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An Approach for R&D Partner Selection in Alliances between Large Companies, and Small and Medium Enterprises (SMEs): Application of Bayesian Network and Patent Analysis

Keeeun Lee, Inchae Park and Byungun Yoon *

Department of Industrial & Systems Engineering, Dongguk University-Seoul, 30, Pildong-ro 1 gil, Jung-gu, Seoul 100-715, Korea; kelee@dongguk.edu (K.L.); inchae@dongguk.edu (I.P.)
* Correspondence: postman3@dongguk.edu; Tel.: +82-2-2260-8659; Fax: +82-2-2269-2212

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Abstract: The enhanced R&D cooperative efforts between large firms and small and medium-sized enterprises (SMEs) have been emphasized to perform innovation projects and succeed in deploying profitable businesses. In order to promote such win-win alliances, it is necessary to consider the capabilities of large firms and SMEs, respectively. Thus, this paper proposes a new approach of partner selection when a large firm assesses SMEs as potential candidates for R&D collaboration. The first step of the suggested approach is to define the necessary technology for a firm by referring to a structured technology roadmap, which is a useful technique in the partner selection from the perspectives of a large firm. Second, a list of appropriate SME candidates is generated by patent information. Finally, a Bayesian network model is formulated to select an SME as an R&D collaboration partner which fits in the industry and the large firm by utilizing a bibliography with United States patents. This paper applies the proposed approach to the semiconductor industry and selects potential R&D partners for a large firm. This paper will explain how to use the model as a systematic and analytic approach for creating effective partnerships between large firms and SMEs.

Keywords: Bayesian network model; R&D alliances; patent information; collaboration between large and small companies

1. Introduction

SMEs have become an important force in the development of national or regional economy especially, in high-technology industries from the perspective of economy and employment growth. The contribution of SMEs on GDP is over 50% in the USA and 76.6% of industrial production value increase is attributable to SMEs in China [1]. The 73% of 150 million employees work in China SMEs and the staffs of SMEs are 70% of 49 million employees [2]. It means SMEs are considered as principal drivers of economic and employment growth. Even though the benefits can improve a national economy, SMEs generally face limitations of resources. To overcome this problem, one of manifold solutions is a bilateral collaboration between large and small companies because of the following reasons. First, in aspect of SMEs, the collaboration with large firms accelerates commercialization of high-tech products. In particular, in the biotechnology industry, strategic alliances between SMEs and large companies are common because R&D expenditure is high and commercialization cycles are long for SMEs [3,4]. Second, each company obtains external information and knowledge resources by strategic R&D cooperation [5]. Limited resources are restricting SMEs' capacity for developing new products and partnerships, explaining the reason to access necessary resources. Third, from the perspective of a large firm, partnering with a small company is a way to obtain people who have the right combination of specialized skills to develop new products [6]. Small firms also enable large firms to monitor the development of new technology and equipment, because collaborative SMEs have the narrowing of the innovation gap in the product innovations [7].

