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Identifying and evaluating strategic partners for collaborative R&D: Index-based approach using patents and publications

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ABSTRACT

Identifying and selecting appropriate strategic partners have been the subject of many previous studies: but most have dealt with partner selection that has relied heavily on experts' judgements: the value of a literature-based quantitative approach as a source of technology intelligence has seldom been addressed. This paper therefore aims to develop a systematic framework to guide strategic partner selection, taking a literature-based approach. Reviewing the factors that can lead to successful R&D partnerships to develop partner selection criteria, we designed 14 indexes – grouped into four major categories – to reflect desirable partner characteristics, and used the literature data to suggest a framework for prioritising potential partners. As data sources, the United States Patent and Trademark Office (USPTO) and the ISI Web of Science databases are adopted for patent analysis and publication analysis, respectively. This research applied the framework to identify strategic R&D partners for Korean firms and found that the use of literature data enabled a wide ranging search for potential partners and the quick analysis of their characteristics, with results that provided objective evidence for selection decisions. It also investigated the relative importance of literature databases and that of the four decision criteria by industry, and examined the relationships between the indexes to improve the application of the framework. The suggested framework is expected to be valuable as a complementary tool for decision-making about R&D collaboration.

1. Introduction

Collaborative R&D has been considered a useful means of technology acquisition (Belderbos et al., 2004; Benfratello and Sembenelli, 2002; Butcher and Jeffrey, 2005; Das and Teng, 2000; Nakamura, 2003; Niedergassel and Leker, 2011; Pisano, 1990; Tyler and Steensma, 1995). Though the benefits of collaborative R&D are apparent, there still remains a big question: how best to select collaboration partners? Partner selection is a specific – and important – decision in the creation of a strategic alliances (Wu et al., 2009), as the success of collaborative R&D is mainly determined by the quality and willingness of partners to interact and exchange information (Ariño and de la Torre, 1998)—so strategic partner selection has been of great concern to both academia and practice for a long time (Arranz and Fdez. de Arroyabe, 2008; Li, 2010). Much effort has been taken to develop guidelines for selecting the right partners (Ariño et al., 1997; Ellram, 1990; Geringer and Hebert, 1991; Hitt et al., 2000; Li and Rowley, 2002; Luo, 1998; Pidduck, 2006) by identifying effective criteria for partner selection decisions (Brouthers et al., 1995; Dacin et al., 1997; Geringer, 1991), analysing the trends and characteristics of R&D networks based on statistical approaches (Hagedoorn, 2002; Narula, 2004; Wen and Kobayashi, 2001), or using the analytic network process (ANP) to suggest ways of prioritising potential partners (Wu et al., 2009).

In most studies, partner selection processes have relied to a great extent on experts' knowledge, but have failed to incorporate quantitative data, which can provide a wider scope of useful knowledge for partner selection. In practice, generally, firms think that they know their potential partners quite well. However, due to this point, the search for potential partners is limited to the known partners, which results in the limited boundary of partners. To search the unexpected and unknown potential partners which can provide the great synergies, firms need to incorporate the massive and quantitative data. For this purpose, firms should exploit the quantitative knowledge from the outside database.

Communicating with and accessing knowledge from the outside world is increasingly important in R&D systems, since the strategic acquisition and utilisation of technological information

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from both within and beyond the organisation is becoming critical for successful innovation (Mothe et al., 2006). One source of information worth in the partner selection context is the scientific literature, which is a valuable source for technology intelligence. Especially when potential R&D partners might be scattered all over the world, the bibliometric analysis of scientific literature can be useful for potential partner analysis, by enabling a comprehensive search for candidates and their quick evaluation. Finding the right partner requires careful screening, which can be a time-consuming process (Dacin et al., 1997)—while these difficulties are increased by the growing dynamism and complexity of the business environment, they can be eased by extracting meaningful knowledge from scientific literature to support expert decision making. Therefore, a framework for partner selection that incorporates quantitative technological data, which can help firms develop collaborative R&D plans effectively, is urgently needed.

To meet the need, this research aims to develop such a systematic framework for strategic partner selection, taking a literature-based approach, and to get implications on the use of data from patents and publications for the purpose of potential partner identification and evaluation. We chose these data for this research because: first, they are important proxy measures for technical processes and innovation activities in real-world situations; second, the sources include not only technological but also managerial information (such as technology owners, inventors and inventing countries) and thus can be used to investigate the characteristics of potential collaborators; and finally, the scope of the information they include is global, thus supporting a wide-ranging general analysis of potential collaborators. The proposed framework was developed through a series of steps involving literature reviews and expert surveys. We first reviewed factors for a successful R&D partnership which could form the basic criteria for partner selection and identified four: technological strength, R&D openness, R&D linkage, and collaboration effect. We then designed 14 indexes to reflect potential collaborators' characteristics with regard to these four factors, and assigned values obtained from the literature data. Finally, we suggest a framework for prioritising potential partners, which incorporates not only quantitative and objective information but also expert opinions, and uses the analytic hierarchical process (AHP) to compensate for the limitations of the data-driven approach.

The suggested framework was applied to identify strategic R&D partners for Korean firms and to establish a government policy on international R&D cooperation in Korea. At the request of Korea Institute for Advancement of Technology (KIAT) – a Korean government agency established to promote industrial development and technology innovation – the proposed framework was applied to the strategic partner selection for R&D collaboration in Korea. The United States Patent and Trademark Office (USPTO) and the ISI Web of Science database are adopted for patent analysis and publication analysis, respectively, since these two databases contain the most representative data for technological information in accessible formats. What we found from our experience is that using literature data enabled a wide ranging search for potential partners and the quick analysis of their characteristics, and provided objective evidence for the selection results. The results of our case study also enabled us to identify a way to improve the proposed framework, which we expected to be useful as a complementary tool to support experts' decision making, especially for firms entering new technological areas and in a dynamic industry environment where collaborative R&D is indispensable. The various indexes developed in the study can be used for a range of purposes, such as analysing technological superiority, openness, linkages, and so on.

The paper is organised as follows. The research background is explained in Section 2. The research framework is proposed in Section 3, with the framework and indexes to evaluate potential R&D partners. Section 4 describes the results of applying the proposed approach to the real case of KIAT and suggests implications. Section 5 provides implications which should be considered to utilize this suggested framework in practice. Finally, Section 6 concludes with limitations and suggests future research directions.

2. Literature review

2.1. Collaborative R&D and partner selection

Making successful collaborative partnerships is a major challenge in the current marketplace. As competitive market environments create uncertainties that cannot be dealt with within single firms (or even single nations), firms are utilising external knowledge and technology and allocating increasing resources to collaborative R&D to speed up the pace of their innovation and diversify their technological capabilities. R&D collaborations maintain clear, significant and systematic interdependence between the firms involved, with partners undertaking innovative activities to develop technology, products or services (Narula, 2004), and can be sources of competitive advantage in terms of both incorporating external sources and sharing significant amounts of information (Belderbos et al., 2004). The importance of collaborative R&D cannot be overemphasised in high-tech or emerging industries, where technological progress is rapid and complex, and – especially in emerging markets – R&D collaborations have been regarded as important means by which firms can 'jump up' to the next level of innovation. Such alliances can help firms reduce uncertainty in terms of cost and risk (Das and Teng, 2000; Tyler and Steensma, 1995), shorten innovation cycles (Pisano, 1990), and deal with regulations and industry standards more effectively (Benfratello and Sembenelli, 2002; Nakamura, 2003).

