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# Identifying promising technologies using patents: A retrospective feature analysis and a prospective needs analysis on outlier patents☆

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ABSTRACT

This study suggests a patent-based methodology for identifying emerging technologies by combining a retrospective technological feature analysis and a prospective market-needs analysis. To do this, first, the candidate promising technologies were identified by applying bibliographic coupling to patents, thus producing a list of outlier patents. Then, the measures to evaluate both technological and market characteristics of the candidate technologies were developed, where retrospective patent analysis and sentiment analysis on customer opinions are required. Finally, the candidate technologies are mapped onto two-dimensional space according to the values of the two measures; the final promising technologies are determined to be those that have high values for either technological characteristics or market characteristics. The suggested methodology was applied to an automobile industry, through which its feasibility and usability were verified. This study is one of the few studies to develop technology-evaluation measures based on an ad-hoc analysis of technological characteristics. In addition, it attempts to link patent databases to market databases, aiming to directly reflect customer needs to evaluate the potential of a technology in a market. The approach suggested in this study can be applied to recent patents with little citation information for assessing their value to be deemed as promising technologies; this is expected to contribute both academically and practically to the existing literature on patent analysis.

## 1. Introduction

Technology forecasting is one of the most significant activities for the discovery of new business opportunities and for the minimization of Research and Development (R&D) risks in new technology developments, accordingly attracting attention from both industries and academics (Cho et al., 2016). In particular, patent documents, characterized by enormous size and variety of technological information, have been one of the most frequently used data sources to forecast and identify promising technologies (Ernst, 1997). Patent analysis enables to understand technology development directions and trends in an effective way (Kim and Lee, 2015; Albino et al., 2014; Wu and Leu, 2014; Jeong et al., 2015). Hence, previous studies have attempted to identify the following types of technologies (Noh et al., 2016): vacant technologies, where further R&D is possible (Lee et al., 2009b); converging technologies, where increasingly active knowledge exchanges are observed or drivers of such technologies (Geum et al., 2012; Caviggioli, 2016; Karvonen and Kässi, 2013); and emerging technologies, where more R&D investments are being made (Park et al., 2016, Joung and Kim, 2017) based on patent data. The findings from these studies can be used as a basis for identifying promising technologies. In these studies, not only bibliometric parts but also descriptive parts of patent documents have been analyzed using various data analysis techniques such as data mining and text mining (Noh et al., 2016, Madani and Weber, 2016).

In spite of their meaningful contributions by developing a novel patent-based approach to help identify new opportunities from promising technologies, the existing studies are subject to several limitations. First, a number of existing studies relies on patent-citation information to assess technological superiority. It is assumed that a patent highly cited by subsequent patents is a valuable technology; therefore, a promising technology is defined as a collection of highly cited patents (e.g., Noh et al., 2016; Park et al., 2016) or a technological area with a relatively high share of such patents (e.g., Lee et al., 2009a, b). However, citation frequency increases with time, which resulted in a disadvantage for newly published patents. To overcome such limitations,

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the concept of a modified citation frequency was suggested in which the patterns of patent citation are analyzed to predict a citation frequency for the total life cycle of the patent (e.g. Noh et al., 2016; Park et al., 2016). Nevertheless, for the most recent patents with no citations, the modified citation frequency cannot be applied.

Second, the previous studies have mainly emphasized the technological characteristics of identifying promising technologies; few studies have focused on linking these technological characteristics to market needs. Until a new technology is implemented in products or services, their market information is hardly available. Yet, market needs are one of the most critical criteria to evaluate whether a technology will be promising or not (Tuominen and Ahlqvist, 2010; Reinhardt and Gurtner, 2011; Pichyangkul et al., 2012).

Finally, though extensive research has been dedicated to the identification of promising technologies, little effort has been made to conduct an ad-hoc analysis to investigate if the technologies evaluated as promising have actually become promising. To prove the utility of the methodologies suggested in a number of previous studies, the promising technologies identified by those methodologies should be monitored to examine the evolution trajectory for those technologies via ad-hoc analyses. Nevertheless, there is a lack of studies that investigate the validity issues regarding the suggested methodologies through comparison of projected results with actual results.

Recognizing these limitations, this study suggests a patent-based methodology for identifying emerging technologies by combining a retrospective technological feature analysis and a prospective market-needs analysis. To do this, we defined a promising technology as "a technology that is likely to have a substantial impact on other technologies as well as those that can respond to market needs." Then, the candidate promising technologies were identified, from which the final promising technologies were selected according to several criteria developed to evaluate the characteristics of the technology and market. More specifically, first, the candidate promising technologies were identified from outlier patents; these are patents that have recently published but have little similarity with the existing patents in terms of their contents, thus not having been included in any of the established major technological areas. Here, bibliographic coupling was adopted to cluster patents and find outlier patents. It is a method to group patents based on their similarity in references, and hence can be used to cluster patents without citation information according to their content similarity. However, the outlier patents may include the output of trial-run projects or academic projects, or even decoy patents, and thus are only "candidates" of promising technologies; further analyses are required to filter such less-valuable patents from the all outlier patents and leave only meaningful ones. Second, the measures to evaluate the technological characteristics of candidate technologies were developed by comparing the technological characteristics the can be observed at the early stage of patent applications, and by choosing only those that present statistically significant differences between promising technologies and non-promising technologies at the late stage of patent applications. We expect that these characteristics can be antecedents of promising technologies. Third, measures to evaluate market characteristics of candidate technologies were developed by extracting market needs on the products or services toward which the technologies are targeted directly from an online customer center. Opinion mining can be a suitable technique not only in identifying customer needs but also in understanding whether the needs pertain to increasing satisfaction (i.e., stimulating excitement) or reducing complaints. Finally, the candidate technologies are mapped onto two-dimensional space according to the two criteria of technological characteristics and market characteristics; the final promising technologies are determined to be those that have high values for either technological characteristics or market characteristics.

This study is one of the few studies to develop technology evaluation measures based on the ad-hoc analysis of technological characteristics. In addition, it is one of earliest attempts to link patent data to market data, aiming to directly reflect customer needs for evaluating the potential of technology in a market. In addition, it attempts to link patent data to market data, aiming to directly reflect customer needs to evaluate the potential of a technology in a market. Although previous studies have tried to consider a market potential of a patent, they have relied mostly on patent information. Unlike them, this study combined two different data sets – patents and customer reviews to measure a market potential, which differentiate this study from the existing literature. The approach suggested in this study can be applied to recent patents with little citation information for assessing their value as promising technologies, which is expected to contribute both academically and practically to the existing literature on patent analysis.

The present study is organized as follows. After the theoretical and methodological background is explained in Section 2, the approach proposed in this study is described in Section 3. Then, the case study results, in which the proposed approach was applied to automobile technologies, are presented, and the feasibility and utility of the proposed approach are discussed in Section 4. Finally, contributions, limitations, and future research directions are addressed in Section 5.

## 2. Background

### 2.1. Theoretical background

The term "promising (or emerging) technology" has been frequently used in a number of studies; however, no definition of it exists. To fill this research gap, Cozzens et al. (2010) reviewed literature and summarized four major concepts pertaining to the definition of emerging technologies: (1) fast recent growth, (2) transition to something new, (3) untapped market or economic potential, and (4) an increasing basis in science. Later, in a similar manner, Rotolo et al. (2015) defined four aspects of emerging technologies: (1) radical novelty, (2) relatively fast growth, (3) coherence, and (4) uncertainty and ambiguity. Based on these studies, we can conclude that promising technologies are recently emerged technologies with high uncertainties but with high possibilities of technological growth and market impact. According to these normative definitions, the criteria for a promising technology are defined and used to identify such technology (Noh et al., 2016).

The existing approaches to evaluate promising technologies can be classified into two types: 1) qualitative evaluation by experts and 2) quantitative evaluation based on data. In addition, various approaches have been adopted to identifying and prioritizing promising technologies, such as analytic hierarchy process (AHP) (e.g., Lee et al., 2014), Delphi (e.g., Bañuls and Salmeron, 2008), clustering (e.g., Song et al., 2012), roadmaps (e.g., Fleischer et al., 2005), and foresights (e.g., Bierwisch et al., 2015). However, as the complexity of technology increases and the scope of technological applications expand, the validity of qualitative evaluation by experts may be limited. To complement expert decision-making, quantitative approaches have been developed. Among them, one of the most commonly adopted approaches is patent analysis. Patent documents contain semi-structured bibliographic information in addition to the descriptive information that explains the technological components, principles, and benefits in detail. Patent data are easy to assess, being open to the public, and have been accumulated for several decades. Owing to these distinguishing characteristics of patent data, these data have continuously been regarded as main knowledge sources for innovation studies (Kim and Lee, 2015).

