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A patent-based approach for the identification of technology-based service opportunities

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ABSTRACT

One of the most crucial activities for new technology-based service development is an opportunity identification. Previous studies have mainly been customer-centered, lacking data and quantitative methodologies. This study proposes a new approach to identify technology-based service opportunities based on business method patent analysis. First, patent co-classification analysis is applied to construct interrelationship matrices. Second, the analytic network process is employed to derive the priorities of technology-based services. Third, data envelopment analysis window analysis is conducted to calculate the importance and its increase rate of technology-based services. Finally, a portfolio map is constructed to identify and manage opportunities for technology-based services. A case study of mobile services is performed to provide the operation of the proposed approach. It is expected that proposed approach could help planners of technology-based service firms to reduce the uncertainty in the fuzzy front-end stage of new technology-based service development.

1. Introduction

As a single competence can no longer meet the needs of the market, the convergence between heterogeneous areas is increasing. Especially, the convergence between technologies and services has been accelerated and so the boundaries of manufacturing and service industries are rapidly deteriorating. Manufacturing companies have embraced service orientation and/or develop more and better services (i.e. servitization), and service companies have evolved service components to include a product or a new service component marketed as a product (i.e. productization). In the academic fields, the focus on service innovation research is moving to technology-service convergence. Beyond the distinction between a technologist approach that service innovation follows the path of technological innovation and a service-oriented approach that emphasizes organizational innovation and customer interrelationships, there are growing attempts in an integrative approach in which a more advanced framework is needed to analyze technology-service convergence (Chang, Linton, & Chen, 2012; Spohrer & Maglio, 2008; Wang, Zhao, & Voss, 2016).

Technology-based services are one of the representative examples of technology-service convergence (Chang, Miles, & Hung, 2014). Technology-based services represent a type of services in which the efficiency and effectiveness of service delivery are improved mainly through the service companies' adoption of technological innovation (Walker, Craig-Lees, Hecker, & Francis, 2002). Technology-based services provide service providers with benefits such as reduction of labor costs, creation of value-added services, and improvement of service quality and customer satisfaction (Zhu, Wymer, & Chen, 2002), and give customers the convenience of transaction with reliable information (Agnihothri, Sivasubramaniam, & Simmons, 2002). The importance of technology-based services has been found in many cases. Apple has been a huge success with its technology-based service platform, App-store, and has evolved not just by offering new types of mobile services, but has also changed the paradigm of the mobile communications industry. In addition, investment in start-up companies related to IT-based financial services, i.e. 'Fin-Tech', is increasing explosively and it is expected to reach about US $ 6 billion globally in 2018. Furthermore, recent advances in new technologies such as internet of things, cloud, big data, and artificial intelligence are expected to provide various opportunities for new technology-based service development. Therefore, in the current business environment, which is undergoing a major paradigm shift of the Fourth Industrial Revolution, identification of technology-based service opportunities and their potential possibilities is crucial to the survival and competitiveness of companies and industries.

To identify technology-based service opportunities, two basic

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questions need to be answered. First, where the opportunities come from? A typical source of technology-based service opportunities is the customer, which means that opportunities can be identified by analyzing customers' experiences or requirements (Kim, Lee, & Park, 2013; Ozdemir, Trott, & Hoecht, 2007). However, customers may have a fundamental weakness in that they do not know what they want and do not feel the need for it until they try out new services (Riquelme, 2001). These characteristics are more prominent in technology-based services, because technology-based services are relatively radical and innovative and therefore customers would generally find it difficult to know what to expect from them (Jeong, Jeong, Lee, Lee, & Yoon, 2016). As the sources for opportunity identification are diverse, it is necessary to consider a wide range of issues that are difficult to be acquired from customers (Johne & Storey, 1998). Second, what method is used? The existing methods to identify technology-based service opportunities include survey (Mojtahed, Nunes, & Peng, 2013), interview (Uchihira et al., 2015), morphological analysis (Geum, Jeon, & Lee, 2016), text mining (Lee & Lee, 2015), and case-based reasoning (Geum, Noh, & Park, 2016). Although these methods are known to be useful for a variety of purposes, they have focused only on specific types of technology-based services. In addition, they needed customers' or experts' judgement and so it takes much time and effort to apply these customer- and expert-oriented approaches to technology-based services with diverse and complex characteristics (Lee, Song, & Park, 2012). Therefore, it is necessary to use a quantitative approach to comprehensively understand the technology-based service opportunities through rapid and large-scale analysis.

In response, this study proposes a new approach to identify technology-based service opportunities through quantitative data and systematic processes. At first, the business method (BM) patent database is used as a source of technology-based service opportunities. BM patents are defined as the methods of administering, managing, or operating an enterprise or organization (No, An, & Park, 2015). Even if BM patents deal with the process and methods of general businesses, their main application area has been the service industry (Niemann, Moehrle, & Walter, 2013). For this reason, literature has discussed the characteristics of BM patents as related to technology-based services, taking into consideration that they contain a vast amount of information on the real-world technology-based service innovation (Geum, Park, & Lee, 2013; Lee & Sohn, 2017). Since the innovation in technology-based services can be regarded as the effort to continuously obtain opportunities (Chen, 2016), BM patents can play a role as the source of technology-based service opportunities and their analysis could provide a lot of empirical implications that have not been provided in previous customer-oriented studies. Next, quantitative analysis methods with BM patents are used as a methodology. The analytic network process (ANP) is applied to the BM patents' co-classification information to produce the priorities of technology-based services. Specifically, the priorities from three perspectives of interrelationship - intensity, relatedness, and cross-impact - are respectively derived. With the derived priorities, data envelopment analysis (DEA) window analysis is applied to calculate the importance and its increase rate of technology-based services, putting three perspectives of interrelationship together. A portfolio map is then constructed for exploring and managing technology-based service opportunities. Portfolio management is known to be a useful method for evaluating opportunities and allocating resources (Stevenson & Plath, 2006; van Riel et al., 2013). Technology-based service opportunities need to be managed through a portfolio more than traditional service opportunities. Even opportunities that are considered difficult to succeed should not be thrown away. Since changes in the environment surrounding technology-based services are relatively more dynamic than traditional services, opportunities that are not promising can be attractive in the near future. Therefore, managing technology-based service opportunities as a portfolio is essential for the successful development of new technology-based services. The proposed approach is not only useful for identifying promising technology-based service opportunities, but it can also contribute to reducing the inherent uncertainty in the fuzzy front-end stage of the process of new technology-based service development.

This study is composed as follows. Section 2 briefly describes the methodologies related to this study. Section 3 explains the approach proposed in this study. Section 4 conducts a case study to confirm the usefulness of the proposed approach. Section 5 discusses the contributions and limitations of this study.

2. Literature review

2.1. Patent-based technological interrelationship analysis

What is at the core of measuring technological interrelationship or linkage is patent information (Kim, Suh, & Park, 2008). Among the measures employed for measuring technological linkage with patents, citation analysis has been the most popular one. The basic assumption of the citation analysis is that the cited patent's knowledge is transferred to the citing patent, so the cited patent affects the citing patent and there is an interrelationship between the two patents (Narin, 1994). Since patents that receive many citations from other patents tend to be more important for technological progress and are of higher economic value than those that receive only a few (Harhoff, Narin, Scherer, & Vopel, 1999), citation analysis has long been used to analyze technological importance (Ernst, 2003; Lee, Kim, Cho, & Park, 2009; Block, Miller, Jaskiewicz, & Spiegel, 2013). However, it shows that the time lag between citing and cited patents exceeds 10 years on average and the importance of the relatively new patents may be undervalued compared to that of older ones (Hall, Jaffe, & Trajtenberg, 2001). Moreover, since citation analysis only considers citing-cited relationships between individual patents, it is difficult to identify technological characteristics such as technological importance, technological knowledge flow, and technological cross-impact from a perspective of technological fields (Yoon & Park, 2004).

In contrast, co-classification analysis has several advantages over citation analysis. Co-classification analysis is based on the fact that patents are classified into multiple classification codes considering their characteristics. Unlike citation analysis, co-classification analysis is based on the patent classification system, and therefore it is possible to grasp the interrelationship between technological fields at an upper level than individual patent levels. Since the patent classification system has a hierarchical structure, it can be analyzed by different levels of technology according to research purpose. In addition, patent classification is information at the time of patent registration, so that the possibility of error due to time lag is relatively low in analysis.

