Exploring the Top-Priority Innovation Types and Their Reasons

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Abstract

This is a foresight study to explore the top priorities of innovation types and the reasons behind them with respect to artificial intelligence (AI), big data, and the Internet of Things (IoT). This study set up two research strategies. One of the research strategies is to make the research design and methods fit with this study's intellectual queries. Another strategy is to use the triangulations of method, analysis, data source, and researcher. This study selected expert panels, the Delphi technique, and interviews. In the collection of the qualitative and quantitative data from 23 experts through the Delphi surveys, it organized respectively the qualitative and quantitative data analysis. This study conducted the two main data analyses – Delphi results and interview data.

Service innovation of AI and process innovation of IoT are chosen as a top-priority-innovation type. Marketing innovation of big data, as non-technological innovation, is selected as a top-priority innovation type. Through the interviews with 17 experts, for each of the pairs, all the experts said that the three technologies can have greater technological capabilities going beyond the existing capacities of relevant technologies. AI as hyper-intelligence can help to provide more customized or sophisticated converging offerings, the regulation of various non-standardized services and service provisions through the interaction between AI and customers or employees. The technological capacity of big data and the need of customer preferences can lead marketing innovation. IoT can create the new or improved process of the manufacturing, production, and supply chain areas through hyper-connectivity in terms of quality, quantity, speed, and coverage of information.

Keywords: top-priorities; innovation types; technological performance; reasons; artificial intelligence; big data; Internet of Things

Paper type: Research Article

Citation: Kim J.-S., Kang J. (2022) Exploring the Top-Priority Innovation Types and Their Reasons. *Foresight and STI Governance*, 16(3), 6–16. DOI: 10.17323/2500-2597.2022.3.6.16

Introduction

This is a foresight study to explore the top priorities of innovation types and their reasons in terms of artificial intelligence (AI), big data, and the Internet of Things (IoT). It uses the eight-innovation types relevant to the new wave of industrial revolution (Kim, Kang, 2019). Emerging technologies such as AI, big data and IoT have revolutionary characteristics (Kang et al., 2019): AI as a new strong driver shaping the new industrial revolution (Bughin et al., 2017; Cockburn et al., 2018; Kim, 2018; OECD, 2016a, 2017); the era of the big data revolution (Erevelles et al., 2016; Gobble, 2013; OECD, 2015); and IoT as a new revolutionary technology (OECD, 2016b; Porter, Heppelmann, 2014). It was noted that these three technologies could have huge impacts upon each firm's activities, industries, and the economy and society. In the phenomena of blurring boundaries between manufacturing and service areas (Kim, 2018; Miles, 2016; Santamaria et al., 2012), a firm's innovation on each technology will drive or reflect those trends, which draw a part of the picture of the new industrial revolution (Kim, Kang, 2019; Schwab, 2017).

Since the emergence of information and communication technology (ICT), there has been rapid growth of service innovations, managerial innovations, and business model innovations (Birkinshaw et al. 2008; Ettlie, 2000; Miles, 2016; Mowery, Bruland, 2005; Spieth et al., 2014). It can be expected that those innovations will continue to grow in the three technologies within the framework of the new industrial revolution (Erevelles et al., 2016; Gobble, 2013; Li, 2018; Ransbotham et al., 2017). While there have been various studies on innovation types regarding AI, big data, and IoT (Bughin et al., 2017; Cockburn et al., 2018; Erevelles et al., 2016; Gobble, 2013; Huang, Rust, 2018; Kim, Kang, 2019; Makridakis, 2017; Porter, Heppelmann, 2014; Yu et al., 2016) in a systematic manner, the discrepant impact of three technologies on innovation types have been insufficiently examined in the literature on this new wave of industrial revolution. Generally, the new emerging innovation or dominant innovation types of each technology, historically driving the phenomena of industrial revolution, have been demonstrated (Feldman, 2002; Freeman, Locua, 2001; Kang et al., 2019; Mowery, Bruland, 2005; Rindfleisch et al., 2017). By using Delphi surveys, this study attempts to explore different top-priority innovation types for each technology. This can give us some important theoretical and practical insights into a firm's innovation behaviors regarding these three technologies as part of the new phenomena of the industrial revolution. Most of all, by exploring the reasons why a top-priority innovation type is selected, this study can search for an explanation for why a top-priority innovation type in terms of each technology was selected. Thus it could be possible to offer us some theoretical insights into firm behavior concerning a specific innovation.

To implement this foresight study, multiple methods are utilized: an expert panel, Delphi surveys, and two different interview methods, after having conducted the literature review and outlining the research questions. Following the explanation of the research methods, this study presents the findings and draws conclusions.