Patent data provide objective technological information, which help understand new innovative technologies; thus, they been widely used for the assessment of technological levels or for the investigation of R&D trends (Trappey et al., 2012; Kim and Lee, 2015; Jin et al., 2015). The data have also been used to identify promising technologies and to further take advantage of new business opportunities from those technologies. For example, they were used to discover vacant technologies via technologies defined by patents (e.g. Lee et al., 2009b, Jun et al., 2012; Choi and Jun, 2014), assess promising technologies using patent citation analysis (e.g. Breitzman and Thomas, 2015; Shen et al., 2010), or examine technological knowledge flows and possible technology convergence (e.g. Geum et al., 2012; Caviggioli, 2016).

These studies can be divided into two major categories according to their basis of analysis. The first defines a technology as a collection of patents, where a promising technology is considered as a collection of patents as well. This category is divided into two sub-categories. One of them defines technologies by assigning patents to each one of them and by carrying out analysis based on the pre-defined technologies employed to investigate their trends, that is, a sequence of *technology definition* and *patent evaluation*. For example, Geum et al. (2012) used international patent classification (IPC) codes to assign relevant patents to information technology (IT) and biotechnology (BT) in their studies to investigate converging IT and BT areas. Then, by defining one IPC code as one technology, they analyzed the characteristics of patents in each of the IPC codes to identify emerging technologies. The other subcategory extracts valuable patents and defines technologies later by grouping them based on their content similarity. Unlike the previous approach, this approach follows the sequence of *patent evaluation* and *technology definition*. For instance, Noh et al. (2016) have extracted core patents that are expected to yield relatively high technological impacts, which are called hot patents, using citation information; they then defined emerging-technology areas by grouping those patents into several groups with similar contents, using bibliographic coupling.

On the other hand, the second category regards a single patent as a theoretical focal point of analysis. In this case, the purpose of these analyses is focused on identifying a valuable patent rather than a valuable technological field. For example, Lee et al. (2016) developed an algorithm to predict expected citation frequencies of patents, and used the prediction results to evaluate patents. Jeong et al. (2015) tried to identify emerging technologies from outlier patents, which were not included in any of the major technological areas and were thus novel with regard to prior technologies. These approaches can be effectively applied to patent evaluation.

Whichever unit of analysis is selected, these studies undergo an evaluation process and utilize a set of indices for such an evaluation. These indices are developed in advance of the applications according to the definition of emerging technologies or constitute of the indices commonly used for patent valuation. However, these studies have seldom been focused on ad-hoc analysis to ensure that technologies evaluated as promising have actually evolved to be promising technologies. In addition, most of the studies have greatly relied on citation information that is not applicable to recently granted patents; market information, which is applicable to relatively new patents, was seldom used for the identification of promising technologies from patent databases.

### 2.2. Methodological background

The main methods for this study include *patent index analysis* and *opinion mining*. The former is adopted to define the attributes of promising technologies with which the patent indices to identify such technologies are developed. The latter aims to extract key contents of technologies from patent documents and from customer needs expressed in online customer centers, where the contents are analyzed to find patents that can meet the needs.

#### 2.2.1. Patent index analysis

In patent index analysis, technological characteristics of a patent are investigated based on its bibliometric information (Trappey et al., 2011; Bermudez-Edo et al., 2013). As technological characteristics can be analyzed in different contexts, various patent indices have been developed for different purposes, such as for competitor intelligence (Ernst, 1998; Ernst, 2003; Ernst and Omland, 2011) or R&D partner selection (Geum et al., 2013; Song et al., 2016). Among these, this study uses patent index analysis for the following two reasons.

First, patent indices that can directly indicate if a particular patent is promising are designed, or adopted from the existing studies and modified for this study. Though the definition of "promising technology" may vary in studies (Noh et al., 2016), there are several indices that have been commonly used for the estimation of a patent value. Patent citation is one of the most popular methods to extract information for technology valuation. It provides information to measure a patent value in terms of technological impact by evaluating the degree that a technology has contributed to its subsequent technologies. In general, technologies that are more frequently and widely used in subsequent technologies are regarded as valuable technologies (Harhoff et al., 1999; Trajtenberg, 1990; Geum et al., 2012). On the other hand, patent renewal information is often used to evaluate a patent; a valuable patent is more likely to be renewed, in spite of its high renewal cost (Pakes and Schankerman, 1984; Lanjouw et al., 1998). These three indices are used to determine promising technologies in this paper.

Second, in addition to the indices listed above, other indices are used to investigate the characteristics of technologies. Previous studies have attempted to examine the technological characteristics of patents from various perspectives on the basis of patent claims, IPCs, applicants, inventors, and bibliographies, among which the number of claims and the number of IPCs have commonly been used to indicate the scope of rights (Tong and Frame, 1994; Lanjouw and Schankerman, 1997) and the scope of the application (Lerner, 1994), respectively. On the other hand, information regarding applicants and inventors provides the number and the diversity of inventors that have been involved in developing a technology (Balconi et al., 2004; Sternitzke et al., 2008). Finally, bibliographic information denotes the degree of novelty for the technology; in broad terms, if a particular patent has a short list of references (Lanjouw and Schankerman, 1997; Harhoff et al., 2003), consisting largely of non-patent references, it is more likely to be a novel technology (Narin et al., 1997; Meyer, 2000).

In this study, the aforementioned patent indices that have been used for assessing a technological value and for investigating technological characteristics have been adopted, while more patent-related indices are developed as precedent characteristics of promising technologies. Then those indices are merged into a single index – technology index – to be used as one of the two criteria to develop a patent portfolio map. A patent portfolio is a map that positions target patents onto two-dimensional space using two criteria of interest; it has an obvious advantage as a decision-supporting tool by structuring a complex problem into two comprehensive set of criteria. It was first proposed mainly for decision-makings on R&D investment (Ernst, 2003; Ernst et al., 2004) at the organizational level and has been used widely to support various decision-makings for technology planning, such as technology opportunity analysis (Fabry et al., 2006; Lee et al., 2008; Lee et al., 2009a), strategic alliance (Song et al., 2016; Geum et al., 2013), and portfolio valuation (Grimaldi et al., 2015). It has also been applied at the industry level to investigate industry dynamics with respect to converging trends (Geum et al., 2012), competitive landscape (Ha et al., 2015; Huang, 2016; Jeong et al., 2017), and emerging technologies (Boccardi et al., 2014). Similarly, this study adopted the concept of portfolio map to summarize the information obtained from various analysis, using two criteria of market and technology potential, and visualize the results in a more concise format.

#### 2.2.2. Opinion mining

Text-mining analysis is used in this study to analyze text data of patent documents in addition to bibliometric data. In particular, with the emergence of big data environments, where enormous amounts of data in diverse formats are created and distributed, text-mining techniques are regarded as key techniques to extract a value from such data, generating business intelligence and enabling the management of knowledge (Williams, 2014). Text-mining analysis helps uncover insights from unstructured data, as well as from structured data, and provide an additional tool for applying these insights to rapidly changing external environments. It refers to a process of analyzing natural languages, from which only necessary information from users are screened and are provided in a refined format (Fayyad et al., 1996). Unlike traditional data-mining analysis, focusing on structured data, text-mining analysis emphasizes the use of a large amount of unstructured text data to uncover meaningful knowledge – patterns or classifications (Tseng et al., 2007).

One of the most common approaches of text-mining analysis is the use of a feature vector, which has keywords as vector attributes and their frequencies for each patent as vector values for each patent and is frequently used as basic information to classify or summarize patent documents. In this study, two types of feature vectors are constructed.

The first is a feature vector on patent documents. When developing a patent-based feature vector, we should determine which section of the patent documents should be used for analysis. While a different section (a title, an abstract, a claim, or a description part) has been adopted for analysis by different researchers (Noh et al., 2015), for this study, we selected a whole document. In this study, patent documents are used to match their keywords with the keywords used in online customer centers to evaluate how well a particular patent meets customer needs in a market. Though key ideas of an invention are contained in the Abstract section of patent documents, possible application areas of the invention along with its benefits, which are closely related to customer needs, tend to be expressed in the Description section of the patent documents; therefore, whole patent documents were used for the development of a feature vector.