Although the number of collaborative efforts between SMEs and large firms is growing, they often have problems which are caused by asymmetrical power relationships [8,9]. To solve this issue, Sawers *et al.* [6] examine the effect of using formal and informal safeguards to prevent knowledge flows of SMEs in collaboration with large firms. Kim *et al.* [10] propose 10 long-term policies in relation to theories of mutually-beneficial cooperation between large and small businesses, such as conflict resolution programs and joint brands. However, there are several limitations on previous research concepts and partner selection methods. First, these papers have some problems such as over-dependency on experts in measuring some criteria for partner selection. To overcome the issue, several quantitative approaches are utilized such as partner selection methods using patents [11], Data Envelopment Analysis (DEA) [12], nonlinear integer programing [13], and an analytic hierarchy process (AHP) approach using fuzzy numbers [14]. Second, however, is that these methods have shortcomings in that they pay little attention to technology development collaboration between large firms and SMEs. The collaboration between them has risks being in a "swimming with sharks" dilemma. Thus, the analysis considering such case-specificity is necessary since there are risks on misappropriation of technology secrets under the R&D collaboration between large firms and SMEs [15]. Lastly, previous studies on partner selection between large firms and SMEs adopt the perspective of vertical collaboration and the selected indices are insufficient to explain the complex relationship between large firms and SMEs [16]. Most of the indices are composed on the perspective of vertical collaboration without considering horizontal collaboration between large firms and SMEs [17]. It is necessary to develop the indices using data of large firms and SMEs in order to overcome the limitations of previous partner selection indices and develop partner selection method based on the success probabilities after reviewing trends of technical cooperation. In addition, informative and quantitative data are necessary to assist in performing objective decision-making and consider various types of R&D collaboration. To overcome these limitations, this paper aims at proposing a new method of partner selection for R&D collaboration between large firms and SMEs. In order to develop this method, a technology roadmap (TRM) of a large firm and a Bayesian network (BN) model are considered. A TRM can help develop a consensus about a set of needs and the technologies required to satisfy those needs, and provides a mechanism to help experts forecast technology development in targeted areas [18]. BN is suitable to the target recognition problem, where the category, identity, and class of a target track are to be determined [19]. To select the partners which are well matched to firms' needs, it is essential to consider complex environments and rank the priority of candidates. The Bayesian model is the most appropriate method in that it expresses the likelihood of cooperation as a number that is able to be used as a reference for decision-making and it enables the ability to consider many criteria and relationships to matching process. These models can contribute to identify a necessary technology and an appropriate R&D partner. This study contributes to the literature in several ways. First, quantitative analysis has been attempted to apply on the concept of technology capability; while most of the literature has focused on experts' opinions, and on the cost of selecting a potential R&D collaboration partner. Second, patent information easier to collect than other types of information, in a situation where it is difficult to find adequate sources of information on companies. Finally, the proposed approach will promote R&D alliances between large firms and SMEs. The results will be helpful to formulate critical advices for policy makers and managers of R&D.

This paper is structured as follows: in Section 2, the theoretical background behind partner selection and the Bayesian network is described. Section 3 proposes a method of partner selection for R&D alliances, using patent information. In Section 4, in order to illustrate this methodology, a case study of the semiconductor industry is constructed. Sections 5 and 6 provide results and discussions, and concluding remarks.

2. Theoretical Background

2.1. R&D Partner Selection for Alliances between Large Firms and SMEs

A successful strategic partnership for R&D activities accompanies many inherent risks especially, in the context of the knowledge misappropriation of multinational enterprises (MNEs). However, SMEs require R&D collaboration with large corporations in spite of risks on misappropriation of technology secrets according to resource-based theory and, to achieve it, protection on their own critical technology by strong Intellectual Property Policy (IPP) is critical [20]. In addition, the increase of multi-technological products of large cooperation causes R&D outsourcing and collaboration. SMEs desire sufficient resources, otherwise large firms desire to obtain the novel knowledge and technology to create value. One of the principle success factors in the partnership between large enterprises and SMEs is trust in the situation of providing adequate information with each other [21]. According to Diestre and Rajagopalan [22], ventures prefer collaboration with large firms to create value and consider appropriation, as well. Since large firms and SMEs are different in the perspectives on collaboration, the detailed partner selection method necessarily refers to their differences, as shown in Table 1.

To support their collaboration in R&D projects, it is important to understand that open innovation is a concept of sharing their knowledge with each other. Open innovation is a methodology to maximize efficiency and enhance value-added activities by reducing innovation cost and considering a probability of success based on open, whole-innovation processes with universities, institutions, and other firms. Enterprises create profits by launching new products which use comparative advantage concentrating on development, otherwise a firm utilizes external resources to speed up their technology innovation by highlighting an open innovation concept when the firm has a lack of ability than others. Chesbrough [23] proposes significant differences between closed innovation and open innovation according to the types of new markets entered, knowledge management systems, and R&D systems. Van de Vrande *et al.* [24] analyzes cases of open innovation according to size, industry, and the types of open innovation; technology exploitation and technology exploration. The findings are that medium firms imply open innovation activities than small companies and their motivations to perform collaboration are associated to market environments, such as new market development, realizing the needs of customer. Lichtenthaler [25] describes open innovation strategy and its effects of firm size to the degree of selection of this tactic.

Table 1. Differences between large firms and SMEs in concept of innovation and collaboration.

Concepts	Methods	Large Firms Level	SMEs Level	Researchers
Purpose of development	Qulitative analysis	Product platform development	Product development basd on key technology	[26]
Global operation	Structural Equation modeling	Focusing on global market	Focusing on domestic market	[27]
Knowledge requirements	Probit model	Preferring internal knowledge	Preferring external knowledge	[28]
Collaboration effect	Probit model	An influence on process	An influence on products	[7]
Appropriability	Univariate general linear model	Stong appropriability	Weak appropriability	[29]

2.2. Bayesian Network

The Bayesian network is a directed acyclic graph (DAG) and a stochastic model expressing the conditional probabilities of factors with nodes and arcs. Prior probabilities for respective nodes and arcs are necessary in order to structure a Bayesian network model, in addition, posterior probability and criteria are also necessary to employ the methodology. A conditional probability table based on Bayesian inference is used to generate sought-after probabilities.

