving (479 applications, 99 grants), machine learning (710 applications, 99 grants), network structure (359 applications, 72 grants), knowledge processing system (1,514 applications, 794 grants), problem reasoning and solving, machine learning (1 application, 1 grant), machine learning, network structure (65 applications, 13 grants), problem reasoning and solving, machine learning, network structure (5 applications, 5 grants), problem reasoning and solving, network structure, knowledge processing system (1,032 applications, 1,032 grants), and problem reasoning and solving, machine learning, network structure, knowledge processing system (80 applications, 59 grants). These data indicate that most of the AI patents are in the fields of knowledge processing systems and problem reasoning and solving.

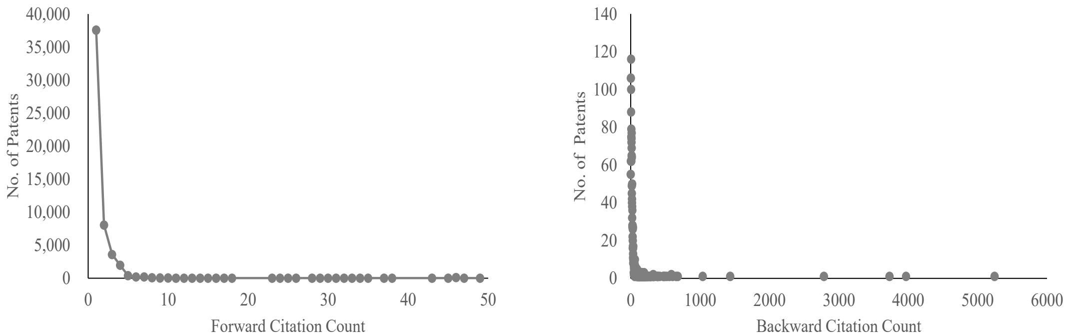
<Table 1> Number of Patents by Sub-technological Fields of AI

Sub-Technological Fields of AI	No. of Applications	No. of Grants
Problem reasoning and solving	479	99
Machine learning	710	99
Network structure	359	72
Knowledge processing system	1,514	794
Problem reasoning and solving, Machine learning	1	1
Machine learning, network structure	65	13
Problem reasoning and solving, Machine learning, Network structure	5	5
Problem reasoning and solving, Network structure, Knowledge processing system	1,032	1,032
Problem reasoning and solving, Machine learning, Network structure, Knowledge processing system	80	59
Total	4,245	2,174

<Figure 5> shows the top 10 patent applicants by year. Major applicants for AI patents are Microsoft



<Figure 5> Top 10 Companies by Patent Applications



(a) Forward Citation Count Distribution

(b) Backward Citation Count Distribution

<Figure 6> Patent Citation Count Distribution

(707 cases, 16.7%), Samsung Electronics (269 cases, 6.3%), Intel (251 cases, 5.9%) Alphabet (241 cases, 5.7%) Fujitsu (219 cases, 5.2%), Canon (206 cases, 4.9%), SAP (193 cases, 4.5%), Facebook (180 cases, 4.2%), Amazon (176 cases, 4.1%), and Oracle (172 cases, 4.1%), and 10 other companies in Korea, the United States and Japan account for 61.6%.

<Figure 6> shows the count distribution of forward citations and backward citations. In general, a patent with many forward citations is more likely to be a source technology, whereas a patent with many backward citations is more likely to be an upgraded technology (Bae et al., 2015). From these figures, it can be seen that most patents have fewer forward citations than backward citations.

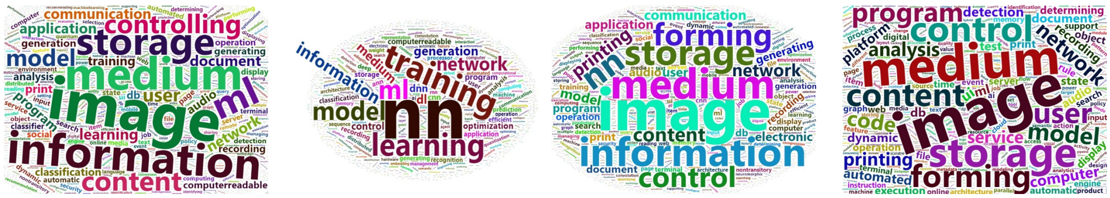
<Table 2> and <Table 3> show the top 10 forward citation patents and backward citation patents. These patents are related to computer systems based on specific computational models. Specifically, the majority of the top 10 forward citation patents are related to information retrieval, database structures, and file system structures, while the majority of the top 10 backward citation patents are related to digital computing or data processing equipment or methods.

