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Technology opportunity discovery to R&D planning: Key technological performance analysis☆

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ABSTRACT

There is a gap between technological opportunities and R&D planning because opportunity information is too broadly defined. Thus, we suggest a method of transforming such technological opportunities into a customized and detailed R&D plan. We identify key information for R&D planning, extract such information from bibliometric data by chunk-based mining, and convert it to a usable form for R&D planning. A systematic analysis of normalized performance gaps, performance structure, R&D feasibility and technological alternatives identified important and feasible target technological performance metrics as well as R&D solutions. Our method can increase the practical value of technological opportunities while reducing the efforts required of experts.

1. Introduction

Over the last few decades, some innovative companies and entrepreneurs have explored and exploited technological opportunities better than others, thereby gaining competitive advantages (Day et al., 2004; Newbert et al., 2006). At a national level, the causal link from technological opportunities to economic growth has also been observed in many countries (Audretsch, 1995; Hung and Chu, 2006; Olsson, 2005). Consequently, there have been many efforts to better identify technological opportunities in both private and public spheres.

Technological opportunity is defined as a set of possibilities for technological advances to improve either production or functional attributes of a product (Klevorick et al., 1995; Olsson, 2005). According to the current literature, technological opportunities can be divided into two types: 1) innovative opportunities, and 2) arbitrage opportunities (Eckhardt and Shane, 2003; Kirzner, 1997). Researchers have made efforts to identify innovative opportunities to anticipate the future of emerging technologies (Savioz and Blum, 2002). Some researchers focused on the latter, and have tried to identify application opportunities for existing technologies (Shin and Lee, 2013; Yoon et al., 2014). Overall, innovative opportunities have been of interest both in academia and in practice.

Several methods have been suggested to better identify innovative technological opportunities. Early studies depended on expert judgment and entrepreneurial recognition (Baron and Ensley, 2006; Salo and Cuhls, 2003). The increasing complexity of technology, the environment and mutual interactions have reduced the reliability of this method. Researchers have focused on utilizing electronic science and technology data, including patents and journals, as substitutes or complements to recognition. Conceptual frameworks, models and systems have been generated, including Technology Opportunities Analysis (TOA) and technology intelligence (Brenner, 1996; Kerr et al., 2006; Porter and Detampel, 1995). Despite some differences, they all have common characteristics of monitoring and bibliometric analysis.

Focusing on the potential value of bibliometric analysis, some researchers have developed advanced techniques by using social network analysis (Shibata et al., 2011; Von Wartburg et al., 2005), morphology (Xin et al., 2010; Yoon et al., 2014), topology (Shibata et al., 2008), text mining (Kostoff, 2001; Lee et al., 2014), novelty detection (Lee et al., 2015), patent maps (Lee et al., 2009b) and others. These studies are a response to the need for more accurate and comprehensive opportunity identification in the earlier stages of an emerging technology, and they also reduce the weaknesses of bibliometric data such as truncation bias and unequal patent value.

Another important issue is practical operationalization for corporate functions including strategy, planning, research and development (R&D) and product development. Recently, some researchers have linked technological opportunity identification to business planning (Lee et al., 2009a), technology planning (Huang et al., 2014) and product development (Lee et al., 2008; OuYang and Weng, 2011; Yoon et al., 2014). They narrowed searches down to key patents or keywords, identified technological opportunities, extracted information (including business items, technological performance metrics and product

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attributes), linked each opportunity to relevant information and evaluated its strategic priority.

Though these approaches are valuable, some problems remain unsolved. Above all, the key target of technological performance identification depends upon expert judgment, and thus is subject to its typical drawbacks including subjective bias and bounded knowledge. Overall technology/product performance is not easy to optimize because the causal relationships among performance metrics are not sufficiently considered. Trade-offs and synergies between different technological performance metrics must be identified, but this is rarely done. Also, there is little consideration for customization, which reduces planning efficiency because experts have to spend time reviewing and filtering out information, including irrelevant opportunities, unimportant technological performance metrics, and infeasible R&D methods.

To address these issues, we suggest a way of linking technological opportunities to practical R&D planning customized to a company. Customized technological opportunities are identified based on Lee et al. (2008, 2014), which provide a starting point for R&D planning. Sequential iterations of chunk-based text mining and expert judgment enable us to comprehensively identify key technological performance metrics as well as competitors in the target market segment while minimizing several biases due to either text mining or expert judgment.

Combining the normalized performance gap analysis with the decision making trial and evaluation laboratory (DEMATEL), we can narrow potential items down to important target technological performance metrics for a specific company, identify the performance structure of their synergies and trade-offs, and select target performance metrics to maximize R&D effectiveness. Further, we can evaluate the R&D feasibility of target performance metrics, which enables R&D experts to select more feasible target performance metrics by utilizing their existing technological capability. R&D efficiency can be increased by focusing on more feasible performance metrics. Finally, the patent-based technological trajectory is of great help to identify candidates of R&D solutions to achieve targets. A systematic use of these tools can transform a broadly defined technological opportunity to a specific R&D plan with clear target technological performance metrics, solution candidates and competitors.

The remainder of this article is organized as follows. In Section 2, we review existing TOA research. The research framework and our methodology are explained in Section 3. Subsequently, an empirical analysis about battery separator opportunities using membrane technology is provided. Finally, conclusions are drawn after relevant discussions.

2. Technology opportunity analysis

In the 1990s, it became important to identify early signals of technological changes to optimize organizational response options (Brenner, 1996). The first technology signals emerge in scientific and technological discussions or gray literature (Johnson, 2000). Later signals include scientific papers, patents and R&D collaborations. Porter and Detampel (1995) suggested using TOA to recognize the explosion of later signals in electronic technology databases. This method combines monitoring with bibliometrics, which are used to analyze information gleaned from such databases to identify emerging technologies.

Researchers have worked to improve TOA and were driven by the increasing volume of data as well as the need for new opportunities. Key TOA processes consist of monitoring, bibliometric analysis, augmented analysis and visualization (Porter and Detampel, 1995; Zhu and Porter, 2002). There has been some research about the modification and extension of TOA frameworks and systems (Cozzens et al., 2010; Kerr et al., 2006; Porter and Newman, 2011). However, most researchers focused on improving the effectiveness of a particular process.

Bibliometric analysis is an important area of research. Many believe that advanced bibliometric analysis can be used to identify emerging and unexplored technological opportunities more comprehensively and accurately. Simple bibliometric indicators including counts of publications and citations (Albert et al., 1991) have been replaced by advanced indicators (van Raan, 1996). Some researchers appreciate the potential of the bibliometric indicator network such as the citation network, and improve its analytics by using topology (Shibata et al., 2008), clustering (Shibata et al., 2011), citation vectors (Érdi et al., 2013), weighted citation networks (Fujita et al., 2014) and other approaches.

Advances in natural language processing have encouraged researchers to use various mining techniques including text mining (Kostoff, 2001; Porter and Cunningham, 2005), semantic analysis (Gerken and Moehrle, 2012), term clumping (Zhang et al., 2014), Action-Object (AO) analysis (Lee et al., 2014) and others. Some studies integrate two research streams into new methods using a text-mining network (Yoon and Park, 2004) and a Subject-Action-Object (SAO) network (Choi et al., 2011).

However, the most advanced bibliometric approaches depend heavily on expert judgment for evaluation and selection of opportunities. Thus, there have been attempts to improve expert judgments. Qualitative techniques from other disciplines have been introduced to make expert judgment more systematic and comprehensive, and these have been coupled with bibliometric tools, including morphology (Yoon et al., 2014), TRIZ (OuYang and Weng, 2011), and conjoint analysis (Xin et al., 2010). These methods can be used to narrow our focus to valuable and feasible opportunities, but require intensive training and involvement of experts.