Studies on the interrelationship analysis based on patent co-classification have been conducted from the three perspectives - intensity, relatedness, and cross-impact. First, those from the perspective of intensity used co-classification frequency. It assumed that the frequency by which two classification codes are jointly assigned to a patent can be interpreted as a sign of the strength of the relationships in terms of knowledge links and spillovers (Engelsman & van Raan, 1994). Hence, the greater the number of such patents, the more the knowledge flow between the two classification codes. Second, those from the perspective of relatedness applied cosine similarity, which measures the angular separation between the vectors representing the co-occurrences of two classification codes (Jaffe, 1989). Although the concept of relatedness is very broad and encompasses several dimensions, the underlying assumption is that the related technologies share a common or complementary knowledge base (Breschi, Lissoni, & Maleraba, 2003). Therefore, the greater the cosine similarity of two classification codes, the stronger the commonality or complementarity between the two classification codes. Finally, those from the perspective of cross-impact employed the cross-impact index, which is defined as a conditional probability between two classification codes (Choi, Kim, & Park, 2007). When technological events occur as a result of the interactions with each other, an effect of each event of interest on other events is called the cross-impact (Jeong & Kim, 1997). Cross-impact index have a value between zero and one, and the closer a value is to one, the greater the impact of a classification code on the occurrence of the other classification code. The use of patent co-classification information in this study is in line with the other research stream, analyzing the technological importance in terms of the technological knowledge flows, technological commonality/complementarity, and technological cross-impact based on the patent co-classification relationships.

2.2. ANP

Because technology systems are highly interdependent (Archibugi & Pianta, 1996), it is becoming increasingly important to photograph the overall structure and internal linkage of technology networks to analyze technological trends and advances. However, patent co-classification analysis alone cannot grasp the overall relationship and structure of all patents since only individual links between two particular patents are captured. To address this limitation, network analysis has often been used in conjunction with a patent co-classification analysis to measure the flow of technological knowledge between entities and to identify the priority of entities (Park & Yoon, 2014; Yoon, Park, Kim, Lee & Lee, 2014).

To characterize either holistic network features or the positions of individual actors in a network, various centrality measures such as degree centrality, closeness centrality, and betweenness centrality can be calculated. Among them, degree centrality, which can be defined as the number of links incident on a node, has been used implicitly as an indicator of the importance of technologies (Trajtenberg, Henderson, & Jaffe, 1997). However, it cannot successfully capture indirect relationships (Borgatti, 2005). While in traditional network theory, indirect links are generally of less value than direct links, it does not hold true in the case of patent co-classifications analysis. In response, this study used the ANP to produce the priority of technology-based services, taking into account the direct and indirect interrelationship between them.

The ANP is a generalized model of AHP (analytic hierarchical process), one of the most widely used multiple-criteria decision-making (MCDM) methods (Saaty, 1996). AHP breaks down problems into hierarchies of independent decision-making elements, making it impossible to reflect the interrelationships between elements. The ANP is an extension of AHP to the problem with dependence and feedback. It enables the analysis of complex relationships among decision-making elements by replacing the hierarchy of AHP with a network. Specifically, the ANP derives priority or relative importance of decision elements in complex network model reflecting interdependency between them. For this reason, there has been an increase in the use of the ANP to patent information in order to analyze technological interrelationships for various purposes like core technology identification (Kim & Kim, 2015), technological partner selection (Jeon, Kim, Park, & Lee, 2017), and firm performance evaluation (Sheng, 2015).

The ANP and network analysis have the common keyword 'network', but differ significantly in the ultimate objectives and nodes that make up a network. The ANP is a MCDM method that aims to prioritize alternatives or select the best alternative. On the other hand, the purpose of network analysis is to capture the overall structure of a network consisting of the various types of actor through visualization and quantification. If a network is constructed to visualize only the overall relationships among the actors, the ANP has nothing to do with network analysis. However, when measuring the importance of actors or identifying key actors in network analysis, the ANP can also be used for the same purpose by considering actors as alternatives. Then the centralities or the importance of the actors correspond to the priorities of the alternatives (Lee et al., 2009).

The process of the ANP consists of the following four steps (Saaty, 1996).

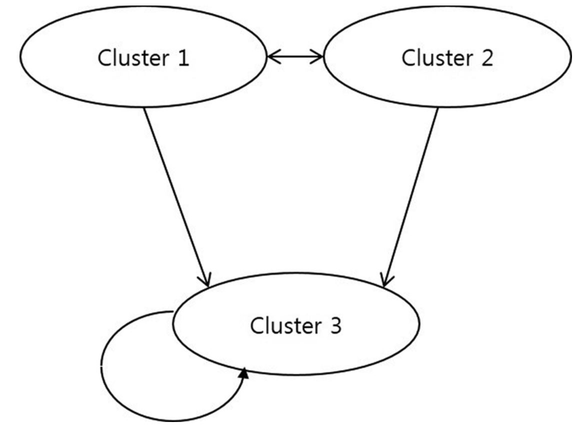

Fig. 1. Example of ANP network.

(1) *Network model construction.* A given decision problem is structured in the form of a network. The basic unit of a network is a cluster, with each cluster containing several elements. If a cluster affects other clusters, this can be expressed by an arc that indicate the relationship of the clusters. In addition, if there is a relationship between elements in the cluster, this is indicated using a looped arc. Fig. 1 shows an example of the ANP network structure consisting of three clusters.
(2) *Pair comparison and priority vector derivation.* The elements of each cluster are compared pairwisely based on their impact on an element in the cluster. In addition, the interdependency among elements of the outside clusters is also compared pairwisely. If cluster weights are required for weighting supermatrix in the next step, pairwise comparisons are also made for the clusters with respect to their impacts on each cluster. The way of pairwise comparison and derivation of priority vector are the same in the AHP. The relative importance values are determined on a scale of 1–9, where 1 indicates that the two elements have the same importance, and 9 indicates that an element is extremely important when compared to another. The diagonal entry, which represents a comparison with itself, is 1, and a reciprocal value is assigned to the inverse comparison. The eigenvector method is then used to obtain the local priority vectors of each pairwise comparison matrix.
(3) *Supermatrix construction and transformation.* A supermatrix is constructed by entering all the local priority vectors into appropriate columns. That is, the supermatrix is a partitioned matrix where each segment represents a relationship between two clusters. The supermatrix of a system of N clusters is denoted as the following:

$$\begin{array}{cc} & \begin{array}{ccccc} e_{11}\cdots e_{1n_1} & \cdots & e_{k1}\cdots e_{kn_k} & \cdots & e_{N1}\cdots e_{Nn_N}\end{array} \\ \begin{array}{cc} C_1 & \begin{array}{c} e_{11}\\ \vdots \\ e_{1n_1}\end{array} \\ \vdots & \vdots \\ C_k & \begin{array}{c} e_{k1}\\ \vdots\\ e_{kn_k}\end{array} \\ \vdots & \vdots \\ C_N & \begin{array}{c} e_{N1}\\ \vdots\\ e_{Nn_N}\end{array}\end{array} & \begin{pmatrix} \mathbf{W}_{11} & \cdots & \mathbf{W}_{1k} & \cdots & \mathbf{W}_{1N} \\ \vdots & & \vdots & \ddots & \vdots \\ \mathbf{W}_{k1} & \cdots & \mathbf{W}_{kK} & \cdots & \mathbf{W}_{kN} \\ \vdots & & \vdots & \ddots & \vdots \\ \mathbf{W}_{N1} & \cdots & \mathbf{W}_{NK} & \cdots & \mathbf{W}_{NN}\end{pmatrix}\end{array}$$

C_k is the kth cluster ($k = 1, 2, \ldots, N$) having n_k elements ($e_{k1}, e_{k2}, \ldots, e_{kn_k}$). W_{ij} is a matrix segment representing a relationship between the ith