A Bayesian network for a set of random variables U = {X1, . . . , Xn} is a pair, B = <G, O>, where G represents its DAG structure, and O represents the parameters that quantify the network [30]. The random variables are represented as vertices, and parental relationships between these random variables are represented as lines. If there is a line from xi to xj, then variable, xi, is the parent of xj, and xj is the child of xi. If a node does not have any parent node, it is called a root node. On the other hand, a node without any child node is called a leaf node. Descendants of a node include its children, children's children, and so on. These variables can be discrete or continuous. For a discrete variable, each node is one of its states, which may be unknown to the decision-maker. A state simply explains the condition of a variable. A variable Xi with its parents, pa(Xi), specifies a conditional probability distribution, P(Xi | pa(xi)). This is a conditional probability table (CPT), for a set of discrete variables. Bayesian networks are used to trace how a change in certainty of one variable may affect the certainty of others [31]. If the joint probability function of all variables is known, P(U) = P(X1, . . . , Xn), this question can be answered by finding the marginal probability distribution of a variable, P(Xi), or finding the conditional distribution of xi, given the evidence, e, P(Xi | e). The joint distribution of P(U) is defined by Bayesian network B as:

$$\mathrm{P}\,(\mathrm{U}) = \prod\nolimits_{i=1}^{n} P(X_i|pa\,(X_i)) \tag{1}$$

There are many application areas of Bayesian network models, such as computing, medicine, and risk management. The methodology is utilized for the purpose of selecting a specific variable, such as a major causative factor, and calculating the probability of a final result. Lee and Choi [32] identified major risk factors related to delirium. The method is utilized to analyze performance of medical services, and risk management for military planners [33,34]. Kubota and Mori [35] selected communication topics, and measured prior probability, using term frequency and inverse document frequency (TF-IDF). Dogan and Aydin [30] defined the probabilities of criteria such as technical capability and strategic fit, using experts' decisions, a technique as a degree of belief.

3. Proposed Approach

3.1. Basic Concepts

This study has focused on the increasingly important cooperative efforts that are being made, especially between large firms and SMEs to foster innovation in research and development (R&D). In order to promote win-win alliances beginning at the planning stage, it is necessary to consider the capabilities of both large firms and SMEs. In pursuit of developing a methodology for partner selection, the concept design is as follows in Figure 1. The first step was to consider the technology roadmapping of large companies, to identify technological areas that are essential to collaboration with SMEs. In addition, patent information was useful for exploring appropriate SMEs that were potential collaborators. The core process can be performed by applying a Bayesian network methodology, which is a directed, graphical model that represents conditional probabilities, among variables of concern. These criteria consider two concepts: technical skills and their adaptation to a large firm, and the qualitative patent information, such as the cited number per patent and average claims per patent, which are used as primary data. Finally, the proposed approach can help a final R&D partner, by means of comparing the posterior probability for each candidate.