There has been much discussion regarding the determinants of success in collaborative R&D (Fritsch and Lukas, 2001; Tether, 2002). Daniel et al. (2002) investigated the tasks, processes, and frameworks involved in value creation in strategic alliances for R&D collaboration, while Belderbos et al. (2004), analysing the impact of R&D cooperation on firm performance, identified four types of R&D partners: competitors, suppliers, customers, and universities and research institutes. The effective selection of partners is recognised as being a core factor affecting collaboration performance (Ireland et al., 2002), and has been of great concern in both academia and practice. Many attempts have been made to identify which factors should be considered in partner selection (Geringer, 1991; Geringer and Hebert, 1991). Brouthers et al. (1995) focused on four factors – complementary skills, cooperative cultures, compatible goals, and commensurate levels of risk – while Nielsen (2003) identified six criteria (with 21 sub-criteria) for partner selection: technological expertise, marketing system and status, local operational expertise, competitive strength, production efficiency, positive prior experience, and labour negotiation expertise. Wu et al. (2009) suggested ANP for partner selection in strategic alliances with five factors as ANP criteria: partner characteristics, marketing knowledge capability, intangible assets, complementary capabilities, and degree of fit. Arranz and Fdez de Arroyabe (2008) developed a framework to investigate the determinants for the choice of partners in cooperative R&D. According to their work, two most common cooperation networks are emphasised: cooperation seeking synergies or complementariness between partners, and cooperation seeking growth effects or market power. Carayannis et al. (2000) examined various characteristics of the partnerships through a survey of firms. In addition, technological relatedness and prior ties have been considered as important factors to the partner selection in collaborative R&D, which means prior ties between universities and firms have a positive effect on the value of joint innovations (Petruzzelli, 2011). However, while many relevant criteria have been suggested and discussed, approaches to partner selection have still relied mainly on subjective judgment, rather than on quantitative factors.

2.2. Use of literature data for partner selection

The bibliometric analysis of patents and publications has been widely employed because the data involved are seen as sources of technological knowledge and are frequently used to measure firms' technological capabilities and collaboration capabilities. While both patent and publication data are valuable, most existing studies have employed patent documents, due to better data accessibility and their importance in the marketplace, and various indexes have been suggested. However, the indexes are suggested separately in the existing studies and never used collectively to make a partner selection decision.

For measuring the technological capability, there have been a lot of previous studies. Generally, two types of information are used to develop an index to measure technological capability: patent share and patent citation. First, patent share is calculated based on the number of patent applications or publications, measuring a firm's technological power in a particular field (Ernst, 2003; Banerjee et al., 2000). The activity index (AI) (Banerjee et al., 2000; Ernst, 2003) or revealed technology advantage (RTA) (Soete, 1987; Le Bas and Sierra, 2002; Mahmood and Singh, 2003), which calculates a firm's (or country's) relative competitive advantage in each field, is a representative indicators employing the concept of patent share. As well as patent share, patent citation has been also used to measure the quality and impact of a technology (Ernst, 2003; Griliches, 1990; Karki, 1997; Thomas, 2001). The number of times a company's patents are cited in other patents is indicative of the technological significance of its inventions (Breitzman and Mogee, 2002). Previous research revealed the prevalence of citation analysis as an important means to measure the technological capability such as citation per publication (CPP) (Albert et al., 1991) or current impact index (CII) (Deng et al., 1999; Thomas and McMillan, 2001; Berman, 2002; Schoenecker and Swanson, 2002).

To measure the collaborative capability, much research has been conducted. The relevant patent indexes have tried to measure the degree of collaboration or closeness of relationships between organisations or countries by measuring the level of co-invention (Guellec and van Pottelsberghe de la Potterie, 2001; Ma and Lee, 2008; Singh, 2008; Picci, 2010), co-assignment (Ma and Lee, 2008; Ernst, 2003) and co-occurrence (Breitzman and Mogee, 2002). A co-invention index is defined as the ratio of total number of inventors or their declared location of residency over total number of corresponding patents. This reflects the level of international cooperation between researchers located in different countries and the exchange/flow of knowledge and expertise across countries (OECD, 2005; Ma and Lee, 2008). Also, a co-assignee index is defined as the ratio of total number of assignees' stated countries of residence over the total number of corresponding patents, reflecting the intents to utilize a patent jointly (Ma and Lee, 2008). Co-occurrence analysis determines the similarities among patents, inventors, or assignees based on the common patterns of citation, words, or classification on the assumption that the similarity of the patterns indicates similarity in technological concern. If two patents are both cited in a single subsequent patent, a co-citation linkage is said to exist between the two, denoting their close relationship and revealing clusters of related patents (Breitzman and Mogee, 2002).

3. Methods

This research aims to develop a framework for selecting strategic R&D partners by providing a holistic approach to the whole process of selecting appropriate collaboration partners and ultimately to draw implications from the use of literature data as an information source of partner identification and evaluation. This research was initially motivated by a policy-level project, which was initiated by a Korean government agency in an attempt to help Korean firms to identify and select global R&D partners suitable for them. Though the research outputs were expected to be used at the country, we developed a general framework that can be used both by countries and firms in their search for R&D partners. That is an index for patent and publication analysis was designed for firm-level analysis, while, for country-level analysis, a hypothetical organisation consisting of “all Korean organisations and individuals that have ever published a paper (ISI-indexed) or applied for a patent in the USPTO” was assumed and the firm-level analysis was conducted to identify potential R&D partners for the hypothetical organisation.

Here, we define a strategic partner as an outside organisation (or nation) that can help enhance a firm's internal technological power via R&D collaboration, seeing appropriate strategic alliance partners for selection as those that have expertise in an operation (Wu et al., 2009), that possess the complementary skills the firm is seeking (Brouthers et al., 1995), as well as sufficient appropriate complementary resources (Miotti and Sachwald, 2003). Especially, this paper limits the definition of partner as country or firm that can be collaborated with maximum potential to create value (including products or technology) via collaborative R&D. Since the collaboration is defined as a type of cross-organisational linkage, which in addition to high levels of integration is characterised by high levels of transparency, mindfulness, and synergies in participants' interaction (Emden et al., 2006), each partner contributes a significant portion of the value creation. Therefore, we exclude the relationships such as simple purchase of component and minor level of interaction. Therefore, customers or suppliers are not considered as strategic partners in this paper.

To select collaboration partners, first, a general framework for selecting strategic partners is developed, where index values are calculated and merged into a single value for prioritising the partner candidates, so they can be listed (sorted by suitability) to support decision-making as to the best candidate. After that, the case study was conducted to illustrate the working of proposed approach. In this case study, strategic partners for Korean R&D collaboration were selected, where three key issues—(1) industrial differences in the relative importance of literature databases, (2) industrial differences in the relative importance of partner selection criteria, and (3) relationships between the indexes to effectively use the framework were investigated, to verify its applicability and draw research implications on the use of literature data for partner selection.

3.1. Criteria for selecting strategic partners

The evaluation criteria for effective R&D partnership are first identified from the literature review so candidates for strategic partnership can be evaluated. These criteria are used as a framework to develop the appropriate indexes to the partner selection, which are mainly composed of two broad categories: partners' characteristics and partners' tendency to collaborate (Brouthers et al., 1995; Dacin et al., 1997; Nielsen, 2003; Wu et al., 2009). These two categories are further divided into four categories: (1) technology strength, (2) R&D openness, (3) R&D linkage, and (4) collaboration effects. Table 1 summarises the evaluation criteria for selecting the strategic partners.

The first two factors focus on partner candidates' basic characteristics. Technology strength denotes candidates' technical capabilities in the proposed collaboration area, including technological and operational knowledge and experience, as well as its human resources (Dacin et al., 1997; Soete, 1987; Le Bas and Sierra, 2002;

Table 1
Evaluation criteria for strategic partner selection.

