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A patent portfolio-based approach for assessing potential R&D partners: An application of the Shapley value☆

Bomi Song [a], Hyeonju Seol [b,*], Yongtae Park [c]

[a] Innovation Strategy Division, Korea Institute of Industrial Technology, 89 Yangdaegiro-gil, Ipjang-myeon, Seobuk0gu, Cheonan-si, Chungcheongnam-do, 31056, Republic of Korea
[b] Department of Military Studies, Daejeon University, 62 Daehak-ro, Dong-gu, Daejeon, 16685, Republic of Korea
[c] Department of Industrial Engineering, College of Engineering, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, 151-742, Republic of Korea

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ABSTRACT

We propose a patent portfolio-based approach for assessing potential R&D partners that can consider the inter-partner resource fit in the assessment process. The concept of an integrated patent portfolio is suggested and its value is designed to reflect the resource fit between potential R&D partners. The Shapley value is applied to assess the contribution of each potential partner to the value of the integrated patent portfolio. A case study of a lighting control system is presented to show the feasibility and advantages of our method. Overcoming the weakness of individual capability-focused evaluation of potential R&D partners, our method can better inform decision makers and experts in the partner selection process by enabling more comprehensive assessment of potential R&D partners.

1. Introduction

As the importance of R&D cooperation has increased, partner selection has become a strategic issue for firms (Cowan et al. 2007) since it affects the success of the partnership (Dodgson, 1992; Das and Teng, 2003; Arranz and de Arroyabe, 2008). Careful screening is essential to select the right partners (Dacin et al. 1997), including the entire process from the identification of candidates to the evaluation of their quality (Nijssen et al. 2001). This process inherently involves complex decision-making problems with multiple criteria and uncertainty on the future performance of the partnership. Moreover, the difficulty and the importance of the partner selection process are even more significant given the rapidly changing business environment and the prevalence of cross organizational collaboration. Consequently, recent years have witnessed an increasing need for appropriate data and methods to facilitate the partner selection process.

A large body of literature has endeavored to provide better understanding and implications of assessing and selecting R&D partners by investigating motivations of cooperation (Bayona et al. 2001; Verspagen and Duysters, 2004), determinants of success (Holmberg and Cummings, 2009) and failure (Kogut, 1989; Lhuillery and Pfister, 2009), and heterogeneity according to the partner type (Arranz and de Arroyabe, 2008) and sector (Hagedoorn, 1993). The theoretical and empirical findings in previous studies have accentuated the importance of partner selection and have offered important criteria in identifying appropriate partners. However, a significant drawback is that they have used post-analysis approaches relying on econometric data and/or expert knowledge after performing R&D cooperation. There has been relatively little concern about the methodological support for decision-making in the partner selection process despite the urgent need for methods in practice to reduce the complexity of the partner selection process.

Emphasizing the need for methodological support, some recent studies have attempted to systemize the tasks involved in the partner selection process. While the specific methods suggested by previous studies vary, they have commonly been based on patents as the primary data source. The detailed information conveyed in the patents such as technical, bibliometric, and citation information can support several tasks in the partner selection process. For instance, (Jeon et al. 2011) applied text-mining techniques to patent claims to identify potenital partners who possess the desired technology. (Geum et al. 2013) designed literature-based indexes based on the bibliometric and citation information of scientific publications and patents to search for and assess appropriate R&D partners. Although the validity and utility of a patent-based approach in the partner selection process have proven to be successful to some extent, these studies have a limitation of only considering potential partners' capabilities individually. Because R&D cooperation is an interactive process among partners, both the capabilities

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* Corresponding author.

E-mail addresses: bms1821@kitech.re.kr (B. Song), hjseol@dju.ac.kr (H. Seol), parkyt1@snu.ac.kr (Y. Park).

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of individual participants as well as their compatibility should be examined in the partner search and partner choice process (Gemünden et al. 1999).

From a resource-based point of view, the resource fit between R&D partners has been highlighted as a main motive to cooperate and a crucial factor to create synergy from the cooperation (Das and Teng, 2000). However, to the best of our knowledge, few methodological attempts have been made to assess the resource fit between potential R&D partners. Focusing on resource complementarity, (Wang, 2012) conducted a series of patent analyses to identify complementary technologies for developing particular products and discussed possible partners based on their technological complementarity. However, that work still has some drawbacks in considering resource fit in the partner selection process as follows. First, resource complementarity is an important dimension of resource fit but not the only one. While cooperation with those who have complimentary resources can be a means of filling the resource gap and of creating unexpected innovation from combining unrelated knowledge in different domains (Das and Teng, 2000; Barney, 1991; Rothaermel, 2001), there needs to be preliminary knowledge in the related domains to absorb and utilize the external knowledge (Lane and Lubatkin, 1998). Therefore, R&D partners should have resources that are not only complementary but also similar to each other to some extent (Cohen and Levinthal, 1990). A methodological framework for the partner selection process needs to offer a comprehensive view of resource fit among partners with the capability of reflecting resource complementarity as well as resource similarity. Second, resource complementarity has been qualitatively investigated between two firms by comparing their technological competitiveness in the target technological fields (Wang, 2012). However, R&D cooperation often involves multiple partners, where a complicated task of comparing multiple resource portfolios is required to investigate resource fit among multiple partners. A quantitative approach for modeling and assessing resource fit can be useful to reduce such complexity.

This research proposes a way to consider the inter-partner resource fit in assessing potential R&D partners. A patent portfolio was chosen for this research because it is a representative way of exploring and managing technological resources (Brockhoff, 1992; Ernst, 1998; Ernst, 2003). It enables us to assess firms' competitive positions in a particular technological field as well as examine the composition of their technological resources (Ernst, 2003; Lin et al. 2006). At the heart of our approach for utilizing patent portfolios in the partner selection process is (1) the concept of an integrated patent portfolio in which its value is so designed that the resource fit between potential partners is reflected; and (2) the application of the Shapley value to assess the contribution of each participant to the value of the integrated patent portfolio. The Shapley value is a solution concept in cooperative game theory (Shapley, 1953; Roth, 1990) that offers answers about how important each player is to the overall cooperation and what payoff each player can reasonably expect. Thus, regarding R&D cooperation as a cooperative game to produce an integrated patent portfolio, the application of the Shapley value can present a useful and convenient instrument for evaluating the importance of each participant in creating the value of an integrated patent portfolio.

This paper is organized as follows. Section 2 presents the related work on partner selection in R&D cooperation, patent portfolio analysis in managing technological resources, and background of the Shapley value. The proposed approach is explained in Section 3, and illustrated in Section 4 with the case of a lighting control system. Finally, the conclusions are presented in Section 5.

2. Background

2.1. Partner selection in R&D cooperation

Given the great uncertainty about the future business environment (Wheelwright and Clark, 1992; Freeman and Soete, 1997) and the growing need for multidisciplinary knowledge to handle such uncertainty in R&D decision-making, many firms have engaged in R&D cooperation to incorporate multiple external sources of knowledge (Hagedoorn, 2002). R&D cooperation allows a firm not only to access external resources but also to reduce the innovation time span, share the risks associated with the innovation, and increase the performance of the innovation (Hagedoorn, 1993; Hagedoorn, 2002; Laursen and Salter, 2006; Leiponen and Helfat, 2010).