Literature Review and Research Questions

Literature Review

Many studies have attempted to theoretically categorize various firms' innovation activities into innovation types (Abernethy, Utterback, 1978; Birkinshaw et al., 2008; Christensen, 1997; Coombs, Miles, 2000; Damanpour et al., 1989; Davenport, 1993; Ettlie, Reza, 1992; Ettlie, Rosenthal, 2011; Francis, Bessant, 2005; Gault, 2018; Henderson, Clark, 1990; Johnson et al., 2008; Kim, Kang, 2019; Miles, 2007; Nijssen et al., 2006; Tushman, Anderson, 1986; Utterback, 1996). By establishing the new parameters, they are willing to distinguish a new innovation type from the existing innovation categories. A variety of empirical and case studies seek to validate new innovation types. This study endeavours to clarify the literature and illustrate the scope of innovation types. It does not deal with the individual-level or policy-level innovations because it focuses on firm-level innovation activities regarding AI, big data, and IoT. The main directions of existing studies on the classification of innovation types are represented in Table 1. Those studies have proposed the combinative usage of innovation types for a given purpose to understand a firm's innovation activities on the criteria of demarcation. Another approach of an innovation-type study is to use innovation surveys to identify firm innovative behaviors. One of the best examples is the community innovation survey in some European and Asian countries, which is used to measure to which extent innovative activities have been conducted by leveraging (non-) technological innovations from existing innovation studies (Eurostat, 2014, 2016). Many studies used the results of the community innovation survey to understand firms' innovation behavior (Battisti, Stoneman, 2010; Martinez-Ros, Labeaga, 2009; Sirilli, Evangelista, 1998). A variety of innovation types can be suggested according to the diverse parameters set by researchers (Gault, 2018).

Many studies noticed AI, big data, and IoT can be regarded as key technologies in the new wave of the industrial revolution (Cockburn et al., 2018; Kang et al., 2019; OECD, 2015, 2017; Porter, Heppelmann, 2014). In the consideration of these three technologies, this study intends to use eight innovation types relevant to the new wave of the industrial revolution. Kim and Kang (2019) identified eight innovation types through a Delphi survey of the fourth industrial revolution. Thus, this study defined and classified eight-innovation types in three technological dimensions (see Table 2).

Research Questions

Although the existing studies made contributions to understanding some innovation types regarding AI, big data, and IoT, they are not able to explain which innovation types for each technology could be highly prioritized and why top-priority innovation types of each technology are selected. Because AI, big data, and IoT have a revolutionary impact upon firms' activities, examining the top priorities of innovation types in each technology can be important to theoretically explaining and practically capturing a firm's innovative behaviors in the new wave of the industrial revolution. The current studies of innovation types do not fully examine the impacts upon innovation types for each technology. Hence, this study considers different magnitudes of innovation types with respect to AI, big data, and IoT. In the consideration of different priority innovation types for these three technologies, we ask the following:

RQ1: What are the top-priority innovation types for each technology?

By identifying the top priorities of eight innovation types with respect to AI, big data, and IoT, this study tries to understand the reasons why a high priority innovation type is selected. Because the three technologies could drive new phenomena of the industrial revolution (Kang et al., 2019; Kim, Kang, 2018; OECD, 2015, 2017; Schwab, 2017), they could imply a dominant innovation type for each despite still being in the embryonic stage. Regarding the usage of technology, the plausible reasons for an innovation type to be selected as a top-priority for each technology can give us a better theoretical and practical understanding of a firm's innovative behavior. Thus, we pose the following research question:

RQ2: Why was a top-priority innovation type for each technology selected?

Research Methods

Research Design

This study has set up two research strategies regarding the use of multiple methods, particularly in terms of its research questions. One of the research strategies is to make the research design and methods fit with this study's intellectual queries. We selected the expert panels, the Delphi technique, and interviews. The method selection is concerned with the ways to achieve the purpose of this study (Popper, 2008b). At first, the expert panel can provide relevant expertise to answer the intellectual queries (Miles et al., 2016). This study used the expert panel to judge which innovation types to prioritize for each technology. However it may require balanced expertise in terms of technological and industrial differences. Compared to the large-scale surveys or other experiments, targeted expert panels can offer more insightful judgements concerning of top-priority innovation types in term of resource constraints and the maturity of technology development and diffusion. Secondly, the Delphi technique is often used to examine new phenomena such as the industrial revolution (Miles et al., 2016; Kim, Kang, 2019; Kang et al., 2019). It was selected to exploit expert assessments of these innovations in AI, big data, and IoT. Finally, an interview is a guided and purposeful conversation between two or more people (Popper, 2008b). It can be useful to gather knowledge of why top-priority innovation types for each technology were selected.