Less attention has been paid to other processes. Some researchers have recognized the importance of opportunity information visualization, but they cannot go beyond simple clusters, maps and networks (Shibata et al., 2008; Zhang et al., 2014; Zhu and Porter, 2002). Advanced monitoring methods including real-time Delphi (Gordon and Pease, 2006) and scouting networks (Rohrbeck, 2010) have been suggested, but they are not tightly integrated with TOA in academic disciplines.

Opportunity identification itself has been a primary focus of TOA. However, the issue of practical operationalization forces researchers to broaden the scope of TOA. In response to this trend, some researchers have suggested ways of linking technological opportunities to strategy and planning. Pioneering research in the field of TOA has focused on facilitating expert-based strategic planning methods including TRIZ and brainstorming by providing core keywords and patents related to opportunities (Lee et al., 2008; OuYang and Weng, 2011). Going a step further, recent research has created keyword links between technologies and products, thereby making the link more specific (Yoon et al., 2014).

An important issue related to the appropriateness and usefulness of opportunity information used by strategic planning experts remains unsolved. Many opportunities described by keywords and patents are too ambiguous to be easily used for planning. Thus, in practical strategic planning, several experts must spend a lot of time to understand, evaluate and specify opportunities. They identify key technological performance metrics, select target performance metrics, and create specific plans for R&D and new product development. This time-consuming process decreases R&D planning efficiency while reducing the application value of TOA information. Thus, to boost the practical value of TOA, opportunity information that strategist/planners need should be identified, extracted and provided to them in a suitable form along with the appropriate tools and processes.

3. Methodology

3.1. Research framework

Our method consists of seven phases, as shown in Fig. 1. Once a company is selected, we identify its customized technological opportunities based on Lee et al. (2008, 2014). An expert-based technological attribute-application table is created and used to identify technological opportunities and its technological capability. Using multiple keyword matching, we select relevant and feasible opportunities customized to

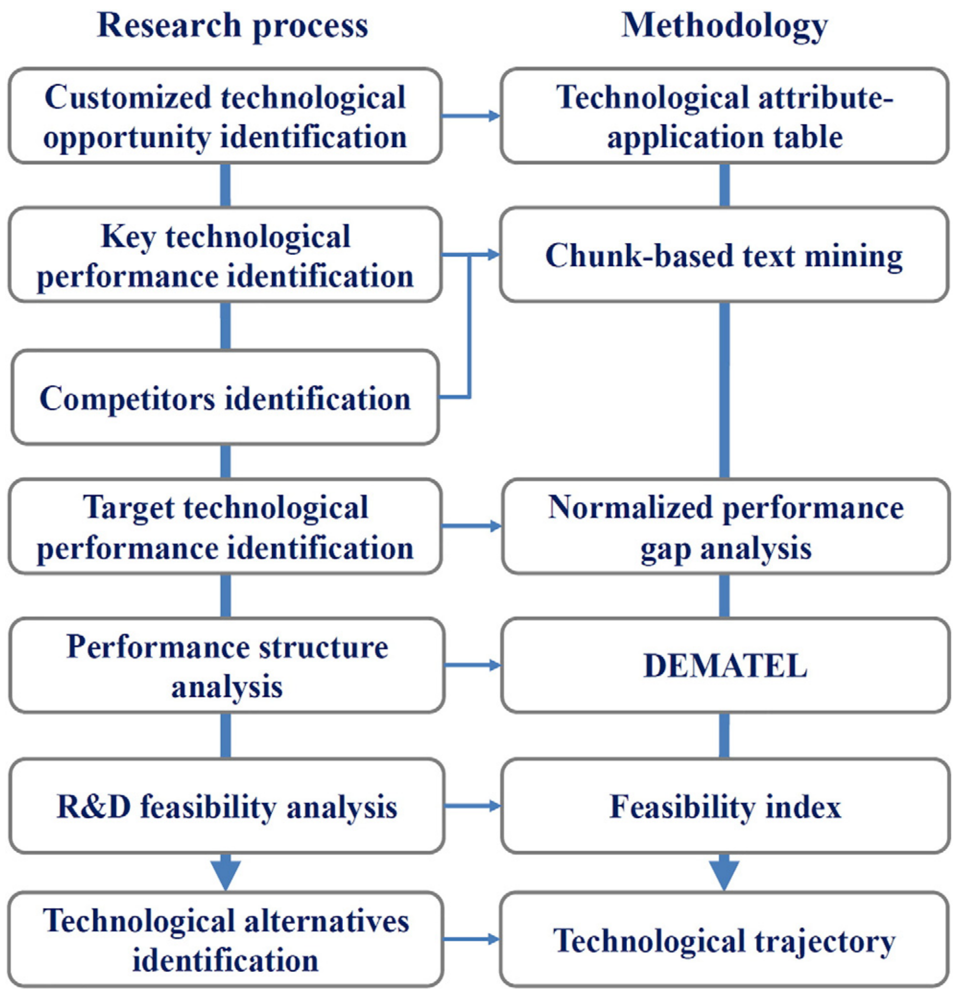

Fig. 1. Research framework.

the company. Focusing on these opportunities, five experts create a list of key product/technological performance metrics. Quantitative product/technology performance data are retrieved and collected from patents and technological documents by using chunk-based text mining. If unexpected performance information is found, then experts examine the data and improve the list. These processes are iterated twice to make the list more comprehensive and up-to-date. Then, we identify key competitors including technology and market leaders by combining performance data with patent assignee information.

To gain a technological advantage, the company must identify target technological performance metrics that should be achieved to catch up with competitors. Thus, we measure the performance gap between the focal company and competitors, and select target technological performance metrics that are crucial to competition. The performance gap is normalized to compare the importance of various performance metrics. However, different target performance metrics can result in synergies, but may also involve conflicts or trade-offs. Thus, we quantify causal relationships among performance metrics using DEMATEL as the performance structure, and we rank technological performance metrics based on their overall effects. At this point, we can select target technological performance metrics to maximize the sum of total positive effects while minimizing negative effects.

Due to budget constraints, companies are forced to focus on more feasible technological performance metrics that can be achieved based on their technological capabilities because R&D failures can result in significant losses. We developed an R&D feasibility index to measure the feasibility of technological performance metrics and evaluate their R&D priority. The R&D feasibility index is defined as the ratio of corporate R&D capability to the normalized performance gap. Given clear target technological performance metrics, there are always debates on what R&D solutions are appropriate. To facilitate this process, we generate patent-based technological trajectories of different technological alternatives of solutions, visualize these, and thus help the R&D planning team easily recognize the advantages, feasibility and limitations of each option.

3.2. Customized technological opportunity identification

Some recent research has suggested ways of identifying technological opportunities customized to a particular company (Lee et al., 2008, 2014). Lee et al. (2008) extract core keywords of product and technology attributes over three periods and used these to generate a keyword evolution map. Using this map, experts can understand the dynamics of key product/technology attributes, identify better opportunities for an organization, and then create technology/product roadmaps. This method can retrieve product/technology attribute data from patents, but is subject to the typical drawbacks of expert judgments because it depends on experts for customized opportunity identification and evaluation.

Lee et al. (2014) improved this approach by using a combination of action-object (AO) analysis and structured expert judgment. Experts construct a technological attribute-application table in some technology discipline, and identify basic opportunities. AO analysis finds additional technological attributes, applications, and relevant new opportunities. A set of expanded opportunities is created. Key technological attributes of a focal company are extracted from their patents, and are matched with the expanded set of opportunities. Then, some opportunities are identified that are customized to a company's technological capability. This method has the advantages of reducing the negative effects of bounded knowledge and subjective bias and utilizing existing technological capability.

Lee et al. (2014) addressed the need for opportunity information customized to a company better than Lee et al. (2008). Thus, we use the method by Lee et al. (2014). However, it does not consider product performance metrics that must be included for product/technology planning. Thus, we added a column of key product performance metrics for possible business applications in the technological attribute-application table.