While the strategic importance of R&D cooperation is apparent, the formation and performance of R&D cooperation largely depend on the partners' capability and attributes. Many failures in R&D cooperation have resulted from incompatibility between partners (Ariño, 2003; Büyüközkan et al. 2008), so choosing the right partners is the most significant factor for the success of R&D cooperation (Cowan et al. 2007; Dodgson, 1992; Das and Teng, 2003). With respect to different purposes of cooperation, from minimizing transaction costs to exploiting complementary resources between partners (Das and Teng, 2000; Kogut, 1988), a vast amount of literature has investigated partners' characteristics as determinants of inter-firm alliances, such as partners' attributes (e.g., firm size, R&D intensity, and sales) (Veugelers, 1997; Becker and Dietz, 2004), inter-firm trust and mutual interest (Kanter, 1994; Inkpen and Currall, 1997), cultural fit (Littler et al. 1995), and the resource fit between partners (Das and Teng, 2000; Barney, 1991; Rothaermel, 2001; Lane and Lubatkin, 1998). The results and insights from these studies have accentuated the importance of partner selection in successful R&D cooperation and have suggested a set of important criteria to evaluate potential R&D partners.

Although the theoretical and empirical literature has facilitated our understanding of the role of partners' characteristics in R&D cooperation, many prior studies have centered on the explanation of R&D cooperation after it was established. As a consequence, the literature has failed to support the decision-making process involved in partner selection with a structured process and formalized methods that are specific to partner selection. Many firms have relied heavily on experts' knowledge and experience when searching for and evaluating potential R&D partners. However, the search for an external knowledge source is not without cost and can be time-consuming, expensive, and laborious (Laursen and Salter, 2006). Moreover, the expert-based approach becomes more costly with the trend toward open innovation (Chesbrough, 2003) where a pool of potential R&D partners is extremely extended in terms of regions and industrial sectors. In this circumstance, decision makers in the partner selection process need assistance through quantitative data and appropriate methods to make the right decisions.

In more recent years, some studies have attempted to systemize the tasks involved in the partner selection process. Patents have often been employed as the data source to search for candidates that might be scattered all over the world and to assess technological and relational capabilities of these candidates. For example, (Jeon et al. 2011) explored appropriate partners that possess the desired technologies to meet particular technological requirements by applying text-mining techniques to patent documents in the context of technological mediation. (Geum et al. 2013) also suggested a data-based approach to search for appropriate R&D partners. By analyzing academic publications and patent data, they designed 14 relevant indexes to reflect desirable partner characteristics. These efforts to derive useful information from patent data for decision-making in the partner selection process have highlighted the validity and utility of methodological support. However, these studies have failed to address the resource fit between potential partners, even though resource fit has been emphasized as an important requirement of R&D partners, thus motivating the current study.

From a resource-based point of view, a goal of R&D cooperation for a firm is to access external resources, in particular technological resources that are difficult for one firm to possess by itself in a cost-effective way. Hence, the incentive to cooperate and the synergy from the cooperation are likely to increase as resources of the partners fit well with each other (Das and Teng, 2000; Barney, 1991; Rothaermel, 2001; Lane and Lubatkin, 1998). Two representative but conflicting dimensions of resource fit are resource complementarity and resource similarity. Resource complementarity is related to the perspective that inter-firm cooperation aims to fill the resource gap and enhance the chance of innovation by combining participants' resources and by creating new knowledge (Das and Teng, 2000; Barney, 1991; Rothaermel, 2001). Because the opportunities of recombinative innovation rely on the heterogeneity of the knowledge base (Cantner and Meder, 2007), the learning effect of R&D cooperation decreases when the participants have similar knowledge (Wersching, 2005). On the other hand, resource similarity relates to the perspective that R&D cooperation is a learning process between participants (Lane and Lubatkin, 1998). Understanding the partners' resources is a prerequisite for expanding the existing knowledge base and creating new knowledge by sharing and combining the participants' resources (Cantner and Meder, 2007). In this regard, the learning costs become higher the more the cooperating partners differ in their respective knowledge bases because the ability to incorporate external knowledge largely depends on the prior related knowledge (Cohen & Levinthal, 1990). Therefore, while a sufficient degree of technological overlap between partners ensures communications, diversity and different knowledge bases increase the opportunities for knowledge creation and for innovative outcomes (Cohen & Levinthal, 1990).

2.2. Patent portfolio analysis in managing technological resources

Among the various methods used to analyze patent data and derive valuable information from the data for technological management, patent portfolios have an advantage of facilitating decision-making in technological resource management by structuring and visualizing the complex managerial issues of technological resources while focusing on the most relevant decision-making criteria (Ernst, 2003). The structure and utility of patent portfolios can differ depending on which dimensions are employed and what the purposes are of using the portfolios. The dimensions which have been mostly adopted as criteria for managing technological resources include patent activity, patent quality, technology share, and R&D emphasis. The specific operational definitions are different across studies but the dimensions are usually derived through an analysis of the number of patent applications in a technological field, and sometimes are derived together with a citation analysis. In terms of the purposes of using patent portfolios, the two directions that have been suggested are the internal and external management of technological resources (Ernst, 1998; Ernst, 2003). For the purpose of internal management, patent portfolios can help identify technological competitiveness and technological strategies against competitors. Patent portfolios can also help firms monitor and investigate external knowledge sources to identify external innovation opportunities (Ernst, 1998). Although these advantages of patent portfolios are apparent when assessing potential R&D partners, the suggestions in previous studies (Ernst, 1998; Ernst, 2003) for exploring external knowledge are only conceptual and are unable to investigate the fitness of technological resources. Thus, in this study, the patent portfolio analysis is tailored to the purpose of assessing potential R&D partners regarding the resource fit by suggesting the concept of integrated patent portfolios and applying the Shapley value.

2.3. Shapley value

The Shapley value is a well-known solution concept in cooperative game theory, which provides a means of dividing the total value of the cooperative game among individual players according to their marginal contribution to the coalition (Shapley, 1953; Roth, 1990). Among the various solution concepts in cooperative game, the Shapley value describes an effective approach to the fair allocation of gains obtained by cooperation among the players of the cooperative game. Since some players may contribute more to the total value than others, an important requirement is to distribute the gains fairly among the players. In this respect, the concept of the Shapley value takes into account the relative importance of each player to the game in deciding the payoff to be allocated to the players. Thus, the Shapley value can support our purpose to assess the importance of potential partners in R&D cooperation as contributors to the value of integrated patent portfolios.

The mathematical formulation is as follows. Suppose that a given cooperative game (N, ν), where $N = \{1,2,...,n\}$ is the set of players and v: $2^N \rightarrow R$ is real-valued mapping with $\nu(\varphi) = 0$. Note that 2^N is the set of all possible subsets of N, each of which is called a coalition except for the empty set. Mapping ν is called the characteristic function. Given any subset S of N, $\nu(S)$ is the value of the coalition S and represents the total utility that can be achieved by the players in S through cooperation. The Shapley value of player i for cooperative game (N, ν) is given by

$$\phi_i(\nu) = \sum_{all\, H \subseteq N\ \{i\}} \gamma_n(L)[\nu(H \cup \{i\}) - \nu(H)], \tag{1}$$

where $r_n(h) = \frac{h!(n-h-1)!}{h!}$;

n is the total number of all players;
and h is the number of players in coalition H.