The second is a feature vector on customer reviews. Customers tend to express their satisfaction or dissatisfaction on a product/service they have purchased during their review processes. Thus, if well analyzed, customer review data can be an invaluable source of information that can help establish a product/service development strategy to improve customer satisfaction, while reducing complaints (Park and Lee, 2011). Nevertheless, a simple keyword extraction process fails to distinguish keywords relating to satisfaction from those concerning complaints, which is essential for the retrieval of meaningful insight for new product/service design.

Accordingly, instead of simply extracting keywords, we applied opinion-mining analysis, which is also known as sentiment analysis. It uses natural language processing; however, it aims to consider the attitude of a writer toward a particular keyword (i.e., a particular topic) or the overall document. A particular keyword can be related to *positive* attitudes, such as satisfaction, and *neutral*, or *negative* attitudes, such as dissatisfaction. Keywords and customers' general attitudes toward the keywords are also useful in providing suggestions to a firm in terms of what to improve and what to market. Opinion mining has been widely applied for the purpose of marketing or customer services. In the present study, a patent with more keywords that relate to customer satisfaction or dissatisfaction are regarded as more promising in a market. Moreover, a recommendation system that suggests a set of the most appropriate patents to respond to a particular customer need can be designed.

#### 2.2.3. Bibliographic coupling and outlier analysis

Bibliographic coupling is based on the concept that patents with more co-citations will be from a similar technological area (See Fig. 1). As patent citation data are created by an inventor or an examiner who is generally an expert in the fields, technology grouping through bibliographic coupling is likely to produce relatively accurate grouping results, even when the analysis is conducted by non-experts in the fields. In this study, we first developed a bibliographic coupling matrix, presenting a share of co-citations between patents, based on which the similarities of patents were measured by applying a cosine similarity to the matrix. Then, patents with high similarities were grouped together to form technology groups. Finally, patents that were not assigned to any of the groups were identified as outliers, which required further investigation.

A network analysis, with whatever method it takes to measure similarity between patents, including bibliographical coupling, citation analysis, co-classification analysis, or semantic analysis, has been frequently used to identify key research areas putting an emphasis on the clusters of patents in the form of network (e.g., Noh et al., 2016). On the contrary, more recent attention has been given to the outliers that are isolated from the networks of other patents. For example, Yoon and Kim (2012) regarded outlier patents as potential technologies with the great possibilities of technological jumps, and identified outlier patents using semantic similarity. Aharonson and Schilling (2016) also argued that patents in the position of outlier technology are worth to investigate, considering their possibilities to become key technologies. Unlike the previous studies, Takano et al. (2016) tried to link outlier patents to the other patents in the network, using based on patent family data, as neglecting such outlier patents in a patent network may cause a significant loss of information (Shibata et al., 2010). This study is in line with the previous works by Yoon and Kim (2012), and Aharonson and Schilling (2016), considering outlier patents as candidates for emerging and promising technologies, as they are distinguished from the existing technologies.

## 3. Research framework

This section describes the overall research process, particularly focusing on core algorithms to develop technology and market indices for the identification of promising technologies.

### 3.1. Overall research process

This study adopts two types of index analysis as an attempt to evaluate emerging technologies: 1) technology index analysis using patent data and 2) market index analysis using customer review data. Here, the first step to implement the analysis is to design appropriate indices. The technology indices are designed based on the patent characteristics that present significant differences between promising and non-promising technologies at the early stage of their technological life cycle; those characteristics will be antecedents of promisingness. Hence, an experiment to identify such characteristics was implemented with patents that had been applied a long time ago; thus, enough time had passed to observe their evolutionary patterns, that is, whether they were evolved to be promising technologies or not. On the other hand, to develop market indices, customer review data on products/services need to be collected and analyzed to classify keywords from the data into positive and negative ones from the perspective of customer needs through sentiment analysis. Then, using the keywords, the degree of relationships between “customer needs and technologies” as well as “customer complaints and technologies” was measured to be used as an index value of promisingness from a market perspective. If a patent is more closely related to customer needs or complaints, it tends to become a technology that can be used to meet the needs or resolve the complaints.

Once the evaluation indices are developed, they are used to identify promising technologies. Regarding patents that are more recent in the field of interest, we first applied bibliographic coupling to identify candidates of promising technologies by finding outlier patents, which are expected to be novel in content. Then, an evaluation was performed on the candidate technologies using previously developed technology and market indices. Finally, we performed in-depth analysis on highly evaluated technologies, which were our main study focus, to investigate their characteristics and ultimately, to gain meaningful insights for strategic technology development. To achieve this, a technology portfolio with two axes, namely a technological index value axis and a market index value axis, was designed, on which the potential emerging technologies— top patents according to technology index values and those according to market index values— were mapped for visualization purposes.

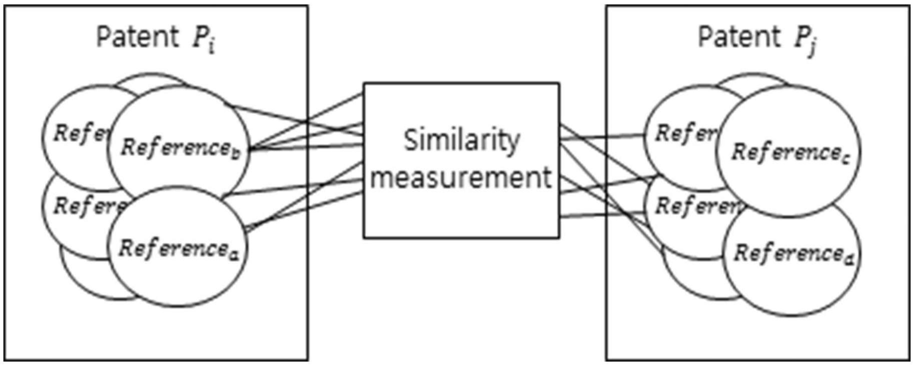


**Fig. 1.** Bibliographic coupling.

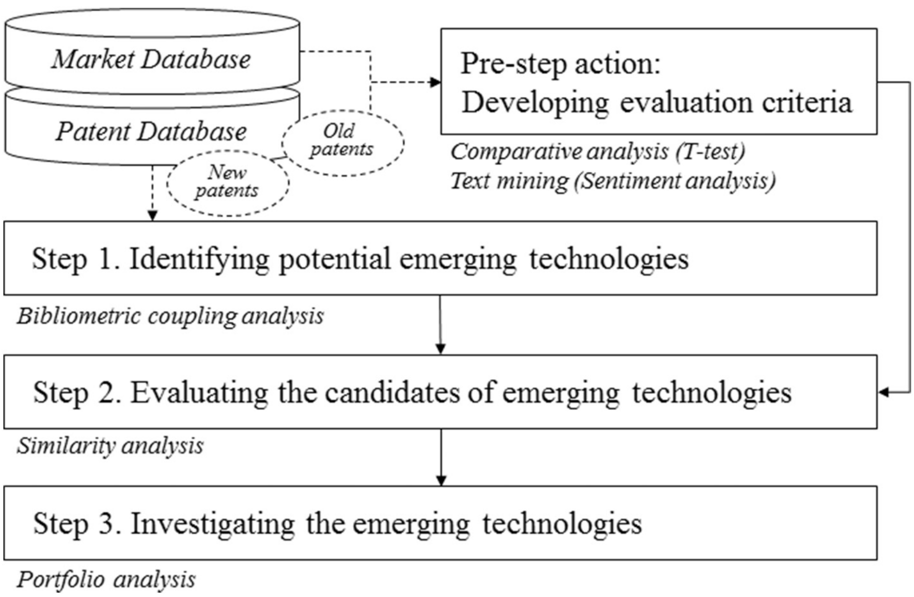


**Fig. 2.** The overall process.

**Table 1**
Patent indices to measure their promisingness.

| Index | Operational definition | Description |
|---|---|---|
| Impact | $I_i$ = the number of forward citations for patent *i* | Technologies that are likely to impact on the development of subsequent technologies |
| Applicability | $A_i$ = (the number of different IPCs for patents citing patent *i*) ÷ (the number of patents citing patent *i*) | Technologies that are likely to influence a wide range of subsequent technologies |
| Sustainability | $S_i$ = 1 if patent *i* was renewed; 0 otherwise | Technologies that are likely to be used continuously |

Here, it should be noted that innovation may come from not only technology-push but also market-pull. For example, some innovations such as a motorcycle rather than a bike, and a smart phone rather than a feature phone come mainly from technology-push approaches in an attempt to apply new technology principles or to link different technologies. On the other hand, the analysis of customer needs in the form of customer reviews are still useful in obtaining ideas to improve product and service because customer explicitly express their satisfaction and dissatisfaction with the products and services they experienced (Park and Lee, 2011; Tucker and Kim, 2011). Considering that different types of innovation can be derived from different approaches, we developed a portfolio matrix with two index values rather than a single integrated value to identify promising patents. The overall research process is described in Fig. 2, and further information on detailed procedures is provided in the following sections.