3.3. Chunk-based text mining

Text chunking is used to divide sentences into non-overlapping segments called chunks (Abney, 1992). This method can identify non-recursive portions of noun phrases (NP chunks), and thus is useful for specific entity recognition and extracting relevant information (Zhang et al., 2002). When there are not many patterns of NP chunks and assuming they can be easily identified by experts, the rule-based chunking approach is efficient and appropriate (Aggarwal and Zhai, 2012). However, it is of little use when experts have difficulty recognizing the pattern.

Rule-based methods generally proceed as follows (Aggarwal and Zhai, 2012). A set of rules composed of a pattern and an action is defined by experts. A pattern is a regular expression defined by tokens and features. An action usually identifies a specific entity and labels the entity as a sequence of tokens. Text is broken into words, phrases, symbols and other meaningful elements called tokens. Then, each token is represented by a set of features. Text is compared against the rules, and the specified action is made if a pattern is found in the text.

For instance, we can define a pattern as a sequence of an article or a possessive case (pc) of a pronoun, any number of adjectives (adj), and a noun. Whenever the algorithm finds this pattern in the text, the action is to label these tokens as an NP-chunk. As shown in Fig. 2, this rule finds two NP-chunks comprising 'the new material' and 'its thermal safety' in the example sentence.

3.4. Decision making trial and evaluation laboratory (DEMATEL)

DEMATEL was developed by Fontela and Gabus through the Science and Human Affairs Program of the Battele Memorial Institute of Geneva. DEMATEL can recognize causal relationships among evaluation criteria, thereby identifying key criteria to maximize the effectiveness of solutions (Fontela and Gabus, 1976). Thus, DEMATEL has been used to solve a number of complex problems including decision making, marketing strategies, airline safety measurements, hospital service management and others (Chiu et al., 2006; Liou et al., 2007; Shieh et al., 2010). Other multi-criteria decision analysis methods (such as analytic network processes) can measure the influences of one variable over others, but they have difficulty identifying complex causal relationships among variables. DEMATEL can overcome such weaknesses by quantifying direct, indirect, and interdependent relationships among variables (Lee et al., 2013). However, it is subject to the drawback of inadequate weight of causality between objectives because of changing human judgment in uncertain multi-person and multi-criteria decision environments.

Application of DEMATEL proceeds through five phases as follows (Lee et al., 2013; Shieh et al., 2010).

1) Phase 1: evaluation of direct influence between criteria.
Each expert evaluates the direct influence of a criterion on another one based on a pair-wise comparison. The evaluation score can be 0 (no influence), 1 (low influence), 2 (medium influence) to 3 (high influence), or 4 (highest influence). For each expert, an $n \times n$ non-negative matrix X^k is generated, in which x_{ij}^k denotes the influence of the ith criterion on the jth criterion by the kth expert ($1<k<M$). Then, we can obtain the average matrix A, where a_{ij} is calculated as follows.

$$a_{ij} = \frac{1}{M}\sum_{k=1}^{M} x_{ij}^k \quad (1)$$

2) Phase 2: normalization of direct influences.
Multiplying the matrix A by S, we can obtain the normalized matrix N. S is defined as follows.

$$S = \text{Min}\left[\frac{1}{\max(1 \le i \le n)\sum_{j=1}^{n} a_{ij}}, \frac{1}{\text{maxmax}(1 \le j \le n \sum_{i=1}^{n} a_{ij}}\right] \quad (2)$$

3) Phase 3: calculation of total influences.
Given the normalized direct influence matrix, N, the second indirect influence matrix is N^2. Thus, the total influence matrix T can be obtained as follows.

$$T = \lim_{n \to \infty}\left(N + N^2 + \ldots + N^n\right) = N(I-N)^{-1} \quad (3)$$

4) Phase 4: calculation of the total influence of a criterion.
In matrix T, the ith row sum (r_i) represents the total direct and indirect influences by the ith criterion. Also, the jth column sum (c_j)

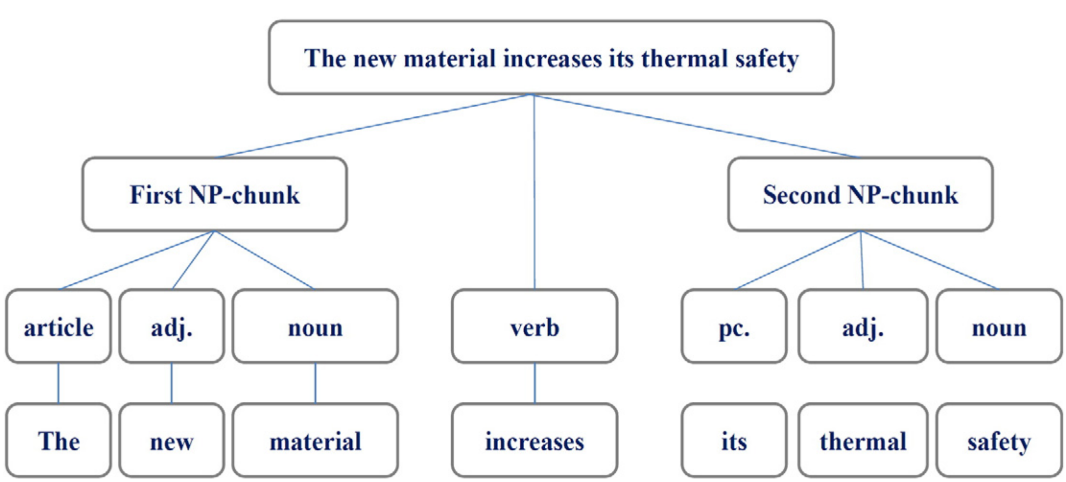

Fig. 2. Example of rule-based NP-chunks identification.

shows the total influences of other criteria on the jth criterion. Thus, adding r_i to c_i, we can obtain the total influence given and received by the ith criterion. If r_i is larger than c_i, the ith criterion is a net cause. An r_i value that is less than the corresponding c_i makes the ith criterion a net effect.

5) Phase 5: generation of a cause and effect diagram
The threshold value is used to eliminate minor causes and effects. Then, a cause and effect diagram is generated by mapping all coordinates of $(r_i + c_i, r_i - c_i)$, or simply by visualizing the causal relationships among criteria.

4. Empirical analysis

4.1. Background: membrane technology and Company A

Membranes are used as selective barriers for separation of individual substances or mixtures. Membranes have the advantage of less energy consumption than thermal separation methods, including distillation and crystallization. Also, membranes can separate some chemicals that cannot be separated by thermal methods. Thus, membrane technology is widely used in various fields, including medical dialysis, waste water treatment, food purification and other applications. Recently, the application areas for membranes have been widened to include secondary batteries and fuel cells.

The performance of a membrane is governed by its pore characteristics (Khulbe et al., 2008). The pore characteristics depend mainly on the material and pore diameters. Thus, membranes can be divided into four classes based on pore diameter. When a pore diameter is less than one nanometer (nm), it can remove salt and small organic molecules by reverse osmosis. A membrane with a pore size between 1 and 2 nm can be used in nanofiltration processes and can separate viruses and ions. Microfiltration is used to remove bacteria, proteins and other contaminants when the pore diameter of a membrane ranges from 2 nm to 100 nm. A membrane with pore sizes larger than 100 nm can remove particles and yeast by means of a microfiltration process.

Membranes can also be distinguished based on material. Polymeric membranes have been widely used in practical applications because they are low cost and provide superior separation performance. Ceramic membranes are better at removing toxic and aggressive substances with better thermal stability, and thus have been used in situations where such substances exist in high temperature operations.

Company A has been developing hydrophobic membranes made of polyethylene and polyethylene terephthalate for waste water treatment. Its membranes have excellent chemical and microbial resistance, and can exhibit a hydrophilic nature when air is introduced into the micropores of the membrane. Company A is a supplier for several large companies because of these technical advantages, and thus has annual sales of about US$260 million. However, it cannot keep growing due to the saturated domestic market, and it is also struggling to find financing. In other words, the company has difficulty in the areas of market expansion and new technology-based growth. This is a typical small company, and it must find new technological opportunities while utilizing existing technology where possible.