<Table 2> Top 10 Forward Citation Patents

Application Year	Title	Applicant/Assignee	IPC	Forward Citation Count
1999	Database management system which synchronizes an enterprise server and a workgroup user client using a docking agent	Siebel systems, Inc.	G06F17/30	49
1999	Method of synchronizing independently distributed software and database schema	Siebel systems, Inc.	G06F9/445	49
1996	Computer method for updating a network design	NetSuite development, L.P.	G06F3/00	47
1999	Method of upgrading a software application in the presence of user modifications	Siebel systems, Inc.	G06F9/445	47
2001	Development tool, method, and system for client server applications	Siebel systems, Inc.	G06F944	47
2000	Implicit rating of retrieved information in an information search system	Rightnow technologies, Inc	G06F17/30	47
2001	Method and apparatus for mapping between XML and relational representations	Siebel systems, Inc.	G06F17/30	47
2003	Method, apparatus, system, and program product for attaching files and other objects to a partially replicated database	Siebel systems, Inc.	G06F17/30	47
2002	User interface for processing requests for approval	Siebel systems, Inc.	G06Q10/00	47
2002	Prototyping graphical user interfaces	Siebel systems, Inc.	G06K15/00	47
2003	Method and architecture for providing data-change alerts to external applications via a push service	Oracle America, Inc.	G06F15/177	47

<Table 3> Top 10 Backward Cited Patents

Application Year	Title	Applicant/Assignee	IPC	Backward Citation Count
2016	Methods and apparatus for altering audio output signals	Apple Inc.	G06F17/00	5,245
2015	Language identification from short strings	Apple Inc.	G06F17/20	3,969
2015	Text prediction using combined word N-gram and unigram language models	Apple Inc.	G06F17/20	3,732
2018	Intelligent automated assistant for media exploration	Apple Inc.	G06F17/00	2,786
2015	Presenting an application change through a tile	Microsoft technology licensing, LLC	G06F15/00	1,433
2015	Application reporting in an application-selectable user interface	Microsoft technology licensing, LLC	G06F15/00	1,038
2016	Module specific tracing in a shared module environment	Microsoft technology licensing, LLC	G06F9/44	679
2016	Intra-datacenter attack detection	Cisco technology, Inc.	G06F17/00	654
2016	Portable multifunction device, method, and graphical user interface for viewing and managing electronic calendars	Apple Inc.	G06F15/00	604
2017	Model-based virtual system provisioning	Microsoft technology licensing, LLC	G06F9/44	587
2015	Scaling event processing using distributed flows and map-reduce operations	Oracle international corporation	G06F17/00	587



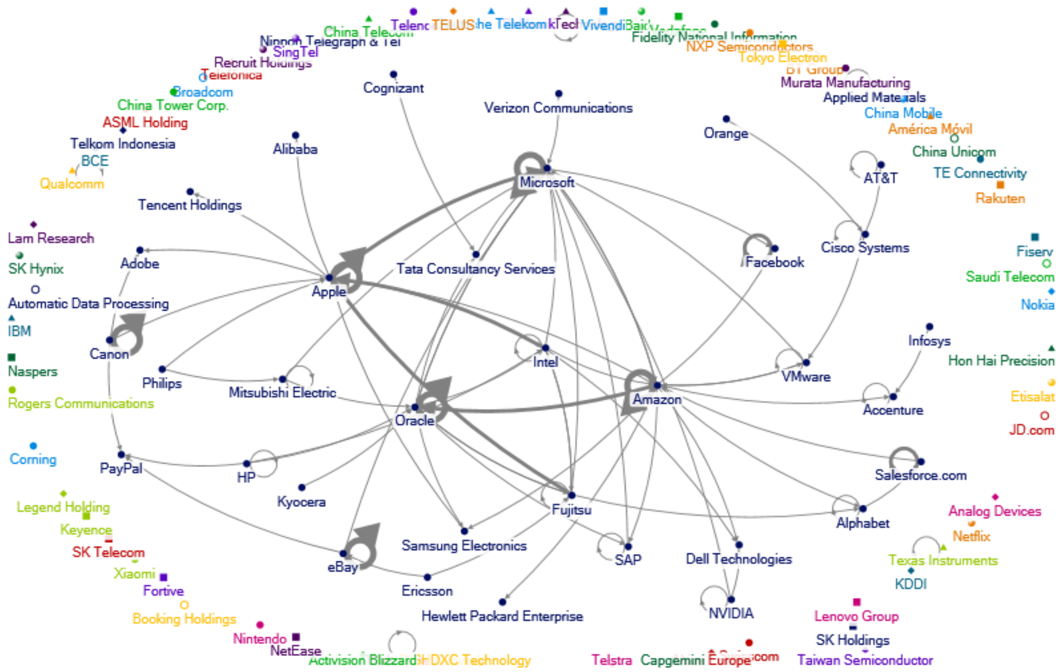
(a) Problem Reasoning and solving (b) Machine Learning (c) Network Structure (d) Knowledge Processing System

<Figure 7> Word Usage Frequencies by Sub-technological Fields of AI

The keywords of patents filed for each AI field are shown in <Figure 7>. The main keywords in the field of problem reasoning and solving are edium (150), information (148), storage (128), machine learning (127), and forming (108); the main keywords in machine learning are neural network (201), training (93), learning (84), machine learning (73), and model (71); the main keywords in the network structure field are image (206), medium (146), information (139), storage (127), and neural network (123); and the main keywords in the knowledge processing system field are image (206), application (202), information (195), medium (177), and storage (144). These data indicate that the main keyword in the AI subfields is neural network.