In Eq. (1), as H is a coalition without player i, $H \cup \{i\}$ denotes a set of players which includes player i. The term $r_n(H)$ represents the probability of entering into coalition M, while the term $[\nu(H \cup \{i\}) - \nu(H)]$ represents the marginal contribution of player i to the value of coalition H. Hence, Shapley value $\phi_i(\nu)$ can be interpreted as the average marginal contribution of player i in any coalition of N assuming all orderings are equally likely. As a result, the Shapley value of a player accurately reflects the bargaining power of the player and the marginal value the player brings to the cooperative game. There are several equivalent alternative formulations for the Shapley value, and we use Eq. (2) instead of Eq. (1) to reduce the computational complexity.

$$\phi_i(\nu) = \frac{1}{n!} \sum_{\pi \in \Omega} [\nu(M_i(\pi) \cup \{i\}) - \nu(M_i(\pi))], \tag{2}$$

where Ω is the set of all possible permutations on N,

π is a permutation in Ω
$M_i(\pi)$ is the set of all players appearing before player i in permutation π.

3. Proposed approach

We consider the situation where R&D cooperation aims to solve particular technological needs (TNs). While the basic technological capabilities to meet given TNs are essential, another important requirement of good R&D partners is the resource fit. Accordingly, a purpose of this study is to expand the scope of methodological support for the partner selection process by incorporating an analysis of the resource fit between partners beyond the basic TNs.

As shown in Fig. 1, our proposed approach consists of four steps: data collection and preprocessing, identifying potential R&D partners, constructing patent portfolios of potential R&D partners, and assessing potential R&D partners regarding resource fit. The first and second steps are to collect patent data and then to screen potential partners from patent assignees that have basic technological capabilities. The third step is to construct the patent portfolios of each potential partner. Finally, in the fourth step, the resource fit among potential R&D partners and the contribution of each potential partner are assessed by measuring the value of the integrated patent portfolios and the Shapley value of each partner.

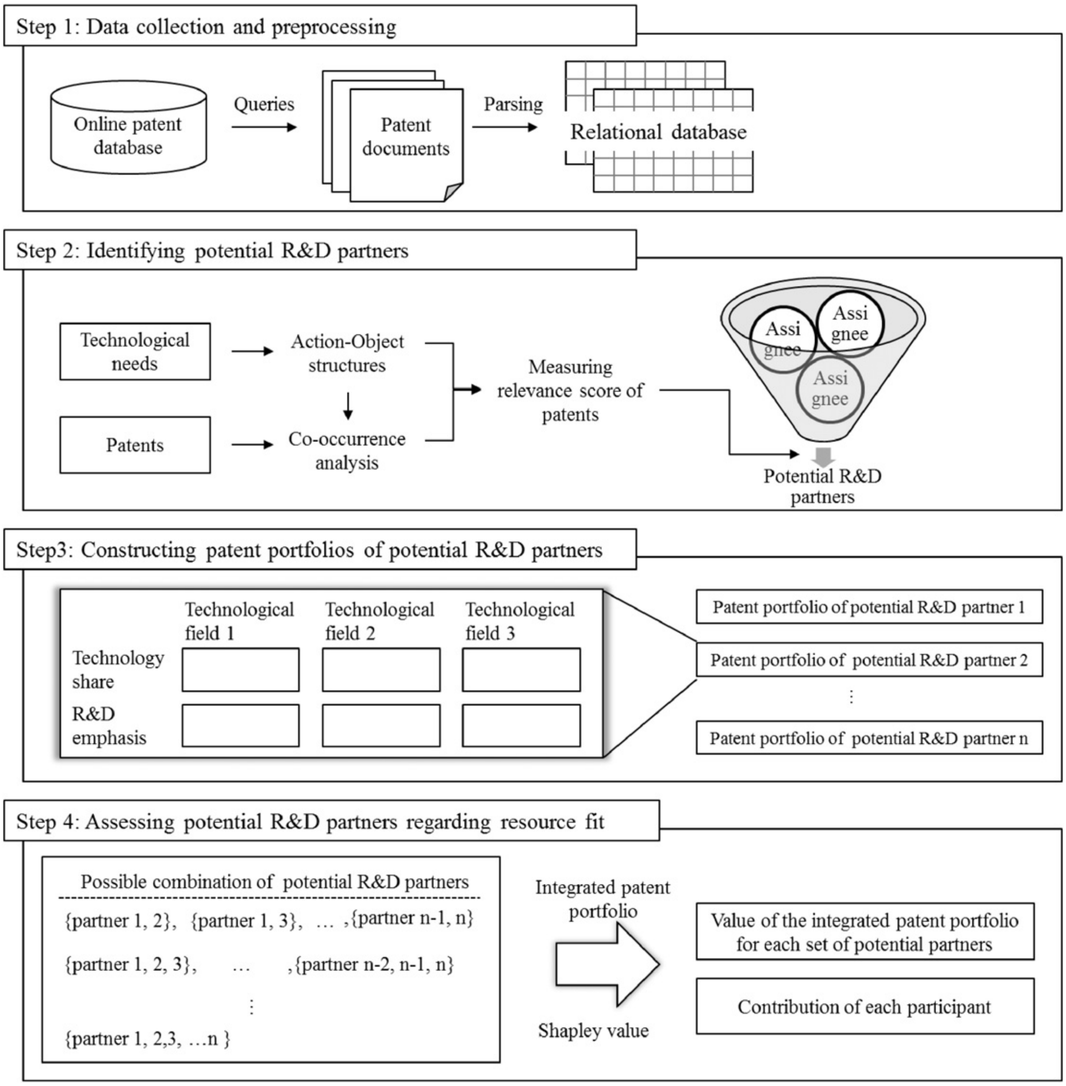


Fig. 1. Overall process.

3.1. Step 1: data collection and preprocessing

Patent documents related to the focal technologies are collected from online patent databases. Many internet services allow easy access to patents throughout the world, such as the United States Patent and Trademark Office (USPTO). The collected patent documents in an unstructured format are then preprocessed and transformed into relational forms using a database management system. Each patent document is parsed based on its structure to extract the information required for further analyses, such as assignees, patent classification code, title, abstract, and claims. Finally, the extracted information is stored in a relational database.

3.2. Step 2: identifying potential R&D partners

An important purpose of technological cooperation considered in this study is to develop new technologies and/or products that satisfy particular TNs. Thus, knowledge and experience in the related technological fields (TFs) are the basic qualifications for R&D partners. In this step, we assess firms' basic technological capabilities by investigating the relevance of the patents that the firms hold to the TNs. We then select firms with a high potential of becoming R&D partners, namely initial candidates.

First, the TNs are represented as action-object (AO) structures to form a basis for analyzing patent documents. For instance, if a firm is searching for technologies that detect locations, “detect” is the action (A) element and “location” is the object (O) element. The A and O elements for the given TNs are first determined by domain experts and then rearranged based on the results of the text mining on the collected patents to include the abbreviations, synonyms, and singular/plural forms.

Second, the relevance of the patents to the TNs is measured as the normalized co-occurrence frequency of the A and O elements at the sentence level. For patent P_i, its relevance score to the jth TN is calculated as: $RS_i(j) = f_i(A_j, O_j)/\sqrt{f_i(A_j)f_i(O_j)}$, where A_j and O_j are constituents of the AO structure for jth TN; $f_i(A_j)$ and $f_i(O_j)$ are the frequency of A_j and O_j in P_i; and $f_i(A_j,O_j)$ is the co-occurrence frequency of A_j and O_j at the sentence level in P_i. The value of $RS_i(j)$ ranges from zero to one, with zero indicating that P_i has no sentence having both A_j and O_j and one indicating that A_j and O_j always appear together in a sentence in P_i. Thus, high value of $RS_i(j)$ means that P_i has a high possibility to include AO structures for the jth TN. Because the AO structures represent the problems to be solved in the technical sentence (Cascini et al. 2004), the high value of $RS_i(j)$ implies that P_i is likely to convey the technological inventions related to the jth TN. To consider multiple TNs, the total relevance score of P_i (TRS_i), is measured as the sum of $RS_i(j)$ over j.