4.2. Data

Our method requires bibliometric data and several experts. Five experts were involved in identifying opportunities, technological performance metrics and competitors. They also reviewed the results of the following tasks: target performance metrics identification, performance structure analysis and feasibility evaluation. When analytic results are in conflict with their knowledge, they examine the analytic processes and data. The panel of experts consisted of two researchers, one R&D strategist, one manufacturing expert and one sales manager in the focal company. They all had more than five years of experience, and there were only small differences in age and position rank.

In bibliometric analysis, there have been debates on the advantages and disadvantages of using patents as a proxy for technological innovation as well as capability, but there is a consensus that patents are better than other documents in terms of information quantity, quality and standardization (Griliches, 1990; Jaffe and Trajtenberg, 2002). We selected the United States Patent and Trademark Office (USPTO) database to review because membrane technologies are more often documented in the USPTO than in other patent offices. However, recent performance data cannot be found in patents because of the time-lag between R&D and patenting (Nagaoka et al., 2010). To compensate for this weakness, 91 internal technology reports, magazine articles, and other technology documents related to competitors were also collected.

4.3. Customized technology opportunity identification

Guided by the work of Lee et al. (2014), the researchers and five experts created the technological attribute-application table shown in Appendix A. As shown, 6023 USPTO membrane patents were collected by using a two-stage forward citation process (Von Wartburg et al., 2005). Company A has two US, and seven Korean patents for hydrophobic membrane technology. These patents represent its existing technological capability. Thus, using these patents, we extracted keywords for technological attributes related to the material, shape, and separation process. Matching these with keywords of opportunities in the technological attribute-application table, we identified suitable technological opportunities for the focal company.

Battery separators and fuel cells were selected as opportunities to utilize existing technological capability more so than the others in Table 1. Company A's membrane technology uses the same material, has the same shape, and adopts a similar separation process. It has better thermal stability performance than others in the wastewater treatment market. Thus, thermal stability could be an advantage to exploit for new opportunities. Additionally, challenges also become clear. Company A has little technological capability for lithium separation, and this may represent a technological challenge or opportunity. Polymer electrolyte membrane fuel cells are another opportunity, but these require other electrical and mechanical technologies such as inverters and reformers. Considering the existing technological capability of Company A, experts decided that the opportunity in battery separators is more appropriate.

4.4. Key technological performance identification

To expand the column of product performance metrics in the technological attribute-application table, the five experts created a list of product performance metrics, technological performance metrics and units of performance measurement. Using this, we developed a rule-based method for NP-chunk identification to extract performance information from 1319 USPTO patents about battery separators using membrane technology. We used this method to improve the list. Technological performance data are typical NP chunks including performance (noun), figures, and units of measurement (a mix of nouns, symbols and figures). Our rule defines four patterns: 1) any number of performance keywords (adjectives or nouns) with figures followed by a unit of measurement, 2) any number of figures followed by a unit of measurement, 3) iterations of any number of figures followed by a unit of measurement, and 4) iterations of any number of performance keywords and figures followed by a unit of measurement. This rule says that an NP-chunk is formed whenever our algorithm finds such patterns. NP-chunks are automatically labeled as product/technological performance metrics, patent assignees and year of patent application, and they are then stored in the database.

Our algorithm often finds NP-chunks for either new performance keywords or units of measurement. Reviewing these, experts improved the keyword list of units and performance metrics. Then, a new search begins to improve the performance data. This process is iterated twice

Table 1
Customized opportunity for Company A.

Material	Shape	Substances to be separated	Separation process	Product performance	Application
Polyethylene[a] (PE)	Film[a]	Lithium	Ion[a], electrolyte, anode, cathode	Capacity Thermal safety[a]	Battery separator
PET[a] (polyethylene terephthalate),	Film[a]		Ion[a], electrolyte, anode, cathode	Capacity Thermal safety[a]	Fuel cell

[a] Same with keywords of Company A's technological capability extracted from its patents.

until no new keywords are found. The final list includes all similar keywords as shown in Table 2. There are six key technological performance metrics: shrinkage, melting point, punctual strength, tensile strength, thickness and air permeability.

4.5. Competitor identification

Note that the objective of R&D planning in Company A is to gain a technological advantage in a specific market segment. Thus we selected a target market segment, and identified key competitors using our technological performance data and input from experts. The battery separator market can be divided based on size. Small batteries are used in electric watches, mobile phones, notebooks and other small devices. Medium and large batteries usually power automobiles, submarines and other vehicles, and they are also used in energy storage systems. We divided our patent data into two groups consisting of small and medium/large batteries using these keywords related to usage and battery size.

Combining our technological performance data with patent assignee information, we identified key competitors in each group. Asahi Kasei, Tonen and SK innovation are active key competitors in the small battery market, and they account for more than 70% of the market share. The medium/large battery market is more fragmented. Key competitors include Ube, Mitsubishi, Sumitomo, LG Chemical, Vielene, Evonik and Celgard.

To identify a target market, we measured the gap in technological performance metrics between Company A and the market average. For each technological performance metric in a specific market, the market average equals the sum of technological performance for the above-mentioned competitors divided by the number of competitors. In Table 3, Company A's performance is closer to average in the small battery market than in the medium/large battery market. In other words, there might be high hurdles to achieve technological performance metrics required to compete in the medium/large battery market. Thus, Company A may pursue technological opportunities in the small market with less R&D effort while more effectively utilizing its existing technological capability.

Once the small battery market was identified as the target market, we had to find key competitors because their technological performance metrics would provide the basis for R&D targets. We defined three kinds of key competitors: 1) market leaders, 2) technology leaders and 3) survivors. A company that has the largest market share is defined as the market leader. Similarly, the technology leader has at least one best technology performance among the six key performance metrics. Survivors have the worst technology performance, but retained its market share more than three years.

As shown in Table 4, Company A has better technological performance metrics than the survivor, and thus has the minimum technological performance metrics required to enter this market. However, compared with the leaders, it must increase the performance metrics related to the melting point, shrinkage, and air permeability. Company A has advantages in terms of punctual strength, tensile strength and thickness. However, target technological performance metrics cannot be determined because the required performance to gain a competitive technological advantage is not clear.

4.6. Target technological performance identification

The absolute difference in technological performance between the focal company and market/technology leaders is not enough to select target technological performance metrics. R&D planning must determine how the company can achieve a competitive advantage against key competitors. To achieve this objective, the target technological performance can be used to differentiate technologies/products. Also, six key technological performance metrics have different units of measurement.

Considering this, we normalized all performance metrics of Company A by scaling between 0 and 1. The performance gap between company A and the market leader is then divided by the performance gap between the technology leader and the worst technology performance player. Note that Company A has better punctual strength and thickness than the technology leader, as shown in Table 5. These absolute performance gaps are negative, implying that Company A has technological advantages. Normalized performance gaps between Company A and the market leader show that it must improve air permeability, melting point and shrinkage to compete with the market leader. Considering this, we can narrow target technological performance metrics down to air permeability, shrinkage and melting point.

4.7. Performance structure analysis

R&D must create synergies among technological performance metrics while minimizing their conflicts to increase R&D effectiveness

Table 2
Product performance, technological performance and unit of measurement.