Another strategy is to use the triangulation technique of method, analysis, data source, and researcher — all of which were adopted in this study. The method triangulation can be considered as a way to complement the weaknesses of each method and to overcome the problems of research bias (Cox, Hassard, 2005). The use of the Delphi technique and interviews to examine top-priority innovation types of each technology can be complemented. Multiple methods in this study intrinsically indicate the use of multiple data sources, such as quantitative or qualitative judgements. The analytical triangulation of qualitative and quantitative data can help one achieve in-depth understanding of results (Kang et al., 2019). After obtaining the Delphi results, the statistical validity of them is examined through a statistical test. Moreover, this study encouraged each of the researchers to separately analyze the results in two different places (respectively) located in two cities as well as to comparing and discussing them, establishing whether there are different results after analyzing the results from the Delphi survey and interview methods. This process can prevent researcher's bias, thus maximizing the accuracy and reliability of such analysis.

Research Process and Design of the Methodological Framework

The description of how to conduct the research process is shown in detail in Figure 1. The selection and use of three methods in the methodological framework — expert panels, the Delphi technique, and interviews (including e-mail interviews) — are designed so that they can complement or support each other.

Firstly, the literature on innovation types, technologies, and the industrial revolution was reviewed so that the relevant intellectual queries and gaps are understood. Secondly, the Delphi surveys and their questionnaires were designed, while the literature review was used to design the Delphi surveys, the interviews, and their questionnaires after three expert panel groups were composed in the triangulation of the recommender, who takes on the role of identifying and suggesting experts. Seven recommenders from 10 institutions were involved. Thirty experts were appointed and individually assigned three expert panel groups representing a group of (1) academic scholars and general experts, (2) public research and development institutes, and (3) private sector representatives (see Table 3). The expert panels were used for the Delphi survey and interviews. Thirdly, the Delphi survey was used to collect qualitative and quantitative information. Twenty-three responses were collected from among 30 experts during each Delphi survey. The first Delphi survey was performed to grasp the properties of innovation types and technologies for complementing and verifying the results from the analyses of Delphi surveys and interviews. By using the eight innovation types, the second Delphi sur-

Table 1. **The Existing Studies on the Classification of Innovation Types**

Direction	Literature
The identification of new innovation types as business model innovation and disruptive innovation, etc.	Christensen, 1997; Francis, Bessant, 2005, Miles, 2016; Pisano, 1996; Tidd, Bessant, 2018; Utterback, 1996
The demarcation between product and service innovations	Coombs, Miles, 2000; Hipp, Grupp, 2005; Miles, 2016
The distinction between product (or service) innovation and process (or service delivery) by focusing on manufacturing or service production	Davenport, 1993; Miles, 2016; Pisano, 1996; Sjodin et al., 2018; Utterback, 1996
The demarcation between technological and non-technological innovation, including managerial innovations	Birkinshaw et al., 2008; Damanpour et al., 1989; Erevelles et al., 2016; Francis, Bessant, 2005
The classification of innovation types based on the degree of technological change and product (or services) change	Abernathy, Utterback, 1978; Christensen, 1992a; 1992b; Henderson, Clark, 1990
The degree of technological continuity in terms of capabilities and market	Gatignon et al., 2002; Tushman, Anderson, 1986
The demarcation of business innovation and product (or service) innovation at different levels of a firm's activities	Afuah, 2014; Spieth et al., 2014; Tidd, Bessant, 2018
The rise of social innovations	Gault, 2018
The framework of four innovation types for a firm's capability development	Francis, Bessant, 2005

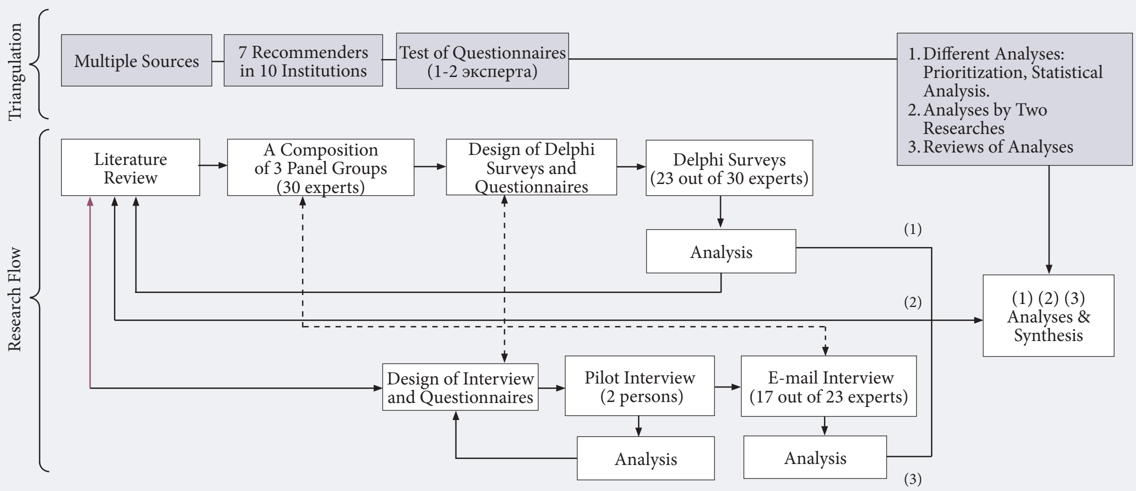
Source: authors.