Lastly, the patent assignees holding patents with total relevant scores higher than the predefined threshold value are identified as potential R&D partners. They are considered to have basic technological capabilities as R&D partners and should be further assessed in terms of resource fit.

3.3. Step 3: constructing patent portfolios of potential R&D partners

In this step, patent portfolios of potential R&D partners are constructed. At first, important TFs in the focal technology should be identified. For this purpose, a cluster analysis is conducted on the classification codes in the patent data, which have been designated in patents to represent related TFs (No and Park, 2010; Curran and Leker, 2011). Specifically, the classification codes to which patents have been frequently assigned are selected as the initial set. Then, a cluster analysis is performed on the classification codes in the initial set based on the co-classification relationship, and the resulting clusters used as TFs of patent portfolios. The classification codes that have been frequently co-assigned to patents in a certain technology are considered to have a close relationship in constructing and developing that technology. Therefore, the use of clusters of classification codes as TFs not only reduces the complexity of patent portfolios but also reflects the structure of the focal technology.

After determining the TFs, the value of the dimensions of the patent portfolios are calculated for each potential R&D partner. This study employs patent indicators of technology share (TS) and R&D emphasis (RnDE) as dimensions of the patent portfolios (Ernst, 2003). The TS of a firm in a particular TF is measured as the firm's relative share of all patents in that TF. Hence, the TS captures a competitive technological position of a firm in a TF compared to other firms. On the other hand, the RnDE of a firm in a particular TF is measured as the TF's relative share of all patents possessed by the firm. The RnDE indicates the importance placed on a certain TF within the firm's overall R&D portfolio. Therefore, patent portfolios with the TS and RnDE as dimensions allow us to investigate potential partners' technological competitiveness in a TF and their strategic emphasis on a TF simultaneously.

3.4. Step 4: assessing potential R&D partners regarding resource fit

In the last step, we model and assess the resource fit among potential R&D partners. The three sub-tasks are 1) constructing integrated patent portfolios, 2) designing and measuring the value of integrated patent portfolios, and 3) applying the Shapley value to the value of integrated patent portfolios. We note that our focus is not to evaluate the results of R&D cooperation, but is to assess the compatibility of potential partners in the light of the resource fit to aid partner selection-related decisions. Thus, we evaluate how well the patent portfolios of potential R&D partners compatible with each other for generating the synergetic value of the R&D cooperation.

3.4.1. Constructing integrated patent portfolios

Integrated patent portfolios are constructed for each possible combination of potential R&D partners. The construction of an integrated patent portfolio is similar to that of a patent portfolio for individual potential R&D partners, as explained in step 3, except that it brings together patents held by participants. Namely, the TS and RnDE of integrated patent portfolios are calculated based on the total patents of all firms in the combination. Thus, the integrated patent portfolio offers a unified scheme whereby the technological resources of participants are organized, allowing an investigation of the expected pool of technological resources resulting from the potential cooperation and capturing the possibility of resource assimilation and resource expansion through the cooperation. This reflects the resource-based point of view that R&D cooperation allows the participants to share and acquire partners' technological resources. In addition, the integrated patent portfolio serves as the baseline for evaluating the resource fit between participants.

3.4.2. Designing and measuring the value of integrated patent portfolios

A simple way to examine the resource fit between potential R&D partners might be to compare their patent portfolios qualitatively. However, the complexity of the qualitative comparison increases with the number of potential partners. In addition, a qualitative approach is inefficient to provide decision makers with refined information from the result of the analysis. To overcome these drawbacks, this study suggests a quantitative approach to assess the resource fit between potential R&D partners by designing and measuring the value of an integrated patent portfolio. Specifically, an integrated patent portfolio is evaluated in three aspects: *weighted completeness* (WC), *technological resource overlap* (TRO), and *technological emphasis overlap* (TEO). Then, the *value of an integrated patent portfolio* (V_IPP) is measured based on the impact of WC, TRO, and TEO on the desirable condition of resource fit for successful R&D cooperation.

Table 1 summarizes the operational definitions and meanings of evaluation indices for an integrated patent portfolio. First, WC is devised to evaluate how competitive an integrated patent portfolio is in the focal technological area. Operationally, WC is defined as the weighted sum of product of TS and RnDE over the TFs ($\sum\limits_f w_f TS_f RnDE_f$), which is multiplied by the portion of TFs where the integrated patent portfolio has patents over the total TFs (m/M). In the definition, $\sum\limits_f w_f TS_f RnDE_f$ and m/M capture the competitive position and the degree of completeness of the integrated patent portfolio, respectively. Therefore, by multiplying these two terms, WC reflects both the depth and the width of an integrated patent portfolio in assessing the degree of technological competitiveness of the integrated patent portfolio.

Second, TRO investigates the degree of overlap among technological resources of potential R&D partners. By comparing the patent portfolios of the potential R&D partners, TRO is defined as the portion of the overlapped number of TFs where more than two potential partners own patents over the total TFs. Thus, TRO can examine the similarity in overall composition of technological resources among potential R&D partners.

Third, TEO is devised to evaluate the degree of overlap among technological emphasis areas of potential R&D partners. To this end, firstly, we identify the TFs with the value of RnDE higher than a predefined threshold as *core TFs*. As RnDE is a proxy of the extent to which a TF is important within a firm's overall patent portfolio, such a definition of core TFs captures where a firm places special emphasis. Finally, TEO is measured by comparing the core TFs of potential R&D partners: the portion of the overlapped number of core TFs over the entire universal set of core TFs.

Table 1
Evaluation indices for an integrated patent portfolio.

Evaluation index	Definition	Meaning
Weighted completeness (WC)	$(\sum\limits_f w_f TS_f RnDE_f) \times \frac{m}{M}$, where w_f is the importance weight of TF $f(\sum_{f=1}^{M} w_f = 1)$; m is the number of TFs having patents in an integrated patent portfolio ($0 \le m \le M$); and M is the total number of TFs.	Degree of technological competitiveness of integrated patent portfolios
Technological resource overlap (TRO)	The overlapped number of TFs/the total number of TFs	Degree of overlap among technological resources of potential R&D partners
Technological emphasis overlap (TEO)	The overlapped number of core TFs/the entire universal set of core TFs of participants, where a core TF is the TF with the higher value of RnDE than the threshold.	Degree of overlap among technological emphasis areas of potential R&D partners

The V_IPP is modeled based on the relationship of WC, TRO, and TEO with the possibility of establishing the R&D cooperation and producing innovative outcomes. First, since one purpose of R&D cooperation is to secure the relevant resources for a focal technology area, the larger the value of the WC, the better. This positive impact of WC is formulated as *Im_WC* in Eq. (3), which is a positive linear function of WC ranging from zero to one as depicted in Fig. 2(a). Second, the overlap among technological resources makes a trade-off between opportunities of recombinative innovation and the effectiveness of knowledge assimilation. Therefore, the value of TRO is in an inverted *U*-relationship with the performance of the R&D cooperation. This study formulates the inverted *U*-impact of TRO as *Im_TRO* in Eq. (4), a quadratic function opening upward. As shown in Fig. 2 (b), Im_TRO becomes the smallest value of zero when TRO takes an extreme value (i.e., 0 or 1), whereas it becomes the largest value of one when TRO takes a median value (i.e., 0.5). Third, as for TEO, a smaller value is preferred because a higher value implies the possibility of market competitors. Firms competing in the market can weaken incentives for R&D cooperation with each other even if they share complementary resources and similar knowledge base to appropriate extent (Branstetter and Sakakibara, 2002). Such a negative impact of TEO is modeled as *Im_TEO* in Eq. (5), which is a linear function with a negative slope that decreases from one to zero as the value of TEO increases from one to zero (See Fig. 2(c)).