Product performance	Technological performance	Unit of measurement
Thermal stability	Shrinkage	%, percent, percentage
	Melting point (melt integrity, melting temperature, melt-down)	degree C, degrees C, degree, degrees
Mechanical stability	Puncture strength (puncture resistance, resistance to puncture) Tensile strength (tensile elongation, tensile modulus)	N cm sup^{-1}, b kg cm sup^{-2}, kPa, g/Denier, %, g/d, psi Newtons/m, kg f/mm·sup^{-2}, N/cm, g/mil, kg f/mil, Newtons, mN/25 mu·m, g f, grams/25 mu·m; N/mu·m, kg/mm, Pa, mil, grams, psi g, g/mu·m, N, grams/mil, N/50 mm, grams force per mil, cN/mu·m·Mpa
Capacity	Thickness	μm, mu·m, mm, micron, microns, mu, N m, inches, inch, Angstroms, micrometers, mils, ANG, mil, nanometer
	Air permeability (gas permeability, Gurley number, MacMullin number)	sec, seconds/100 cc, sec/100 cm^3, cm/s, sec/100 cm^3, cc/cm·sup^{-2}/s, cfm/ft·sup^{-2} s/100 mL, sec/10 ml, sec/10cm^3, m·sup^{-3}/min/m·sup^{-2}, sec/100 cm·sup^{-3}, mm Hg

Table 3
Technological performances level of company a against market average.

Technological performance (units)	Market average		Company A	Relative performance level of Company A	
	Small size	Medium/large size		Against small market average	Against medium/large market average
Melting point (°C)	186.7	212.3	185.00	99%	85%
Shrinkage (%)	3.03	2.9	5.00	61%	59%
Punctual strength (N/20 mu·m)	3.27	1.7	2.50	69%	67%
Tensile strength (kg f/cm·sup^{-2})	1233.3	707.5	1025.00	80%	69%
Air permeability (sec/100 cm^3)	255.0	156.0	240.00	94%	65%
Thickness (mu·m)	20.3	28.6	20.60	99%	61%

(Valderrama and Mulero-Mendigorri, 2005). Thus, we must identify causal relationships among target technological performance metrics to maximize performance metrics.

To address this issue, we used a slightly modified DEMATEL that has no assumptions about negative influences. Relaxing this assumption, we allowed influences to be either positive or negative, which allowed us to quantify synergies and trade-offs among performance metrics. Five experts were asked to evaluate the direct influences between six technological performance metrics by a score from −3 (high negative influence) to 0 (no influence) to 3 (high positive influence). We created the average matrix, normalized it, and obtained the total relationship matrix shown in Table 5.

Two negative causes were recognized. If Company A makes its membrane thinner or more air permeable, it will reduce thermal and mechanical stability. However, it can improve thermal and mechanical stability without hurting other performance metrics. Six performance metrics were ranked based on their total effect. Shrinkage had the only positive total effect as well as the largest causal effect. Therefore, it should be considered as the first priority for R&D. Melting point was in the second position. As shown in Table 5, Company A must improve these two performance metrics to catch up with key competitors. Thus, to maximize R&D effectiveness for market penetration, the strategy should focus on the shrinkage and melting point.

Air permeability is difficult to improve, but is of great importance for competition. To be on the leading edge in the battery separator market, Company A must achieve a technological advantage in air permeability performance. However, higher air permeability has a negative effect on other key performance metrics. Also, deviations from uniform permeability might produce uneven current density distribution, thereby causing the formation of crystals on the anode. In other words, R&D to improve air permeability is a high-risk and high-return investment (Table 6).

4.8. R&D feasibility analysis

In many cases, some technological performance objectives cannot be achieved due to a lack of R&D capability. Target technological performance is of little use for gaining a technological advantage if R&D fails to achieve it. Thus, under budget constraints, R&D planning must be both effective and efficient (Braunschweig and Becker, 2004). In other words, R&D priority should be given to more feasible technological performance metrics than others to reduce R&D failures.

Considering this, we evaluated the R&D feasibility of three key technological performance metrics for Company A. The R&D feasibility index is defined as the ratio of corporate R&D capability to the normalized performance gap. Higher R&D capability and small performance gaps increase the feasibility of closing the performance gap.

Five experts rated the R&D capability of Company A to improve each technological performance metric. The ratings ranged from 0 (no capability), 0.2 (little capability), 0.5 (weak capability), 0.7 (strong capability to achieve the target), and 1 (same capability as the leader). Normalized performance gaps between the focal company and market leader, shown in Table 5, were used. As shown in Table 7, Company A can easily reach the melting point performance of the market leader, but it has difficulty in improving air permeability up to the same level. Considering R&D efficiency more than effectiveness, the company established an R&D priority order of melting point, shrinkage and air permeability.

4.9. Identification of technological alternatives

Given important and feasible target technological performance metrics, the next task of R&D planning is to decide how those performance targets can be achieved. Benchmarking of leading companies is usually used to identify the principal methods. To reduce the burden of this time-consuming process, we created technological trajectories of key competitors in the target performance space using our performance data. The horizontal axis represents time, and the vertical axis represents the target performance. We can understand the advantages and disadvantages of several methods, and thus choose the most appropriate method for the focal company by comparing the dynamics of performance improvement for key competitors over the last few years.

Fig. 3 shows the technological trajectories of Sumitomo, Mitsubishi, LG, Evonik, Asahi Kasei and Tonen. As mentioned previously, these companies are key competitors in the small and medium/large size battery markets. Another common characteristic is that they have the top thermal stability performance metrics (melting point) compared to others. Note that the melting point is the target performance for Company A to maximize its R&D efficiency.

In the small battery market, the co-extrusion of polymer and another head-resistant material is a typical dry production method, and this has been used by several companies in the 2000s. However, its performance improvement is close to a limit of 200 °C. Nonwovens composed of a sheet, web, or mat of directionally oriented fibers were attractive methods in the early 2000s, and these broke the ceiling of 200 °C. These materials had superior performance compared to others, even in 2012, but the performance has not improved much recently. The inorganic composite method was an emerging technology in 2010, and has shown steady performance increases over the last several years. It

Table 4
Technological performances of market leader, technology leader, and survivor.

Technological performance	Market leader	Technology leader	Survivor	Company A
Melting point (°C)	195.67	288.50	171.00	185.00
Shrinkage (%)	1.77	0.25	6.15	5.00
Punctual strength (N/20 mu·m)	1.93	2.25	1.30	2.50
Tensile strength (kg f/cm·sup^{-2})	687.00	1108.00	307.00	1025.00
Air permeability (sec/100 cm^3)	116.67	75.00	245.00	240.00
Thickness (mu·m)	23.12	20.75	38.93	20.60

Table 5
Absolute and normalized performance gap.

Technological performance (units)	Absolute performance gap		Normalized performance		Normalized performance gap
	Market leader—Company A	Technology leader—Company A	Company A	Market leader	Market leader—Company A
Melting point (°C)	10.67	103.5	0.12	0.21	0.09
Shrinkage (%)	3.23	4.75	0.19	0.74	0.55
Punctual strength (N/20 mu·m)	−0.57	−0.25			
Tensile strength (kg f/cm·sup^{-2})	−338.00	83	0.89	0.47	−0.42
Air permeability (sec/100 cm^3)	123.33	165.00	0.03	0.75	0.72
Thickness (mu·m)	−2.52	−0.15			

also cannot overcome the barrier of 200 °C. Sumitomo has developed expanded polymer films with better elastic recovery and heat resistance by using their own dry process. This method has the best thermal stability, but is too difficult to develop. Company A can choose the co-extrusion and inorganic composited methods, but might face limitations in performance improvement in the near future.

5. Discussion

Our method does not simply link opportunity information from bibliometric analysis to expert-based R&D planning. In such simple linking approach, the experts must be extensively involved in the whole process of bibliometric information evaluation, analysis and integration. This has the advantage of overcoming bounded knowledge and subjective judgment, but in many cases, there are few differences in the results. Considering the tremendous effort required for bibliometric data collection, analysis and expert involvement, some corporate managers have doubted the effectiveness and efficiency of the method.