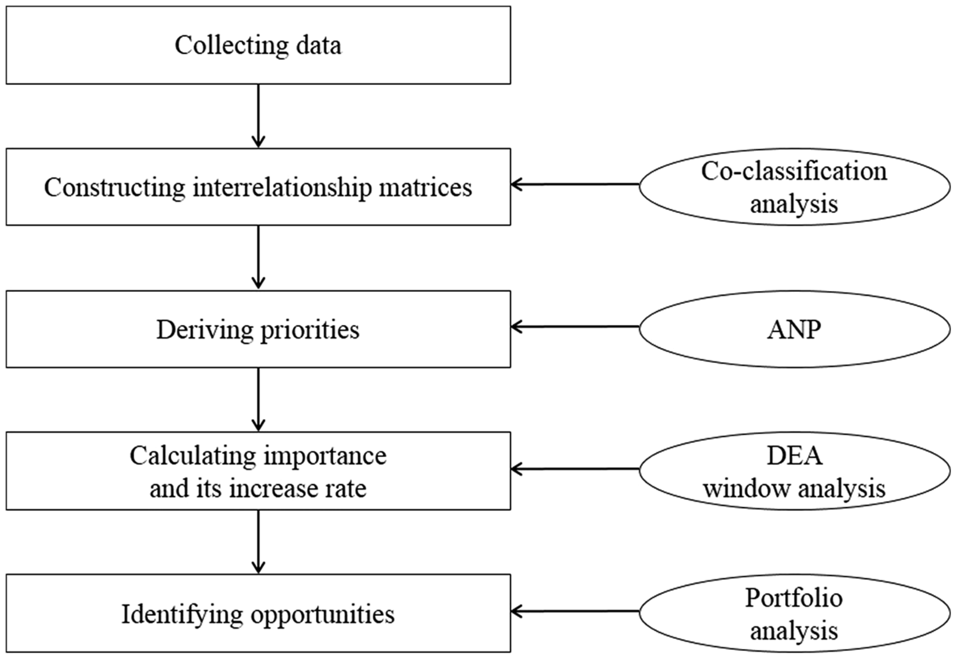

Fig. 2. Overall process of proposed approach.

cluster and the jth cluster. Each column of W_{ij} is a local priority vector obtained from the corresponding pairwise comparison. If there is no relationship between clusters, the corresponding segment is a zero matrix. Then, the supermatrix is transformed into the weighted supermatrix by multiplying the cluster weight for all the segments constituting the supermatrix and normalizing it. When the sum of each column of a matrix is all one, it is known that multiplying this matrix infinitely converges to a unique form. This 'column stochastic' feature of the weighted supermatrix allows the convergence of the limit supermatrix. Finally, the weight supermatrix is transformed into the limit supermatrix by raising itself to powers until the weighted supermatrix converges.

(4) *Final priority derivation.* The column vector value of the limit supermatrix is the final priority of the alternatives, which reflects all the direct and indirect effects of each element on the others.

2.3. DEA and window analysis

DEA is a method of evaluating the relative efficiency of decision making units (DMUs) with multiple inputs and outputs, not pre-assigning criteria weights (Charnes, Cooper, & Rhodes, 1978). In DEA, the efficiency of a DMU is measured by estimating the ratio of the weighted sum of outputs to the weighted sum of inputs and comparing it with the ratio of other DMUs. The efficiency of all DMUs is restricted to 1 or less. Under these constraints, efficiency is measured based on the weight of each element that maximizes the efficiency of the target DMU. There are two types in DEA model: CCR (Charnes-Cooper- Rhodes) model for constant returns to scale (Charnes et al., 1978) and BCC (Banker-Charnes-Cooper) model for variable returns to scale (Banker, Charnes, & Cooper, 1984). DEA models can also be classified by the objective: maximize outputs (output oriented) or minimize inputs (input oriented). While DEA was originally developed for measuring the efficiency of multiple units performing a transformation process of several inputs and several outputs, it is now playing a broader role as a tool for MCDM problems (Bouyssou, 1999). The applications of DEA to patent information include patent-enhancing strategy formulation (Lee et al., 2016), technological strength analysis (Seol, Lee, & Kim, 2011), and firms' technical efficiency calculation (Suh & Oh, 2015).

The general DEA is a cross-sectional model, observing each DMU only once and focusing on its efficiency at a specific period. However, in many actual cases, DMUs can be observed more than once over multiple time periods. In this case, DEA window analysis is a useful approach to analyze DMUs' efficiency (Asmild, Paradi, Aggrawall, & Schaffnit, 2004). The basic assumption of window analysis is moving average analysis and the efficiency of each DMU is represented multiple times in the window instead of being represented as a single summary score (Charnes, Clark, Cooper, & Golany, 1984). Each DMU belonging to another period is treated as a different DMU, and the performance of a DMU in a period is compared to its own performance in other periods as well as to the performance of other DMUs. Accordingly, DEA window analysis can be used not only to produce the time-series efficiency of DMUs, but also to track the dynamic changes of DMUs' efficiency by modelling the evolution of their efficiency over time. The use of DEA window analysis in this study is included in the former: it is applied to calculate the importance and its increase rate of technology-based services with their time-series efficiency scores.

3. Proposed approach

3.1. Overall process

The process of identifying technology-based service opportunities consists of five steps. First, the technology-based service field to be analyzed is selected and BM patent data on it is collected. Second, the index of intensity, relatedness, and cross-impact between technology-based service pairs are calculated with the co-classification information of the collected BM patent data, and then three types of interrelationship matrix (intensity matrix, relatedness matrix, and cross-impact matrix) are constructed. Third, the ANP is respectively applied to the constructed three interrelationship matrices in order to derive priorities of technology-based services. Fourth, DEA window analysis is conducted to the derived priorities to calculate the importance and its increase rate of technology-based services, putting three interrelationships together. Finally, with the calculated importance and its increase rate of technology-based services, a portfolio map is constructed to investigate technology-based service opportunities. Fig. 2 depicts the overall process of this study. More detailed explanations are provided below.

Table 1
Interrelationship matrix.

	TBS_1	TBS_2	…	TBS_n
TBS_1	1	$Inter(T_1 \rightarrow T_2)$	…	$Inter(TBS_1 \rightarrow TBS_n)$
TBS_2	$Inter(TBS_2 \rightarrow TBS_1)$	1	…	$Inter(TBS_2 \rightarrow TBS_n)$
…	…	…	1	…
TBS_n	$Inter(TBS_n \rightarrow TBS_1)$	$Inter(TBS_n \rightarrow TBS_2)$	…	1

3.2. Collecting data

The data source of this study is the BM patents registered in the United Stated Patent and Trademark Office (USPTO) database. In the USPTO, patents are classified under a hierarchical patent classification system, the Unites States Patent Classification (USPC) (United Stated Patent and Trademark Office, 2012). Each subject matter division in the USPC includes a major component called a class and a minor component of a class called a subclass. Subclass also has a hierarchical structure. The highest level component of a subclass is called a mainline subclass, and the component just below a mainline subclass is called a one-dot indent subclass. BM patents are categorized into the class 705 defined as 'Data processing: financial, business practice, management, or cost/price determination' (Kim, Choe, Choi, & Park, 2008). Class 705 includes six mainline subclasses and 52 one-dot indent subclasses.

After determining the analysis period, the BM patent data related to interested technology-based service field is collected.

3.3. Constructing interrelationship matrices

The interrelationship matrices are constructed by using the interrelationship values between all the pairs of technology-based services, calculated with the co-classification information of the collected BM patent data. As explained in Section 2.1, there are three types of interrelationship related to patent co-classification – intensity, relatedness, and cross-impact – and therefore the interrelationship matrices of each interrelationship are the intensity matrix, the relatedness matrix, and the cross-impact matrix, respectively.

Suppose that M patents are classified into one or more classification codes, respectively. Let F_{Am} denote the binary value of whether a patent m is classified into a classification code A. That is, $F_{Am} = 1$ if a patent m is classified into a classification code A, $F_{Am} = 0$ otherwise. Then the number of patents classified into the classification code A is given by $N_A = \sum_{k=1}^{M} F_{Ak}$. In addition, the number of patents co-classified into two classification codes A and B, N_{AB}, is $\sum_{k=1}^{M} F_{Ak}F_{Bk}$. If the number of all co-classifications of M patents is N, the intensity index between the two classification codes A and B is N_{AB}/N, the normalized number of patents co-classified into A and B. Next, the relatedness index between the two classification codes A and B can be calculated through a cosine similarity $\sum_{k=1}^{M} F_{Ak}F_{Bk}/(\sqrt{\sum_{k=1}^{M} F_{Ak}^2}\sqrt{\sum_{k=1}^{M} F_{Bk}^2}) = N_{AB}/\sqrt{N_A N_B}$, which measures the angular separation between the vectors representing the co-occurrences of the classification codes A and B with all the other classification codes. Finally, the cross-impact index between the two classification codes A and B can be obtained through a conditional probability N_{AB}/N_A. The three interrelationship indices have in common that they measure interrelationships by scaling the frequency of co-occurrences between two classification codes. However, there are some differences between them. For the intensity index, the denominator is fixed regardless of the occurrence frequencies of each classification code. It relies only on the frequency of co-occurrences between two classification codes, indicating that the higher the frequency of co-occurrence between two classification codes, the greater the interrelationship between them. On the other hand, for the relatedness index and the cross-impact index, the interrelationship between two classification codes is not necessarily proportional to the frequency of co-occurrence between them because the value of the denominator changes with the occurrence frequencies of one or all of the two classification codes. Although the frequency of co-occurrence between two classification codes is high, the interrelationship can be measured not to be strong when the denominator is large as well. The difference between the relatedness index and the cross-impact index is symmetric or not. The relatedness index has a symmetric value. In other words, the interrelationship between the classification code A and B and the interrelationship between the classification code B and A are the same. However, the knowledge flow from the classification code A to B is not in general equal to the knowledge flow from the classification code B to A. In contrast, cross-impact index allows asymmetric values, more realistically representing the knowledge flow between two classification codes. With the values of the intensity, relatedness, and cross-impact index between classification codes, the square matrices whose row and column stand for the classification codes can be constructed by assigning interrelationship values to their relevant positions. This is called an interrelationship matrix, and is classified into an intensity matrix, a relatedness matrix, and a cross-impact matrix according to the types of interrelationship.