vey was conducted with the three expert panel groups from August 18 to September 19, 2017. The questionnaires were designed in a relatively short-term period to assess the relative importance of each innovation type, through measurement on a nine-point scale for AI, big data, and IoT. Although performance improvements of each technology can be expected, through the interviews with experts, this study shows that the current development status of AI, big data, and IoT can be applicable at least over the five-year period. This period can fit with the purpose of this study. Therefore, it can help to foresee a firm's innovation behaviors with regard to each technology. Finally, on the initial analysis of the Delphi results, the semi-structured interviews were organized to confirm the results and to explore the reasons for the top-priority innovation types of each technology.

Two main questions formulated were with regard to (i) the agreement on top-priority innovations of each technology (three sub questions: AI, big data, and IoT) and (ii) the reasons for the top-priority innovation for each technology. The interview was constructed in two stages, comprising of (1) pre-interviews with two experts from October 2019, (2) e-mail interviews with experts were collected from November 18 to December 2, 2019. The e-mail interview was devised in combination with other interview techniques: face-to-face and telephone interviews regarding the resource constraints and physical limits. At the pre-interview stage: two interviews were conducted as telephone and face-to-face interviews, respectively. Two interviewers of different nationalities are the leading experts in the field of innovation and ICT.

Hence, the preliminary outcomes could be explored from the interview questions and what should be investigated was secured by obtaining information regarding innovation and the three technologies. The e-mail interview targeted 23 experts, who participated in the Delphi surveys. The e-mail interview can take the role

Figure 1. **Research Process and Flows**



Source: authors.

Table 2. **Category, Definition, and Sources of Eight-Innovation Types**

Technological Dimension	Types	Definition*	Selected Sources
Both	Business Model Innovation	A firm's innovation to introduce a new business model or modify an existing business model	Afuah, 2014; Andries, Debackere, 2013; Spieth et al., 2014
Technological Innovation	Product Innovation	A firm's innovation to develop a new product or improve an existing product	Francis, Bessant, 2005; Henderson, Clark, 1990; Yu et al., 2016
	Process Innovation	A firm's innovation to develop new or improved ways (or techniques) of producing goods or changing supply chains	Abernathy, Utterback, 1978; Davenport, 1993; Pisano, 1996
	Service Innovation	A firm's innovation to introduce a new service or improve an existing service	Coombs, Miles, 2000; Huang, Rust, 2018; Miles, 2016
	Service Process Innovation	A firm's innovation to introduce a new or improved ways of producing service	Andersson, Mattsson, 2015; Miles, 2006, 2016
Non-technological Innovation	Marketing Innovation	A firm's innovation to introduce new or improved marketing strategies or practices (or methods)	Birkinshaw et al., 2008; Erevelles et al., 2016; Moreira et al., 2012
	Organization Innovation	A firm's innovation to introduce new or improved organizations (or structures, forms)	Birkinshaw et al., 2008; Francis, Bessant, 2005; Lin, Lu, 2005
	Human Resource Management Innovation	A firm's innovation to introduce new or improved human resource managerial practices, processes, structures, and techniques	Birkinshaw et al., 2008; Laursen, Foss, 2003; Munteanu, 2015

Note: The definitions of the innovation types refer to the ones from OECD/Eurostat (2018) and the other sources.
Source: authors.