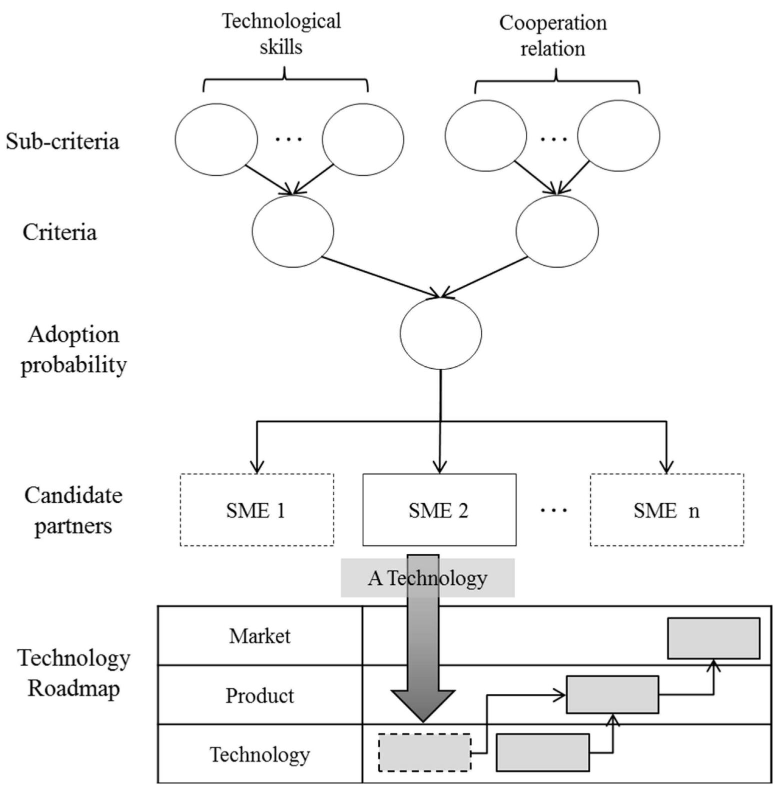

Figure 1. Research concept.

3.2. Data

Since this research aims at finding the appropriate partner focused on a R&D alliance, patent information is necessary to identify the technical competitiveness and R&D capability of a firm. Patent-related criteria can be utilized to find the information of R&D competency by remedying the limitation of the economic state [36] and determine R&D trends and competitive advantages [37]. In addition, this paper needs various criteria and a voluminous data size, and patent data can be the information source of multivariate analysis. Utilizing patent information is appropriate in this research because of overwhelming advantages in extracting new technology opportunities, future trends, and the competitive edge of a firm [38].

To select an R&D alliance partner, all data were from patent information from the United States Patents and Trademark Office (USPTO) database, because they were easy to use and a representative international patent database. In addition, the secondary patent data involves not only technological knowledge, but also a collaborative relationship between industry, inventors, firms, and so on. For example, the citation per publication represents the technological capability, and Salton's index discovers the strength of the collaborative relationship by simple calculation, using patent information. The definition of large firms is that the company has over 500 employees, in reference to SBA's standard [39]. SMEs are the companies that have fewer than 500 employers, excepting subsidiary companies, related universities, and non-practicing entities. To capture a company's structure and size, several sources were consulted, including Hoover's Company records, and LinkedIn directories.

3.3. Criteria

An appropriate partner is essential for the establishment of a successful alliance. When selecting a partner for technical cooperation, consideration must be given to many factors, such as its scale, size, technological level, management style, correlations, and so on [40]. Even though many criteria are applied to the selection of a partner, in only a few instances is the collaboration between large firms and SMEs considered. This research referred to previous research studies, to determine the factors that are required for an R&D alliance.

By examining six cases of R&D alliances between large and small businesses, this paper discovered that large firms supported infrastructures, technology skills, and funding to small businesses. SMEs developed a new technology directly, and then provided the technology to large firms [41]. Most of SME partners which demonstrated excellent technical skills in their field can be characterized as suppliers. The main categories of criteria, which are to select the R&D partner, are technological skills and cooperation relationship, according to the literature review [11,37,42]. Especially, the reason of R&D collaboration between large and small firms is based on the resource-based view and transaction cost economics. The resource-based view suggests the potential value creation through association with complementary technologies and resources [43,44] between different firms, which want to exchange their needed resources. Transaction cost economics demonstrates that strategic cooperation is arranged to minimize transaction costs, which are incurred in making an economic exchange [45]. In this paper, the required factors should measure the technical skills to know how create critical value based on the resource-based view, and the cooperation between partners based on the transaction cost economics. The criteria in Table 2 were measured to assess the possibility of R&D collaboration between large and small firms. These criteria reflect the associations of large and small companies, which result in different results, depending on the information of both large and small companies.

Table 2. Detailed criteria information for partner selection.

Node Label	Name	Operational Definition	Type	Section	Dividing Method
X1	Technical experience (TE)	The number of patents in a SME	Small firm	High/Medium/Low	Dividing into three equal parts
X2	Absorptive capacity (AC)	Average value of backward citation in a SME's patents	Small firm	Good/Fair/Poor	Dividing into three equal parts
X3	Technology lifecycle (TL)	The stage according to ratio of recent patents in a SME	Small firm	Introduction (I)/ Growth & Maturity (G)/Decline (D)	TL = 1/ 0 < TL < 1/TL = 0
X4	Collaboration experience (CE)	The number of joint patents regardless of partner types -1	Small firm	Yes/No	Experienceor not
X5	Geographical distance (GD)	The distance between large and small assignees' country	Small and large firms	Nearness (N)/ Common (C)/ Far (F)	Dividing into three equal parts
X6	Technological skills (TS)	The number of joint patents between large and small firms	Joint patents	Good/Fair/ Poor	Dividing into three equal parts
X7	Cooperation relation (CR)	Joint patents/$\sqrt{(\text{the number of large firm's patents} \times \text{small firm's patents})}$	Joint patents	Good/Fair/ Poor	Dividing into three equal parts
X8	Success (S)	Average value of forward citation in joint patents	Joint patents	Yes/No	Yes (more than 1), No (=0)