4.2. Company Classification

The knowledge network using the AI patent citation relationship among the top 100 digital companies is shown in <Figure 8>. From this figure, it is noted that there is only a weak patent citation relationship



<Figure 8> AI Patent Citation Network among the Top 100 Digital Companies

between the majority of companies.

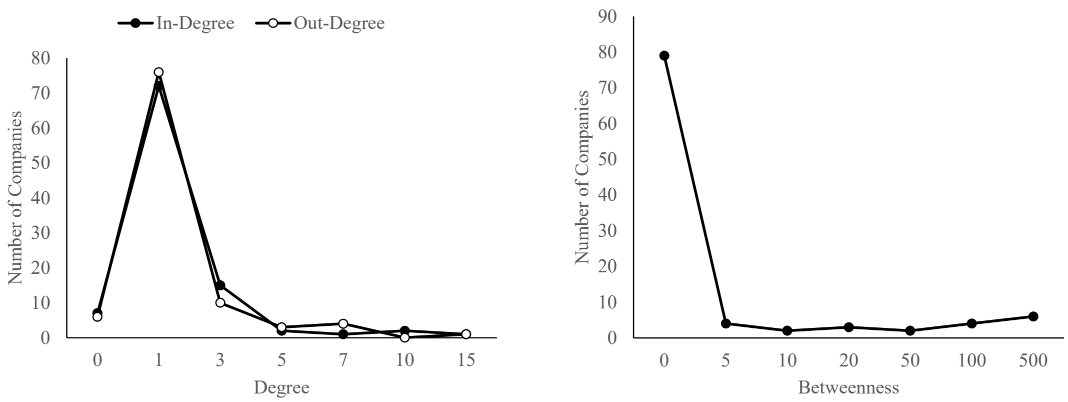
The centrality distribution of patent citations among the top 100 digital companies is presented in <Figure 9>. In-degree centrality, out-degree centrality, and betweenness centrality refer to backward citation, forward citation, and a broker's role, respectively. In other words, a higher in-degree centrality means that more knowledge is absorbed from other companies, and a higher in-degree centrality means that more knowledge is disseminated to other companies. A company with a high betweenness centrality plays a role as a broker to facilitate the dissemination and absorption of knowledge. Therefore, we can see that the majority of companies do not disseminate and absorb knowledge.

To examine the flow of knowledge, the top 100 digital companies were classified into knowledge producer-based brokers (KPBs), knowledge absorber-based brokers (KABs), knowledge absorbers (KAs), and knowledge producers (KPs) using the O-I index and betweenness centrality. <Figure 10>, which shows the flow of knowledge among the top 100 digital companies by sub-technological fields of AI, indicates that the majority of the companies are knowledge absorbers or knowledge producers. However, Amazon is a knowledge producer-based broker, while Apple and Microsoft are knowledge absorber-based brokers.

4.3. Comparison of Exploitative Innovation

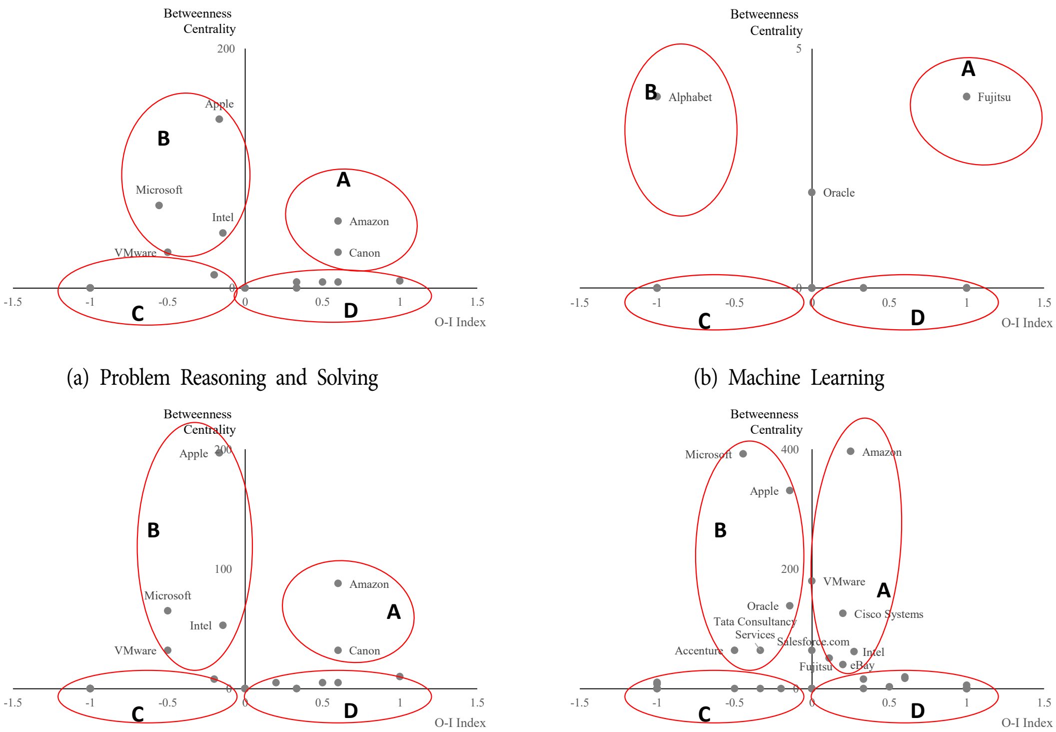
We investigated whether there is a difference in exploitative innovation in the sub-technological fields of AI and present the results of multiple comparisons in <Table 4>. From these results, it is concluded that the degree of exploitative innovation is in the order of (problem reasoning and solving = network structure) > (machine learning = knowledge processing system).