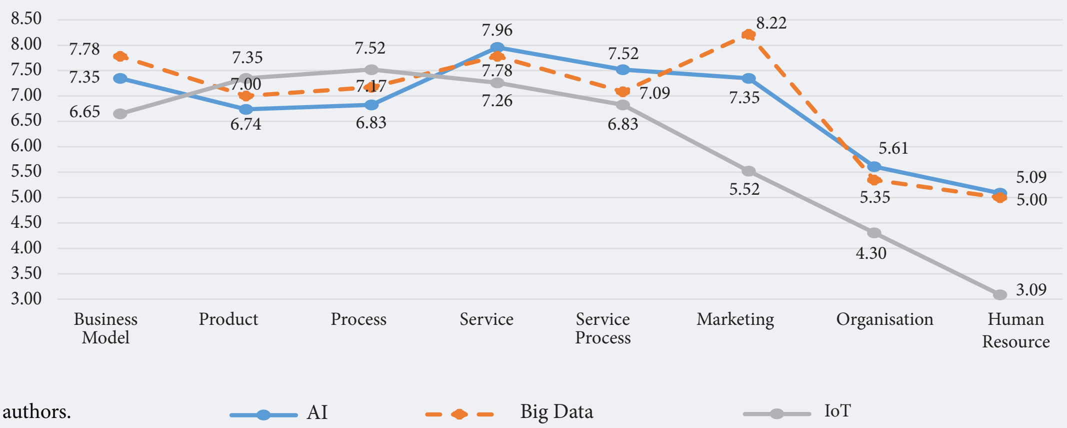
of complementing the results or exploring the reasons for the results. Seventeen responses were returned, but three of them contained no answers, along with some comments (see Table 3).

Data Analysis

In order to manage data from the expert assessments from the Delphi surveys and 19 interviews, each expert was allocated a unique identification (ID). By using their IDs, their data were anonymously and digitally sorted and managed. Their opinions and judgments were tabled to conduct the data analysis. In order to conduct the data analysis, the extensive studies of innovation types, technologies, and the fourth industrial revolution were reviewed as the means to obtain contextual knowledge for this study. At the first layer of analysis, the properties of innovation types along with AI, big data, and IoT were obtained. We attempted to identify the unique definition, characteristics, and intellectual geography of eight innovation types and each technology. This information can be used to complement the second-step analysis.

With regard to the top (different) priorities of innovation types for each technology, this study calculated the relative importance of each innovation type, which was collected from the Delphi survey, doing so by using the value of the mean through MS-Excel. After calculating the mean values of eight innovation types for each technology from the highest to lowest values, this study described the prioritized eight innovation types of AI, big data, and IoT, which are shown in Figure 2. To complement the results of differently prioritized inno-

Figure 2. **Relative Importance of Innovations Types amongst AI, Big Data, and IoT**



Source: authors.

Table 3. **A List of Experts' Affiliations and Participation in the Delphi Surveys and Interviews**

Affiliation	Delphi Survey	Interview
Academy and General Area (7)		
Catholic University of Korea	P	N
Han Yang University	P	(RP)
Institute for Information and Communication Technology Promotion	P	P
Korea Aerospace Industry Association	P	P
Korea Electronics Technology Institute	P	P
Korea Internet & Security Agency	P	P
Sungshin University	P	P
Industry (7)		
Deloitte Consulting Korea* (Inbyu.com)	P	P
EnerIdeas* (Seoul National University)	P	P
Hana Institute of Finance	P	P
Hyundai Research Institute	P	(RP)
Korea Small Business Institute* (Dashin Financial Group)	P	P
LG Economic Research Institute	P	N
Technovation	P	N
Public R&D Institute (9)		
Electronics and Telecommunication Research Institute	P	N
Korea Information Society Development Institute	P	P
Korea Institute of Energy Research	P	P
Korea Institute of Machinery & Materials	P	N
Korea Institute of Science and Technology Information	P	P
Korea Basic Science Institute	P	(RP)
Korea Research Institute of Bioscience & Biotechnology	P	P
Korea Research Institute of Chemical Technology	P	P
Science and Technology Policy Institute	P	N

Note 1: * Indicates the change of expert›s affiliation (New affiliation).
Note 2: P means Participation, (RP): Reply, N: No Response.
Source: authors.

vation types for the three technologies, a statistical test was conducted to confirm the differences between the eight innovation types of each technology and to check the differences among the three technologies and innovation types. Through the Delphi survey, this study obtained 184 cases respectively on the eight innovation for AI, big data, and IoT (Total: 552). The data are of the ordinal level. It is worthwhile to confirm the validity of this research through the statistical tests, although it is hardly applicable for inferential statistics, because expert selection can be a purposeful sampling, being considered non-probability sampling (Healey, 2002). The analysis of variance (ANOVA) was employed through means of the SPSS program and proved that the results are statistically meaningful. However, an important purpose of this study is to examine the different top priorities of the eight innovation types for each technology and therefore it ranked their mean values for each technology. This study identifies the top prioritized innovation types of each technology along with the other priorities.

In order to understand the reasons for the top-priority innovation types of each technology, this study conducted another analysis of the two pre-interviews with two experts and the e-mail interview data from the 17 experts responding to queries about (i) the agreement of top-priority innovations with regards to AI, big data, and IoT, and (ii) the reasons for each of the three top pairs. This study can identify whether or how many expert opinions are in agreement with the top-priority innovation types with respect to AI, big data, and IoT. By sorting the common content and comparing the different justifications for prioritizing innovations, this study can elucidate various reasons for experts' judgements on the three top pairs. Finally, different researchers individually analyzed the experts' opinions in different places and then compared their analyses in order to prevent an individual researcher's bias and increase the reliability of this study's analyses. In the next section, we present those results.