### 3.2. Development of technology indices

To develop technology indices, we collected the patents filed in technological fields of interest at a certain period in the past, that is, time t. It should be noted that the patents were required to be old enough for us to judge whether they have evolved to promising technologies or not at the current time T. Specifically, two types of data are necessary to design the indices.

The first type is the accumulated bibliometric information of a patent, which is used to measure the degree of its promisingness now. The promising technologies are defined from three viewpoints: 1) impact (Type 1), 2) applicability, (Type 2), and 3) sustainability (Type 3). The operational definition and description of patent indices concerning the viewpoints are provided in Table 1.

The second type is the patent bibliometric information for technology at its first appearance, which is used to understand its technological characteristics (see Table 2). In addition to the indices commonly used in the existing studies, two additional indices were

**Table 2**
Patent indices to measure technological characteristics.

| Index | Operational definition | Description |
|---|---|---|
| Scope of rights | $SR_i$ = the number of patent claims for patent *i* | If a patent has a broader scope of rights, it is more likely to be evolved into a promising technology. |
| Scope of application | $SA_i$ = the number of IPCs for patent *i* | If a patent is more widely applicable, it is more likely to be evolved into a promising technology. |
| Size of contributors | $SC_i$ = (the number of applicants for patent *i*) + (the number of inventors for patent *i*) | If a patent is developed via collective efforts by a larger number of applicants or inventors, it is more likely to be evolved into a promising technology. |
| Technology-base | $TB_i$ = the number of references | If a patent is less based on the existing technologies and thus is thus novel, it is more likely to be evolved into a promising technology. |
| Science-base | $SB_i$ = the ratio of non-patent references over the total references | If a patent is more based on basic technologies, and thus at an early technological stage, it is more likely to be evolved into a promising technology. |
| Applicant type | $AT_i$ = 1 if patent *i* include any organization in applicants; 0 otherwise | If a patent is developed with the support of an organization, it is more likely to be evolved into a promising technology. |
| Recency | $Re_i$ = (the number of patents applied in the recent three years in the reference list) ÷ (the number of all patents in the reference list) | If a patent references technologies that are more recent, it is more likely to be evolved into a promising technology. |

considered for the analysis. The *Application type* index is to judge if the technology development was driven by an individual or an organization; if the technological development actors include an organization, the possibilities of continuous investment on the subsequent technologies will increase, offering advantages to be classified as a promising technology. The *Technology recency* index aims to reflect the degree to which recent technologies are used in the development of the relevant technologies, on the assumption that a technology referencing technologies that are more recent is more likely to evolve into an emerging technology.

For the patents evaluated as outliers at the stage of their emergence, an ad-hoc analysis to judge whether they were evolved into a promising technology is conducted with regard to their impact, their applicability, and their sustainability after enough time has passed since they first emerged (Fig. 3). As to the impact and the applicability indices, patents with values above average were evaluated as promising for each of the perspective. Regarding the sustainability index, if patents were renewed continuously, they would be defined as promising technologies. Finally, for each of the promisingness perspectives, the technology characteristics indices that showed statistically significant differences between promising patents and non-promising patents were identified by applying Mann–Whitney's *U* test. These are indices worth considering for the classification of patents that are expected to evolve into promising technologies in future and those that are not. Unlike most previous studies following a normative approach, the first step of this study is to find meaningful indices by following an inductive approach.

We expect that different indices will be identified as meaningful indices for different perspectives of promisingness. Therefore, after the promisingness of a new patent, $P_i$, was evaluated via three different perspectives using a set of indices relating to each of the perspective, the evaluation results were combined to produce the final value of promisingness. Here, the evaluation results for $P_i$ from each of the three perspectives, denoted here as $I_{Pi}$, $A_{Pi}$, and $S_{Pi}$, may have different scales. Thus, the results were normalized using a 0 to 1 scale, assigning 1 to the maximum value and 0 to the minimum value among the patents evaluated together and were transformed to $TI1_{P_i}$, $TI2_{P_i}$, and $TI3_{P_i}$. The final promisingness index value for $P_i$, which is a technology index value ($TI_{Pi}$), is obtained as a weighted average value of $TI1_{P_i}$, $TI2_{P_i}$, and $TI3_{P_i}$ values (see the Eqs. 1). A different set of weights ($u_1$, $u_2$, and $u_3$) can be used for different contexts and purposes; a different notion of "promising technology" may lead to different weights of $TI1_{P_i}$(impact), $TI2_{P_i}$(applicability), and $TI3_{P_i}$(sustainability). For example, if a patent with more technological impact is regarded as a more promising technology, a substantial weight should be given to $TI1_{P_i}$, with a large value of $u_1$ compared to $u_2$ and $u_3$.

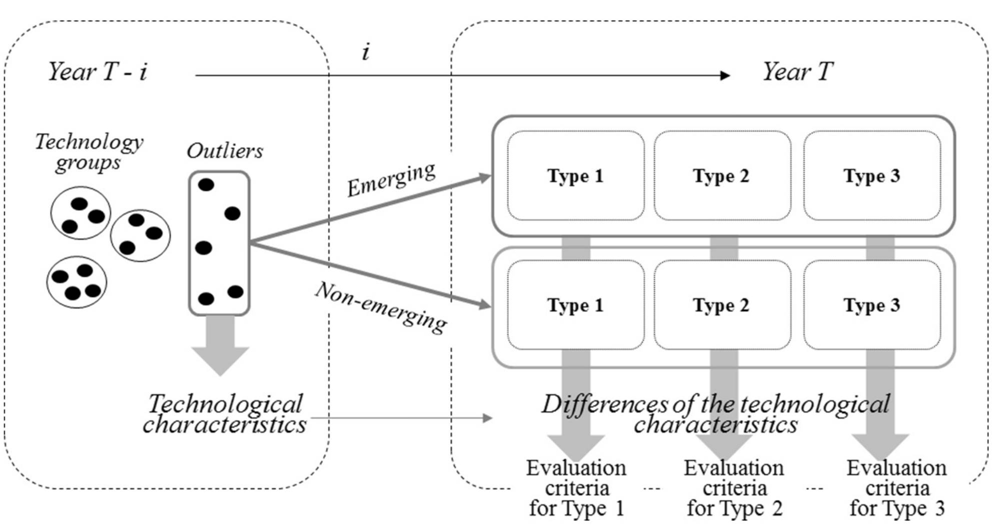


**Fig. 3.** A process to identify patent indices for technology factors.

$$TI_{P_i} = TI1_{P_i}\cdot u_1 + TI2_{P_i}\cdot u_2 + TI3_{P_i}\cdot u_3$$
$$s.\ t.\quad TI1_{P_i} = \frac{I_{P_i} - \min_{P_i} I_{P_k}}{\max_{P_i} I_{P_k} - \min_{P_i} I_{P_k}}$$
$$TI2_{P_i} = \frac{A_{P_i} - \min_{P_i} A_{P_k}}{\max_{P_i} A_{P_k} - \min_{P_i} A_{P_k}}$$
$$TI3_{P_i} = \frac{S_{P_i} - \min_{P_i} S_{P_k}}{\max_{P_i} S_{P_k} - \min_{P_i} S_{P_k}}$$
$$u_1 + u_2 + u_3 = 1,\quad u_1, u_2, u_3 \geqq 0 \tag{1}$$