$$\begin{aligned}\mathrm{Im\_WC} &= \mathrm{a}_1 \times \mathrm{WC},\\ &\quad \text{where } \mathrm{a}_1 = 1.\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{Im\_TRO} &= \mathrm{a}_2 \times (\mathrm{TRO}-\mathrm{b})^2 + \mathrm{c},\\ &\quad \text{where } \mathrm{a}_2 = -4, \mathrm{b} = 0.5, \text{ and } \mathrm{c} = 1.\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{Im\_TEO} &= \mathrm{a}_3 \times \mathrm{TEO} + \mathrm{d},\\ &\quad \text{where } \mathrm{a}_3 = -1, \text{and } \mathrm{d} = 1.\end{aligned} \tag{5}$$

Finally, V_IPP is defined as Eq. (6), which integrates the positive impact of WC, the inverted *U*-impact of TRO, and the negative impact of TEO. w_1, w_2, and w_3 are the relative importance of WC, TRO, and TEO, respectively, and are determined with the aid of domain experts.

$$\begin{aligned}\mathrm{V\_IPP} &= \mathrm{w}_1 \times \mathrm{Im\_WC} + \mathrm{w}_2 \times \mathrm{Im\_TRO} + \mathrm{w}_3 \times \mathrm{Im\_TEO},\\ &\quad \text{where } \mathrm{w}_1 + \mathrm{w}_2 + \mathrm{w}_3 = 1,\\ &\quad \text{and } \mathrm{w}_1 > 0, \ \mathrm{w}_2 > 0, \text{ and } \mathrm{w}_3 > 0.\end{aligned} \tag{6}$$

If potential R&D partners are compatible with each other regarding their resources, their resources maintain a balance between resource complementarity and resource similarity (Cohen and Levinthal, 1990). In the suggested model of V_IPP, by definition, TRO and TEO obviously represent the two different aspects of resource similarity. On the other hand, WC and TRO have a positive and negative correlation with resource complementarity. For instance, if two firms are in a completely complementary relationship with each other, they have resources that are required to develop a focal technology but are not owned by the counterpart firm. Accordingly, in the integrated patent portfolio for these two firms, all the TFs have the relevant patents and the patents in each TF should be from one firm, and thus WC and TRO of the integrated patent portfolio become one and zero, respectively. To sum up, V_IPP can reflect both resource complementarity and resource similarity by considering the impact of WC, TRO, and TEO. Such a relationship between the suggested model of V_IPP and resource complementarity and similarity enable us to identify which set of potential R&D partners is appropriate regarding the resource fit by measuring and comparing V_IPP for all possible combinations of potential R&D partners.

3.4.3. Applying the Shapley value to the value of integrated patent portfolios

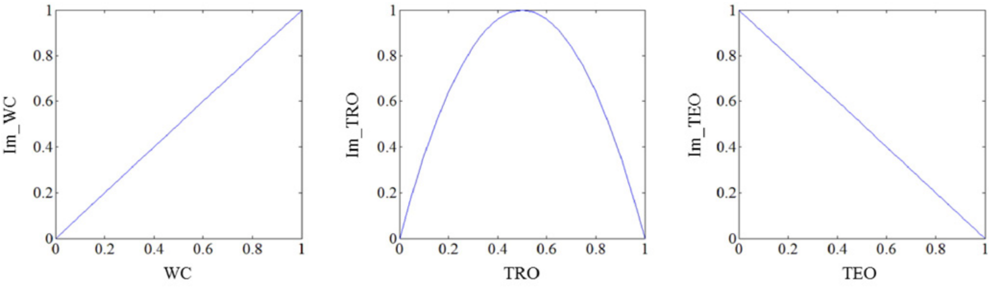
In this step, potential R&D partners are evaluated with respect to their contribution to forming the value of the integrated patent portfolio by applying the Shapley value. Mathematically, the coalitional game (N, ν) addressed in this study is defined as follows. Player set N is a set of potential R&D partners who are screened in step 2. Given S, which is a subset of N, characteristic function v(S) is the value of the integrated patent portfolio of S, which is formulated as V_IPP in Eq. (6). By applying Eq. (2) to our characteristics function, we can obtain the Shapely value of each potential partner, which represents the relative importance of the potential R&D partners in forming a desirable integrated patent portfolio regarding the resource fit.

All of the tasks explained so far, including constructing integrated patent portfolios, measuring V_IPP, and applying the Shapely value, are conceptually simple but the operation process becomes complicated as the number of potential R&D partners increases. For n potential R&D partners, these steps should be conducted on 2^{n}-(2^{1}–1) sets of the possible combinations of potential R&D partners. To overcome the computational complexity, we developed a MATLAB code for these tasks.

4. Case study: lighting control system

We conducted a case study to illustrate how the proposed approach could be applied in practice. A lighting control system was selected for the following reasons. First, a global market for lighting control systems is expected to grow continuously given the rapid development of information technology, the price decline of light emitting diodes, and the tremendous pressure for energy conservation. Second, the development of a lighting control system involves different technological areas, such as electrical energy, sensing and controlling, and information and communication. Moreover, as lighting control systems become intelligent, more heterogeneous and multidisciplinary knowledge is required to develop a lighting control system. Accordingly, R&D cooperation could benefit the development of a lighting control system by acquiring external knowledge sources in different areas.

The purpose of cooperative R&D considered in this case study is to develop lighting control system technologies that satisfy the basic TNs of 1) interpreting information from multiple sensors and 2) controlling the variance and color of the lighting apparatus and applications. Given this situation, we searched for a set of potential R&D partners having



(a) Positive impact of WC (b) Inverted *U*-impact of TRO (c) Negative impact of TEO

Fig. 2. Formulation of the impact of evaluation criteria.

basic technological capabilities and assessed their resource fit by applying the proposed approach.

Table 2
Features of the related patents of Potential R&D partners.

Potential R&D partners	The number of the related patents*	Average TRS of the related patents	Average number of claims of the related patents	The latest issue year of the related patents
A_1	1	1.57	25	2008
A_2	1	1.57	11	2011
A_3	1	1.57	15	2008
A_4	2	1.86	50	2009
A_5	1	1.57	13	2001
A_6	2	1.57	68	2005
A_7	1	1.71	21	2010
A_8	11	1.57	46.09	2007
A_9	1	1.57	20	2010
A_{10}	1	1.52	69	2002
A_{11}	24	1.57	81.75	2003
A_{12}	1	1.71	15	2005
A_{13}	1	1.57	81	2008
A_{14}	1	1.57	29	2002
A_{15}	1	1.57	12	2006

* A related patent refers to the patent of which the total relevance score was over 1.52.

4.1. Step 1: data collection and preprocessing

The USPTO online database was selected as the primary data source. This data source is appropriate for our purpose of searching and assessing potential R&D partners since it contains a large number of patents from all over the world and covers the most advanced technologies. Using a keyword search in the USPTO online database and our self-developed java-based crawling program, we gathered 2888 patent documents containing the keywords “light,” “control,” and “system” in the abstracts of patents issued between January 2001 and November 2011.