Characteristics	Criteria	Subcriteria
The basic characteristics of candidates	Technology strength (TSt)	Technology share
		Technology leadership
		Technological impact
	R&D openness (RdO)	Openness of organisation
		Openness of technology field
		Openness of technology
The relational characteristics of candidates	R&D linkage (RdL)	Joint ownership
		Joint development
		Joint operation
	Collaboration effect (CoE)	Knowledge inflow
		Knowledge criticality
		Knowledge similarity

Mahmood and Singh, 2003; Miotti and Sachwald, 2003; Nielsen, 2003; Patel and Vega, 1999; Chen et al., 2008). Technical capability can be determined quantitatively by the number of relevant technologies in which a candidate has capabilities either across all technologies or only with respect to leading technologies, considering their impact in technological or market terms. So the strength of a partner candidate's technology is assessed according to three sub-factors: technology share, technology leadership and technology impact (both technological and market).

R&D openness indicates a firm's tendency to collaborate and its willingness to communicate with other partners (Brouthers et al., 1995; Dacin et al., 1997; Gulati and Gargiulo, 1999). This is related to the firm's willing to share expertise, which is closely linked to the openness. Again, this can be determined by three sub-factors: organisational tendency to be open, nature of technological field, and nature of technology—when all three types of openness are high, the possibilities for collaboration will be increased.

The last two concern the relationship between a firm and those candidates, which are related to the corporate complementary effects (Brouthers et al., 1995). R&D linkage represents the level of prior experience of R&D collaboration. Most firms prefer to collaborate with firms who they have worked with before (Nielsen, 2003; Gulati, 1995; Gulati and Gargiulo, 1999; Li and Rowley, 2002; Chen et al., 2008), so prior research has suggested previous mutual collaboration experience as a selection criteria (Wu et al., 2009). In terms of R&D linkages, three sub-criteria can be considered: joint ownership of technology, joint development of technology and joint operation of technology. Once established, intensive linkages are lie to underpin further collaborations, but the selection of these sub-criteria needs to be based on the type of R&D collaboration envisaged: R&D does not happen in a single pattern, so partner selection must consider different kinds of R&D linkages.

Collaboration effect denotes the degree of synergy expected from a proposed collaboration (Dacin et al., 1997; Miotti and Sachwald, 2003; Wu et al., 2009), which is likely to increase where knowledge inflows from a partner are intensive and significant, and where they match the knowledge the firms is interested in. Again, this element of collaboration is measured via three sub-factors—degree of knowledge inflow, knowledge criticality and knowledge similarity.

3.2. Indexes to evaluate potential partners

In order to analyse patent and publication databases, indexes need to be developed to measure the technological capability and collaborative capability of candidate partners. Each index is developed based on the evaluation criteria earlier in Section 3.1: technology strength, R&D openness, R&D linkage, and collaboration effect. The indexes we developed were based on patent data but could also be applied to publication data. The weights of patents and publication can be determined by industry experts using AHP. Since this framework can be applied for private–private partnership as well as for the public–private partnership, the weighting of patents and publication can provide an important role to determine the partner selection. Generally, when searching for academic partners, publication is more important than patents. On the contrary, when searching for commercial partners or a firm (private–private partnership), patents are considered to be more important. As well, using the weights, the importance of the two literature sources can be adjusted according to the context.

3.2.1. Technology strength (TSt)

The first and foremost criterion for partner selection is clearly technology strength. Its first sub-criterion – technology share – has been one of the most frequently used indexes to evaluate technology strength, and is measured by the relative number of patents the organisation owns, or publications it has been involved in, compared to the numbers logged by the organisation with the most patents or publications (Ernst, 2003). Patent share, which is based on the number of patent applications or publications, has been effectively utilised to measure a firm's technological power in a particular field—so, conceptually; it captures a firm's competitive position in R&D (Ernst, 2003). One of the most representative measures is the activity index (AI) (Banerjee et al., 2000; Ernst, 2003), which is defined as a ratio (expressed as a percentage) of the number of a country's patents in a year over its numbers over a decade, compared to the ration of global patent numbers in the same periods, producing a doubly normalised index. Another commonly used index is revealed technology advantage (RTA) (Soete, 1987; Patel and Vega, 1999; Le Bas and Sierra, 2002; Mahmood and Singh, 2003), which calculates a firm's (or country's) advantage in each field compared to other firms/countries. The second measure is technology leadership, which is calculated by the number of the firm's valuable patents (or publications) compared to the industry mean (Almeida, 1996; Berman, 2002; Mowery et al., 1998): a high technology leadership value indicates high leadership capabilities. The final measure is technology impact, which consists of technological impact and market impact. A candidate's technological impact, which indicates its technological capability, can be measured by the portion of its patents (or publications) that have high impact compared to the industry mean (Ernst, 2003): again, high values suggest high technology strength. Finally, technology marketability is measured by the average number of family patents granted by the organisation in the technology areas of interest to the firm compared to the industry mean (Ernst, 2003). The number of family patents represents the number of different nations in which a patent is published (Lanjouw et al., 1998; Breitzman and Mogee, 2002; Harhoff et al., 2003). The number of international patent families has been considered as indicating the level of R&D or technological activity relevant to international exploitation, implying marketability as well as technological strength.

Table 2 summarises the indexes for technology strength, which are characterised in three ways: adopted, adopted & modified, and developed. An “adopted” index follows a definition from the literature, while an “adopted & modified” index generally follows the concept of existing indexes, with some modification. Finally, a “developed” index has been developed by the authors, to reflect the implication of references.

Table 2
Technology strength indexes for patent analysis.

Index	Operational definition	Reference	
		Type	Reference
Technology share (TS)	$TS = \frac{p_p(i)}{p(i)}$ $p_p(i)$: total number of partner p's patents in the technology area i $p(i)$: total number of patents in the technology area i	Adopted	Ernst (2003)
Technology leadership (TL)	$TL = p_{p\_more}(i)$ $p_{p\_more}(i)$: the number of partner p's patents in the technology area i cited *more than the average number* of citation in the area i	Adopted and modified	Almeida (1996), Michel and Bettels (2001), Ernst (2003)
Technology impact: Technological (TI)	$TI = \frac{p_{p_{10}}(i)}{p_{10}(i)}$ $p_{p_{10}}(i)$: the ratio of partner p's patents within upper 10% in the technology area i $p_{10}(i)$: the ratio of patents cited within upper 10% in the technology area i	Developed	Almeida (1996), Michel and Bettels (2001), Ernst (2003)
Technology impact: Market (TM)	$TM = \frac{fp_p(i)}{fp(i)}$ $fp_i(i)$: the average number of partner p's family patents in the technology area i $fp(i)$: the average number of family patents in the area i	Adopted and modified	Ernst (2003)

Table 3
R&D openness indexes for patent analysis.

Index	Operational definition	Reference	
		Type	Reference
Organisational openness (OO)	$OO = \frac{(p_c a_p/p_p)}{(p_c a/p)}$ p_ca_p: total number of partner p's co-assigned patents p_p: total number of partner p's patents p_ca: total number of co-assigned patents p: total number of patents	Adopted and modified	Ma and Lee (2008), Ma et al. (2009)
Field openness (FO)	$FO = \frac{(p_f a_p(i)/pf_p(i))}{(p_f a(i)/pf(i))}$ $p\_fa_p(i)$: total number of partner p' co-assigned patents in the technology area i $pf_p(i)$: total number of partner p' patents in the technology area i $p\_fa(i)$: total number of co-assigned patents in the technology area i $pf(i)$: total number of patents in the technology area i	Adopted and modified	(Ernst, 2003; Ma and Lee, 2008; Ma et al. (2009)
Technology openness: Co-assignee intensity (CAI)	$CAI\_P = \frac{1}{J}\sum_j^J ac_j$ j: patent indicator J: total number of patents ac_j: the number of affilitations (nationalities) of assignees for patent j	Adopted	Ma and Lee (2008)
Technology openness: Co-invention intensity (CII)	$CII\_P = \frac{1}{J}\sum_j^J ic_j$ j: patent indicator J: total number of patents ic_j: the number of affiliations (nationalities) of inventors for patent j	Adopted	Ma and Lee (2008)

3.2.2. R&D openness (RdO)

R&D openness is the second evaluation criteria for strategic partner selection and includes organisational openness, field openness, and technology openness. Organisational openness can be measured by the ratio of co-assigned patents (or publications) with the candidate's partners compared to the ratio of total co-assigned patents (Ma and Lee, 2008), while field openness is measured by the ratio of co-assigned patents or publications in the technology field compared to the overall mean in all fields (Ma and Lee, 2008). A more sophisticated index is designed for technology openness, which is measured by co-assignee intensity and co-invention intensity. The co-invention intensity is available only for patent analysis, since there is no clear distinction between invention and application in publication. Again, higher index values denote greater R&D openness increases: the indexes and the relevant operational definitions for patent analysis are summarised in Table 3.