### 3.3. Development of market indices

Customer review data on a technology (products or services in which a technology of interest is embodied) were collected to develop market indices. Sentiment analysis was conducted on the data to extract $\text{Term}_j$ (j = 1,…, J), where the terms are classified into positive and negative ones. Then, patents relating to the technology were collected to extract the keywords that each patent possesses; a patent with more keywords corresponding to a set of positive keywords identified from the customer review data can be regarded as a technology offering attractive utilities to the users. On the other hand, a patent with more keywords related to a set of negative keywords from the customer review data may be conceived as a technology overcoming customer complaints. Accordingly, a patent index to measure the marketability of patent $P_i$, $MI_{P_i}$, can be operationalized as Eq. (2). Similarly to $TI_{P_i}$, two components are considered in evaluating the final value for $MI_{P_i}$, which include $MI1_{P_i}$ (a measure to assess the degree of offering attractive values to customers) and $MI2_{P_i}$ (a measure to assess the degree of offering solutions to customer complaints). Again, different weights can be given to the two components in different situation. If a particular focus is to search for patents that can be used to resolve major customer complaints, a weight value for $MI2_{P_i}(v_2)$ should be greater than that for $MI1_{P_i}(v_1)$.

$$MI_{P_i} = MI1_{P_i}\cdot v_1 + MI2_{P_i}\cdot v_2$$
$$s.\ t.\quad MI1_{P_i} = \frac{PTI_{P_i} - \min_{P_i} PTI_{P_k}}{\max_{P_i} PTI_{P_k} - \min_{P_i} PTI_{P_k}}$$
$$MI2_{P_i} = \frac{NTI_{P_i} - \min_{P_i} NTI_{P_k}}{\max_{P_i} NTI_{P_k} - \min_{P_i} NTI_{P_k}}$$
$$v_1 + v_2 = 1,\quad v_1, v_2 \geqq 0$$
$$PTI_{P_i} = \sum_{j=1}^{J} PT_j\ \ (j = 1, 2, \ldots, J)$$
$$s.\ t.\quad PT_j = 1,\ \text{if}\ \ Term(positive)_j \in \text{keywords set of}\ p_i;\ 0,\text{otherwise}$$
$$NTI_{P_i} = \sum_{m=1}^{M} NT_m\ \ (m = 1, 2, \ldots, M)$$
$$s.\ t.\quad NT_m = 1,\ \text{if}\ \ Term(negative)_m \in \text{keywords set of}\ p_i;\ 0,\text{otherwise} \tag{2}$$

## 4. Case study: an automobile door system

A case study was conducted on "an automobile door system" technology, which relates to a particular subsystem of a car. The results from this study were reviewed by an expert who had been working on the automobile door system for more than ten years and thus had enough domain knowledge on this technology field. He is an engineer and has been involved in numerous R&D projects to develop a new technology in this field. Now, he is a senior manager and needs to play a significant role in identifying emerging technologies and evaluating potential R&D projects to acquire those technologies. Thus, he is the right expert for this study.

Regarding the technology, both market needs and technology advances play a significant role in its evolution, and continuous patenting activities on the technology are observed. Furthermore, as disruptive innovation in the door system is expected with the emergence of unmanned vehicles, there are urgent needs in the technology and the market information analysis. We accessed the United States Patent and Trademarks Office (USPTO) database to obtain technological information. It is one of the most representative databases for innovation studies, and it is easily accessible, thus being frequently used in the existing studies (Kim and Lee, 2015). On the other hand, we selected two automobile evaluation websites—Cars.com and Autobytel.com— as market databases. These two websites are ranked within the top five global automobile evaluation websites, and were thus expected to provide reliable data. The statistical program R was used for text-mining, cosine similarity and bibliographic coupling analyses.

### 4.1. Developing evaluation indices

#### 4.1.1. Technology attributes

Assuming that an analysis of technology evolution requires at least 10 years, we set the period of patent data collection from January 1, 2000 to December 31, 2004 (10 years before the analysis point) for the

**Table 3**
Mann–Whitney's U test results on outlier patents.

| Patent index | Impact (p-value) | | Applicability (p-value) | | Sustainability (p-value) | |
|---|---|---|---|---|---|---|
| Scope of rights | 1444.0 | (0.470) | 1543.0 | (0.884) | 119.5 | (0.427) |
| Scope of application | 1454.0 | (0.500) | 906.0 | (0.000**) | 112.0 | (0.345) |
| Size of contributors | 1238.0 | (0.036**) | 1464.5 | (0.510) | 84.0 | (0.117) |
| Applicant type | 1540.0 | (0.752) | 1428.0 | (0.114) | 6142.0 | (0.564) |
| Technology-based | 1256.5 | (0.069*) | 1298.0 | (0.115) | 6116.5 | (0.448) |
| Science-based | 1399.5 | (0.068*) | 1564.0 | (0.965) | 151.5 | (0.546) |
| Recency | 1242.5 | (0.044**) | 1462.5 | (0.513) | 64.0 | (0.056*) |

* $p < 0.1$
** $p < 0.5$

**Table 4**
Semantic analysis results.

| Types | Range | Keywords (sentiment value) |
|---|---|---|
| Positive | ≥ 0.3 | Comfort (0.444); smooth (0.360); size (0.341); stereo (0.335); interior (0.331); style (0.315) |
| | 0.2–0.3 | Exterior (0.297); mileage (0.296); sound (0.288); space (0.283); power (0.273); design (0.266); fit (0.266); Bluetooth (0.253); snow (0.214); speed (0.204); camera (0.202) |
| | 0.1–0.2 | Wheel (0.196); trunk (0.195); mpg (0.189); control (0.174); radio (0.164); engine (0.147); highway (0.141); seat (0.138) |
| | 0–0.1 | Shift (0.081); passenger (0.066); accelerate (0.041); light 0.033); lock (0.008) |
| Negative | < 0 | Mirror (− 0.054); noise (− 0.048); brake (− 0.022) |

development of the technology indices. Then, using the keyword "door" together with "vehicle", "automobile" or "car" to search patents on the automobile door system, a total of 576 patents were obtained. The next step was to conduct bibliographic coupling the collected patents to identity outlier patents, which were defined as novel technologies—candidates of promising technology. From the analysis, 112 out of 576 patents were regarded as outlier patents, which were not linked to any of the other patents, when patents with a cosine similarity value over 0.5 were linked together (see Appendix A).

Based on outlier patents, their technological characteristics at their emergence and their promisingness were evaluated as shown in Table 3. First, the 112 outlier patents were divided into two groups – a promising group and a non-promising group, using their values on impact, applicability and sustainability indices. Here, a median value for each index was used as criteria for each grouping and so each group had 61 patents. Since three different perspectives on promisingness were considered, a patent in a promising group from the perspective of impact may belong to a non-promising group from the perspective of applicability. Then, as the data in this study were not normally distributed, a non-parametric analysis of Mann–Whitney's *U* test on the seven indices was carried out for each perspective to compare the technological characteristics between a promising group and a non-promising group.

The analysis results show that patent indices with a statistically significant difference between the two groups at a significance level of 0.05 include the "size of contributors (impact)," the "recency (impact)," and the "scope of application (applicability)" indices. However, owing to the small size of non-parametric data being analyzed in this study, we extended the significance level to 0.1 in selecting antecedents of promising technologies. Accordingly, three more indices, the "technology-based (impact)," the "science-based (impact)," and the "recency (sustainability)" indices, were added to the existing list of significant indices.

Further investigation regarding promisingness was conducted. First, with regard to the impact, patents with more contributors to relevant technology development and with more references, particularly those that were recent and science-based, are likely to have a higher impact of subsequent technologies. These patents were not clustered with other patents during the bibliographic coupling process, in spite of their long of references list, as the patents they referred to tended to originate from other technological fields. In other words, these patents show the features of converging technologies; we expect that technologies developed by a number of inventors or applicants with a diverse knowledge basis will greatly affect subsequent technologies. Second, as to the applicability, patents that were assigned more IPCs when they were registered were found to be used in more diverse subsequent technologies, which is quite obvious. Actually, many previous studies have adopted the number of IPCs as a proxy of technological applicability; the validity of using this measure was verified from the present analysis. Finally, the recency index showed a relationship with sustainability. Technologies referencing more recent patents or publications tend to reflect more emerging trends of technological changes, thus, the relevant patents are more apt to be renewed. Finally, these indices will be used to evaluate candidates of promising technologies from technological perspectives.

#### 4.1.2. Market attributes

The market data to assess market promisingness ranged from the years 2008 to 2015. The customer opinions on automobiles stored in the two target websites correspond to 21,521 items (for a particular carmaker), among which 1413 items concerned the automobile door systems. Semantic analysis was conducted on the data, using Semantria, to extract keywords from customer opinions as well as positive and negative attitudes toward the keywords. We first selected keywords that occurred > 100 times, among which only 33 were finally identified as meaningful ones in representing customer needs and complaints regarding the automobile door systems. Table 4 summarizes the sentiment analysis results regarding the 33 keywords. In the table, positive values indicate positive meanings, while negative values correspond to negative meanings. The greater the values are, the stronger is the negative or the positive feelings.