Top-Priority Innovation Types for and among the Three Technologies

Based on different values of innovation types regarding each of the three technologies, this demonstrates the different priorities of innovation types for them (see Figure 2). Twenty-three experts judged that service innovation is highly prioritized for AI (7.96). For big data, marketing innovation achieved the highest priority (8.22) among the eight innovation types. The analysis indicates that the highest innovation type for IoT is process innovation (7.52). After having the three top matches, twenty-three experts were given the statistical results of the three top matches for the interviews. Thirteen of the 17 experts agreed on the match between service innovation and AI. Thirteen out of the 17 experts consented to the match between big data and marketing innovation, which belongs to non-technological innovation. However, some disagreements of the match between IoT and process innovation were raised, compared to the other two matches. Three of the 17 experts said they partly disagreed on this match. One of them said it could be difficult to distinguish between which innovation types would be critical for IoT. Some experts argued that the emphasis on the process for IoT would reflect the business perspective rather than technological ones. As an engineer, one of the experts similarly found that the technological characteristics of IoT would not sufficiently explain what "process" innovation intends to achieve, while 10 out of the 17 experts agreed on the match between process innovation and IoT. Thus, there is a need to explore the reasons behind each match. They can be shown at the next section.

Table 4. **Differences in Eight Innovation Types on Each Technology: AI, Big Data, and IoT**

Section	BMI (sd)	PI (sd)	PPI (sd)	SI (sd)	SPI (sd)	MI (sd)	OI (sd)	HRMI (sd)	F (p-value)
AI	7.35 (2.145)	6.74 (1.514)	6.83 (1.337)	**7.96 (1.461)**	7.52 (1.504)	7.35 (1.668)	5.61 (1.644)	5.09 (1.649)	**8.420 (0.000)**
Big data	7.78 (0.998)	7.00 (1.348)	7.17 (1.193)	7.78 (0.998)	7.09 (1.411)	**8.22 (1.166)**	5.35 (1.774)	5.00 (2.000)	**15.754 (0.000)**
IoT	6.65 (1.873)	7.35 (1.555)	**7.52 (1.377)**	7.26 (1.738)	6.83 (1.800)	5.52 (1.928)	4.30 (1.964)	3.09 (1.756)	**19.532 (0.000)**

Note 1: Each innovation type's mean value is offered along with the value of standard deviation (SD).

Note 2: BMI (Business-model innovation), PI (Product Innovation), PPI (Process Innovation), SI (Service Innovation), SPI (Service Process Innovation), MI (Marketing Innovation), OI (Organization Innovation), HRMI (Human Resource Management Innovation).

Source: authors.

This study found that the results are statistically significant for (i) the difference among the three technologies in terms of the eight innovation types and (ii) the difference among the innovation types with respect to the three technologies. In order to understand the differences between the eight innovation types for each technology, this study conducted an analysis of variance (ANOVA). It obtained an F-value for the differences between the eight innovation types on AI, big data, and IoT. The outputs of ANOVA indicate that the eight innovation types of each technology are significantly different (See F-value of AI: 8.420; big data: 17.754; IoT: 19.532) (See Table 4). It implies that there would be different prioritizations among the eight innovation types of each technology.

By using the two-way ANOVA (factors: technologies, factor: innovation), it illustrates the differences between the three technologies: AI, big data, and IoT (F-value: 15.469). Otherwise, this study distinguishes between the eight innovation types (F-value: 37.299). Moreover, this statistical output shows the effects of interactions among the technologies and innovation types (F-value: 3.461). Accordingly, there are significant interaction effects. Thus, this study finds there are differences among the three technologies with respect to the eight innovation types and that there are differences among the innovation types with respect to the three technologies (see Table 5).

Reasons for the Top Three Pairs

In this section, we explore the reasons of why the three pairs were selected. The findings concern each pair.

AI and Service Innovation

The highest priority innovation type for AI goes to service innovation. Through the interviews, we discovered that the unique characteristics of AI are hyper-intelligence. An expert said AI already established the new technological paradigm through machine learning, such as deep learning and neural networks. In addition, the experts recognized that large amounts of data, as in big data, are required to effectively use AI. Although the ultimate technological development of AI will head for Artificial General Intelligence, a specialized AI has already reached the stage where the machine can play beyond the human being's intelligence through machine learning in some areas such as Go-game. An expert asserted that, as seen in the example of reinforcement learning having carrot-and-stick system functions, the technological property of AI may become similar by imitating the learning mechanism of a human being. Otherwise, one of the experts pointed out the convergence of AI with other technologies such as big data or robots, which leads to the convergence of the manufacturing and service areas. Thirteen experts stated that the real values from AI can be captured more in, or driven by, service innovation. They stated that the unique technological strength and advances of machine learning would be a strong reason firms are expected to be engaged in service innovation.