In addition, the top 100 digital companies were classified using the I-O index and betweenness centrality to investigate differences in exploitative innovation among groups. The results of multiple comparisons for testing the difference in exploitative innovation between the subgroups for all AI patents are presented in <Table 5>. The adjusted significance probabilities for the differences between KPB, KAB, KA, and KP are less than 0.05, suggesting that there



(a) Degree Distribution of citations (b) Betweenness Distribution of Citations

<Figure 9> Centrality Distribution of Citation among the top 100 Digital Companies



(a) Problem Reasoning and Solving

(b) Machine Learning

(c) Network Structure

(d) Knowledge Processing System

<Figure 10> AI Knowledge Flows among the Top 100 Digital Companies by Sub-technological Fields of AI

<Table 4> Pairwise Comparison on Sub-technological Fields of AI

Sub-technological fields of AI		Test statistic	Std. error	Std. test statistic	Sig.	Adj. sig
Machine learning	Knowledge processing system	-192.452	99.746	-1.929	0.054	0.322
	Problem reasoning and solving	376.208	102.183	3.682	0.000	0.001
	Network structure	-387.566	102.266	-3.790	0.000	0.001
Knowledge processing system	Problem reasoning and solving	183.756	46.905	3.918	0.000	0.001
	Network structure	195.114	47.087	4.144	0.000	0.000
Problem reasoning and solving	Network structure	-11.357	52.050	-0.218	0.827	1.000

are significant differences in exploitative innovation between the groups. Specifically, the degree of exploitative innovation is in the order of KP > KAB > KA > KPB.

The results of examining whether there is a difference in exploitative innovation among subgroups by sub-technical fields of AI are shown in <Table 6>. In the field of problem reasoning and solving,

<Table 5> Pairwise Comparison on Company Classification

Company classification		Test statistic	Std. error	Std. test statistic	Sig.	Adj. sig
KPB	KA	-120.830	39.531	-3.057	0.002	0.013
	KAB	-266.276	38.498	-6.917	0.000	0.000
	KP	-545.356	43.102	-12.653	0.000	0.000
KA	KAB	145.446	33.682	4.318	0.000	0.000
	KP	-424.526	38.861	-10.834	0.000	0.000
KAB	KP	-279.080	37.810	-7.381	0.000	0.000

Note: KPB=Knowledge producer-based broker, KAB = Knowledge absorber-based broker, KA = Knowledge absorber, KP = Knowledge producer

<Table 6> Pairwise Comparison of Company Classification by Sub-Technological Fields of AI