3.2.3. R&D linkage (RdL)

R&D linkage measures the level of previous R&D collaborations between the firm and partner candidates, and is determined by analysing three types of information described in the literature databases – co-assignee relationships, co-invention relationships, and co-operation relationships – which have been captured in the design of three corresponding indexes (Guellec and van Pottelsberghe de la Potterie, 2001). The first index, joint ownership (the most commonly used to analyse R&D linkages—Ma and Lee, 2008) uses co-assignee information to measure the proportion of patents (publications) co-assigned with a partner candidate to all the firm's patents (publications). The second, joint development uses co-invention information to calculate the ratio of patents (publications) co-invented with the partner candidate to all the firm's co-invented patents (publications). The final index, joint operation (which only relates to patent analysis) uses cooperation information to develop two ratios: of patents assigned by the partner candidate to all patents invented in the organisation, and of patents invented by the partner candidate to all patents assigned by the organisation. As before, the higher the index value, the more intense the network linkage, as Table 4 explains. (Since there is no clear distinction between invention and application, the second and third indexes are not applicable to the publication analysis.)

3.2.4. Collaboration effect (CoE)

This final criterion measures the level of the effects expected from the collaboration: three relevant indexes, all based on citation analysis, are adopted from previous research to predict such effects. The first is knowledge inflow, which captures the degree of previous knowledge inflow from a partner candidate towards the organisation (Berman, 2002; Karki, 1999; Sternitzke et al., 2007). High knowledge inflow means the knowledge is very necessary, and that significant outcomes can be expected from the collaboration. The second is knowledge criticality, which considers the importance of the knowledge flowing from the partner candidate (Berman, 2002; Karki, 1999; Sternitzke et al., 2007). The final index uses previous co-citation relationships between the organisation and the candidate as a proxy measure of similarities between their knowledge bases (Mowery et al., 1998). In all these indexes, higher values equate to higher expected effects: as before, Table 5 summarises.

3.3. A framework for identifying and selecting strategic partners

Based on the indexes developed in this research, Fig. 1 proposes a 3-stage framework to help firms to select strategic partners.

Table 4
R&D linkage indexes for patent analysis.

Index	Operational definition	Reference	
		Type	Reference
Joint ownership (JOn)	$\text{JOn}=\frac{p_c a_{p\&I}}{ca_I}$ $p\_ca_{p\&I}$: the number of patents co-assigned with the partner p in the firm I (country I) ca_I: the number of all co-assigned patents in the firm I (country I)	Adopted and modified	Ernst (2003), Ma and Lee (2008), Ma et al. (2009)
Joint development (JDe)	$\text{JDe}=\frac{p_c i_{p\&I}}{ci_I}$ $p\_ci_{p\&I}$: the number of patents co-invented by the partner p in the firm I (country I) ci_I: the number of co-invented patents in the firm I (country I)	Adopted and Modified	Guellec and van Pottelsberghe de la Potterie (2001), Ernst (2003), Ma and Lee (2008), Ma et al. (2009)
Joint operation (JOp)	$\text{JOp}=\frac{p_c i_{I_c} a_p}{ci_I}+\frac{p_c i_{p_c} a_I}{ca_I}$ $p\_ci_I\_ca_p$: the number of patents invented by the firm I (country I) and assigned by the partner p ci_I: the number of co-invented patents in the firm I (country I) $p\_ci_p\_ca_I$: patents invented by the partner p and assigned by the firm I (country I) ca_I: the number of co-assigned patents in the firm I (country I)	Developed	Guellec and van Pottelsberghe de la Potterie (2001), Ernst (2003), Ma and Lee (2008), Ma et al. (2009)

Table 5
Collaboration effect indexes for patent analysis.

Index	Operational definition	Reference	
		Type	Reference
Knowledge inflow (KI)	$\text{KI}=\frac{b_c itation_{I,p}(i)}{b_c itation_I(i)}$ $b\_citation_{I,p}(i)$: the average number of backward citations made by the firm I (country I)'s patents to the partner p's patents in the area i $b\_citation_I(i)$: the average number of backward citations made by the firm I (country I)'s patents in the area i	Adopted and Modified	Karki (1999), Michel and Bettels (2001), Ernst (2003), Pilkington and Meredith (2009)
Knowledge criticality (KC)	$\text{KI}=\frac{f_c itation_{I,p}(i)}{f_c itation_I(i)}$ $f\_citation_{I,p}(i)$: the average number of citation made by the firm I (country I)'s patents to the partner p's patents in the area i $f\_citation_I(i)$: the average number of forward citation of partner p's patent in the area i	Adopted and Modified	Karki (1999), Michel and Bettels (2001), Ernst (2003); Pilkington and Meredith (2009)
Knowledge similarity (KS)	$\text{KS}=\frac{co-citation_{I,p}(i)}{p_p(i)}+\frac{co-citation_{I,p}(i)}{p_I(i)}$$co-citation_{I,p}(i)$: the number of co-citations made by the partner p and the firm I (country I) in the area i $p_p(i)$: total number of c partner p's patents in the area i $p_I(i)$: total number of patents of firm I (country I) in the area i	Developed	Mowery et al. (1998), Ernst (2003), Pilkington and Meredith (2009)

The first stage is to define a clear strategy specific to the intended collaboration's purpose, which involves determining the scope of analysis – including which literature databases to use and which technology to consider – and then adopting suitable indexes for supporting the chosen collaboration strategies. As the definition of what is an appropriate strategic partner may vary depending on the type and purpose of the collaboration, the suggested partner selection criteria – technology strength, R&D openness, R&D linkage, and collaboration effect – must be customised before use: for example, the relative importance of each criterion and of each literature database can be determined via the AHP technique, which can be applied by a panel of experts.

As one of the most widely used multi-criteria decision making (MCDM) method, AHP decomposes a problem into several hierarchical levels in which each decision element is considered to be independent, and eases decision-making by using pairwise comparisons between these elements to more accurately prioritise them. In this paper, the main role of AHP is to determine the weights for each criteria of partner selection and the weights for each database (patents and publications). Each criteria of partner selection contributes differently, and also differs in importance.

Second, data for analysis (including patent applicants and authors' affiliations) are collected to identify potential partner candidates, and the relevant values of whichever indexes have been selected used to evaluate each candidate's characteristics. (Individual indexes must be calculated according to their operational definitions, so the evaluation criteria in Table 1 must be measured according to their operational definitions as illustrated in Tables 2–5.)