Table 1 shows the form of the interrelationship matrix. TBS_i denotes the i-th of N classification codes, and $Inter(TBS_i, TBS_j)$ denotes the value of the interrelationship index between the two classification codes i and j. All the diagonal values in the interrelationship matrix are assigned a value of one because there is an interrelationship of 100% between the same classification codes. Since the next step, priority derivation, is conducted based on the interrelationships among technology-based services at the upper and lower level in the patent classification system, the interrelationship matrices at both level need to be constructed. In addition, the interrelationship matrices should be constructed over each time period. For example, if analysis period is 10 years, a total of 60 (= three interrelationships × two levels × 10 years) interrelationship matrices need to be constructed.

3.4. Deriving priorities

The ANP is applied to the constructed interrelationship matrices to derive the priorities of technology-based services, taking into account the direct and indirect relationships among all technology-based services. The procedure for this is as follows. First, a network model is constructed. The original ANP network model is constructed through expert judgment of the abstract decision problem. On the other hand, the ANP network in this study is built on the basis of the interrelationships. In other words, clusters of the ANP network correspond to upper level technology-based services, and elements of each cluster are lower level technology-based services. Unlike the general ANP network model which consists of a goal cluster, criteria clusters, and the alternative clusters, the ANP network model of this study consists only of the alternative clusters. Therefore, the evaluation of alternatives is made only in terms of interrelationships between technology-based services, not criteria or goal.

Second, the priority vectors are derived. For the ANP, pairwise comparisons are usually made through qualitative judgment using value between one and nine. However, in this study, pairwise comparisons do not have to be conducted and the pairwise comparison matrix is the same as the interrelationship matrix, because the interrelationship values between a pair of node are the proxies for the degree of influences. The priority vectors of clusters are, therefore, the same as the normalized interrelationship matrices at the upper level, whose column sum to be one (Lee et al., 2009). In addition, local priority vectors of elements can be obtained by normalizing the partial matrix corresponding to the two clusters to be compared in the lower level interrelationship matrix. If there are N clusters, a total of N^2 ($= N \times N$) local priority vectors need to be constructed.

Third, the supermatrix is constructed and transformed. All local priority vectors are gathered to construct the supermatrix, which is a partitioned matrix where each segment represents a relationship

Table 2
Window analysis of technology-based services *i*.

Alternative	Window	Period								Window's efficiency	Alternative's efficiency	Increase rate of efficiency
		1	2	3	…	•	•	P–1	P			
i	1	$E^i_{1,1}$	$E^i_{1,2}$	$E^i_{1,3}$	⋯	$E^i_{1,K}$				$WI_{1,i}$	TI_i	R_TI_i
	2		$E^i_{2,2}$	$E^i_{2,3}$	⋯	$E^i_{2,K}$	$E^i_{2,K+1}$			$WI_{2,i}$		
	…				…					…		
	M					$E^i_{M,P-K+1}$	⋯	$E^i_{M,P-1}$	$E^i_{M,P}$	$WI_{M,i}$		

between two clusters. The supermatrix is transformed into the weighted supermatrix by multiplying each local priority vector by cluster weights, and then normalizing the sum of the columns to one. Here, cluster weight is the corresponding value of the cluster-level priority vector. Then, the limit supermatrix is derived by converging each column of the weighted supermatrix the same. The columns of the limit supermatrix are called the limit centralities that reflects all direct and indirect relationships among technology-based services.

Finally, the final priorities of technology-based services can be identified based on each limit centrality of technology-based services.

This process except network model construction should be conducted for each interrelationship over each time period. For example, if analysis period is 10 years, a total of 30 (= three interrelationships × 10 years) priority sets need to be derived.

3.5. Calculating importance and its increase rate

DEA window analysis is employed to the derived priority values in order to calculate the importance and its increase rate of technology-based services. When considering the issue of calculating the importance of technology-based services to be a problem of MCDM that selects high-priority technology-based services in terms of three interrelationships, technology-based services, interrelationships, and importance correspond to alternative, criteria, and evaluation score, respectively. If DEA is used as an MCDM tool in this respect, then the technology-based services are assigned to the DMUs, the priority values match to the outputs, and importance corresponds to the efficiency score derived by applying DEA.

Suppose that the number of the alternatives of technology-based services, number of time period for which data are available, length of window, and number of windows are N, P, K, and M, respectively. In this case, the number of windows M can be calculated by Eq. (1) (Chung, Lee, Kang, & Lai, 2008).

$$M = P - K + 1 \tag{1}$$

For the choice of the window length, there is no straightforward methods and it is largely a matter of judgement (Ross & Droge, 2002). An important advantage of the window analysis, however, is that it increases the discriminatory power of DEA by increasing the total number of DMUs. Itoh (2002) proposed a methodology to design the window length so as to maximize the total number of DMUs, which can be expressed by $NKM = NK(P - K + 1)$ as the number of DMUs in each window is NK. It is maximized when the differential of the right hand side with respect to K is set to be zero. This leads to

$$K = \frac{P+1}{2} \tag{2}$$

DEA is applied to NK DMUs belonging to the same window to evaluate their efficiencies. Because only the priority values for the three interrelationships are treated as output and no inputs exist, an output-oriented BCC model with no inputs (pure output model) suggested by Lovell and Pastor (1999) is adopted for applying DEA. This process is repeated M times to get all efficiencies for the entire windows. The importance of a technology-based service i (TI_i) can be calculated by averaging the efficiency scores of the DMUs belonging to all the windows of the technology-based service i as the Eq. (3), where $E^i_{w,j}$ is the efficiency score of a technology-based services i at period j in a window w. TI_i has values between zero and 100 because the efficiency score in the DEA is between zero and 100 percent.

$$TI_i = \frac{\sum_{w=1}^{M}\sum_{j=w}^{w+K-1} 100E^i_{w,j}}{K \times M} \tag{3}$$

Next, the increase rate of TI_i (R_TI_i) is obtained as follows. At first, the importance of a window w belonging to a technology-based service i ($WI_{w,i}$) is $\sum_{j=w}^{w+K-1} 100E^i_{w,j}/K$, averaging efficiency scores of the DMUs in the window w. The increase rate of $WI_{w,i}$ is calculated as the importance of the current window divided by the importance of the previous window ($WI_{w,i}$ / $WI_{w-1,i}$). Then, R_TI_i can be defined as the geometric mean of the increase rates of all windows' importances except for the first window as the Eq. (4).

$$R\_TI_i = \left[\prod_{w=2}^{M}\left(\frac{WI_{w,i}}{WI_{w-1,i}}\right)\right]^{\frac{1}{M-1}} = \left(\frac{WI_{M,i}}{WI_{1,i}}\right)^{\frac{1}{M-1}} \tag{4}$$

The efficiency values and relevant evaluations for a technology-based service i are shown in Table 2.