Although these sentiment values were not used directly to the further analysis, they provide meaning insights on product and service development or can be used as weights for keywords when identifying emerging technologies. According to the table, most keywords regarding the automobile door system represent positive meanings, signifying that customers are relatively satisfied with the current door systems of the carmaker of interest. Nevertheless, these are associated with the functions that increase customer satisfaction. In particular, it is worth focusing on the six keywords that encapsulate the greatest positive sentiment values—*comfort*, *smooth*, *size*, *stereo*, *interior*, and *style*, because these may attract customers by providing quality that unexpectedly delighted customers or that is superior to that offered by other competitors. On the contrary, customers are found to be complaining about *brake*, *mirror*, and *noise*; these may result in dissatisfaction when not fulfilled, and should thus be considered first in the product development. These 33 keywords became the dimensions for the construction of the feature vector on market needs and were used for assessment from a market perspective. The patents having more keywords related with these customer needs (positive) and complaints (negative) will be regarded as promising, since it is highly likely that such patents are closely related with the needs and complaints defined by the 33 keywords.

### 4.2. Identifying emerging technologies

#### 4.2.1. Identifying potential promising technologies

At this stage, we applied the market and technology indices developed in the previous stages to more recent patents, and we identified potential promising technologies. This analysis was based on the automobile door systems patents granted by the USPTO during the period from January 1, 2013 to December 31, 2015. During this period, a total of 293 relevant patents were granted by the USPTO, on which bibliographic coupling was conducted. Then, applying a similarity cut-off value of 0.5, we could identify 73 outlier patents, which were regarded as candidate technologies.

#### 4.2.2. Evaluating the candidates for emerging technologies

For the 73 patents, further analysis was conducted to investigate their technology and market attributes. First, we evaluated the technological promissingness using the indices identified as precedents of

**Table 5**
Promising technologies expecting high impact — impact.

| Rank | ID | Patent title | Index value |
|---|---|---|---|
| 1 | P201 | Door mirror device for a vehicle | 1.000 |
| 2 | P48 | Cable feed device on a vehicle door, or flat cable connection | 0.862 |
| 3 | P189 | Cable guide on a vehicle door | 0.800 |
| 4 | P79 | Door assembly for a vehicle | 0.784 |
| 5 | P187 | Switch engagement assembly for an automobile door panel | 0.733 |

**Table 6**
Promising technologies expecting broad applications — Applicability.

| Rank | ID | Patent title | Index value |
|---|---|---|---|
| 1 | P164 | Method for the installation of an apparatus for spring-assisted swinging of a liftgate or door in a vehicle | 1.000 |
| 2 | P19 | Method for manufacturing motor vehicle door hinge | 0.667 |
| | P21 | Door inner panel for automobile and method of manufacturing same | |
| 4 | P27 | Lighting system arranged in vehicle door | 0.500 |
| | P59 | Vehicle door lock | |
| | P150 | Circuit for selectively producing switching signals, especially for a vehicle door locking, a vehicle, system and method equipped therewith for protecting areas of risk as well as a system, system components and method for hermetically transferring validatable data | |
| | P234 | Clutch, motor and vehicle door opening/closing device | |

**Table 7**
Promising technologies expecting continued usability — Sustainability.

| Rank | ID | Patent title | Index value |
|---|---|---|---|
| 1 | P5 | Vehicle trunk door structure | 1.000 |
| 2 | P8 | Door weather strip for motor vehicle | 0.786 |
| 3 | P116 | Back door for automobile | 0.611 |
| 4 | P161 | Vehicle door opening warning system | 0.500 |
| 5 | P79 | Door assembly for a vehicle | 0.423 |
| | P90 | Outside handle device for vehicle door | |

promising technologies from three perspectives, namely impact, applicability, and sustainability. Four indices with different scales were used to measure the degree of impact, and thus, the normalization process was performed by assigning the value 1 to the maximum value, and 0 to the minimum value for each index. Then an arithmetic mean for the four index values was used to obtain the final index value for *impact*. Tables 5, 6 and 7 provide a list of patents having the top five index values for each of the three perspectives. It is interesting that no patents were ranked high (top five) for more than one index; the definition of what constitutes a promising technology can affect the analysis result significantly. In this study, considering all three perspectives, the final technology index values were obtained by averaging the three index values.

To obtain market index values, we first counted the number of distinct keywords a patent contained in its documents related to the negative and positive keywords. As the frequency of keywords can be affected by the size of patent documents, we used the binary value—-whether a particular keyword appears in a patent document— instead of the raw value. In addition, we redesigned a single index in preference to the two separate indexes as shown in Eqs. (2) – one for positive keywords and the other for negative keywords – because only three negative keywords were obtained. We were interested in technologies both for offering attractive values to customers and for dealing with customer complaints. Thus, the final index value was calculated by normalizing the number of distinct keyword frequency, where 1 was assigned to the maximum value and 0 to the minimum value. Table 8

**Table 8**
Promising technologies aligning with market needs.

| Rank | ID | Patent title | Index value |
|---|---|---|---|
| 1 | P150 | Circuit for selectively producing switching signals, especially for a vehicle door locking, a vehicle, system and method equipped therewith for protecting areas of risk as well as a system, system components and method for hermetically transferring validatable data | 1.000 |
| 2 | P107 | Motor vehicle having a mechanism for moving a panel or door | 0.500 |
| | P27 | Lighting system arranged in vehicle door | |
| 4 | P122 | Door attached to cabin for work vehicle | 0.450 |
| 5 | P141 | Damping stop for hinge, especially for vehicle door hinge | 0.400 |
| | P16 | Replacement door handle for vehicle | |
| | P259 | Temperature control apparatus for heating a side door of a vehicle | |
| | P261 | Automated vehicle cargo door opener | |
| | P91 | Door module for installation in a motor vehicle door | |

lists the top nine patents with respect to market needs. More detailed information is provided in Appendix C.

#### 4.2.3. Investigating the emerging technologies

As a result, the technologies with the top ten values in the technology index or the market index were selected as an emerging technology. In this study, we selected only ten patents since we focused only on a specific area of automobile (a door system) and ten is a good size for visualization. However, the number of patents to be selected is adjustable as the proposed approach generates a priority of outlier patents rather than a threshold value to distinguish more promising patents from less promising ones. Particularly, when a larger size of data is used for analysis, it is worth considering more patents for further investigation.

Then, for those ten technologies, a portfolio map was developed to understand their characteristics, as shown in Fig. 4. The values to develop the map are summarized in Appendix D. The portfolio analysis shows an interesting result; no patents are observed in the first quadrant—emerging technologies from both technological and market perspectives. Customer opinions are likely to be based on the existing products and their direct experiences with the products—the satisfactory and dissatisfactory functions that users have experienced are frequently expressed in an online community. A typical example is P90, which concerns the *outside handle device for vehicle door*. On the other hand, the technological perspective considers more innovative ideas, such as *door weather strip for motor vehicle* (P8), and the technologies that users may experience indirectly, such as manufacturing technologies (P19). Despite the differences in the characteristics, all these technologies can be regarded as emerging technologies, and are thus worth considering for R&D planning.