Sub-technological fields of AI	Company Classification		Test statistic	Std. error	Std. test statistic	Sig.	Adj. sig
Problem reasoning and solving	KA	KPB	60.825	25.918	2.347	0.019	0.114
		KAB	72.151	25.579	2.821	0.005	0.029
		KP	-185.377	31.601	-5.866	0.000	0.000
	KPB	KAB	-11.326	19.917	-0.569	0.570	1.000
		KP	-124.552	27.222	-4.575	0.000	0.000
	KAB	KP	-113.225	26.900	-4.209	0.000	0.000
Machine learning	KAB	KP	-5.356	10.270	-0.522	0.602	1.000
		KPB	18.861	12.990	1.452	0.147	0.879
		KA	-31.782	8.782	-3.619	0.000	0.002
	KP	KPB	13.505	13.227	1.021	0.307	1.000
		KA	26.426	9.128	2.895	0.004	0.023
	KPB	KA	-12.921	12.108	-1.067	0.286	1.000
Network structure	KPB	KAB	-18.149	21.188	-0.857	0.392	1.000
		KA	-19.964	24.253	-0.823	0.410	1.000
		KP	-130.073	29.158	-4.461	0.000	0.000
	KAB	KA	-1.815	23.741	-0.076	0.939	1.000
		KP	-111.924	28.733	-3.895	0.000	0.001
	KA	KP	-110.108	31.062	-3.545	0.000	0.002
Knowledge processing system	KA	KPB	106.936	39.405	2.714	0.007	0.040
		KAB	189.401	35.974	5.265	0.000	0.000
		KP	-352.078	38.223	-9.211	0.000	0.000
	KPB	KAB	-82.465	33.923	-2.431	0.015	0.090
		KP	-245.142	36.289	-6.754	0.000	0.000
	KAB	KP	-162.677	32.542	-4.999	0.000	0.000

Note: KPB = Knowledge producer-based broker, KAB = Knowledge absorber-based broker, KA = Knowledge absorber, KP = Knowledge producer

KPs are the most effective innovators, while KABs are more effective than KAs. However, there is no significant difference in exploitative innovation between KPB and KAB or between KPB and KA. In the field of machine learning, KA exhibits greater exploitative innovation than KAB and KP, but KA has statistically the same exploitative innovation as KPB. In addition, there is no significant difference in the exploitative innovation of KPB, KAB, and KP. In the field of KP, exploitative innovation is the greatest, while exploitative innovation in KPB, KAB does not significantly differ. In the field of knowledge processing systems, the exploitative innovation of KP is significantly greater than that of KPB and KAB. However, there is no significant difference between the exploitative innovation of KPB and KAB.

Ⅴ. Conclusions

In this study, we aimed to investigate the difference in exploitative innovation according to the company's position in the knowledge network of AI technology on innovation. To this end, AI patents of the top 100 digital companies registered with the US Patent Office were collected and analyzed. Our empirical analysis reveals that a few of the top 100 digital enterprises disseminate, absorb, and mediate knowledge, while the majority do not. We also find that there is a difference in exploitative innovation according to the structural position in the patent citation network. That is, exploitative innovation is in the order of knowledge producer, knowledge absorber-based broker, knowledge absorber, and knowledge producer-based broker (greatest to least).

This study provides important contributions for academic researchers and industrial practitioners. First, previous studies on knowledge networks have focused on revealing network metrics such as centrality and density that influence exploitative innovation from a network perspective (Guan and Liu, 2016; Ma et al., 2020; Wen et al., 2021). In the business ecosystem, the roles of companies are diverse, including such functions as knowledge transfer, absorption, and mediation. This study classified companies into knowledge producer-based brokers, knowledge absorber-based brokers, knowledge absorbers, and knowledge producers from the perspective of knowledge creation and flow. This classification method helps to better understand whether there is a difference in exploitative innovation according to the structural position within the patent citation network. Second, patents for industrial intelligence account for a large proportion of patents, with knowledge producers leading exploitative innovation. Therefore, latecomers need to expand their resources and capabilities by citing patents owned by leading companies and converge to existing industries into AI-based industries.

This study has the following limitations. First, this study collected patents from the US Patent Office in terms of the top 100 companies to identify the structural position that influences the flow of knowledge and innovation in the AI patent citation network. However, as the leaders in the field of AI are the United States, Europe, and China, it is necessary to collect patents from the patent offices of all these regions. Second, IPC allows redundant classification, but only the patents of the main IPCs that represent AI were analyzed. As the industrial structure changes through the recent convergence of industry and AI, it is necessary to collect AI patents not only for the main IPC but also for all other IPCs. Accordingly, it would be beneficial for future studies to be conducted in consideration of these limitations.

<References>

[1] Bae, S. U., Kwag, D. G., and Park, E. Y. (2015). The study of the aviation industrial technology convergence through patent analysis. *Journal of the Korea convergence Society, 6*(5), 219-225.

[2] Bernal, P., Maicas, J. P., and Vargas, P. (2019). Exploration, exploitation and innovation performance: disentangling the evolution of industry. *Industry and Innovation, 26*(3), 295-320.

[3] Bhattacharya, M., and Bloch, H. (2004). Determinants of innovation. *Small Business Economics, 22*(2), 155-162.

[4] Bonchi, F., Castillo, C., Gionis, A., and Jaimes, A. (2011). Social network analysis and mining for business applications. *ACM Transactions on Intelligent Systems and Technology (TIST), 2*(3), 1-37.

[5] Boschma, R. A., and Ter Wal, A. L. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy. *Industry and Innovation, 14*(2), 177-199.

[6] Bruck, P., Réthy, I., Szente, J., Tobochnik, J., and Érdi, P. (2016). Recognition of emerging technology trends: class-selective study of citations in the US Patent Citation Network. *Scientometrics, 107*(3), 1465-1475.