Finally, the candidates are prioritised according to their index values. After individual index values for each criterion for patents and for publications have been obtained, the final step is to integrate these values into a single value for prioritising potential candidates (see Fig. 2). Since different indexes may be differently scaled, their sub-criteria scores must be normalised before they can be integrated, by dividing them by a maximum value minus a minimum value, so as to re-scale them from 0 to 1, as follows:

$$\text{Normalised } \mathrm{II}_i = \frac{\mathrm{II}_i - \mathrm{Min}(\mathrm{II}_i)}{\mathrm{Max}(\mathrm{II}_i) - \mathrm{Min}(\mathrm{II}_i)} \quad \mathrm{II}_i : \text{individual index } i \tag{1}$$

After the normalisation, two successive processes for merging index values are required. The first process averages sub-criteria values to merge them into single integrated values for each index (technology strength, R&D openness, R&D linkage and collaboration effect) for both patents and publications. The next process is to merge these eight values into a single index value. Two types of weightings are used, which are determined as part of the AHP process: one to weigh the four separate criteria, and the other to

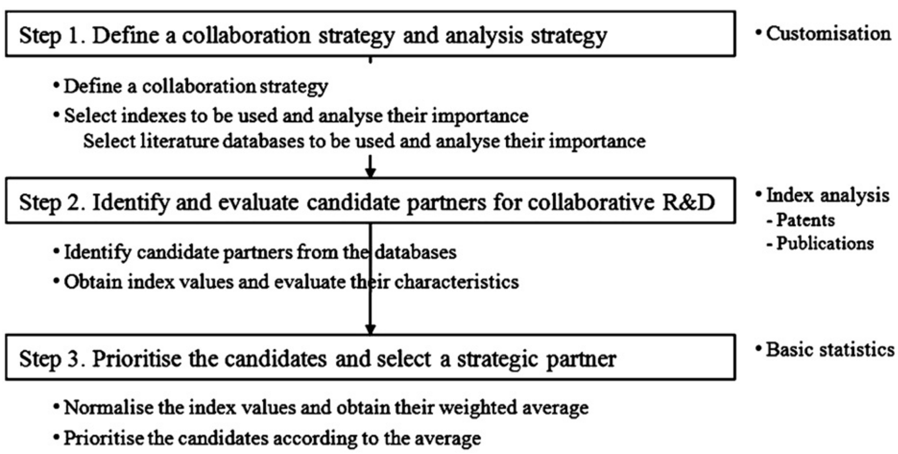

Fig. 1. A framework for identifying and selecting strategic partners.

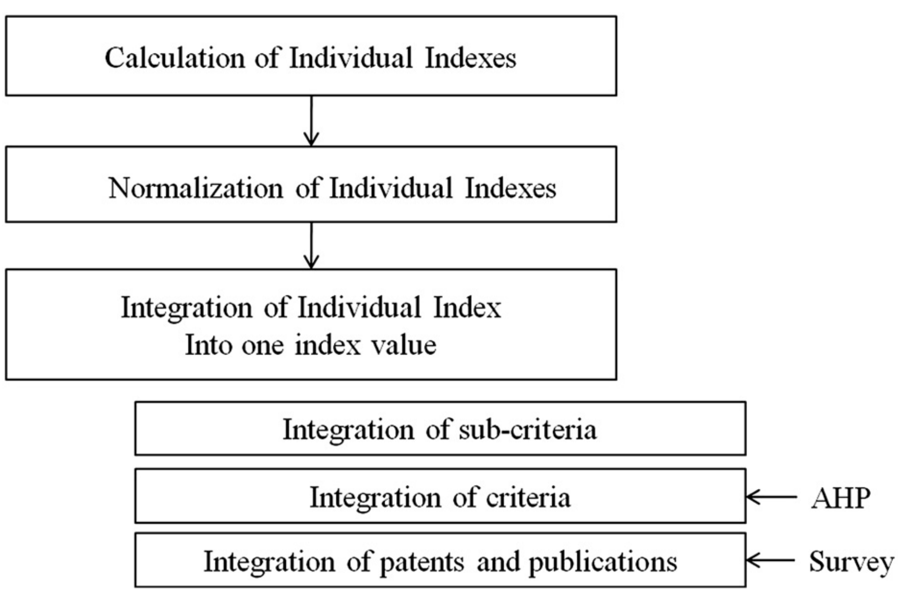

Fig. 2. Index value merging process.

weigh patents and publications so their separate sets of indexes can be merged. After the sub-indexes are merged into a single value for both patent and publication, the patent and publication indexes are combined to get the final score that represents the organisation's overall attractiveness as a collaboration partner. This merging process can be described as follows:

$$\text{Total score}_i = w_{ph} \times \left(\sum_{j=1}^{m} w_{hpj} \times \mathrm{NII}_{pj_i} \right) + w_{rh} \times \left(\sum_{j=1}^{n} w_{hrj} \times \mathrm{NII}_{rj_i} \right)$$

w_{ph} : weight of patents in the sector h

w_{rh} : weight of publications in the sector h

w_{hpj} : weight of criteria j for patents in the sector h

w_{hrj} : weight of criteria j for publications in the sector h

NII_{pj_i} : (normalised) individual score of each criteria for patents i

NII_{rj_i} : (normalised) individual score of each criteria for publication i (2)

4. R&D collaboration for Korean firms

The suggested framework was applied to a partner selection process for KIAT, which allowed us to verify its feasibility and utility. KIAT was established in May 2009 as a public institute under the Ministry of Knowledge Economy to promote industrial development and technology innovation in Korea. The Korean government identified 31 industry sectors that were expected to be growth drivers in Korea, and 546 technologies it wished to emphasise in the near future. This work is conducted by domain knowledge for each industry. The purpose of the application of the framework was to assist KIAT to select 300 key technologies, 100 organisations, and 10 nations as suitable for strategic technology collaboration with Korean firms.

4.1. Collaboration and analysis strategy

The purpose of collaboration and the key technology areas involved have to be defined before strategic partners are identified. In this case, a key technology area was defined as "one where domestic technological power could be enhanced greatly by R&D collaboration", which was the government's main purpose in facilitating international R&D cooperation. We used two databases for the analysis: the USPTO database for patents, and the ISI Web of Science database for publications. The ISI Web of Science database is an international database commonly utilised for all around the world. The USPTO database is a representative international patent database. Since key patents are applied not only for the local country but also for several other countries with high impact, the USPTO database seems to encompass key and powerful patents (Kim and Lee, 2012). Nevertheless, the research results are somewhat dependent on the selection of database, and thus the selection of different sources for patent data can result different collaboration partners. Therefore, when selecting partners, firms should select the most appropriate patent database according to their purpose. For example, if a firm wants to collaborate with European organizations, a database such as the European Patent Office (EPO) one may be an appropriate choice.

We used keyword searches to extract patents and publications data, such as title, abstract, registered year, inventor, assignee, citation, claim, and description for 546 candidate technologies in 31 industry sectors. The framework was used to identify and evaluate "all potential" technology partners, all indexes were used for analysis, but limits of time and effort lead to the three collaboration effect indexes being omitted.

Once the analysis strategy had been established, an expert survey was conducted using AHP to determine the relative importance of the four partner selection criteria as well as of patents and publications. Here, 31 industry sectors are given different weightings. For each industry sector, experts with domain knowledge in particular industry sectors were asked to evaluate the relative importance of patents and publication. As well, the relative importance of four criteria: technological strength, R&D openness, R&D linkage, and collaboration effect, is asked for each industry sector (see Table 6). The weights are calculated using AHP, an Eigen value approach to the pair-wise comparisons. This requires $n(n-1)/2$ comparisons, where n is the number of elements with the considerations that diagonal elements are equal or 1 and the other elements will simply be the reciprocals of the earlier comparisons (Vaidya and Kumar, 2006). It provides a methodology to calibrate the numeric scale for the measurement of quantitative as well as qualitative performances. The scale ranges from 1/9 for least valued than, to 1 for equal, and to 9 for absolutely more important than, covering the entire spectrum of the comparison (Vaidya and Kumar, 2006). Note that weights can be varied according to the case of a country or a firm, since the internal or external circumstances of a firm or country can be different. Some consider the candidates with high technology capability whereas the others can emphasise the openness of a partner firm. Thus, it can be varied and should be determined. As well, this can be developed using some kind of balanced scorecard approach.