The findings from the map provide some useful insights on the upcoming innovation in the door system. First, from a technological perspective, the innovation in the door system is likely to be based on its core components, by suggesting effective solutions to their technical problems. Further technology development is expected to emerge to yield more subsequent innovation in such areas as 1) *door structure* to prevent trunk deformation (P5); 2) *door weather-strip* to improve its durability and prevent abnormal operative noise (P8); 3) *door hinge manufacturing* that provides a sufficient strength of hinge (P4); 4) *door apparatus* for its spring-assisted swinging (P164); and *door assembly* for sliding door (P79). From a market perspective, innovation can also come from improving the key areas where the users are troubled and thus want improvements. In this study, those areas include: 1) *door locking* mechanism (P150); 2) *door moving* mechanism (P107); 3) *lighting system* attached to door (P27); 4) *door handle* replacement (P16); 5) *door heating* system (P259); and a few other technologies related to door

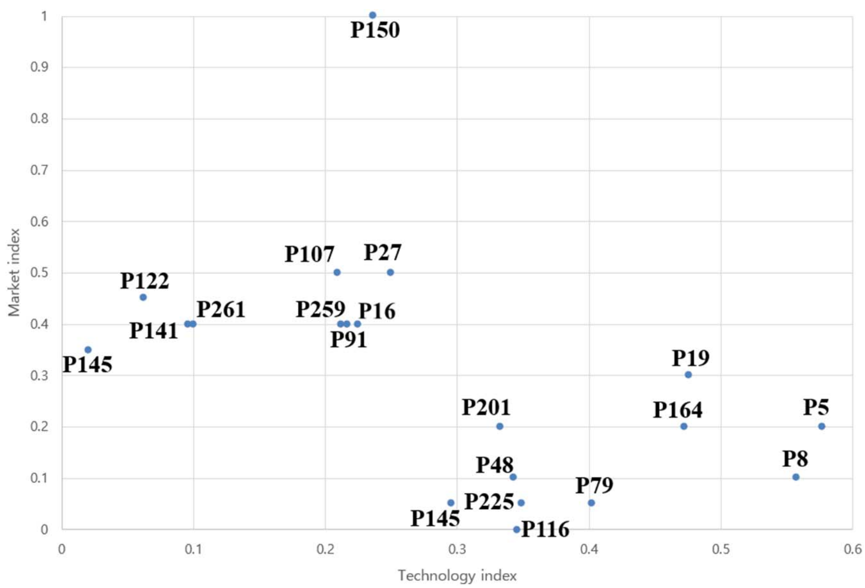


**Fig. 4.** Emerging technology portfolio map.

*design* (P91, P122), *opener* (P261) and *hinge* (P141). As the proposed approach emphasized the use of outlier patents, all those technologies are relatively recent and unique. However, it should be noted that the final decision as to whether such technologies are worth pursuing in an organization should be made after careful consideration. Involving an expert, or a group of experts, with various knowledge on relevant technological fields, market needs, and business strategies, in this stage of analysis can be greatly helpful to assess those technologies from a commercial perspective.

### *4.3. Discussions*

There were several issues raised during the analysis processes. First, much in-depth discussion on the concept of promising technology is necessary. Although some previous studies have suggested that the basic attributes of a promising technology are common, we argue that these attributes may vary according to the purpose of identifying such a technology; some organizations place more emphasis on technological attributes, while others may emphasize more on market attributes. To address this issue, instead of developing a single index, this study suggests a portfolio map based on the two attributes. If a firm considers both technological and market attributes to be equally important, it will select the patents in the first quadrant as the prioritized promising technologies. On the other hand, if a firm needs to identify a technology that attracts market interest regardless of its technological superiority, its scope of prioritized patents can be expanded to the second quadrant. Likewise, patents of interest in the portfolio map may change according to the definition of promising technology and the purpose of its identification.

Related to the first issue, the suggested approach can be more effective for the following three purposes of identifying promising technologies than the others. First, it will be useful to analyze the patent strength of a firm; the firm can check whether its patents belong to the portfolio of promising technologies. If they are, their positions in the portfolio map can be examined to confirm whether they are more inclined toward market needs or technological superiority, indicating the strategic directions for corporate R&D. Second, in a similar manner, R&D strategies of competitors can be uncovered by observing their patents in the portfolio maps. Finally, the suggested approach can be used to find a patent for technology in-sourcing. This would help a firm to identify a promising technology at its early stage of development and to acquire it through technology transfer, enabling the establishment of a strong promising technology portfolio.

It is also worth reviewing the process of identifying patent indices as antecedents of technology promisingness. Of course, we referenced the existing studies to find theoretically meaningful indices; however, these were antecedents of technological promisingness and not the indices having causal relationships with technological promisingness. Hence, further analysis is needed to investigate the cause-and-effect relationships between these indices and technological promisingness. In addition, it should be noted that different patent indices may be identified as meaningful in different technological sectors. The indices identified in this study are applicable only to the automobile door systems, and their validity should be tested by extending the scope of the analysis to other industry (technological) sectors. Further analysis may distinguish generalizable indices across industry sectors with customized indices for a particular industry sector.

In addition, this study adopted a simple Mann-Whitney's *U* test to determine the patent indices that can be used to distinguish promising patents from non-promising ones, trying to make the suggested approach simple and intuitive since it was supposed to be used in practice. Indeed, the correlation analysis results on the patent indices showed low or insignificant correlations between them (see Appendix D), and thus all the five patent indices identified as meaningful are worth to use, evaluating different aspects of promisingness. Nevertheless, the use of more advanced algorithms based on a generalized linear model (e.g., a logistic regression analysis) or other machine learning approaches is required to elaborate the approach in this study for better prediction of promising technologies.

Finally, a case study was conducted in an automobile industry sector, which has rich customer review data. Customer review data are more reliable than surveys as they are more useful in offering opinions. Moreover, additional efforts are not required to design surveys and collect data. If customer data are collected by nations, distinguishing customer needs in geographically different markets can be gathered and analyzed; however, the focus of this study was restricted only to the US customer database. Nevertheless, if we fail to choose an appropriate (non-representative) database, we might be in danger of having a biased set of market needs and consequently identifying a biased set of promising technologies. Hence, the utility of the suggested approach may depend on the quality and representativeness of the customer review data. There might be other alternative data on market needs, apart from customer review data; further research is required to obtain more datasets.

## 5. Conclusions

There have been increasing efforts to monitor emerging technologies and discover new opportunities from such technologies based on patent information. As one of these attempts, this study proposed a systematic approach to identify promising technologies from patents. In particular, this study focused on overcoming the limitations of the existing studies in which few criteria applicable to recently published patents have been suggested. Therefore, we conducted a retrospective analysis by comparing technological characteristics commonly observed in promising technologies at their early stage of development to those observed in non-promising technologies, following an exploratory approach rather than a normative approach. While a number of previous studies have suggested new approaches to identify promising technologies, few of them have investigated the actual evolutionary trajectory of the technologies they predicted to be promising. This is one of the earliest attempts to identify the characteristics observable in patent indices between promising and non-promising technologies. In addition, this study tried to incorporate market attributes in the process of discovering promising technologies unlike the existing studies, which mostly relied on technological attributes for the evaluation of the promisingness of technologies. The Description sections of patent documents explain the expected effects of technologies, having a number of keywords that are frequently used in customer reviews on products or services in a market; the customer review data were used to develop criteria for measuring how well a technology can satisfy customer complaints or requirements. Accordingly, this study can address the problem that citation information or renewal information, which are one of the most commonly used information in evaluating the quality of patents, are not applicable to recently published patents, which actually need to be considered as one of the most significant candidates for promising technologies. The research findings will be a basis for further studies to replace the existing citation- or renewal-based indices for technology evaluation with those that can be applied to more recent patents.

In spite of meaningful contributions, this study has some limitations, and a further study is required. First, as was mentioned earlier, several definitions of promising technologies exist, among which this study adopted only three. Analysis on defining promising technologies and customized approaches that are appropriate for each of the definitions will be needed. Second, further analysis is required to improve the patent indices describing the characteristics of technologies at their early stage of development. As various patent indices exist, presenting technological characteristics, more indices need to be considered to identify antecedents of promising technologies. Third, since the market index presented in this study is analyzed based on customer review data, it can work well only for the domain where customer opinions are accumulated enough to offer reliable and trustworthy information on market needs. As was addressed in the discussion section, searching for other market databases to extract intelligence about future innovation is needed to ensure wider use of the approach suggested in this study. Forth, the period of patent data collection might cause difference on the results, which was not tested in this study. We expect the technological characteristics investigated in this study are stable over time, and thus the effect of the time window for the analysis of technology attributes may not be significant. Nevertheless, such effect needs to be carefully considered and so further studies are required to address this issue. Finally, we applied a simple arithmetic mean to merge several index values into a single value. However, a more sophisticated approach based on multi-criteria decision-making techniques can be used to merge index values. Furthermore, we used a simple index based on a binary value showing whether a patent has a particular keyword associated with customer satisfaction or complaint, without assigning any weights to the keyword. An elaborated market index can be developed by assigning weights to keywords or considering keyword frequencies in a patent document. Future research will address these issues.