The unique dimension of service is to offer services with tangible products in the manufacturing or service industries. The technological capacity of AI is capable of offering customers more service-fitted products or enhanced service offerings. Some of the experts concluded

Table 5. **Differences of Three Technologies on Each Innovation Type**

Source	Sum of Squares	Degree of Freedom	Mean Square	F	p-value
Differences in the three technologies	79.609	2	39.804	15.469	0.000
Differences in the innovation types	671.819	7	95.974	37.299	0.000
Interaction	124.681	14	8.906	3.461	0.000
Error	1358.609	528	2.573		
Total	2234.717	551			

Source: authors.

that a product can be fitted with a function of service, then an AI-fitted product can be used for a non-human-involved service. One example is the auto truck fitted with a self-driving function. In the meantime, the voice-recognition-function installed speaker can be used in a part of the telecommunication service. The second dimension of service is the interaction with customers or employees in simultaneous production and consumption as opposed to tangible products or manufacturing production. Three experts showed some consent that AI can have a more capacity to intellectually respond to humans or others through machine learning. The intellectual ability of AI can modify the interaction process of service provision with customers (or suppliers) or employees, by offering more sophisticated interactions with or without any human intervention. Thirdly, one of the experts suggested that, because services have less or non-standardized (or heterogeneous) patterns compared to manufacturing, through machine learning AI can increase the functional capacity to recognize and predict the patterns of (more complex) human behaviors. It can increase service capacity and regulate various non-standardized services, leading to new service offerings. However, technological properties of AI show probability functions in a manner similar to those a human uses in solving a problem. This can help people to implement AI decision-making function in various service fields. As the 13 experts mentioned, firms could eventually perceive the advantages or benefits of service innovation with respect to AI.

Big Data and Marketing Innovation

Marketing innovation is selected as a highly prioritized innovation part of big data. The experts seemed to agree with the four Vs of big data: volume denotes the huge amount of data; velocity indicates the speed at which data are collected, accessed, and analyzed, ideally in real time; variety refers to the different structured and unstructured types of data; and the use of data increases socio-economic value (OECD, 2015). Contrary to the function of AI, an expert mentioned that big data technologically plays a role in exploring the hidden relationships between data, which have not been explored due to the shortage of collected data and the lack of computing capability to proceed and analyze the large volume of unstructured and structured data. It is able to help to identify the hidden patterns. However, two experts stated no big differences between big data techniques and the existing data processing techniques, such as a data mart or data warehouse, whilst most experts confirmed that big data can provide better technological performance. An expert said that the unique technological properties of big data are to achieve efficiency in speedily dealing with a huge amount of data and to expand the applicable range of big data, compared to existing data techniques. Thirteen experts mentioned that the benefits or values of the marketing innovation of big data, which firms are able to realize, are the reasons they are engaged in the marketing innovation of big data. The usage of big data can help firms to identify the hidden relationship between customers or market data by speedily proceeding the huge amount of data.

One of the experts emphasized that marketing innovation is the basis for big data usage. The adoption of big data can bring about a change in customer (or market) analytical practices in the technological capacity of big data, even though the origin of data analytics started in the field of marketing. The three experts mentioned that, through an analysis of customer or market big data, intelligence can lead to marketing innovations. Because the utilization of data correlates with the selection of a value or values to be explored, it can be asserted that big data has a strong influence upon the path of marketing innovation. One example is that, by analyzing the patterns and purposes of users' usage of social network services, it can create better contextual marketing strategies than what the social network service firms did before the use of big data. An expert said that big data is able to offer a firm some important market insights leading to marketing innovation. More importantly, some experts held the opinion that the use of big data in terms of customers or markets can create each firm's new activities, which can be connected especially to its business model innovation and product (or service) innovation. Most experts said that the technological capacity of big data and the need of customer preferences can lead marketing innovation.

IoT and Process Innovation

Process innovation is selected as the highest priority of innovation for IoT. This study noted that the unique characteristic of IoT can be abstracted into "hyper-connectivity" as a sensor network. A device attached to the node of each network can take on the role of transmitting data. The device can be a sensor or contain it. IoT is capable of expanding its coverage beyond the coverage of the devices traditionally connected to the Internet, such as laptops and smartphones, by including all kinds of objects and sensors that permeate public spaces, workplaces, and homes, monitoring other humans, animals, bodies of water, and other places, where people cannot reach. With (or without) human involvement, sensors can technologically work to gather data and to exchange data with one another. They need to have a good network capacity or speed, such as a fifth-generation network. Greatly enhanced network capacity is an indispensable factor in IoT. Some experts described IoT as another dimension of ubiquitous computing, such as the ability to compute anywhere, regardless of whether such a concept has been previously suggested or is now outdated. Despite of those arguments, most of all they highlighted the importance of sensor technology, because the current development of sensor technology is still in the embryonic stage. There are various emerging sensor technologies, including nano-robots, actuating technologies, etc.