[7] Chang, S. B., Lai, K. K., and Chang, S. M. (2009). Exploring technology diffusion and classification of business methods: Using the patent citation network. *Technological Forecasting and Social Change, 76*(1), 107-117.

[8] Cho, T. S., and Shih, H. Y. (2011). Patent citation network analysis of core and emerging technologies in Taiwan: 1997-2008. *Scientometrics, 89*(3), 795-811.

[9] Choe, H., Lee, D. H., Kim, H. D., and Seo, I. W. (2016). Structural properties and inter-organizational knowledge flows of patent citation network: The case of organic solar cells. *Renewable and Sustainable Energy Reviews, 55*, 361-370.

[10] Davenport, T., and Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal, 6*(2), 94.

[11] De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K. U., and von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing, 51*, 91-105.

[12] Érdi, P., Makovi, K., Somogyvári, Z., Strandburg, K., Tobochnik, J., Volf, P., and Zalányi, L. (2013). Prediction of emerging technologies based on analysis of the US patent citation network. *Scientometrics, 95*(1), 225-242.

[13] Greve, H. R. (2007). Exploration and exploitation in product innovation. *Industrial and Corporate Change, 16*(5), 945-975.

[14] Grigoriou, K., and Rothaermel, F. T. (2017). Organizing for knowledge generation: Internal knowledge networks and the contingent effect of external knowledge sourcing. *Strategic Management Journal, 38*(2), 395-414.

[15] Guan, J., and Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy, 45*(1), 97-112.

[16] Haefner, N., Wincent, J., Parida, V., and Gassmann, O. (2020). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, 120392.

[17] Holmes, W., Bialik, M., and Fadel, C. (2019). *Artificial intelligence in education*. Boston: Center for Curriculum Redesign.

[18] Holzinger, A., Langs, G., Denk, H., Zatloukal, K., and Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9*(4), e1312.

[19] Huang, M. H., and Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*, 30-50.

[20] Jung, S. H., Gu, G. J., Kim, D., and Kim, J. W.

(2020). Predicting stock prices based on online news content and technical indicators by combinatorial analysis using CNN and LSTM with self-attention. *Asia Pacific Journal of Information Systems, 30*(4), 719-740.

[21] Kim, D. H., Lee, H., and Kwak, J. (2017). Standards as a driving force that influences emerging technological trajectories in the converging world of the Internet and things: An investigation of the M2M/IoT patent network. *Research Policy, 46*(7), 1234-1254.

[22] Kim, E., Cho, Y., and Kim, W. (2014). Dynamic patterns of technological convergence in printed electronics technologies: Patent citation network. *Scientometrics, 98*(2), 975-998.

[23] Kim, H. S., and Lee, S. (2019). Multi-Purpose Hybrid Recommendation System on Artificial Intelligence to Improve Telemarketing Performance. *Asia Pacific Journal of Information Systems, 29*(4), 752-770.

[24] Lai, H. C., and Weng, C. S. (2016). Exploratory innovation and exploitative innovation in the phase of technological discontinuity: the perspective on patent data for two IC foundries. *Asian Journal of Technology Innovation, 24*(1), 41-54.

[25] Lanjouw, J., and Schankerman, M. (1999). The quality of ideas: Measuring innovation with multiple indicators. *Working Papers*, NBER.

[26] Le, P. B., and Lei, H. (2019). Determinants of innovation capability: the roles of transformational leadership, knowledge sharing and perceived organizational support. *Journal of Knowledge Management 23*(3), 527-547.

[27] Lee, J., Davari, H., Singh, J., and Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters, 18*, 20-23.

[28] Lee, R., Lee, J. H., and Garrett, T. C. (2019). Synergy effects of innovation on firm performance. *Journal of Business Research, 99*, 507-515.

[29] Lee, S., and Kim, W. (2017). The knowledge network dynamics in a mobile ecosystem: A patent citation analysis. *Scientometrics, 111*(2), 717-742.

[30] Lee, S., Kim, W., Lee, H., and Jeon, J. (2016). Identifying the structure of knowledge networks in the US mobile ecosystems: Patent citation analysis. *Technology Analysis & Strategic Management, 28*(4), 411-434.

[31] Li, X., Chen, H., Huang, Z., and Roco, M. C. (2007). Patent citation network in nanotechnology (1976-2004). *Journal of Nanoparticle Research, 9*(3), 337-352.

[32] Love, J. H., and Roper, S. (1999). The determinants of innovation: R & D, technology transfer and networking effects. *Review of Industrial Organization, 15*(1), 43-64.

[33] Ma, D., Zhang, Y. R., and Zhang, F. (2020). The influence of network positions on exploratory innovation: An empirical evidence from china's patent analysis. *Science, Technology and Society, 25*(1), 184-207.