However, leading companies successfully combine bibliometric information with a human-centered approach to create an improved corporate foresight process that includes technological opportunity identification, technology strategy, R&D planning and business planning (Heger and Rohrbeck, 2012; Rohrbeck, 2010). Bibliometric information is provided to experts in an appropriate context, and thus improves expert judgment while increasing efficiency of foresight, strategy and planning. Well-designed information integration is crucial to such success, and is also crucial to the operationalization of TOA.

The effectiveness and efficiency of R&D planning depends on the appropriateness of target technological performance metrics and R&D solutions. Focusing on this, we extracted key technological performance metrics information from bibliometric data and converted it to an easily understandable and usable form for strategists and R&D experts. Also, sequential processes were designed to complement the analytic output in the previous process. For instance, target technological performance identification cannot consider the causal relationships among performance metrics. The performance structure analysis revealed their synergies and trade-offs, thereby increasing the usefulness and reliability of the analytical results.

In our membrane case, all five experts concurred that they did not have to collect other complementary data because the information related to performance metrics and competitors was reliable. Also, they appreciated the ease of use and usefulness of the three analytic tools, which included the normalized performance gap analysis, feasibility index and technological trajectory. Rather than consisting of an open discussion and simple scoring method, these tools helped make the process of strategy and planning less difficult and time-consuming while reducing biases such as the bandwagon effect, bounded knowledge and subjective judgment.

In previous R&D planning sessions, Company A used about 400 man-hours (five experts and 80 h per each expert) to complete the first R&D plan. Simple brainstorming and open off-line discussion were used. Using our approach, five experts took 290 man-hours. This time reduction (27.5%) is mainly due to reduced information asymmetry and bounded rationality among experts. Experts have limited information regarding technological performance metrics, their relationship and competitors. Therefore, they need considerable time to share their information. Given comprehensive and structured information by bibliometric analysis, they could focus on evaluating technological alternatives while cutting the discussion time down by more than 60%.

However, they had difficulty in using DEMATEL because the scaling can vary from expert to expert. A model to quantify the causal relationships among performance metrics figures would be more practically useful. Another complaint was that the pros and cons of technological alternatives were not provided in an integrated form. A visualization tool that compares alternatives based on several criteria would meet their needs well.

Two challenges became apparent in our approach. Above all, it is difficult to use the best experts in other departments. Heads of other departments recognize the importance of R&D planning, but are not always willing to assign the best experts to their core tasks. This increases the risk of a technology performance-oriented R&D plan with little consideration for product feasibility and market need. Another challenge is to design cross-departmental communication protocols between experts and bibliometric analysts. Communication mistakes frequently occur due to differences in culture and expertise, and this can slow the process. Top management commitment, problem identification and action plans must be carefully implemented to deal with these challenges.

From a strategic perspective, the goal of our approach is to set an R&D plan to gain a technological advantage against competitors. This might be suitable for either small or medium companies to obtain competitive advantages in the business-to-business market because either better technological performance or low cost can be achieved through

Table 6
Total relation matrix of key technological performances.

Effect Cause	Thickness	Air permeability	Shrinkage	Melting point	Puncture strength	Tensile strength
Thickness	0.	0.1515	−0.2304	−0.2209	−0.2670	−0.3579
Air permeability	0	0	−0.1704	−0.2128	−0.2050	−0.2050
Shrinkage	0	0	0.0009	0.1836	0.0723	0.0723
Melting point	0	0	0.0343	0.0062	0.0631	0.0631
Puncture strength	0	0	0.0306	0.0056	0.0022	0.0022
Tensile strength	0	0	0.0306	0.0056	0.0022	0.0022
Causal effect	−0.9248	−0.7933	0.3383	0.1667	0.0406	0.0406
Total effect	−0.9248	−0.6418	0.0429	−0.0066	−0.2917	−0.3826

Table 7
R&D feasibility evaluation.

Criteria	Melting point	Shrinkage	Air permeability
Normalized performance gap (Company A—market leader)	0.09	0.55	0.72
R&D capability	0.62	0.88	0.28
R&D feasibility index	6.89	1.6	0.39

a technology-oriented R&D plan. However, in the business-to-consumer markets, technological advantages do not always result in competitive advantages because product value and customer satisfaction are dependent on other factors, including design and brand image. Thus, market and customer information must be collected, analyzed and provided to a broader pool of experts, including marketing managers and designers.

A large company has its full lineup of products in a specific market segment, and often runs businesses across industries. These types of companies should compare a number of technological opportunities, and utilize their existing capabilities across different business units and R&D organizations. Our method has limitations and may not be able to deal with such complex processes. Therefore, it needs to be extended to use complex concepts and models including portfolios, system dynamics, road mapping and other strategies.

6. Conclusion

Focusing on the weak link from TOA to practical R&D planning, we suggested a practical way of strengthening it. Using our method, R&D experts can reduce their efforts to determine the best customized R&D plan because the information that they need is provided in a suitable form. Compared with simple brainstorming and open discussion, our approach reduced time for R&D planning by more than 25% while identifying two more technological alternatives in our membrane case. Biases associated with human-centered approaches and lack of reliable data were also reduced.

Thus, we can increase R&D efficiency as well as effectiveness while reducing expert involvement in selection and evaluation of technological opportunities. Therefore, TOA can be more valuable in strategy and planning practices. Some important R&D project selection criteria, including R&D feasibility and technological performance, were used to select target technological performance metrics and R&D methods in the R&D planning process. This method can facilitate the next process of R&D project selection, making the overall R&D process faster and more efficient.

Academic contributions come mainly from clarification of the linkage between TOA and R&D planning. We identified key information for R&D planning, provided appropriate tools and processes to extract such information from bibliometric data, and suggested how this information can be converted to a suitable form for R&D planners and experts. Put differently, we found an integrated form of TOA information analytics that best serves the needs of R&D experts. Also, our systematic approach continuously complements weaknesses in analytic output in the previous process. Thus, a set of data and tools to overcome several bottlenecks in R&D planning were also provided.

Our study has some technical limitations such as using bibliometric data that results in time-lag. Our method might be of little use to short lifecycle technologies less than two years old because the average time-lag between patent applications and grants is more than 18 months. Also, the R&D feasibility indicator cannot compare absolute values. It is only possible to perform relative feasibility comparisons between performance metrics. Chunk-based mining does not cover all performance units and keywords, and thus has difficulty in finding some rarely used but important items. Furthermore, the direct-relation matrix in the DEMATEL to infinite power might not converge to zero. This infeasibility needs to be resolved. Lastly, it should be noted that the effect of our approach on the efficiency improvement needs to be statistically tested.

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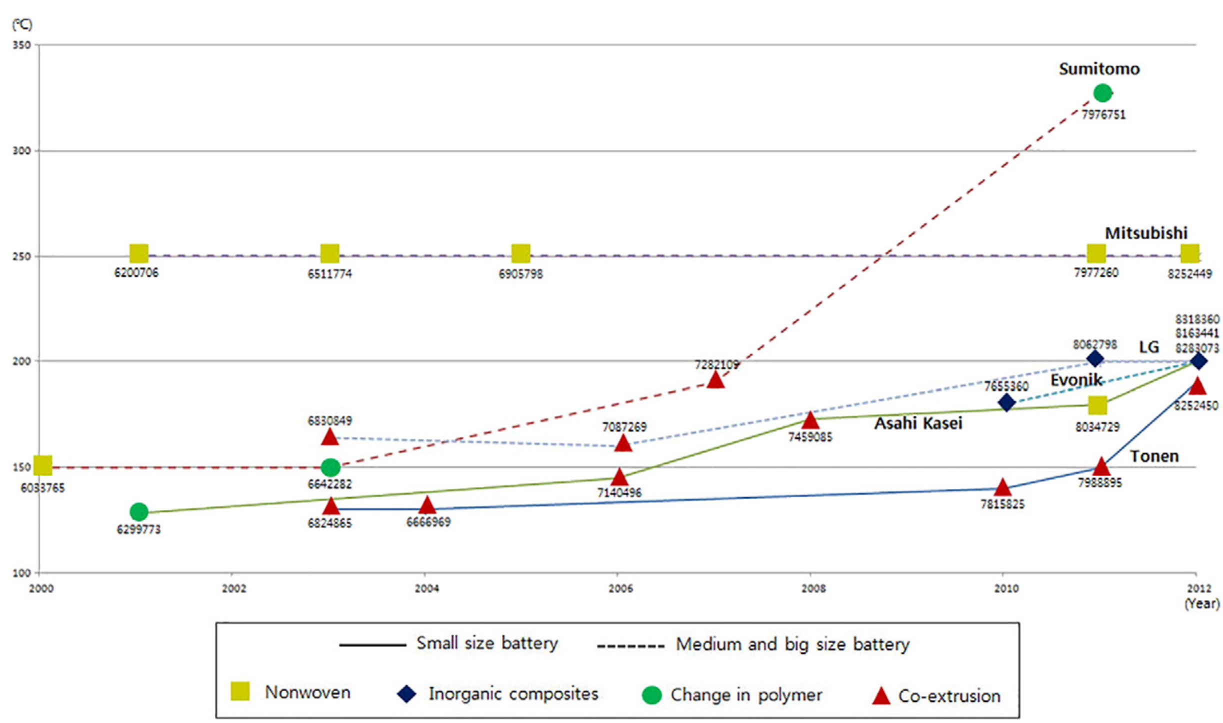