The relational database was constructed by parsing the collected patent documents and extracting information required for further analyses, such as the patent number, title, abstract, assignee, inventor, issue date, claim, and class. After consolidating the assignees' names by cleaning out misspellings and variations, 1021 different institutional assignees were identified. As personal assignees were not considered to be potential partners in this study, 2451 patents that had been registered by the institutional assignees were selected to be further analyzed.

4.2. Step 2: identifying potential R&D partners

With the aid of domain experts and a text-mining program, the AO structures for the two TNs were determined. A TN can be represented as multiple AO structures. For instance, the first TN of interpreting information from multiple sensors was represented with three A elements (“interpret,” “detect,” “sense”) and eight O elements (“temperature,” “sound,” “movement,” “touch,” “time,” “date,” “pressure,” “humidity”), resulting in 24 (3×8) AO structures being generated. Similarly, 2 (1×2) AO structures were obtained for the second TN of controlling variance and color of lighting and apparatus and applications with one A element (“control”) and two O elements (“variance,” and “color”).

Based on the AO structures, the relevance scores of each patent to given TNs were calculated with the aid of the text-mining program for the sentence-level co-occurrence analysis. Although any information about a patent in a free-text form can be used, patent claims were used in this study to capture the essential features of the invention (Tong and Frame, 1994; Shin and Park, 2005). The specific procedure was as follows. First, the frequency and co-occurrence frequency of A and O elements in the claim sentences of patent i were counted by the text-mining program. Second, $RS_i(1)$ and $RS_i(2)$ were calculated for TN_1 and TN_2, respectively. Third, the total relevance score TRS_i was derived as the sum of $RS_i(1)$ and $RS_i(2)$. Since the relevance score for each TN ranges from zero to one, the range of the total relevance score became zero to two. The average total relevance score ($\overline{TRS}$) was 0.786, while the maximum and minimum values were 0 and 1.857, respectively.

Finally, 15 institutional assignees (which are denoted as $A_1, \ldots, A_{15}$) were selected as potential R&D partners who held at least one *related patent* to the given TNs, which had been defined as patents with a total relevance score of over 1.52 with a percentile rank of 98. This means that the 15 potential R&D partners owned the top 2% of patents that were likely to include the technical solution to the given TNs. Thus, they were regarded as those having basic technological capabilities as R&D partners to develop the lighting control system of interest in this case study. Table 2 depicts some features of the related patents of potential R&D partners. Note that merely a small variation in the average total relevance scores of the related patents is observed across the potential R&D partners. In addition, some potential R&D partners show similar average total relevance scores of the related patents, but differ in the number of related patents, the number of claims of the related patents, and the latest issue year of the related patents. This means that while relevance scores allow us to identify initial candidates for R&D partners having basic technological capabilities over a certain level for the given TNs, it is vague and might be risky to decide with whom to cooperate based only on this information. Thus, additional investigation is essential for assessing potential R&D cooperation, and this study focuses on the resource fit among R&D partners which is critical for the motivation and outcomes of R&D cooperation.

4.3. Step 3: constructing patent portfolios of potential R&D partners

To identify important TFs related to the lighting control system technology, 21 USPC classes, which accounted for 77% of the USPC codes in our patent data, were selected as the initial set. Next, a co-classification matrix was constructed among these 21 USPC classes using joint conditional probability for normalization (see (McCain, 1995) for more details). Finally, K-means clustering analyses were performed, taking the co-classification matrix as input (i.e., distance matrix). After performing a series of analyses with different values of K, we chose five as the number of clusters that produced the result where no cluster had an extremely large number of elements and every cluster contained at least three elements. The resulting five clusters were selected as the TFs of the patent portfolios of the potential R&D partners for developing lighting control system technology (see Table 3).

For these five TFs, the TS and RnDE of each potential partner were calculated, as reported in Tables A.1 and A.2.

4.4. Step 4: assessing potential R&D partners regarding resource fit

Given the 15 potential R&D partners, we further examined 32,765 ($=2^{15}$-(2^1-1)) combinations of them in terms of their resource fit using MATLAB-based coding. First, for every combination, an integrated patent portfolio was constructed. Second, to evaluate the integrated patent portfolios, the suggested indices such as WC, TRO, and TEO were calculated according to the definitions in Table 1. Third, V_IPP was measured by incorporating the impacts of WC, TRO, and TEO

Table 3
TFs of lighting control system technology.

TF (cluster of USPC classes)	USPC class number
TF_1	356, 359, 372, 385, 398
TF_2	250, 315, 347, 355
TF_3	235, 351, 369, 396, 600
TF_4	340, 362, 382, 701
TF_5	345, 348, 353

according to Eq. (6). The integrated patent portfolio for a certain set of potential R&D partners has a unique value of WC, TRO, and TEO. In contrast, V_IPP can vary depending on how the weights of WC, TRO, and TEO are set, which are respectively denoted as w_1, w_2, and w_3 in Eq. (6). We can suppose the extreme cases where one of the weights is one and the others are zero: $(w_1, w_2, w_3) = (1, 0, 0)$ or $(0, 1, 0)$ or $(0, 0, 1)$. Accordingly, V_IPP merely becomes Im_WC, Im_TRO, or Im_TEO, respectively, where only the impact of corresponding criterion is taken account of. For instance, when $(w_1, w_2, w_3) = (1, 0, 0)$, V_IPP is determined only by completeness of the integrated patent portfolio. In the case of lighting control system, it was the integrated patent portfolio involving all 15 potential R&D partners that had the maximum value of V_IPP with $(w_1, w_2, w_3) = (1, 0, 0)$. Obviously, however, that integrated patent portfolio is undesirable regarding TRO and TEO. To avoid such extreme cases and consider the evaluation criteria from a balanced perspective when evaluating the resource fit among potential R&D partners, we set the value of weights equally, i.e., $w_1 = w_2 = w_3 = 1/3$. Fig. 3 depicts the histogram of V_IPP for all combinations of potential R&D partners.

The histogram of V_IPP shows a right-skewed shape of which the mean, median, and standard deviation are 0.17, 0.16, and 0. 10, respectively. This indicates that most sets of potential R&D partners have a low value of V_IPP, and they are expected to have poor R&D cooperation performance when it comes to the resource fit. Specifically, about 96% of sets of potential R&D partners had V_IPP under 0.5, and 84% of them had V_IPP even under 0.3. In contrast, 0.17% of sets of potential R&D partners whose values of V_IPP are between 0.6 and 0.7 can be considered to be in good condition regarding the resource fit. Among them, in particular, A_1, A_9, and A_{15} were identified as the potential R&D partners that generated the integrated patent portfolio with the maximum value of V_IPP.

By applying Eq. (2) to the result of V_IPP, the Shapley values of potential R&D partners were calculated (see Table 4). By comparing the Shapley values, we could perceive the relative importance of each potential R&D partner in producing the value of the integrated patent portfolio. In addition, the Shapley values based on the V_IPP enable decision makers to examine the expected relative impact of inclusion or exclusion of a certain potential R&D partner on the value of the integrated patent portfolio. For instance, from the cooperation of A_1, A_9 and A_{15}, the expected relative impact of exclusion of A_9 is much larger than that of exclusion of A_1. Such information can be useful in the partner selection process because there could be a situation where strategic factors other than the resource fit require inclusion or exclusion of some particular potential R&D partners.