Four criteria on technical skills were as follows: (1) technical experience (TE); (2) absorptive capacity (AC); (3) technology lifecycle (TL); and (4) the patent impact index (PII). The first three primary criteria were quantitative, and the other showed the qualitative situation of a patent. First, the quantitative technology skills were indicated by the number of patents in a specific field, called technical experience. In accessing to needed technology, identifying in-house capacity is important. Using this criterion, the R&D capability of a firm is evaluated to make a needed technology in collaboration. Second, absorptive capacity can be measured by the number of backward citations, which is the learning ability to create a new technology. This ability can improve detectability and present a great contrast to former competency [46]. Therefore, information-sensing ability is a vital indicator of success through the learning performance. Third, the technology lifecycle is important to select a partner on which information of concentrated technology is desired. According to a stage of the technology lifecycle—introduction, growth, maturity, and decline—the R&D strategies and partners should be changed. When the technical change is high, the combination of complementary resources has a positive effect on the performance [47]. This means that a technology in the introduction stage will be more successful in collaboration than in the decline stage. In this paper, TL is designed to explain assignee A's patenting activity in the past T years in the specific field [37] and the function is as follows:

$$\text{TL} = PA_t/PA \tag{2}$$

where PA_t is the number of patents in the past t years and PA is the number of patents. In addition, if the TL is 0, the assignee has a technology in the decline stage, if the TL is 1, the technology is evaluated as a technology in the introduction stage. When the TL is larger than 0 and lower than 1, the technology is in the growth and maturity stage. Finally, the number of joint patents was a factor that measured the qualitative level of technology innovation performance.

The cooperative relation between large and small firms can be seen in three criteria, as follows: (1) collaboration experience (CE); (2) geographical distance (GD); and (3) cooperation relationship (CR) between collaboration firms. First, previous successful collaboration experience causes a positive relation in the next cooperation because it reduces the uncertainty [48,49]. The business-to-business agreement has a tentative relationship due to dissymmetry of information [50] and experience can improve communication skills to overcome an uncertain future [51,52]. In this paper, if a candidate has joint patents, the CE score is 1, if a candidate does not have joint patents, the CE score is 0. Second, trough the international business strategy has a larger transaction cost than a domestic alliance [53], geographical distance and location affect partner selection. Büyüközkan and Görener [49] suggest a similar criterion, geographical position, which means the different culture and tax regulations according to the partner location. However, a geographical effect level is not the same, depending on the type of industry, such as IT and heavy industry. The IT industry, through communication and collaboration by an increase of Internet use, can collaborate across a larger geographic distance, whereas the heavy industry company should contact local communities and customers to develop customized products. Therefore, companies in the heavy industry prefer accessible sites to far distance locations in R&D collaboration more than the IT industry. The geographical distance criteria distinguishes distance between a target company and candidates with three levels; nearness, common, and farness. When the nation of assignee distance between a pair of partners are on the same continent, the distance level is nearness. If the partner's location and a candidate's continent are contiguous, the geographical distance score is common. However, a pair of partners' distance is not near and in adjacent locations, this distance is evaluated on farness. Finally, the cooperation relationship is measured by Salton's Index, which provides information about the intensity of the collaboration. Salton and McGill [54] suggested this criterion as a model of information retrieval and document clustering [55]. In addition, applying to R&D collaboration, this model provides the level of collaboration tenacity. In this study, based on Salton's Index, the CR is given by:

$$\text{CR} = \frac{P_{ij}}{\sqrt{P_i P_j}} \tag{3}$$

where P_{ij} is the number of joint patents between a large (i) and small (j) companies, P_i is the number of large firm's patents, and P_j is the number of small firm's patents.