Fig. 3. Technological trajectories of key competitors on the melting point performance.

Appendix A. Technological attribute-application table for membrane technology

Technological attribute					Product performance	Application
Material	Specific material	Shape	Substances to be separated	Separation process		
Polymer	PES (polyethersulfone), PE (polyethylene), PTFE (polytetrafluoroethylene), PVDF (polyvinylidene fluoride)	Film (sheet), fiber	Virus, bacteria, colloid, microorganism, *E. coli*, Giardia, crypto, yeast, sulfate, colloidal DOC, organic microcontaminant	Molecule, microfiltration, ultrafiltration	Purity, selectivity, energy efficiency	Water treatment (filtration)
			Toxin, endotoxin, inulin, uricacid, pathogen		Purity, selectivity	Medical dialysis hemodialysis
	PA (polyamide), cellulose	Film (sheet), fiber, spiral wound	Sodium, chlorine, magnesium, sulfate, metalion, dissolved salts, TDS (total dissolved solids)	Reverse osmosis, electro dialysis	Purity, energy efficiency	Sea desalination
	PTFE (polytetrafluoroethylene), PE, Nafion, Flemion, Aciplex, PI (polyimide), PAI (polyamideimide), PSF (polysulfone), PES (polyethersulfone), PEK (polyetherketone), Polyolefin PEEK (polyetheretherketone), PP (polypropylene), PBI (polybenzimidazole), PZ (polyphosphazene), PVA (polyvinyl alcohol)	Film (sheet), fiber	Hydrogen, proton	Ion, electrolyte, anode, cathode	Capacity, thermal safety	Fuel cell
	PET (polyethylene terephthalate), PVDF (polyvinylidenefluoride)	Film (sheet)	Lithium	Electrolyte, anode, cathode	Capacity, thermal safety	Battery
	PI (polyimide), PSF (polysulfone), cellulose, PC (polycarbonate), PEI (polyetheramide), PET (polyester), PU (polyurethane), polyether, polystyrene, PMMA, PTMSP, PDMS	Film (sheet), fiber, spiral wound	Hydrogen, helium, carbon dioxide, SO_x, NO_x, smog, fumes, dusts, spores, tobacco smoke, bacteria, virus, spores, human hair	Molecule, microfiltration, ultrafiltration	Purity, energy efficiency	Gas separation (air cleaning)
	PVA (polyvinyl alcohol), Chitosan, PAN (polyacrylonitrile)	Fiber	Volatile organic compound (VOC), Benzene, ketone cyclohexane	Osmosis, evaporation, molecule, microfiltration, ultrafiltration	Purity, energy efficiency	Pervaporation
	PU (polyurethane), PVDF (polyvinylidene fluoride), PTFE (polytetrafluoroethylene), PE (polyethylene), PP (polypropylene), PEI (polyetheramide), PET (polyester)	Film (sheet)	Water vapor (breathable, waterproof, water tight, moisture permeability), urine, ammonia	Molecule, microfiltration, ultrafiltration	Thermal safety, chemical safety	Functional garment
Ceramic	Silica (SiO_2), silicon oxide, alumina (Al_2O_3), aluminum oxide, zirconia (ZrO_2), zirconium oxide, titania (TiO_2), titanium oxide, zeolite	Tube, plate (frame)	Virus, bacteria, colloid, microorganism	Molecule, microfiltration, ultrafiltration	Purity, selectivity, energy efficiency	Water treatment (filtration)
			Volatile organic compound (VOC), Bensen, Keton	Osmosis, evaporation, molecule, microfiltration, ultrafiltration	Purity, energy efficiency	Pervaporation
			Hydrogen, helium, carbon dioxide, SO_x, NO_x, nitrogen, smog, fumes, dusts, spores, tobacco smoke, bacteria, virus, spores, human hair	Molecule, microfiltration, ultrafiltration	Purity, energy efficiency	Gas membrane (air cleaning)
	Silica (SiO_2), silicon oxide, zirconia (ZrO_2), zirconium oxide		Hydrogen, proton	Io, electrolyte, anode, cathode	Capacity, thermal safety	Sensor, fuel cell
Metal	Palladium alloy, tantalum alloy, vanadium alloy, niobium alloy	Tube	Hydrogen, helium, carbon dioxide, SO_x, NO_x, nitrogen Smog, fumes, dusts, spores, tobacco smoke, bacteria, virus, spores, human hair	Molecule, microfiltration, ultrafiltration	Purity, energy efficiency	Gas membrane (air cleaning)

References

Abney, S.P., 1992. Parsing by Chunks. Springer, Netherlands.

Aggarwal, C.C., Zhai, C., 2012. Mining Text Data. Springer Science & Business Media, New York.

Albert, M.B., Avery, D., Narin, F., McAllister, P., 1991. Direct validation of citation counts as indicators of industrially important patents. Res. Policy 20, 251–259.

Audretsch, D.B., 1995. Innovation, growth and survival. Int. J. Ind. Organ. 13, 441–457.

Baron, R., Ensley, M., 2006. Opportunity recognition as the detection of meaningful patterns: evidence from comparisons of novice and experienced entrepreneurs. Manag. Sci. 52, 1331–1344.

Braunschweig, T., Becker, B., 2004. Choosing research priorities by using the analytic hierarchy process: an application to international agriculture. R&D Manag. 34, 77–86.

Brenner, M.S., 1996. Technology intelligence and technology scouting. Competitive Intell. Rev. 7, 20–27.

Chiu, Y.J., Chen, H.C., Tzeng, G.H., Shyu, J.Z., 2006. Marketing strategy based on customer behaviour for the LCD-TV. Int. J. Manag. Decis. Mak. 7, 143–165.

Choi, S., Yoon, J., Kim, K., Lee, J.Y., Kim, C.H., 2011. SAO network analysis of patents for technology trends identification: a case study of polymer electrolyte membrane technology in proton exchange membrane fuel cells. Scientometrics 88, 863–883.

Cozzens, S., Gatchair, S., Kang, J., Kim, K.S., Lee, H.J., Ordóñez, G., Porter, A., 2010. Emerging technologies: quantitative identification and measurement. Tech. Anal. Strat. Manag. 22, 361–376.

Day, G.S., Schoemaker, P.J., Gunther, R.E., 2004. Wharton on Managing Emerging Technologies. John Wiley & Sons, New Jersey.

Eckhardt, J.T., Shane, S.A., 2003. Opportunities and entrepreneurship. J. Manag. 29, 333–349.