3.6. Identifying opportunities

To identify technology-based service opportunities, a portfolio map is developed as shown in Fig. 3. The portfolio map is a two-dimensional form with two axes, importance (TI) and its increase rate (R_TI), and technology-based services are mapped in one of four groups according to the degree of importance and its increase rate. Technology-based services in the first quadrant are 'attractive opportunities'. They are not only important but they can be expected to bring great opportunities because their importance is increasing. Technology-based services in

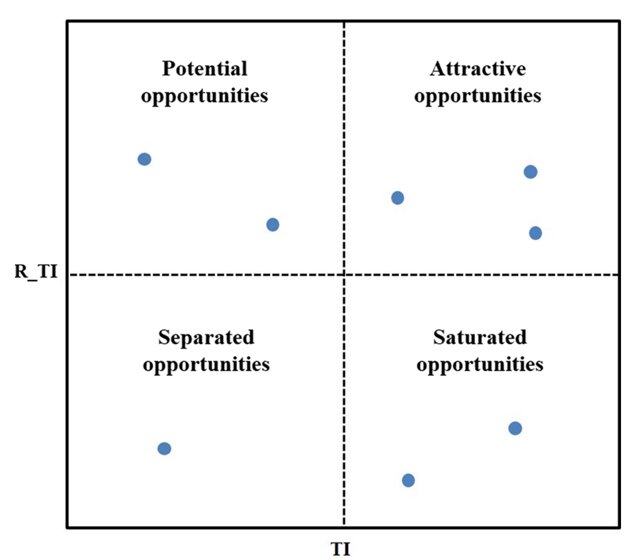

Fig. 3. Portfolio map.

the second quadrant are 'potential opportunities'. Since their importance is relatively low but growing at a rapid pace, they will move to the first or fourth quadrant in the near future. Technology-based services in the third quadrant are 'separate opportunities'. Because both the importance and its increase rate are low, they are separated from other technology-based services in terms of interrelationship. Finally, technology-based services in the fourth quadrant are 'saturated opportunities'. Although the importance is high, its increase rate is relatively low. Therefore, it is expected that such high importance will not be maintained continuously.

Since importance and its increase rate change over time, the portfolio map should be continuously updated. It also provides implications for managing technology-based service opportunities. The focus is to monitor 'potential opportunities' to be placed in 'attractive opportunities' or 'saturated opportunities'. Various opportunities for 'potential opportunities' can be investigated because the direction is not yet determined.

4. Case study

4.1. Collecting BM patents related to mobile services

As a case study, opportunities for mobile services, one of most representative technology-based services, were identified. At first, the BM patents classified into the class 705 and related to mobile services were selected as data. It should be noted that the analysis of co-classification only within the class 705 could restrict the scope of opportunity identification. Considering that the patents classified into the class 705 were mainly software-based and software was pervasive in virtually any technology in the digital era, it is expected that the knowledge of software innovation flows to other domains beyond the class 705. Therefore, the use of co-classification information not only within the class 705 but also across the non-705 classes could derive more opportunities. In this study, however, co-classification information only within the class 705 was illustratively used to verify the usefulness and applicability of the proposed approach to the identification of technology-based service opportunities.

For collecting data related to mobile services, BM patents that were classified into the class 705 were searched from the USPTO database (http://www.uspto.gov). All patents are classified at least by one (main or primary) classification code of the USPC, but usually more classification codes (secondary or supplementary) are assigned to the documents. Although the main classification code describes the central characteristics of the main claim of the patent, the supplementary codes indicate further features of the main claim as well as of the remaining claims of the patent, i.e. they also refer to knowledge creation (Breschi et al., 2003). Following this remark, no distinction was made between main and supplementary codes, and patents classified into the class 705 were searched irrespective of the type of classification code. Using the keyword of 'mobile' or 'wireless' in the title or abstract (Kim et al., 2008), BM patents registered from 2005 to 2014 were searched. Applications were not considered and only granted patents were looked for. Granted patents that are protected as an intellectual property are generally accepted to be more qualified because they have technological novelty, practically implement the technological opportunities, and contribute to technological progress as results of R&D activity (Gupta & Pangannaya, 2000; Park, Yoon, & Kim, 2013). As a result, a total of 2,779 BM patents were collected. Collected BM patents were in html format and need to be converted to the appropriate format for analysis. To this end, we developed our own Java-based software consisting of three modules: file parsing, information processing, and DB constructing. 'File parsing' converted html format files to text format. 'Information processing' extracted the patent number and classification code information of each collected BM patent contained in a text file. In addition, the corresponding parent subclass information (mainline subclass and one-dot indent subclass) of the extracted classification codes were also prepared. For example, if a patent's classification code is 14.3 (Multi-merchant loyalty card system) which is a three-dot indent subclass, the mainline subclass corresponds to 1.1 (Automated electrical financial or business practice or management arrangement) and one-dot indent subclass to 14.1 (Discount or incentive). 'DB constructing' input these information into a table of MS Access defined in advance.

Next, the level of analysis in the USPC hierarchy was determined. In this study, the mainline subclass and the one-dot indent subclass was selected as the upper level and the lower level, respectively. As mentioned in Section 3.1, class 705 has six mainline subclasses and 52 one-dot indent subclasses. If the level of analysis is lower than one-dot indent subclass, the number of classification codes becomes too large and the number of co-classification among classification codes becomes small, which makes meaningful analysis difficult. Of the six mainline subclasses, 80 (Electronic negotiation) and 500 (Miscellaneous) were excluded from the analysis because they had no child subclass and so the interrelationships among mobile services at the upper and lower level did not exist. In addition, of the 52 one-dot indent subclasses, 27 one-dot indent subclasses whose co-classification frequency was less than 10 were also excluded from the analysis because their co-classification frequency mean during the analysis period (10 years) were less than one and so they had little interrelationships with other mobile services. As a result, as shown in Table 3, there remained four mainline subclasses and 25 one-dot indent subclasses and they served as the analysis units for identifying mobile service opportunities. In specific, mainline subclass is used to calculate the cluster weight used for executing the ANP process, and one-dot indent subclass represents the technology-based services.

4.2. Constructing the interrelationship matrices of mobile services

The intensity index, relatedness index, and cross-impact index of all

Table 3
Mobile services for analysis.

Mainline subclass	One-dot indent subclass
50 (Business processing using cryptography)	51 (Usage protection of distributed data files) 60 (Postage metering system) 64 (Secure transaction (e.g., EFT/POS))
1.1 (Automated electrical financial or business practice or management arrangement)	2 (Health care management) 4 (Insurance) 5 (Reservation, check-in, or booking display for reserved space) 7.11 (Operations research or analysis) 13 (Transportation facility access) 14.1 (Discount or incentive) 14.4 (Advertisement) 15 (Restaurant or bar) 16 (Including point of sale terminal or electronic cash register) 26.1 (Electronic shopping) 30 (Accounting) 35 (Finance) 301 (Workflow collaboration or project management) 313 (Real estate) 319 (Social networking) 330 (Shipping) 346 (Customer communication at a business location)
400 (For cost/price)	401 (Postage meter system) 412 (Utility usage) 418 (Time (e.g., parking meter))
901 (Digital rights management)	902 (Licensing digital content) 904 (Usage protection of distributed files)

Table 4
Intensity matrix of mainline subclass level in 2005.

	50	1.1	400	901
50	1.0000	0.4091	0.0000	0.0000
1.1	0.4091	1.0000	0.0909	0.0000
400	0.0000	0.0909	1.0000	0.0000
901	0.0000	0.0000	0.0000	1.0000

the mobile services were calculated by the level and year for the co-classification information of the collected mobile BM patents. Using the calculated interrelationship indices, the intensity matrix, relatedness matrix, and cross-impact matrix were also constructed by the level and year. As a result, a total of 60 interrelationship matrices (=three interrelationships × two levels × 10 years) were constructed. For example, Table 4 shows the intensity matrix at the mainline subclass level in 2005 and Table 5 shows the intensity matrix at the one-dot indent subclass level in the same year.

4.3. Deriving the priorities of mobile services

On The ANP was applied to the constructed interrelationship matrices for deriving the priorities of mobile services. First, the network model for mobile services including four clusters and 25 elements was constructed as portrayed in Fig. 4. Every mainline subclass influenced each other and included a feedback loop that represented interrelationships among one-dot indent subclasses in the mainline subclass itself.

Second, priority vectors were derived. At first, the cluster weights were obtained by normalizing the interrelationship matrices at the mainline subclass level. For example, Table 6 shows the priority vector for clusters in terms of intensity in 2005, which was derived by normalizing Table 4. Next, the local priority vectors for elements were derived by normalizing the interrelationship matrices at the one-dot indent subclass level as well. For example, as shown in Table 7, local priority vector comparing one-dot indent subclasses of mainline subclass 1.1 to those of mainline subclass 50 from the intensity perspective in 2005 was derived by transforming relevant partial matrix in Table 5. What is important here is that the normalization of columns has to be done for each cluster.