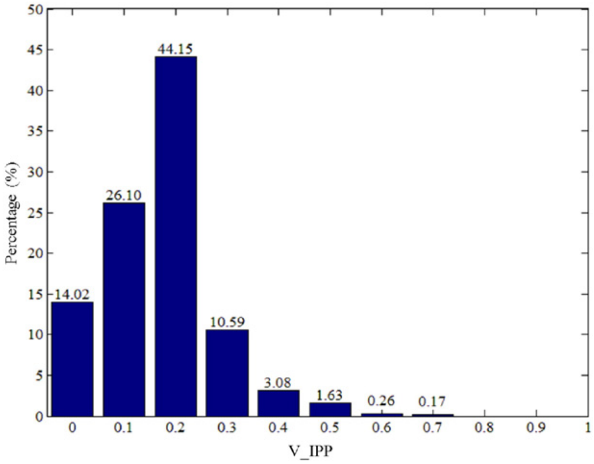


Fig. 3. Histogram of V_IPP.

Table 4
The Shapley value of potential R&D partners.

Potential R&D partners	Shapley value	Ranking
A_1	0.004	13
A_2	0.032	9
A_3	0.207	1
A_4	0.153	3
A_5	0.092	5
A_6	0.116	4
A_7	0.002	14
A_8	0.062	7
A_9	0.016	10
A_{10}	0.033	8
A_{11}	0.014	11
A_{12}	0.012	12
A_{13}	0.179	2
A_{14}	0.078	6
A_{15}	0.001	15

5. Conclusions

The potential utility and contributions of this study can be summarized as follows. First, this study contributes to the partner selection research by making the first attempt to consider resource fit in the methodological framework. Although the resource fit between R&D partners has been emphasized theoretically and empirically as a major requirement of partners, assessment of the resource fit in the partner selection process has received little attention. The suggested approach in this paper can fill such a gap in the partner selection literature by highlighting and addressing the decision makers' need for objective data and quantitative methods to examine the resource fit between potential R&D partners. This study also lays the ground work for further studies on the consideration of resource fit in the partner selection process.

Second, this study crystalizes the efficacy of using patent portfolios to assess the resource fit of potential R&D partners in a systemized analytical framework. The concept and the value of an integrated patent portfolio are devised to model the resource fit between potential R&D partners using patent information. In addition, the application of the Shapley value enables the assessment of the technological resource of potential partners with respect to enhancing the value of an integrated patent portfolio. These substantial methods tailored to the assessment of resource fit in the partner selection process contribute to the literature where the utility of patent portfolios in investigating external sources of innovation has been discussed only conceptually. We expect the suggested approach to be useful for the assessment of potential R&D partners by providing detailed critical information on the technological resources of potential partners and the resource fit between the partners.

Finally, although this study focuses on resource fit in the context of the partner selection process, the suggested approach can serve as a starting point for more general models. A basic principle of the suggested approach is that it conceptually puts together the technological resources of different organizations in an integrated patent portfolio and examines how the technological resources of individual organizations are well matched with each other to establish and achieve successful R&D cooperation. In this respect, the suggested approach could be employed in various research areas where the resources of different fields need to be matched to create synergetic value. For instance, in technological convergence analysis, a main interest is in where sources of knowledge are and how they can be matched to produce new knowledge. The suggested approach could be modified to construct the integrated patent portfolios for “technological areas” instead of “firms” and to design the value of integrated patent portfolios for reflecting the opportunity of new knowledge creation from the convergence of technological areas.

Despite its valuable contribution, this research is still subject to some limitations which should be complemented by future research. First, the suggested approach is not meant to replace but to complement decision makers. This study aims not to produce an optimal solution to select R&D partners, but rather to evaluate their resource fit, which is an important but just one aspect among various qualifications for R&D partners. Therefore, the results of this study should be used as information that supports the decision-making process, but the involvement of experts in relevant domains still remains essential. Second, a void still remains concerning performance improvement of the suggested method. The indicators to construct patent portfolios, such as TS and RnDE, were based on the number of patents, but other information such as the application date and citation information can capture different as well as important aspects of technological resources. Incorporating such information can make our method more reliable and diversified. Third, the power of our method as a decision support tool would increase if visualization methods are incorporated. Decision makers' understanding can be richer if the process and results of analysis are presented in visual format. Finally, our case study is limited to only one industry. More testing from a wider range of industries could help establish the validity of our approach. These topics can be fruitful in areas for future research.

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Appendix A

Table A.1
TS of potential R&D partners.

Potential R&D partners	TS_{i1}	TS_{i2}	TS_{i3}	TS_{i4}	TS_{i5}
A_1	0.011	0.010	0.000	0.001	0.000
A_2	0.009	0.020	0.000	0.027	0.005
A_3	0.000	0.000	0.000	0.000	0.003
A_4	0.177	0.060	0.004	0.109	0.008
A_5	0.014	0.016	0.002	0.377	0.023
A_6	0.120	0.076	0.002	0.041	0.019
A_7	0.000	0.002	0.000	0.001	0.000
A_8	0.008	0.001	0.001	0.000	0.000
A_9	0.185	0.563	0.602	0.334	0.562
A_{10}	0.007	0.030	0.000	0.015	0.002
A_{11}	0.018	0.006	0.000	0.000	0.004
A_{12}	0.445	0.183	0.390	0.079	0.372
A_{13}	0.000	0.024	0.000	0.010	0.003
A_{14}	0.003	0.003	0.001	0.002	0.000
A_{15}	0.003	0.006	0.000	0.004	0.000

Table A.2
RnDE of potential R&D partners.

Potential R&D partners	$RnDE_{i1}$	$RnDE_{i2}$	$RnDE_{i3}$	$RnDE_{i4}$	$RnDE_{i5}$
A_1	0.585	0.366	0.000	0.049	0.000
A_2	0.119	0.175	0.000	0.638	0.069
A_3	0.000	0.000	0.000	0.000	1.000
A_4	0.426	0.095	0.008	0.450	0.021
A_5	0.020	0.015	0.002	0.927	0.036
A_6	0.456	0.191	0.005	0.270	0.077
A_7	0.111	0.333	0.000	0.556	0.000
A_8	0.818	0.091	0.091	0.000	0.000
A_9	0.082	0.165	0.228	0.254	0.271
A_{10}	0.136	0.364	0.000	0.466	0.034
A_{11}	0.696	0.143	0.000	0.000	0.161
A_{12}	0.309	0.084	0.231	0.094	0.282
A_{13}	0.013	0.438	0.000	0.450	0.100
A_{14}	0.316	0.211	0.053	0.421	0.000
A_{15}	0.207	0.276	0.000	0.517	0.000

References

Ariño, A., 2003. Measures of strategic alliance performance: an analysis of construct validity. J. Int. Bus. Stud. 34 (1), 66–79.

Arranz, N., de Arroyabe, J.C.F., 2008. The choice of partners in R&D cooperation: an empirical analysis of Spanish firms. Technovation 28 (1–2), 88–100.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120.

Bayona, C., Garcia-Marco, T., Huerta, E., 2001. Firms' motivations for cooperative R&D: an empirical analysis of Spanish firms. Res. Policy 30 (8), 1289–1307.

Becker, W., Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. Res. Policy 33 (2), 209–223.

Branstetter, L.G., Sakakibara, M., 2002. When do research consortia work well and why? Evidence from Japanese panel data. Am. Econ. Rev. 92 (1), 143–159.

Brockhoff, K.K., 1992. Instruments for patent data analyses in business firms. Technovation 12 (1), 41–59.

Büyüközkan, G., Feyzioğlu, O., Nebol, E., 2008. Selection of the strategic alliance partner in logistics value chain. Int. J. Prod. Econ. 113 (1), 148–158.

Cantner, U., Meder, A., 2007. Technological proximity and the choice of cooperation partner. J. Econ. Interac. Coord. 2 (1), 45–65.