4.2. Literature-based partner selection process

4.2.1. Key technology areas for R&D collaboration

First, the key technology areas for analysis among the 567 candidate areas were identified, along criteria that differed according to the purpose of the intended collaboration. Since our purpose was to identify promising partners to introduce external advanced technology, the selection of key technology areas was based on the two factors: domestic technological power (DT) and expected collaboration effect (eCE). (If the purpose of collaboration had been to create a synergy effect or to establish the technology standards as a leading company or leading nation, the decision criteria could have been differently applied.)

DT measures the performance level in current technology areas; high scores indicated areas where Korea already had considerable technological capability, low scores meant that collaboration was much needed. This measure is closely linked with the well-accepted index, the activity index (AI) (Banerjee et al., 2000) which explain the technological capability of a firm.

eCE was measured by experts considering the technological and economical effects expected from international R&D collaboration. DT and eCE values were obtained in the 546 technologies from both patents and publications. Then the patents-based and publications-based DT values were merged into a single DT value which, together with the merged eCE value, determined the final scores for prioritising key technology areas. This process led to 300 promising technology areas for international R&D collaboration being identified.

4.2.2. Strategic firm-level partners for R&D collaboration

To identify potential R&D partners for the 300 promising technologies, we first identified assignees from the patent database and authors' affiliations from the publication database, a process that involved analysing 26,179 candidates from patents and 82,217 candidates from publications and which identified 101,875

Table 6
Relative importance of the four criteria for selecting a strategic partner by sector.

Industry sector		Criteria weights				Database weights	
		TSt	RdO	RdL	CoA	Pat	Pub
1	Metal	.447(1)	.341(2)	.146(3)	.066(4)	0.630	0.370
2	Nano convergence	.432(1)	.309(2)	.123(4)	.137(3)	0.630	0.370
3	Display	.288(2)	.205(3)	.169(4)	.338(1)	0.677	0.323
4	Digital broadcasting TV	.432(1)	.213(2)	.190(3)	.165(4)	0.800	0.200
5	Robot	.481(1)	.210(2)	.176(3)	.133(4)	0.767	0.233
6	Bio	.239(3)	.281(2)	.340(1)	.140(4)	0.706	0.294
7	Semiconductor	.423(1)	.266(2)	.174(3)	.137(4)	0.750	0.250
8	Manufacturing infrastructure	.330(1)	.330(1)	.140(4)	.200(3)	0.643	0.357
9	Manufacturing system	.298(1)	.245(3)	.176(4)	.281(2)	0.706	0.294
10	Fibre and textile	.423(1)	.266(2)	.137(4)	.174(3)	0.688	0.313
11	Renewable energy	.287(2)	.340(1)	.136(4)	.237(3)	0.600	0.400
12	Energy efficiency increase	.391(1)	.138(4)	.195(3)	.276(2)	0.677	0.323
13	Greenhouse gas	.465(1)	.256(2)	.122(4)	.156(3)	0.667	0.333
14	Medical device	.316(2)	.152(4)	.203(3)	.329(1)	0.565	0.435
15	Automobile	.533(1)	.112(4)	.139(3)	.216(2)	0.697	0.303
16	Resource technology	.245(3)	.254(2)	.167(4)	.334(1)	0.667	0.333
17	Electric power and nuclear energy	.425(1)	.270(2)	.161(3)	.144(4)	0.677	0.323
18	Shipbuilding	.287(2)	.237(3)	.136(4)	.340(1)	0.630	0.370
19	Knowledge service	.243(2)	.343(1)	.172(4)	.243(2)	0.655	0.345
20	Knowledge and information security	.346(1)	.163(4)	.205(3)	.286(2)	0.643	0.357
21	Next-generation mobile	.455(1)	.263(2)	.141(3)	.141(3)	0.737	0.263
22	Clean infrastructure	.434(1)	.195(2)	.177(4)	.195(2)	0.677	0.323
23	Aerospace	.326(2)	.363(1)	.163(3)	.148(4)	0.630	0.370
24	Home network	.237(3)	.287(2)	.340(1)	.136(4)	0.677	0.323
25	Chemical process material	.588(1)	.192(2)	.092(4)	.128(3)	0.697	0.303
26	BcN	.423(1)	.162(4)	.199(3)	.216(2)	0.697	0.303
27	IT convergence	395 (1)	.232(2)	.232(2)	.140(4)	0.630	0.370
28	LED	.346(1)	.163(4)	.205(3)	.286(2)	0.697	0.303
29	RFID/USN	.237(2)	.237(2)	.347(1)	.180(4)	0.655	0.345
30	SW	.330(1)	.330(1)	.140(4)	.200(3)	0.630	0.370
31	U-computing	.210(4)	.246(2)	.298(1)	.246(2)	0.583	0.417

Table 7
Partial results of patent analysis for TSt.

Potential R&D partners		Patent-based				Publication-based			
		TS	TL	TI	TM	TS	TL	TI	TM
1	PP1	0.0004	1	9.8632	0.4551	–	–	–	–
2	PP2	0.0004	1	9.8632	0.1300	–	–	–	–
3	PP3	0.0004	1	9.8632	0.1300	–	–	–	–
4	PP4	0.0017	4	9.8632	4.4863	–	–	–	–
5	PP5	0.0009	0	0	0.7802	0.00005	0.9	8.69423	–

candidates considering the candidates identified from both sources. We then conducted an index analysis on the patent and publication data to identify strategic partners for collaborative R&D and their characteristics in terms of the four criteria: technology strength (TSt), R&D openness (RdO), R&D linkage (RdL), and collaboration effect (CoE). TSt denotes the technological capability of a candidate organisation; RdO examines the degree of an organisation's openness to collaboration with external partners; RdL measures the level of already-existing collaboration with Korean firms, analysing the closeness between the organisation and Korea; and CoE measures the expected synergy effects from the collaboration with Korean organisations. Table 7 shows the results of analysis of the individual TSt indexes using patents and publications. It should also be noted that the operational definition of TS was changed in this case study. TS is normally defined as the number of patents in a technology area assigned by the candidate, divided by the total number of patents in that technology area, but in this case the client requested it be calculated as the number of patents in the area assigned by the candidate, divided by the maximum number of patents in the area assigned by all candidates.

Then, after going through three successive integration processes—of sub-criteria, of criteria, and of patent- and publication-based index values, the final score was calculated. Table 8 shows how this process identified the five best partners for R&D collaboration in the nano sector, with their final index scores.

4.2.3. *Strategic nations*

Summarising the strategic partner selection results, we were also able to identify which nations seemed to offer Korean firms the best opportunities for R&D collaboration in the nano sector, based on their candidate organisation's results. Referencing its number of potential strategic partner organisations, the United States was (by some margin) is the most promising nation, as Table 9 shows.

4.3. Ad-hoc analysis of indexes

4.3.1. Relationships between indexes

Although the sub-criteria of our indexes were developed from a systematic review, the fact that criteria values are measured by composite indexes consisting of three or four components could still cause problems of overlapping and of complexity, which could lead to serious difficulties in calculating index values, especially where data-sets are very large. In this case, it may be desirable to use only representative indexes for each criterion to reduce index numbers. We conducted a separate correlation analysis of relationships between the indexes, analysing 2789 records from the next-generation mobile sector to measure the Pearson correlation coefficient values of different indexes. As expected, we observed a strong correlation between some indexes, as Tables 10 and 11 show. For example, technological impact (TI) and technology leadership (TL) show strong positive correlations, as do technology share (TS) and technology leadership (TL), implying that these indicators ought to be integrated to eliminate the risk of partial overlapping. Considering our analysis results – and the degree of effort involved in getting values for each index – we concluded the following indexes can be used as representative for each criterion: technology leadership (TL) and technology share (TS) for technology strength; field openness (FO) for R&D openness; joint development (JD) for R&D linkage, and knowledge inflow (KI) for collaboration effect. Similar results were derived for other criteria: R&D openness, R&D linkage and collaboration effect.