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## Appendix A

Fig. A1 represents technology grouping results, where patents with a cosine similarity value over 0.5 are linked together. A total of 464 patents were clustered into 50 groups, while 112 patents were identified as outliers. If Patents A and B have one reference (Patent C) in common, they share some technological knowledge (knowledge from Patent C). The more references the two technologies share, the greater the value of their cosign similarity will be. The technologies on automobile door systems seem to have 11 major areas with $>$ 10 patents in each of them as well as 39 minor areas with $<$ 10 patents in each of them, which may include specific sub-technologies of an automobile door system such as back door, door lock and door structure

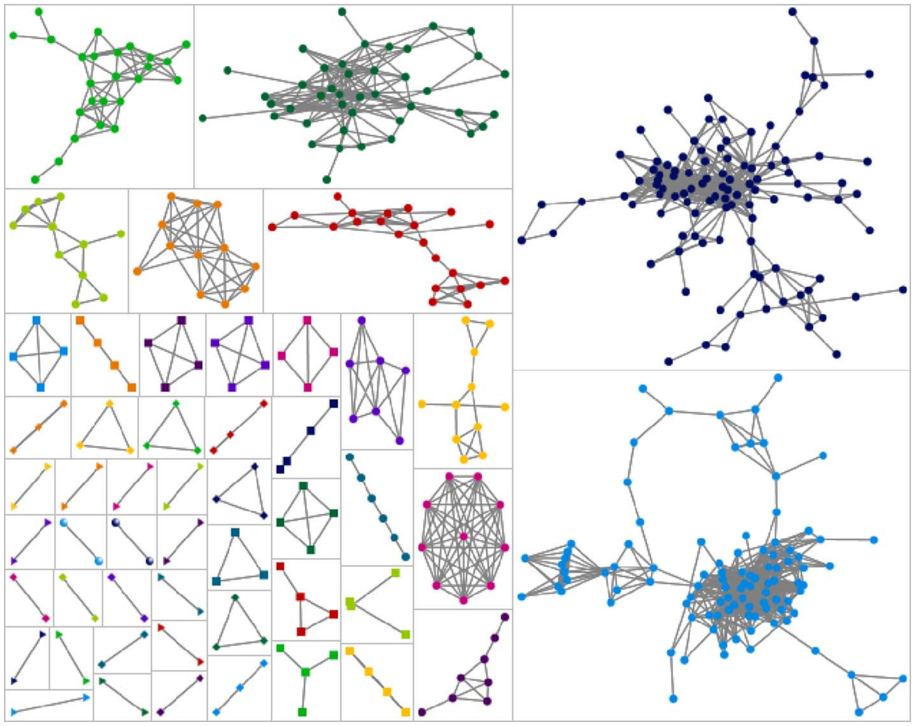

**Fig. A1.** Bibliographic coupling analysis results.

## Appendix B

Table A1
Index analysis results - impact.

| Rank | ID | Size of contributors (normalized) | Technology-base (normalized) | Science-base (normalized) | Recency (normalized) |
|---|---|---|---|---|---|
| 1 | P201 | 9 (0.875) | 8 (0.095) | 0.273 (1.000) | 0.000 (0.000) |
| 2 | P48 | 7 (0.625) | 12 (0.159) | 0.250 (0.917) | 0.000 (0.000) |
| 3 | P189 | 8 (0.750) | 8 (0.095) | 0.200 (0.733) | 0.000 (0.000) |
| 4 | P79 | 3 (0.125) | 65 (1.000) | 0.000 (0.000) | 0.077 (0.423) |
| 5 | P187 | 10 (1.000) | 11 (0.143) | 0.083 (0.306) | 0.000 (0.000) |
| 6 | P5 | 3 (0.125) | 22 (0.318) | 0.000 (0.000) | 0.182 (1.000) |
| 7 | P125 | 9 (0.875) | 18 (0.254) | 0.053 (0.193) | 0.000 (0.000) |
| 8 | P91 | 3 (0.125) | 43 (0.651) | 0.140 (0.513) | 0.000 (0.000) |
| 9 | P107 | 6 (0.500) | 49 (0.746) | 0.000 (0.000) | 0.000 (0.000) |
| 10 | P276 | 6 (0.500) | 34 (0.508) | 0.056 (0.204) | 0.000 (0.000) |

Table A2
Index analysis results - applicability.

| Rank | ID | Scope of application (normalized) |
|---|---|---|
| 1 | P164 | 7 (1.000) |
| 2 | P19 | 5 (0.667) |
| | P21 | |
| 4 | P27 | 4 (0.500) |
| | P59 | |
| | P150 | |
| | P234 | |
| 8 | P225 | 3 (0.333) |
| | P259 | |
| | P252 | |

## Appendix C

Table A3
The keyword occurrence for the top 10 patents – Market.

| Keywords ( ± ) | P150 | P107 | P27 | P122 | P141 | P16 | P259 | P261 | P91 | P145 |
|---|---|---|---|---|---|---|---|---|---|---|
| Seat (+) | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| Interior (+) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 |
| Comfort (+) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Power (+) | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| Mileage (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mpg (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Engine (+) | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| Wheel (+) | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| Light (+) | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Control (+) | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| Lock (+) | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| Speed (+) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Highway (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sound (+) | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| Fit (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Design (+) | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| Style (+) | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Smooth (+) | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Space (+) | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| Radio (+) | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Passenger (+) | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| Accelerate (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Trunk (+) | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Automate (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Exterior (+) | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| Shift (+) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Size (+) | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 |
| Snow (+) | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Bluetooth (+) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Stereo (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Camera (+) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total (+) | 18 | 10 | 9 | 9 | 7 | 8 | 7 | 7 | 7 | 7 |
| Brake (−) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Noise (−) | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| Mirror (−) | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| Total (−) | 2 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 |
| Total ( ± ) | 20 | 10 | 10 | 9 | 8 | 8 | 8 | 8 | 8 | 7 |

## Appendix D

Table A4
Technology and market index values for the top 10 patents.

| Technology perspectives | | | | Market perspectives | | | |
|---|---|---|---|---|---|---|---|
| Rank | ID | Technology index | Market index | Rank | ID | Technology index | Market index |
| 1 | P5 | 0.577 | 0.200 | 1 | P150 | 0.236 | 1.000 |
| 2 | P8 | 0.558 | 0.100 | 2 | P107 | 0.210 | 0.500 |
| 3 | P19 | 0.476 | 0.300 | | P27 | 0.250 | 0.500 |
| 4 | P164 | 0.473 | 0.200 | 4 | P122 | 0.062 | 0.450 |
| 5 | P79 | 0.402 | 0.050 | 5 | P141 | 0.096 | 0.400 |
| 6 | P225 | 0.349 | 0.050 | | P16 | 0.225 | 0.400 |
| 7 | P116 | 0.346 | 0.000 | | P259 | 0.212 | 0.400 |
| 8 | P48 | 0.343 | 0.100 | | P261 | 0.100 | 0.400 |
| 9 | P201 | 0.333 | 0.200 | | P91 | 0.217 | 0.400 |
| 10 | P90 | 0.296 | 0.050 | 10 | P145 | 0.021 | 0.350 |

## Appendix E

Table A5
Correlation analysis results: promisingness.

| | Impact | Applicability | Sustainability |
|---|---|---|---|
| Impact | 1 | | |
| Applicability | − 0.084<br>(0.380) | 1 | |
| Sustainability | − 0.085<br>(0.735) | − 0.110<br>(0.246) | 1 |

Table A6
Correlation analysis results: technological characteristics.

| | Scope of rights | Scope of application | Size of contributors | Technology-base | Science-base | Applicant type | Recency |
|---|---|---|---|---|---|---|---|
| Scope of rights | 1 | | | | | | |
| Scope of application | 0.094<br>(0.323) | 1 | | | | | |
| Size of contributors | − 0.062<br>(0.520) | 0.040<br>(0.674) | 1 | | | | |
| Technology-base | 0.373<br>(0.000) | − 0.020<br>(0.838) | 0.015<br>(0.879) | 1 | | | |
| Science-base | − 0.006<br>(0.950) | 0.064<br>(0.050) | − 0.018<br>(0.851) | − 0.043<br>(0.654) | 1 | | |
| Applicant type | 0.135<br>(0.157) | 0.025<br>(0.794) | 0.146<br>(0.124) | 0.040<br>(0.677) | − 0.094<br>(0.324) | 1 | |
| Recency | − 0.106<br>(0.266) | 0.036<br>(0.703) | − 0.113<br>(0.237) | − 0.121<br>(0.204) | − 0.198<br>(0.037) | 0.081<br>(0.397) | 1 |

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