Cascini, G., Fantechi, A., Spinicci, E., 2004. Natural language processing of patents and technical documentation. In: Marinai, S., Dengel, A. (Eds.), Document Analysis Systems VI. Springer, Berlin, Heidelberg, pp. 508–520.

Chesbrough, H.W., 2003. Open Innovation: The new Imperative for Creating and Profiting from Technology. Harvard Business Press, Boston, MA.

Cohen, W.M., Levinthal, D.A., 1990a. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152.

Cowan, R., Jonard, N., Zimmermann, J.B., 2007. Bilateral collaboration and the emergence of innovation networks. Manag. Sci. 53 (7), 1051–1067.

Curran, C.S., Leker, J., 2011. Patent indicators for monitoring convergence - examples from NFF and ICT. Technol. Forecast. Soc. Chang. 78 (2), 256–273.

Dacin, M.T., Hitt, M.A., Levitas, E., 1997. Selecting partners for successful international alliances: examination of US and Korean firms. J. World Bus. 32 (1), 3–16.

Das, T.K., Teng, B.S., 2000. A resource-based theory of strategic alliances. J. Manag. 26 (1), 31–61.

Das, T.K., Teng, B.-S., 2003. Partner analysis and alliance performance. Scand. J. Manag. 19 (3), 279–308.

Dodgson, M., 1992. The strategic management of R&D collaboration. Tech. Anal. Strat. Manag. 4 (3), 227–244.

Ernst, H., 1998. Patent portfolios for strategic R&D planning. J. Eng. Technol. Manag. 15 (4), 279–308.

Ernst, H., 2003. Patent information for strategic technology management. World Patent Inf. 25 (3), 233–242.

Freeman, C., Soete, L., 1997. The Economics of Industrial Innovation. 3rd ed. MIT Press, Cambridge, MA.

Gemünden, H., Högl, M., Lechler, T., Saad, A., 1999. Starting conditions of successful European R&D consortia. In: Brockhoff, K., Chakrabarti, A., Hauschildt, J. (Eds.), The Dynamics of Innovation. Springer, Berlin, Heidelberg, pp. 237–275.

Geum, Y., Lee, S., Yoon, B., Park, Y., 2013. Identifying and evaluating strategic partners for collaborative R&D: index-based approach using patents and publications. Technovation 33 (6–7), 211–224.

Hagedoorn, J., 1993. Understanding the rationale of strategic technology partnering: nterorganizational modes of cooperation and sectoral differences. Strateg. Manag. J. 14 (5), 371–385.

Hagedoorn, J., 2002. Inter-firm R&D partnerships: an overview of major trends and patterns since 1960. Res. Policy 31 (4), 477–492.

Holmberg, S.R., Cummings, J.L., 2009. Building successful strategic alliances strategic process and analytical tool for selecting partner industries and firms. Long Range Plan. 42 (2), 164–193.

Inkpen, A.C., Currall, S.C., 1997. International joint venture trust: an empirical examination. In: Beamish, B.W., Killing, J.P. (Eds.), Cooperative Strategies: North American Perspectives. New Lexington Press, San Francsico, CA, pp. 308–334.

Jeon, J., Lee, C., Park, Y., 2011. How to use patent information to search potential technology partners in open innovation. J. Intellect. Prop. Rig. 16 (5), 385–393.

Kanter, R.M., 1994. Collaborative advantage: the art of alliances. Harv. Bus. Rev. 72 (4), 96–108.

Kogut, B., 1988. Joint ventures: theoretical and empirical perspectives. Strateg. Manag. J. 9 (4), 319–332.

Kogut, B., 1989. The stability of joint ventures: reciprocity and competitive rivalry. J. Ind. Econ. 38 (2), 183–198.

Lane, P.J., Lubatkin, M., 1998. Relative absorptive capacity and interorganizational learning. Strateg. Manag. J. 19 (5), 461–477.

Laursen, K., Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. Strateg. Manag. J. 27 (2), 131–150.

Leiponen, A., Helfat, C.E., 2010. Innovation objectives, knowledge sources, and the benefits of breadth. Strateg. Manag. J. 31 (2), 224–236.

Lhuillery, S., Pfister, E., 2009. R&D cooperation and failures in innovation projects: empirical evidence from French CIS data. Res. Policy 38 (1), 45–57.

Lin, B.W., Chen, C.J., Wu, H.L., 2006. Patent portfolio diversity, technology strategy, and firm value. IEEE Trans. Eng. Manag. 53 (1), 17–26.

Littler, D., Leverick, F., Bruce, M., 1995. Factors affecting the process of collaborative product development: a study of UK manufacturers of information and communications technology products. J. Prod. Innov. Manag. 12 (1), 16–32.

McCain, K., 1995. The structure of biotechnology R&D. Scientometrics 32 (2), 153–175.

Nijssen, E.J., Van Reekum, R., Hulshoff, H.E., 2001. Gathering and using information for the selection of technology partners. Technol. Forecast. Soc. Chang. 67 (2–3), 221–237.

No, H.J., Park, Y., 2010. Trajectory patterns of technology fusion: trend analysis and taxonomical grouping in nanobiotechnology. Technol. Forecast. Soc. Chang. 77 (1), 63–75.

Roth, A.E., 1990. The Shapley Value: Essays in Honor of Lloyd S. Shapley. Cambridge University Press, Cambridge, MA.

Rothaermel, F.T., 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. Strateg. Manag. J. 22 (6–7), 687–699.

Shapley, L.S., 1953. A value for n-person games. Ann. Math. Stud. 28, 307–317.

Shin, J., Park, Y., 2005. Generation and application of patent claim map: text mining and network analysis. J. Intellect. Prop. Rig. 10 (3), 198–205.

Tong, X.S., Frame, J.D., 1994. Measuring national technological performance with patent claims data. Res. Policy 23 (2), 133–141.

Verspagen, B., Duysters, G., 2004. The small worlds of strategic technology alliances. Technovation 24 (7), 563–571.

Veugelers, R., 1997. Internal R&D expenditures and external technology sourcing. Res. Policy 26 (3), 303–315.

Wang, M.Y., 2012. Exploring potential R&D collaborators with complementary technologies: the case of biosensors. Technol. Forecast. Soc. Chang. 79 (5), 862–874.

Wersching, K., 2005. Innovation and Knowledge Spillover with Geographical and Technological Distance in an Agentbased Simulation Model. University Bielefeld Discussion Paper.

Wheelwright, S.C., Clark, K.B., 1992. Revolutionizing Product Development: Quantum Leaps in Speed, Efficiency, and Quality. Free Press, New York, NY.

Bomi Song is a Senior Researcher at Korea Institute of Industrial Technology (KITECH). She holds a BS, MS, and Ph.D. in Industrial Engineering from Seoul National University (SNU). Her research interests include the areas of technology innovation, technology intelligence, technology forecasting, service engineering, service innovation, and information visualization.

Hyeonju Seol is a Professor in the Department of Military Studies at Daejeon University. He holds a BS, MS, and Ph.D. in Industrial Engineering from SNU. In addition, he received a BS from Korea Air Force Academy(KAFA) and worked as a Professor at KAFA during the last 15 years. His research interests include the areas of technology management, R&D management, business opportunity exploration, and process management.

Yongtae Park is a professor in the Department of Industrial Engineering at SNU. He holds a BS in Industrial Engineering from SNU, and an MS and Ph.D. in operations management, both from the University of Wisconsin-Madison. His research topics cover a wide variety of areas including technology management, technological innovation, knowledge management, and service engineering.