[34] Maddox, T. M., Rumsfeld, J. S., and Payne, P. R. (2019). Questions for artificial intelligence in health care. *Jama, 321*(1), 31-32.

[35] Marketsandmarkets (2018). *Artificial Intelligence Market worth $190.61 billion by 2025 with a Growing CAGR of 36.6%.* https://www.marketsandmarkets.com/PressReleases/artificial-intelligence.asp (accessed on 25 February 2020).

[36] Patrício, D. I., and Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and Electronics in Agriculture, 153*, 69-81.

[37] Phelps, C., Heidl, R., and Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management, 38*(4), 1115-1166.

[38] Powell, W. W., and Snellman, K. (2004). The knowledge economy. *Annual Review of Sociology, 30*, 199-220.

[39] Powell, W. W., Packalen, K., and Whittington, K. (2010). Organizational and institutional genesis and change: The emergence and transformation of the commercial life sciences. *The Emergence of Organizations and Markets*, 379-433.

[40] Purushu, P., Melcher, N., Bhagwat, B., and Woo, J. (2018). Predictive analysis of financial fraud detection using Azure and Spark ML. *Asia Pacific Journal of Information Systems, 28*(4), 308-319.

[41] Quan, X. I., and Sanderson, J. (2018). Understanding the artificial intelligence business ecosystem. *IEEE Engineering Management Review, 46*(4), 22-25.

[42] Ramesh, A. N., Kambhampati, C., Monson, J. R., and Drew, P. J. (2004). Artificial intelligence in medicine. *Annals of The Royal College of Surgeons of England, 86*(5), 334.

[43] Rogers, E. M. (2010). *Diffusion of Innovations*. Simon and Schuster.

[44] Romijn, H., and Albaladejo, M. (2002). Determinants of innovation capability in small electronics and software firms in southeast England. *Research Policy, 31*(7), 1053-1067.

[45] Rousseau, M. B., Mathias, B. D., Madden, L. T., and Crook, T. R. (2016). Innovation, firm performance, and appropriation: A meta-analysis. *International Journal of Innovation Management, 20*(03), 1650033.

[46] Smith, M. J. (2020). Getting value from artificial intelligence in agriculture. *Animal Production Science, 60*(1), 46-54.

[47] Strong, A. I. (2016). Applications of artificial intelligence & associated technologies. *Proceeding of International Conference on Emerging Technologies in Engineering, Biomedical, Management and Science*, 5-6.

[48] Takano, Y., Mejia, C., and Kajikawa, Y. (2016). Unconnected component inclusion technique for patent network analysis: Case study of Internet of Things-related technologies. *Journal of Informetrics, 10*(4), 967-980.

[49] Timms, M. J. (2016). Letting artificial intelligence in education out of the box: Educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education, 26*(2), 701-712.

[50] Tsai, W. (2001). Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal, 44*(5), 996-1004.

[51] Tseng, C. Y., and Ting, P. H. (2013). Patent analysis for technology development of artificial intelligence: A country-level comparative study. *Innovation, 15*(4), 463-475.

[52] Van de Ven, A. H. (1986). Central problems in the management of innovation. *Management Science, 32*(5), 590-607.

[53] Wasserman, S., and Faust, K. (1994). *Social network analysis: Methods and Applications* (Vol. 8). Cambridge University Press.

[54] Wen, J., Qualls, W. J., and Zeng, D. (2021). To explore or exploit: The influence of inter-firm R&D network diversity and structural holes on innovation outcomes. *Technovation, 100*, 102178.

[55] Yang, G. C., Li, G., Li, C-Y., Zhao, Y-H., Zhang, J., Liu, T., Chen, D-Z., and Huang, M-H. (2015). Using the comprehensive patent citation network (CPC) to evaluate patent value. *Scientometrics, 105*(3), 1319-1346.

[56] Yu, K. H., and Kohane, I. S. (2019). Framing the challenges of artificial intelligence in medicine. *BMJ Quality & Safety, 28*(3), 238-241.

[57] Zaheer, A., and Bell, G. G. (2005). Benefiting from network position: firm capabilities, structural holes, and performance. *Strategic Management Journal, 26*(9), 809-825.

[58] Zaltman, G., Duncan, R., and Holbek, J. (1973). *Innovations and Organizations*. New York; Toronto: Wiley.