Érdi, P., Makovi, K., Somogyvári, Z., Strandburg, K., Tobochnik, J., Volf, P., Zalányi, L., 2013. Prediction of emerging technologies based on analysis of the US patent citation network. Scientometrics 95, 225–242.

Fontela, E., Gabus, A., 1976. The DEMATEL Observer. Battelle Institute, Geneva Research Center.

Fujita, K., Kajikawa, Y., Mori, J., Sakata, I., 2014. Detecting research fronts using different types of weighted citation networks. J. Eng. Technol. Manag. 32, 129–146.

Gerken, J.M., Moehrle, M.G., 2012. A new instrument for technology monitoring: novelty in patents measured by semantic patent analysis. Scientometrics 91, 645–670.
Gordon, T., Pease, A., 2006. RT Delphi: an efficient, "round-less" almost real time Delphi method. Technol. Forecast. Soc. Chang. 73, 321–333.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. National Bureau of Economic Research No. w3301.
Heger, T., Rohrbeck, R., 2012. Strategic foresight for collaborative exploration of new business fields. Technol. Forecast. Soc. Chang. 79, 819–831.
Huang, L., Zhang, Y., Guo, Y., Zhu, D., Porter, A.L., 2014. Four dimensional science and technology planning: a new approach based on bibliometrics and technology roadmapping. Technol. Forecast. Soc. Chang. 81, 39–48.
Hung, S., Chu, Y., 2006. Stimulating new industries from emerging technologies: challenges for the public sector. Technovation 26, 104–110.
Jaffe, A.B., Trajtenberg, M., 2002. Patents, Citations, and Innovations: A Window on the Knowledge Economy. MIT Press, Cambridge, MA.
Johnson, P., 2000. Information sources in gray literature. Libr. Collect. Acquis. Tech. Serv. 24, 512–513.
Kerr, C.I.V., Mortara, L., Probert, D.R., 2006. A conceptual model for technology intelligence. Int. J. Technol. Intell. Plan. 2, 73–93.
Khulbe, K.C., Feng, C.Y., Matsuura, T., 2008. Synthetic Polymeric Membranes: Characterization by Atomic Force Microscopy. Springer-Verlag, Berlin Hidelberg.
Kirzner, I.M., 1997. Entrepreneurial discovery and the competitive market process: an Austrian approach. J. Econ. Lit. 35, 60–85.
Klevorick, A.K., Levin, R.C., Nelson, R.R., Winter, S.G., 1995. On the sources and significance of interindustry differences in technological opportunities. Res. Policy 24, 185–205.
Kostoff, R., 2001. Text mining using database tomography and bibliometrics: a review. Technol. Forecast. Soc. Chang. 68, 223–253.
Lee, S., Lee, S., Seol, H., Park, Y., 2008. Using patent information for designing new product and technology: keyword based technology roadmapping. R&D Manag. 38, 169–188.
Lee, S., Yoon, B., Lee, C., Park, J., 2009a. Business planning based on technological capabilities: patent analysis for technology-driven roadmapping. Technol. Forecast. Soc. Chang. 76, 769–786.
Lee, S., Yoon, B., Park, Y., 2009b. An approach to discovering new technology opportunities: keyword-based patent map approach. Technovation 29, 481–497.
Lee, H.S., Tzeng, G.H., Yeih, W., Wang, Y.J., Yang, S.C., 2013. Revised DEMATEL: resolving the infeasibility of DEMATEL. Appl. Math. Model. 37, 6746–6757.
Lee, Y., Kim, S.Y., Song, I., Park, Y., Shin, J., 2014. Technology opportunity identification customized to the technological capability of SMEs through two-stage patent analysis. Scientometrics 100, 227–244.
Lee, C., Kang, B., Shin, J., 2015. Novelty-focused patent mapping for technology opportunity analysis. Technol. Forecast. Soc. Chang. 90, 355–365.
Liou, J.J., Tzeng, G.H., Chang, H.C., 2007. Airline safety measurement using a hybrid model. J. Air Trans. Manag. 13, 243–249.
Nagaoka, S., Motohashi, K., Goto, A., 2010. Patent statistics as an innovation indicator. Handb. Econ. Innov. 2, 1083–1127.
Newbert, S., Walsh, S., Kirchhoff, B., Chavez, V., 2006. Technology-driven entrepreneurship: muddling through and succeeding with the second product. Entrep. Engine Growth 3, 291–312.
Olsson, O., 2005. Technology opportunity and growth. J. Econ. Growth 10, 35–57.
OuYang, K., Weng, C.S., 2011. A new comprehensive patent analysis approach for new product design in mechanical engineering. Technol. Forecast. Soc. Chang. 78, 1183–1199.
Porter, A.L., Cunningham, S.W., 2005. Tech Mining: Exploiting New Technologies for Competitive Advantage. Wiley, New York.
Porter, A.L., Detampel, M.J., 1995. Technology opportunities analysis. Technol. Forecast. Soc. Chang. 49, 237–255.
Porter, A.L., Newman, N.C., 2011. Mining external R&D. Technovation 31, 171–176.
van Raan, A.F.J., 1996. Advanced bibliometric methods as quantitative core of peer review based evaluation and foresight exercises. Scientometrics 36, 397–420.
Rohrbeck, R., 2010. Corporate Foresight: Towards a Maturity Model for the Future Orientation of a Firm. Physica-Verlag HD, Berlin.
Salo, A., Cuhls, K., 2003. Technology foresight—past and future. J. Forecast. 22, 79–82.
Savioz, P., Blum, M., 2002. Strategic forecast tool for SMEs: how the opportunity landscape interacts with business strategy to anticipate technological trends. Technovation 22, 91–100.
Shibata, N., Kajikawa, Y., Takeda, Y., Matsushima, K., 2008. Detecting emerging research fronts based on topological measures in citation networks of scientific publications. Technovation 28, 758–775.
Shibata, N., Kajikawa, Y., Takeda, Y., Sakata, I., Matsushima, K., 2011. Detecting emerging research fronts in regenerative medicine by the citation network analysis of scientific publications. Technol. Forecast. Soc. Chang. 78, 274–282.
Shieh, J.I., Wu, H.H., Huang, K.K., 2010. A DEMATEL method in identifying key success factors of hospital service quality. Knowl.-Based Syst. 23, 277–282.
Shin, J., Lee, H., 2013. Low-risk opportunity recognition from mature technologies for SMEs. J. Eng. Technol. Manag. 30, 402–418.
Valderrama, T.G., Mulero-Mendigorri, E., 2005. Content validation of a measure of R&D effectiveness. R&D Manag. 35, 311–331.
Von Wartburg, I., Teichert, T., Rost, K., 2005. Inventive progress measured by multi-stage patent citation analysis. Res. Policy 34, 1591–1607.
Xin, L., Jiwu, W., Lucheng, H., Jiang, L., Jian, L., 2010. Empirical research on the technology opportunities analysis based on morphology analysis and conjoint analysis. Foresight 12, 66–76.
Yoon, B., Park, Y., 2004. A text-mining-based patent network: analytical tool for high-technology trend. J. High Technol. Managem. Res. 15, 37–50.
Yoon, B., Park, I., Coh, B.Y., 2014. Exploring technological opportunities by linking technology and products: application of morphology analysis and text mining. Technol. Forecast. Soc. Chang. 86, 287–303.
Zhang, T., Damerau, F., Johnson, D., 2002. Text chunking based on a generalization of winnow. J. Mach. Learn. Res. 2, 615–637.
Zhang, Y., Zhou, X., Porter, A.L., Gomila, J.M.V., Yan, A., 2014. Triple helix innovation in China's dye-sensitized solar cell industry: hybrid methods with semantic TRIZ and technology roadmapping. Scientometrics 99, 55–75.
Zhu, D., Porter, A.L., 2002. Automated extraction and visualization of information for technological intelligence and forecasting. Technol. Forecast. Soc. Chang. 69, 495–506.

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