Third, the supermatrix, a 25 × 25 matrix composed of 16 ($=4^2$) blocks, was constructed with the obtained local priority vectors. A block corresponds to a set of local priority vectors, a priority matrix. Table 8 shows a part of the supermatrix of intensity perspective in 2005. Each block of the supermatrix was multiplied by the corresponding cluster weights, and then the weighted column of the supermatrix was renormalized to obtain a weighted supermatrix. Table 9 shows a part of the weighted supermatrix in terms of intensity in 2005. The limit supermatrix was derived by raising the weighted supermatrix to powers. Table 10 shows a part of the limit supermatrix from the intensity perspective in 2005.

Finally, the final priorities were derived. The columns in the limit supermatrix represent the final priorities, that is, limit centralities. Table 11 shows the mobile services' priorities in terms of intensity from 2005 to 2014. Likewise, the mobile services' priorities in terms of relatedness and cross-impact were also derived as shown in Table 12 and Table 13, respectively.

4.4. Calculating the importance and its increase rate of mobile services

DEA window analysis was performed to calculate the importance and its increase rate of mobile services considering all three interrelationships. Since the analysis period is 10 years, the number of windows was given 10–5 + 1 = 6 by Eq. (1) and the length of the window was (10 + 1)/2 = 5.5 by Eq. (2). As the length of the window should be natural number, it is set to be five. The efficiencies of 125 (=25 × 5) DMUs were derived through applying output-oriented BCC DEA model to each window, using the derived priority values of mobile services in terms of three interrelationships as output data and the constant value (e.g. 10) as input data. This process was repeated six times to get all efficiencies for the entire windows. With the calculated efficiencies of each DMU, the importance and its increase rate of mobile services were obtained by Eqs. (3) and (4), respectively, as shown in Table 14. In terms of importance, 14.4 (Advertisement) was the highest, followed by 412 (Utility usage) and 64 (Secure transaction). Because these mobile services had a significant effect on other mobile services, they were core mobile services considering the three interrelationships together. The mobile services with the least importance was 346 (Customer communication at a business location). 902 (Licensing digital content) showed the highest increase rate in importance, followed by 904 (Usage protection of distributed files) and 35 (Finance). As these mobile services had an increasing effect on other mobile services, they were becoming increasingly important. The mobile services with the lowest increase rate was 14.1 (Discount or incentive).

4.5. Identifying mobile service opportunities

In order to identify mobile service opportunities, a portfolio map was constructed using the calculated importance and its increase rate of mobile services as shown in Fig. 5. The median value of the x axis was set to 19.99, the average of the importance of all mobile services. In case of the y axis, the median value was set to 1.00, the state in which importance did not increase or decrease with time.

Table 5
Intensity matrix of one-dot indent subclass level in 2005.

		50			1.1			400			901	
		51	60	64	2	…	346	401	…	418	902	904
50	51	1.0000	0.0000	0.0250	0.0000	…	0.0000	0.3333	…	0.0000	0.0000	0.0000
	60	0.0000	1.0000	0.0125	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	64	0.0250	0.0125	1.0000	0.0000	…	0.0000	0.6667	…	0.0000	0.0000	0.0000
1.1	2	0.0000	0.0000	0.0000	1.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	346	0.0000	0.0000	0.0000	0.0000	…	1.0000	0.0000	…	0.0000	0.0000	0.0000
400	401	0.0000	0.0000	0.0000	0.0000	…	0.0000	1.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	418	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	1.0000	0.0000	0.0000
901	902	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	1.0000	0.0000
	904	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	1.0000

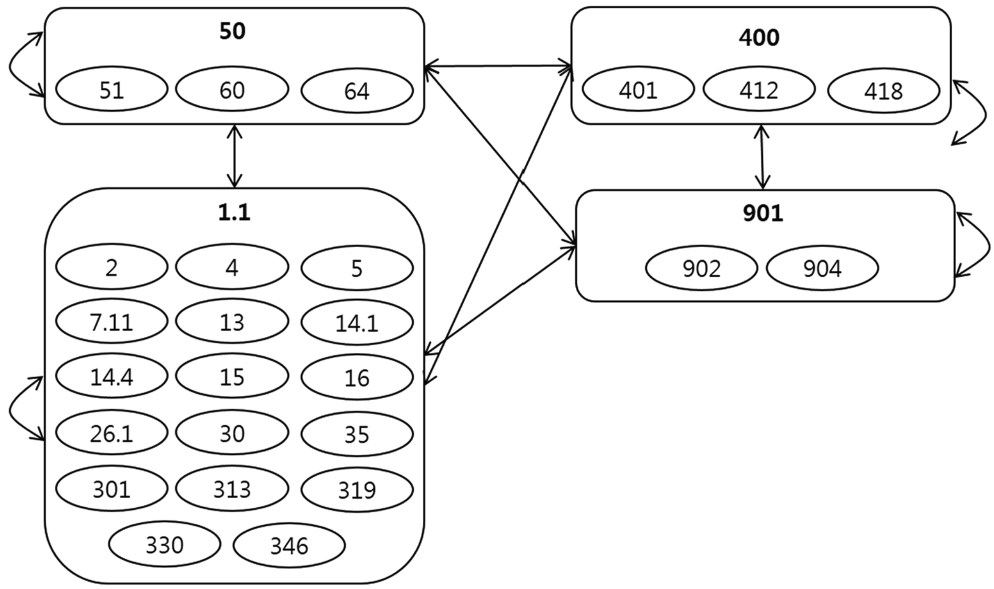

Fig. 4. ANP network for mobile services.

Table 6
Cluster weights from the intensity perspective in 2005.

	50	1.1	400	901
50	0.7097	0.2727	0.0000	0.0000
1.1	0.2903	0.6667	0.0833	0.0000
400	0.0000	0.0606	0.9167	0.0000
901	0.0000	0.0000	0.0000	1.0000

Five mobile services were classified as 'attractive opportunities'. Among them, 14.4 (Advertisement) was the most important and 902 (Licensing digital content) had the highest increase rate in importance. Therefore, it is necessary to develop them first. Compared to these two mobile services, the remaining three mobile services were relatively low in importance or its increase rate, but they were also a promising opportunity. There were five mobile services in 'potential opportunities'. Although their importance was low until now, the increase rate in their importance was high and so it is necessary to monitor whether they moves to the ‘attractive opportunities’ quadrant. In particular, the increase rate in importance of 904 (Usage protection of distributed files) and 35 (Finance) was relatively high, and they are expected to provide promising opportunities in the near future. There were two mobile services in 'saturated opportunities'. The importance was high, but this tendency was unlikely to continue, so careful consideration is needed when developing these mobile services. The 'separate opportunities' included 13 mobile services. It is considered that there is little chance that the increase rate in importance was decreasing as well as importance was low.

5. Conclusions

The contribution of this study is as follows. First, from a theoretical point of view, this study validated the utility of BM patents in the analysis of technology-based service innovation in the recent situation where the need for an empirical approach to discover technology-based service opportunities. Second, from a methodological point of view, this

Table 7
Transformation of intensity matrix into priority matrix in 2005.

Intensitymatrix		50			Prioritymatrix		50		
		51	60	64			51	60	64
1.1	2	0.0000	0.0000	0.0000	1.1	2	0.0000	0.0000	0.0000
	4	0.0000	0.0000	0.0000		4	0.0000	0.0000	0.0000
	5	0.0125	0.0000	0.0000		5	0.1667	0.0000	0.0000
	7.11	0.0000	0.0000	0.0000		7.11	0.0000	0.0000	0.0000
	13	0.0125	0.0000	0.0000		13	0.1667	0.0000	0.0000
	14.1	0.0000	0.0000	0.0000		14.1	0.0000	0.0000	0.0000
	14.4	0.0000	0.0000	0.0000		14.4	0.0000	0.0000	0.0000
	15	0.0000	0.0000	0.0000		15	0.0000	0.0000	0.0000
	16	0.0000	0.0000	0.0000		16	0.0000	0.0000	0.0000
	26.1	0.0125	0.0000	0.0000		26.1	0.1667	0.0000	0.0000
	30	0.0250	0.0000	0.0125		30	0.3333	0.0000	0.3333
	35	0.0125	0.0000	0.0250		35	0.1667	0.0000	0.6667
	301	0.0000	0.0000	0.0000		301	0.0000	0.0000	0.0000
	313	0.0000	0.0000	0.0000		313	0.0000	0.0000	0.0000
	319	0.0000	0.0000	0.0000		319	0.0000	0.0000	0.0000
	330	0.0000	0.0000	0.0000		330	0.0000	0.0000	0.0000
	346	0.0000	0.0000	0.0000		346	0.0000	0.0000	0.0000

Table 8
Supermatrix from the intensity perspective in 2005.