<Appendix> Top 100 Digital Companies

Rank	Company	Country	Rank	Company	Country
#1	Apple	United States	#51	ASML Holding	Netherlands
#2	Microsoft	United States	#52	Salesforce.com	United States
#3	Samsung Electronics	South Korea	#53	Applied Materials	United States
#4	Alphabet	United States	#54	Recruit Holdings	Japan
#5	AT&T	United States	#55	SingTel	Singapore
#6	Amazon	United States	#56	Adobe	United States
#7	Verizon Communications	United States	#57	Xiaomi	China
#8	China Mobile	Hong Kong	#58	Telstra	Australia
#9	Walt Disney	United States	#59	VMware	United States
#10	Facebook	United States	#60	TE Connectivity	Switzerland
#11	Alibaba	China	#61	SK Holdings	South Korea
#12	Intel	United States	#62	Murata Manufacturing	Japan
#13	Softbank	Japan	#63	Cognizant	United States
#14	IBM	United States	#64	NVIDIA	United States
#15	Tencent Holdings	China	#65	eBay	United States
#16	Nippon Telegraph & Tel	Japan	#66	Telenor	Norway
#17	Cisco Systems	United States	#67	Vodafone	United Kingdom
#18	Oracle	United States	#68	SK Telecom	South Korea
#19	Deutsche Telekom	Germany	#69	Vivendi	France
#20	Taiwan Semiconductor	Taiwan	#70	Naspers	South Africa
#21	KDDI	Japan	#71	Infosys	India
#22	SAP	Germany	#72	China Tower Corp.	China
#23	Telefónica	Spain	#73	Swisscom	Switzerland
#24	América Móvil	Mexico	#74	Corning	United States
#25	Hon Hai Precision	Taiwan	#75	Fidelity National Information	United States
#26	Dell Technologies	United States	#76	Rogers Communications	Canada
#27	Orange	France	#77	Nintendo	Japan
#28	China Telecom	China	#78	Kyocera	Japan
#29	SK Hynix	South Korea	#79	NXP Semiconductors	Netherlands
#30	Accenture	Ireland	#80	DISH Network	United States
#31	Broadcom	United States	#81	Rakuten	Japan
#32	Micron Technology	United States	#82	Altice Europe	Netherlands
#33	Qualcomm	United States	#83	TELUS	Canada
#34	PayPal	United States	#84	Capgemini	France
#35	China Unicom	Hong Kong	#85	Activision Blizzard	United States

<Appendix> Top 100 Digital Companies (Cont.)

Rank	Company	Country	Rank	Company	Country
#36	HP	United States	#86	Analog Devices	United States
#37	BCE	Canada	#87	Lam Research	United States
#38	Tata Consultancy Services	India	#88	DXC Technology	United States
#39	Automatic Data Processing	United States	#89	Legend Holding	China
#40	BT Group	United Kingdom	#90	Lenovo Group	Hong Kong
#41	Mitsubishi Electric	Japan	#91	NetEase	China
#42	Canon	Japan	#92	Tokyo Electron	Japan
#43	Booking Holdings	United States	#93	Keyence	Japan
#44	Saudi Telecom	Saudi Arabia	#94	Telkom Indonesia	Indonesia
#45	JD.com	China	#95	Nokia	Finland
#46	Texas Instruments	United States	#96	Fortive	United States
#47	Netflix	United States	#97	Ericsson	Sweden
#48	Philips	Netherlands	#98	Fiserv	United States
#49	Etisalat	United Arab Emirates	#99	Fujitsu	Japan
#50	Baidu	China	#100	Hewlett Packard Enterprise	United States

◆ About the Authors ◆

Hyun Mo Kang

Hyun Mo Kang is a CEO at WatLogic.Co.,Ltd. He obtained his MBA and Ph.D. in MIS from Kyung Hee University. His current research interests focus on patent analysis, IoT, recommendation system, and network analysis

Il Young Choi

Il Young Choi is a lecturer at Graduate School of Business Administration, Kyung Hee University. He obtained his MS and Ph.D. in MIS, and his B.S. in Economics from Kyung Hee University. His current research interests focus on personalized service, bigdata analysis, social network analysis, and business analytics. He has published numerous papers which have appeared in Information Technology and Management, International Journal of Information Management, Online Information Review, and so on.

Jae Kyeong Kim

Jae Kyeong Kim is a professor at School of Management, Kyung Hee University. He obtained his M.S. and Ph.D. in Management Information Systems (MIS) from KAIST (Korea Advanced Institute of Science and Technology), and his B.S. in Industrial Engineering from Seoul National University. His current research interests focus on business analytics, recommender systems, big data analysis, and deep learning. He has published numerous papers which have appeared in IEEE transactions on Systems, Men and Cybernetics, IEEE transactions on Services Computing, Information & Management, International Journal of Information Management, Applied Artificial Intelligence, Artificial Intelligence Review, International Journal of Human-Computer Studies, Expert Systems with Applications, and Group Decision and Negotiations.

Hyun Joo Shin

Hyunjoo Shin is a CEO at Rexia, Inc.. He obtaind his MBA from Kyunghee University. He is a Ph.D candidate in MIS at Kyunghee University. His research focuses on electronic and mobile commerce, big data analysis, and recommendation systems.

Submitted: April 30, 2021; 1st Revision: July 26, 2021; Accepted: August 06, 2021