Table 8
Top five candidates for R&D collaboration in the nano sector.

Potential R&D partners		TS	TL	TI	TM	Final scores
1	TPP1	0.14067	0.11256	0	0	0.09555
2	TPP2	0.14032	0.11256	0	0	0.09540
3	TPP3	0.02480	0.01380	0	0	0.09540
4	TPP4	0.14763	0.09842	0	0	0.09419
5	TPP5	0.07391	0.15356	0	0	0.07938

Table 9
Top five nation candidates for R&D collaboration in the nano sector.

Potential R&D partner nations	Number of strategic organisations	Total scores of organisations
United States	73	217.33
Japan	14	42.50
Great Britain	8	21.67
France	6	20.17
Italy	6	18.83

Table 10
Pearson correlation coefficient of indexes for technology strength (TSt).

	Technological impact (TI)	Technology share (TS)	Technology leadership (TL)	Market impact (TM)
Technological impact (TI)	1	.162(**) *.040(*)*	.484(**) *.340(**)*	.281(**) *–*
Technology share (TS)		1	.823(**) *.782(**)*	.105(**) *–*
Technology leadership (TL)			1	.204(**) *–*
Market impact (TM)				1

The value is for patent-based indexes, but the value in italic is for publication-based indexes.

* Significance value at 0.05 level.
** Significance value at 0.01 level.

Table 11
Pearson correlation coefficient of indexes for R&D openness (RdO).

	Organisational openness (OO)	Field openness (FO)	Co-invention intensity (CII)	Co-assignee intensity (CAI)
Organisational openness (OO)	–	–	–	–
Field openness (FO)		1	.941(**) *.395(**)*	.932(**) *–*
Co-invention intensity (CII)			1	.946(**)
Co-assignee intensity (CAI)				1

Note 1. * Significance value at 0.05 level, **Significance value at 0.01 level.
Note 2. The value is for patent-based indexes, but the value in italic is for publication-based indexes.

4.3.2. Stepwise application of indexes

This research employs the same weights when aggregating sub-criteria indexes (e.g. the technology strength criteria (TSt) value is calculated by averaging the TI, TS, TL, and TM sub-criteria scores). Though this method has the virtue of being easy to apply in practical settings, it can involve problems where there are outlier data: so, if one value is very high and others are rather low, the average may end up being too high. Thus, a firm could score highly as a potential strategic partner if it has, say, a very high score (an outlier) for R&D openness, R&D linkage or collaboration effects (which AHP considers significant factors), even if it has few patents or publications to its name. To illustrate this problem, Table 12 shows the result for the top 10 firms in the next-generation mobile analysis: candidate I5's relatively high R&D openness score (0.244) ensure it is ranked fifth, even though its technology strength is inferior to that of I6. This problem could be addressed by adopting a stepwise approach to candidate screening, using (for instance) technology strength as a first step to screen out the bulk of candidates, and other criteria for subsequent decisions. Of course, this would entail prioritising the indexes, so that the first screen represented the most important criteria.

4.3.3. Relationships between the categories of indexes

Finally, in order to see the relationships between the four criteria for partner selection, that is, the four categories of indicators, we also employed correlation analysis based again on 2789 records from the next-generation mobile sector. Table 13 shows the Pearson correlation coefficient values of the category values. The analysis results indicate that there exist a positive relationship between 'Technology strength' and 'R&D openness', which means that companies with strong technological capabilities tend to collaborate more with others than those with weak technological capabilities in the next-generation mobile sector. We also observe a positive relationship between 'Technology strength' and 'Collaboration effect'. Therefore, the level of the effects

Table 12
Index score of the top 10 organisations in next-generation mobile sector.

Rank	Candidate	Integrated				Patent				Publication			
		TSt	RdO	RdL	CoA	TSt	RdO	RdL	CoA	TSt	RdO	RdL	CoA
1	I1	0.169	0.244	0	0	0.230	0.332	0	0	0	0	0	0
2	I2	0.169	0.244	0	0	0.230	0.332	0	0	0	0	0	0
3	I3	0.168	0.244	0	0	0.230	0.332	0	0	0	0	0	0
4	I4	0.168	0.244	0	0	0.230	0.332	0	0	0	0	0	0
5	I5	0.087	0.244	0	0	0.117	0.332	0	0	0	0	0	0
6	I6	0.206	0	0	0	0.280	0	0	0	0	0	0	0
7	I7	0.169	0	0	0.074	0.230	0	0	0.100	0	0	0	0
8	I8	0.133	0.088	0.005	0	0.163	0.105	0	0	0.031	0.042	0.019	0
9	I9	0.185	0	0	0	0.251	0	0	0	0	0	0	0
10	I10	0.084	0.184	0	0	0.250	0	0	0	0	0	0	0

Table 13
Pearson correlation coefficient of categories of indexes in next-generation mobile sector.

	Technology strength (TSt)	R&D openness (RdO)	R&D linkage (RdL)	Collaboration effect (CoE)
Technology strength (TSt)	1	.088(**)	−.05	.116(**)
R&D openness (RdO)		1	.000	−.030
R&D linkage (RdL)			1	−.006
Collaboration effect (CoE)				1

Note 1: *Significance value at 0.05 level, **Significance value at 0.01 level.
Note 2: The value is for patent- and publication-integrated indexes.

expected from collaboration will increase when a strategic partner has a strong technological capabilities, particularly considering that many Korean companies in the mobile sector are technology leaders in the global market. Except the two, no other significant relationships are found between the categories. However, it is difficult to generalise the analysis results because the relationships will differ by industries or technologies.

5. Implications

5.1. Use of literature data

The framework was used between August and December 2009 in KIAT's technological cooperation division, which supports the international joint technological development of domestic corporations, universities and research centres by promoting connections for global technological exchanges and innovation with major foreign organisations. To facilitate these connections, the division has collected and analysed up-to-date world-wide information regarding industrial technology. The analysis of literature (via the framework proposed in this research) was one of the activities used to develop an international cooperation roadmap to provide information to help Korean firms identify and evaluate potential collaborative R&D partners, and develop a Korean policy for international R&D collaboration. As a result, a large number of candidates all around the world, both organisations and individuals, could be identified from the literature data. Though KIAT was interested only in organisations as a collaboration partners, information about key technology owners was also valuable intelligence for technology strategy-making. In addition, characteristics of candidates were analysed quickly using index analysis, which can be a reference for further investigation. The analysis results are intended to be available to the public through web services so as to provide useful information to Korean firms.

5.2. In-depth analysis for the final partner selection

This paper developed a systematic framework to guide strategic partner selection, taking the patent and publication as a main data source. For this purpose, we developed indexes for patent and publication analysis with special emphasis on the information about assignees and authors, measuring technology strength, R&D openness, R&D linkage, and collaboration effects using patents and publications.

However, these four factors are sometimes not enough to cover full decision criteria of partner selection. In practice, qualitative analysis can help firms make the final decision about who to work with. For example, factors such as geographical proximity or use of a common language have been considered as critical factors to the partner selection in practice. Even if the importance of these factors is recently decreasing due to the rapid growth of the internet and transportation networks, these are still important and thus should be considered in the partner selection. In addition, factors such as strategic fit, similarities in organisational culture, complementarity of resources, trust and commitment are also critical to determine collaboration partners. These are omitted in this study due to the difficulties of extracting from our database: patents and publications. However, it should be certainly considered in the final partner selection process which includes the in-depth analysis of partner candidates based on the expert judgment.