		50			1.1			400			901	
		51	60	64	2	…	346	401	…	418	902	904
50	51	0.9756	0.0000	0.0241	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	60	0.0000	0.9877	0.0120	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	64	0.0244	0.0123	0.9639	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
1.1	2	0.0000	0.0000	0.0000	0.9877	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	346	0.0000	0.0000	0.0000	0.0000	…	1.0000	0.0000	…	0.0000	0.0000	0.0000
400	401	0.0000	0.0000	0.0000	0.0000	…	0.0000	1.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	418	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	1.0000	0.0000	0.0000
901	902	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	1.0000	0.0000
	911	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	1.0000

Table 9
Weighted supermatrix from the intensity perspective in 2005.

		50			1.1			400			901	
		51	60	64	2	…	346	401	…	418	902	904
50	51	0.6924	0.0000	0.0171	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	60	0.0000	0.7009	0.0086	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	64	0.0173	0.0088	0.6840	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
1.1	2	0.0000	0.0000	0.0000	0.6584	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	346	0.0000	0.0000	0.0000	0.0000	…	0.6667	0.0000	…	0.0000	0.0000	0.0000
400	401	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.9167	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	418	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.9167	0.0000	0.0000
901	902	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	1.0000	0.0000
	911	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	1.0000

Table 10
Limit supermatrix from the intensity perspective in 2005.

		50			1.1			400			901	
		51	60	64	2	…	346	401	…	418	902	904
50	51	0.0381	0.0381	0.0381	0.0381	…	0.0381	0.0381	…	0.0381	0.0381	0.0381
	60	0.0163	0.0163	0.0163	0.0163	…	0.0163	0.0163	…	0.0163	0.0163	0.0163
	64	0.0163	0.0163	0.0163	0.0163	…	0.0163	0.0163	…	0.0163	0.0163	0.0163
1.1	2	0.0257	0.0257	0.0257	0.0257	…	0.0257	0.0257	…	0.0257	0.0257	0.0257
	…	…	…	…	…	…	…	…	…	…	…	…
	346	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
400	401	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	…	…	…	…	…	…	…	…	…	…	…	…
	418	0.0652	0.0652	0.0652	0.0652	…	0.0652	0.0652	…	0.0652	0.0652	0.0652
901	902	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000
	911	0.0000	0.0000	0.0000	0.0000	…	0.0000	0.0000	…	0.0000	0.0000	0.0000

study proposed the possibility of integrating different methodologies by linking co-classification analysis, ANP and, DEA window analysis sequentially. Finally, from a managerial point of view, the methods presented in this study can provide useful information in establishing technology-based service strategies or policies for firms or nations.

Despite the contribution, this study is subject to some limitations; these are issues for further research. First, since the data source of this study was BM patents categorized into the class 705, the opportunities of technology-based services were identified only from the information mainly about IT-related services. Not all business method patents are classified into the class 705 and other classes can also contain patents presenting methods according to their technology. Some examples are patents regarding methods of teaching classified into the class 434 (Education and Demonstration), methods of playing games classified into the class 273 (Amusement Devices, Games), and methods of improving crop yields classified into the class 47 (Plant Husbandry) (Love & Coggins, 2001). In addition, co-classification information beyond the class 705 is ignored, and so the opportunities from the patents other than BM patents could not be identified. Further analysis including these classifications could investigate the opportunities for technology-based services more comprehensively. It is also necessary to search DBs related to other types of technology-based services, such as the publication (academic paper) database and the mobile application store database, or to present a more general and flexible approach applicable

Table 11
Priority score of mobile services from the intensity perspective.

Mobile services		Year									
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
50	51	0.0381	0.0292	0.0250	0.0550	0.0468	0.0170	0.0210	0.0234	0.0120	0.0282
	60	0.0163	0.0847	0.1363	0.0000	0.0000	0.0282	0.0000	0.0000	0.0947	0.0000
	64	0.0163	0.0000	0.0000	0.0000	0.1211	0.0000	0.1011	0.1659	0.0000	0.0770
1.1	2	0.0257	0.0257	0.0501	0.0240	0.0406	0.0151	0.0273	0.0414	0.0314	0.0328
	4	0.0000	0.0285	0.0000	0.0000	0.0000	0.0282	0.0312	0.0000	0.0135	0.0293
	5	0.0336	0.0520	0.0250	0.0436	0.0589	0.0284	0.0277	0.0152	0.0069	0.0103
	7.11	0.0000	0.1279	0.0000	0.0000	0.0460	0.0000	0.0000	0.0168	0.0812	0.0295
	13	0.2007	0.0902	0.0835	0.0362	0.0360	0.0980	0.0499	0.0545	0.0785	0.0529
	14.1	0.0712	0.0000	0.0291	0.0234	0.0000	0.0152	0.0000	0.0000	0.0000	0.0000
	14.4	0.1028	0.1906	0.1975	0.2823	0.1954	0.2903	0.1976	0.2580	0.1770	0.3050
	15	0.0336	0.0798	0.0498	0.0000	0.0460	0.0506	0.0275	0.0083	0.0043	0.0196
	16	0.0260	0.0224	0.0508	0.0263	0.0360	0.0281	0.0101	0.0232	0.0284	0.0170
	26.1	0.0283	0.0144	0.0000	0.0282	0.0360	0.0500	0.0328	0.0362	0.0176	0.0349
	30	0.0390	0.0460	0.0549	0.0636	0.0409	0.0973	0.0498	0.0446	0.0354	0.0714
	35	0.0000	0.0000	0.0000	0.0000	0.0000	0.0096	0.0000	0.0263	0.0304	0.0093
	301	0.0644	0.0000	0.0000	0.0228	0.0740	0.0139	0.0284	0.0083	0.0162	0.0055
	313	0.0447	0.0653	0.0540	0.0470	0.0411	0.0618	0.0472	0.0291	0.0283	0.0481
	319	0.0979	0.0333	0.0509	0.0631	0.0735	0.0276	0.0177	0.0239	0.0233	0.0287
	330	0.0000	0.0000	0.0000	0.0432	0.0000	0.0000	0.0000	0.0000	0.0178	0.0150
	346	0.0000	0.0000	0.0278	0.0000	0.0000	0.0000	0.0000	0.0000	0.0048	0.0203
400	401	0.0000	0.0000	0.0387	0.0422	0.0000	0.0000	0.0325	0.0271	0.0270	0.0049
	412	0.0963	0.0913	0.1266	0.1581	0.0631	0.1314	0.0924	0.1222	0.0672	0.1323
	418	0.0652	0.0188	0.0000	0.0409	0.0444	0.0092	0.0313	0.0059	0.0268	0.0279
901	902	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1078	0.0355	0.1480	0.0000
	904	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0665	0.0341	0.0291	0.0000

Table 12
Priority score of mobile services from the relatedness perspective.

Mobile services		Year									
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
50	51	0.0264	0.0361	0.0217	0.0344	0.0532	0.0903	0.0171	0.0166	0.0201	0.0102
	60	0.0362	0.1079	0.4908	0.0000	0.0000	0.0599	0.0000	0.0000	0.1573	0.0000
	64	0.0362	0.0000	0.0000	0.0000	0.1777	0.1222	0.2215	0.1777	0.0000	0.2708
1.1	2	0.0453	0.0116	0.0175	0.0366	0.0382	0.0218	0.0162	0.0213	0.0119	0.0118
	4	0.0000	0.0295	0.0000	0.0000	0.0000	0.0165	0.0064	0.0000	0.0203	0.0043
	5	0.0290	0.0460	0.0320	0.0765	0.0540	0.0308	0.0271	0.0116	0.0090	0.0210
	7.11	0.0000	0.2441	0.0000	0.0000	0.0603	0.0286	0.0000	0.0933	0.1336	0.2645
	13	0.1002	0.0994	0.0702	0.1001	0.0985	0.0277	0.0584	0.0593	0.0867	0.0766
	14.1	0.0632	0.0000	0.0383	0.0875	0.0000	0.0271	0.0000	0.0000	0.0000	0.0000
	14.4	0.1191	0.1221	0.1108	0.1711	0.1293	0.0264	0.0662	0.0773	0.0448	0.1011
	15	0.0290	0.0718	0.0215	0.0000	0.0287	0.0269	0.0289	0.0261	0.0090	0.0254
	16	0.0477	0.0166	0.0182	0.0389	0.0211	0.0000	0.0106	0.0112	0.0056	0.0088
	26.1	0.0230	0.0590	0.0000	0.0183	0.0211	0.0000	0.0512	0.0194	0.0023	0.0188
	30	0.0197	0.0231	0.0214	0.0389	0.0255	0.0094	0.0152	0.0134	0.0064	0.0162
	35	0.0000	0.0000	0.0000	0.0000	0.0000	0.0236	0.0000	0.0052	0.0021	0.0189
	301	0.1291	0.0000	0.0000	0.0521	0.0889	0.0000	0.0290	0.0142	0.0316	0.0325
	313	0.0362	0.0370	0.0236	0.0471	0.0532	0.0542	0.0163	0.0186	0.0086	0.0218
	319	0.0541	0.0185	0.0179	0.0293	0.0541	0.0145	0.0220	0.0150	0.0085	0.0194
	330	0.0000	0.0000	0.0000	0.0321	0.0000	0.0592	0.0000	0.0000	0.0026	0.0128
	346	0.0000	0.0000	0.0586	0.0000	0.0000	0.0451	0.0000	0.0000	0.0080	0.0079
400	401	0.0000	0.0000	0.0121	0.0549	0.0000	0.3158	0.0469	0.0179	0.0018	0.0177
	412	0.0633	0.0355	0.0455	0.1364	0.0428	0.0000	0.0296	0.0202	0.0100	0.0211
	418	0.1421	0.0417	0.0000	0.0457	0.0535	0.0000	0.0169	0.0081	0.0171	0.0183
901	902	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1303	0.1950	0.2030	0.0000
	904	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1902	0.1786	0.1995	0.0000