The majority of the experts argued that IoT can be applied to each of the production processes in manufacturing, the operation of logistics (or supply chain), etc., so that it can help to collect information on each process or control the flows, quality, or speed of information or things during each process beyond the existing ones (although it can be applied to various areas). It can have a huge impact upon production, plant automation, logistics, and so on. It is able to cause the efficiency of process in various ways. One expert asserted that, if small-quantity batch production can be enhanced, the function of IoT can be frequently applied. As regards making a step forward, some experts stated that IoT can be considered as a technology of servitization by modifying or enhancing the processes for customers. Information from sensors or actuation can help each firm to automatically organize input orders for manufacturing and to schedule the delivery or replacement of products. This can be potentially enhanced into business model innovation and service innovation.

As a result, despite the negative opinions concerning this match, most experts concluded that IoT can create changes to the manufacturing, production, and supply chain areas, capturing process innovation. The technological characteristics and capacity of IoT, such as connectivity and sensing, can be suitable for process innovation. However, they stated that process innovation in IoT can direct firms to explore new business models, turning into a variety of business model innovations. Thus, the benefits of the process of innovation on the unique properties and characteristics of IoT are the reasons firms could be engaged in the process innovation of IoT.

Conclusion, Implications and Limitations

This study makes some important theoretical and practical contributions to innovation studies. First of all, by using the eight innovation types relevant to the new industrial revolution, this study identified different priorities for innovation with regard to each of the three main technologies. By forecasting the top-priority innovation types of each technology, service innovation for AI, marketing innovation for big data, and process innovation for IoT can were identified as the top-priority innovation types. The three top matches can imply dominant non- or technological innovation types in the new wave of the industrial revolution. The advantages of a specific innovation for each technology can be the reasons behind why a top priority innovation was selected. This study identified the theoretical implication of technology-push theory through the findings. In addition, the service innovation of AI and the process innovation of IoT can reflect the converging phenomena between the service and manufacturing areas. Through the marketing innovation of big data, this study implies that Damanpour et al.'s (1989) logic can be applied to other various managerial innovations. The three matches can be an indication of a starting point to prepare for the new industrial revolution.

This study has some limitations. The existing studies have identified different innovation patterns between manufacturing and service firms (Ettlie, Rosenthal, 2011; Hipp, Grupp, 2005; Lovelock, 1984; Miles, 2007; 2016; Santamaria et al., 2012). Although this study considers the important phenomenon of new conversion of the service and manufacturing industries, it was not able to identify different priorities and patterns for the eight innovation types between each service and manufacturing industry. Kang et al. (2019) examined the different priorities for technologies between the manufacturing and service industries. Their study implied different priorities of innovation types between the two industries. Therefore, it would be worthwhile to conduct a further study of innovation types between the two industries. Secondly, this study could not contain all types of innovation, including social and open innovation. Some studies noted a linkage pattern: product and process innovation, technological and organizational innovation, etc. This linkage pattern can be found in the combination of the three technologies. However, this study was not able to give a clear understanding of those linkages and did not put the main focus on the mixture of technologies. It would be useful to have a further study to look into the linkages between innovation types, including social and open innovation. The ethical, legal and social aspects (ELSA) of emerging technologies can be discussed within the framework of social innovation.

In practical implications, this study can give managers, engineers, and executive-level officers useful information of what innovation types they need to be concerned regarding AI, big data and IoT. In addition, it can provide some guidance to policymakers on what they should focus on with regard to top-priority innovation types for each technology in the decision-making process. Along with the three matches, specific characteristics of innovation types and technologies should also be considered. Secondly, this study can help firms when they construct their innovation portfolio in terms of their strategies and competencies. Top-priority innovation types for these three technologies can help managers devise their capability-building plan and manage the innovation process.

This study is supported by the Korean Institute of S&T Evaluation and Planning and the KJS Group (Currently KJS & Group). We would like to thank the 23 experts for their participation in our Delphi surveys and seven recommenders for their help in identifying relevant experts for this study. We are also grateful to the 17 experts for graciously agreeing to interviews. Finally, our thanks go to Ian Miles of the Manchester Institute of Innovation Research, UK, for his help. The authors declare no conflict of interest.

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