5.3. Industrial differences

Interestingly, significant differences of importance in the four selection criteria were observed between industry sectors. While technology strength seemed to be the most important factor for selecting an R&D partner in general, R&D openness was regarded as the most important factor in such sectors as manufacturing infrastructure, renewable energy, knowledge service, aerospace and software, and R&D linkage was judged critical for the most advanced telecommunications sector, including home network, RFID/USN and u-computing and in others (display, resource technologies, shipbuilding). Collaboration effect was also seen as significant to partner selection. The comparative importance of patent and publication data also differed: while experts responded that patent data was the more important in most industry sectors, some emerging sectors – such as medical device and u-computing sectors – saw publication data as the more important because in those emerging sectors, basic technologies as well as applied technologies are critical, whose research outputs are presented mostly in publications. (The AHP results are summarised in Appendix A.)

5.4. Improvements in indexes

This paper suggests decision criteria and relevant indexes that would be appropriate for identifying the best key technology areas and potential suitable strategic partners for R&D collaboration, proposing (especially for strategic partners selection) 14 indexes to measure for four criteria: technology strength, technology openness, degree of linkage, and degree of likely effectiveness. Though these criteria have distinct meanings, some of them are highly correlated with each other. Also, some of the criteria (e.g. technology strength) should be a mandatory condition for R&D collaboration. Therefore, the suggested process could still be improved by simplifying the number of indexes needed, by adopting a stepwise process to avoid averaging problems, and by more fine-grained differentiation of types.

Another strategy for improvement could be to differentiate candidates according to types of organisations. For example, if the organisation type is "laboratory," it is likely to have a relatively high level of openness compared to private firms, so technology strength may be a more significant and more differentiated factor than the level of openness – on the other hand openness could be more important than other criteria if the organisation type is 'large multi-national firm'. Taking organisational type properly into account may provide more flexible and meaningful results.

5.5. Object of analysis

The suggested approach can be used for both levels: firms and countries. In other words, this framework can be utilised for the policy makers as well as the managers in the firm. Basically, this paper was written for the viewpoint of policy maker (note that the baseline is "country", as illustrated in Tables 2–5). However, the "partners" that this paper deals with can be varied according to the context it can be an organisation (a firm), or it can be a nation. To select the partners, this paper provides four criteria: technology strength (TSt), R&D openness (RdO), R&D linkage (RdL), and collaboration effect (CoE). Among four factors, the first two (TSt and RdO) measures the internal characteristics of partners. This is measured regardless of firm or nation. However, the last two (RdL and CoE) measure the level of linkage between a partner and a firm (or a country); for example, joint ownership measures the portion of co-assignment with a country. If this framework is applied for firms, one can use this measure, replacing a "country" with a "firm".

5.6. Difference in patents and publications

Basically, publication data is also considered as important sources to measure the technological power. Many articles employed both patents and publication to measure the performance of a firm or country (Archibugi et al., 2008; Castellacci and Archibugi, 2008; UNCTAD, 2005). Especially, basic indicators like shares and averages of absolute publication and citation counts are widely accepted as useful tools in measuring research performance (Garfield and Welljams-Dorof, 1992; Gauffriau et al., 2007). For example, Archibugi and Coco (2004) measured innovative activity based on both patents and scientific publication. However, to measure the partner capability or partner complementarity, the use of publication should be differentiated from patents as follows.

First, in terms of technological strength, there is no "family patent" in publication. The number of family patents represents the number of different nations in which a patent is published, which is related to the technology marketability (Lanjouw et al., 1998; Breitzman and Mogee, 2002; Harhoff et al., 2003). Therefore, we cannot consider the fourth indicator of technology strength – technology impact (market) – in case of publication. Second, patents have both assignee and inventor, which is not true in publication. In publication, these two are considered as one person: author. Therefore, co-assignee intensity and co-invention intensity are both measured by co-authorship intensity. Therefore, technology openness is considered as one measure. This is similar to the R&D linkage. Since joint ownership and joint development can be considered as a same measure, these two can be considered as a single indicator: joint authorship.

6. Conclusion

This research developed a systematic framework to guide strategic partner selection, taking the patent and publication as a main data source. For this purpose, this paper suggested a framework to identify potential R&D collaborators and evaluate them in terms of technology strength, R&D openness, R&D linkage, and collaboration effect, enabling the search to be wide ranging, and to deliver objective evidence about candidates' technological and collaborative capabilities and characteristics. We reviewed previous research on bibliometric analysis and extracted indexes for patent and publication analysis with special emphasis on the information about assignees and authors. Based on this review, a framework for selecting strategic partners for collaborative R&D was developed, in which four factors were identified for index analysis, and AHP applied to evaluate their relative importance. A case study was conducted in Korea to verify the feasibility of the suggested framework, in which potential R&D partners in 31 industry sectors at the national level were identified, and drew out implications on the use of literature database for partner search.

This paper contributes to the field in three ways. First, it summarises a set of evaluation criteria relevant for strategic partner selection, based on identifying four criteria (and 14 corresponding sub-criteria) from the literature review. Second, we suggest indexes that can enable the quantitative analysis of strategic partner candidates in terms of their technological capability and willingness to collaborate, and offer operational definitions to explain their evaluation criteria using the USPTO patent and ISI publication databases. Whereas previous research on partner selection has been limited to expert judgments, this approach has significant value in facilitating a more objective and data-driven analysis for strategic partner selection. We expect the suggested method to be useful for identifying potential R&D collaborators, enabling worldwide searches for candidates, and providing detailed critical information that is required to select the appropriate partners by investigating the technological capability and collaborative capability. Finally, this research tried to analyse the relationships between indexes and also found the industrial differences in giving value to literature databases and partner selection criteria. The research results are useful for improving the suggested approach and can help employ it effectively.

However, despite its valuable contribution, this research is still subject to several limitations, which should be complemented by future research. As the discussion notes, the suggested indexes could be improved from various perspectives. First, the research uses too many indexes, which has made our results overcomplicated. Some of them may be redundant, and further studies on the relationships between indexes could simplify the framework and increase its applicability. Also a different set of indexes may be used in a different context of partner selection and thus further research will deal with the customized use of the indexes according to the purposes of use. Second, we have used simple arithmetic means to integrate the sub-factors, and although we have merged the four criteria into a final index based on their relative importance, one very high index value may lead to results being misleading for the case context, and a stepwise application process might provide more reasonable results. Lastly, we used the same indexes for patents and publications—but since they may show varied characteristics in different technology fields, it might be better to develop discrete indexes for patents and publications to reflect their distinct characteristics.

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Appendix A. AHP analysis results

See Appendix Table A1.

Table A1
AHP analysis results.

	Industry sector	The number of experts involved in the survey	Inconsistency
1	Metal	3	0.05
2	Nano convergence	11	0.03
3	Display	5	0.02
4	Digital broadcasting TV	11	0.04
5	Robot	3	0.1
6	Bio	15	0.02
7	Semiconductor	6	0.05
8	Manufacturing infrastructure	8	0.02
9	Manufacturing system	16	0.07
10	Fiber and textile	13	0.05
11	Renewable energy	13	0.07
12	Energy efficiency increase	16	0.05
13	Greenhouse gas	13	0.03
14	Medical device	4	0.04
15	Automobile	11	0.06
16	Resource technology	3	0.09
17	Electric power and nuclear energy	15	0.02
18	Shipbuilding	5	0.07
19	Knowledge service	4	0.05
20	Knowledge and information security	12	0.07
21	Next generation mobile	12	0.03
22	Clean infrastructure	13	0.01
23	Aerospace	9	0.01
24	Home network	9	0.07
25	Chemical process material	3	0.06
26	BcN	11	0.09
27	IT convergence	16	0.02
28	LED	9	0.07
29	RFID/USN	11	0.09
30	SW	4	0.02
31	U-computing	11	0.02

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