to various technology-based services. Second, for patent collection on mobile services, BM patents that included 'mobile' or 'wireless' in the title or abstract were searched, but it is likely that irrelevant patents are included. Related patents may also be missed because words such as ‘cell’, ‘cellular’, ‘telecommunication’, ‘WiFi’, ‘3G’, ‘smartphone’, etc. can also represent mobile services. It will improve data reliability to develop a keyword dictionary that can explain the mobile services and to search for relevant patents by using it. Third, the interrelationship analysis based on patent co-classification was conducted from the perspectives of intensity, relatedness, and cross-impact, but other perspectives can also be applied to. The major components and subclasses are hierarchically structured, which could be regarded as a prior knowledge. Incorporating this prior knowledge to co-classification may enhance the construction of interrelationship matrices. For example, it may be possible that two one-dot subclasses are correlated as they belong to the same mainline class. Finally, there is a fundamental problem of endogeneity since USPC is continuously changed. For instance, in 2010, the mainline subclass 901 and its child classes were newly introduced due to the development of digital right management services. As the intensity index related to these newly created technology-based

Table 13
Priority score of mobile services from the cross-impact perspective.

Mobile services		Year									
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
50	51	0.0205	0.0183	0.0156	0.0488	0.0227	0.0491	0.0168	0.0151	0.0101	0.0047
	60	0.0168	0.0901	0.4019	0.0000	0.0000	0.0294	0.0000	0.0000	0.2444	0.0000
	64	0.0168	0.0000	0.0000	0.0000	0.1550	0.0638	0.2182	0.1405	0.0000	0.1825
1.1	2	0.0505	0.0092	0.0204	0.0194	0.0262	0.0182	0.0116	0.0126	0.0051	0.0043
	4	0.0000	0.0506	0.0000	0.0000	0.0000	0.0076	0.0421	0.0000	0.0438	0.1454
	5	0.0314	0.0753	0.0182	0.0498	0.0215	0.0052	0.0256	0.0107	0.0058	0.0067
	7.11	0.0000	0.2885	0.0000	0.0000	0.1791	0.0242	0.0000	0.0686	0.0735	0.3454
	13	0.1202	0.1088	0.1350	0.0430	0.0751	0.0147	0.0441	0.0319	0.0761	0.0582
	14.1	0.1704	0.0000	0.0274	0.0566	0.0000	0.0105	0.0000	0.0000	0.0000	0.0000
	14.4	0.0775	0.0810	0.0804	0.1274	0.0747	0.0101	0.0475	0.0608	0.0208	0.0590
	15	0.0314	0.0864	0.0321	0.0000	0.0754	0.0135	0.0500	0.0199	0.0093	0.0295
	16	0.0309	0.0133	0.0188	0.0189	0.0800	0.0000	0.0054	0.0081	0.0039	0.0026
	26.1	0.0138	0.0379	0.0000	0.0356	0.0800	0.0000	0.0399	0.0229	0.0153	0.0098
	30	0.0122	0.0114	0.0191	0.0245	0.0150	0.0105	0.0108	0.0097	0.0037	0.0096
	35	0.0000	0.0000	0.0000	0.0000	0.0000	0.0363	0.0000	0.0766	0.0367	0.0170
	301	0.1771	0.0000	0.0000	0.0424	0.0792	0.0000	0.0222	0.0088	0.0262	0.0320
	313	0.0155	0.0206	0.0140	0.0219	0.0125	0.0335	0.0095	0.0095	0.0032	0.0109
	319	0.0574	0.0103	0.0420	0.1591	0.0542	0.0184	0.0182	0.0118	0.0052	0.0150
	330	0.0000	0.0000	0.0000	0.0373	0.0000	0.0449	0.0000	0.0000	0.0229	0.0143
	346	0.0000	0.0000	0.1134	0.0000	0.0000	0.0114	0.0000	0.0000	0.0059	0.0171
400	401	0.0000	0.0000	0.0239	0.1876	0.0000	0.5986	0.1159	0.0473	0.0128	0.0124
	412	0.0473	0.0312	0.0379	0.0931	0.0166	0.0000	0.0244	0.0144	0.0048	0.0134
	418	0.1102	0.0671	0.0000	0.0347	0.0326	0.0000	0.0371	0.0193	0.0170	0.0101
901	902	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1062	0.1198	0.2261	0.0000
	904	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1546	0.2916	0.1273	0.0000

Table 14
The importance and its increase rate of mobile services.

Mobile services		TI	R_TI
50	51	14.4773	0.9294
	60	34.2647	1.0272
	64	34.1520	1.3207
1.1	2	13.1277	0.9721
	4	7.4387	1.3255
	5	17.0380	0.9009
	7.11	22.3393	1.0675
	13	35.5647	0.9759
	14.1	8.8140	0.7850
	14.4	80.3330	1.0309
	15	15.6633	0.9099
	16	12.4070	0.8859
	26.1	14.9753	1.0542
	30	19.8643	1.0252
	35	4.2570	1.8472
	301	14.8123	0.9042
	313	18.0960	0.9517
	319	19.9487	0.8258
	330	3.5927	0.9753
	346	3.5167	0.8547
400	401	13.3630	0.9900
	412	39.0307	0.9855
	418	12.8443	0.8851
901	902	20.6997	2.5163
	904	19.1710	2.4603

services may be undervalued due to the short period compared to that of other classification codes, their importance may also be undervalued. Though the recent patents were focused on and relatively small changes are expected, fundamental problems still exist. A solution to the problem is to utilize the IPC (International Patent Classification) system, which is relatively static compared to the USPC system. An alternative solution is to classify patents taxonomically with the keywords derived with the contents of the patents. Thus, future research should address these issues.

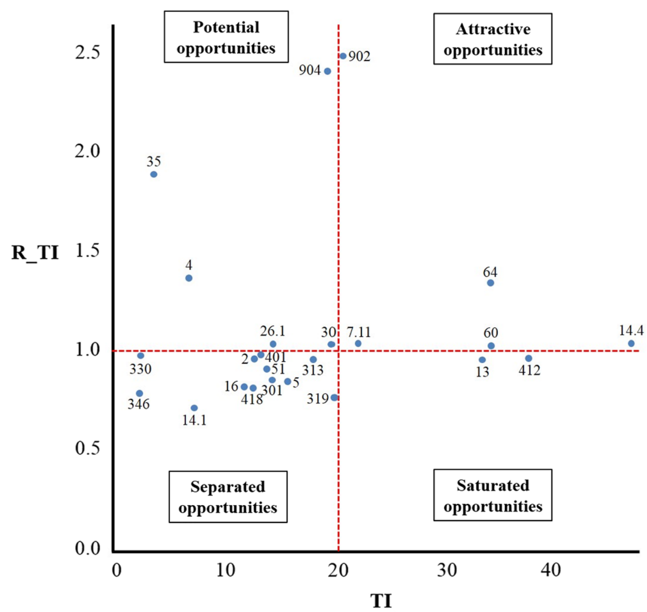

Fig. 5. Portfolio map for mobile services.

CRediT authorship contribution statement

Chulhyun Kim: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization, Funding acquisition. **Hakyeon Lee:** Writing - review & editing.

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