The performance of R&D collaboration between large and small firms is calculated using citation analysis. Usually, success of cooperation is measured by sales volume of products and satisfaction in collaboration [56]. Previous research indicates a joint patent as a successful performance of R&D collaboration. However, joint patents are just launched products and it is difficult to consider success in a market. In this paper, the citation number, along with joint patents between large and small companies, investigates the success of an R&D alliance, meaning that the patents citied are over 1.

3.4. Methodology

Many inference methods, such as case-based reasoning, decision tree, regression analysis, and rule-based systems can be considered in research. Even though many methods can be utilized and provide information of partner selection among candidates, this study should address some issues. First, the proposed method should take both the data of large and small firms, to reflect the large company as an object. This means that the result of analysis can differ, according to the large firm's information and industry. Second, a methodology, containing multiple criteria and quantitative analysis to use these criteria, is necessary. In this paper, to analyze the possibility of collaboration, the Bayesian network (BN) methodology was applied. This model is useful in drawing an inference from uncertain information, because it is possible to deduce other nodes using partial evidence [57], which also reflects these issues. Figure 2 shows the results of the Bayesian network using this research's factors and the probability functions, with eight variables. X1, X2, X3, and X6 are variables of the technological skills, and X4, X5, and X7 are variables, which mean the cooperative relationship. X6 is a child node of X1, X2, and X3; while X7 is a child node of X4 and X5.

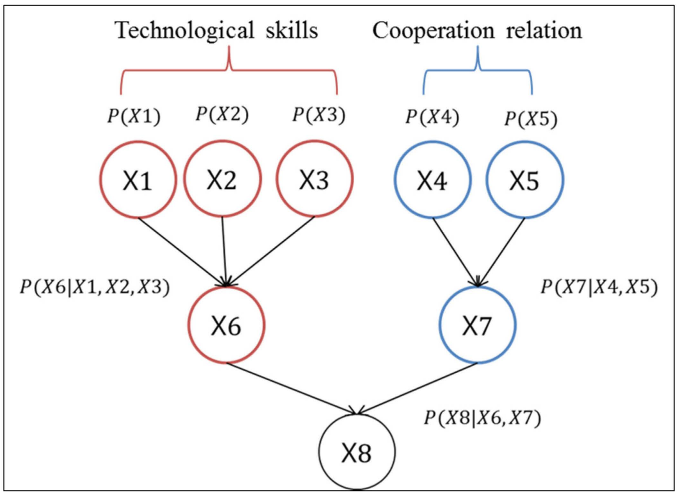

Figure 2. Bayesian network structure for partner selection.

For Figure 2, the joint probabilities can be calculated using conditional probabilities, as follows: P(X1, . . . , X8) = P(X1)P(X2)P(X3)P(X4)P(X5)P(X6 | X1,X2,X3)P(X7 | X4,X5)P(X8 | X6,X7).

To calculate the joint probability function, the probabilities of P(X1), P(X2), P(X3), P(X4), P(X5), P(X6 | X1,X2,X3), P(X7 | X4,X5), and P(X8 | X6,X7) must be specified. To calculate the probability of success in R&D collaboration, X8 = yes is fixed and then the posterior probability of X6 and X7 is calculated. For example, the conditional probability of X6 is P(X6 = good | X8 = Yes, X1 = good, X2 = good, X3 = good), and the conditional probability of X7 is P(X7 = good | X8 = Yes, X4 = good, X5 = good), when all X1 to X5 are good. Using X6 and X7, the posterior probability of X8 is calculated as follows.

$$\mathrm{P}\,(\mathrm{X8} = \mathrm{yes}) = \sum_{\alpha} \sum_{\beta} (X8 = yes|X6 = \alpha, X7 = \beta)\, P\,(X6 = \alpha, X7 = \beta) \tag{4}$$

The modularity and compact representation of the Bayesian network allow us to perform similar inference queries in a more organized and efficient manner. In current research, the R&D partner selection model was constructed and tested using a statistical software, SPSS 18.0.

3.5. Process

Figure 3 shows four main steps involved in the whole process to select an R&D partner for cooperation with small and large firms. First, the firm's technology roadmap is investigated and analyzed to identify a necessary technology field for developing a new product of a large firm. Second, patent context information is identified to generate a list of SMEs sharing some compatibility with a large firm's technology. Third, the conditional probability tables (CPTs) are constructed to catch the selected industry's trends utilizing joint patents of large firms and SMEs. Finally, the Bayesian network based on patent information is utilized to select an SME among the candidates, which is most likely to alliance well with the large company.

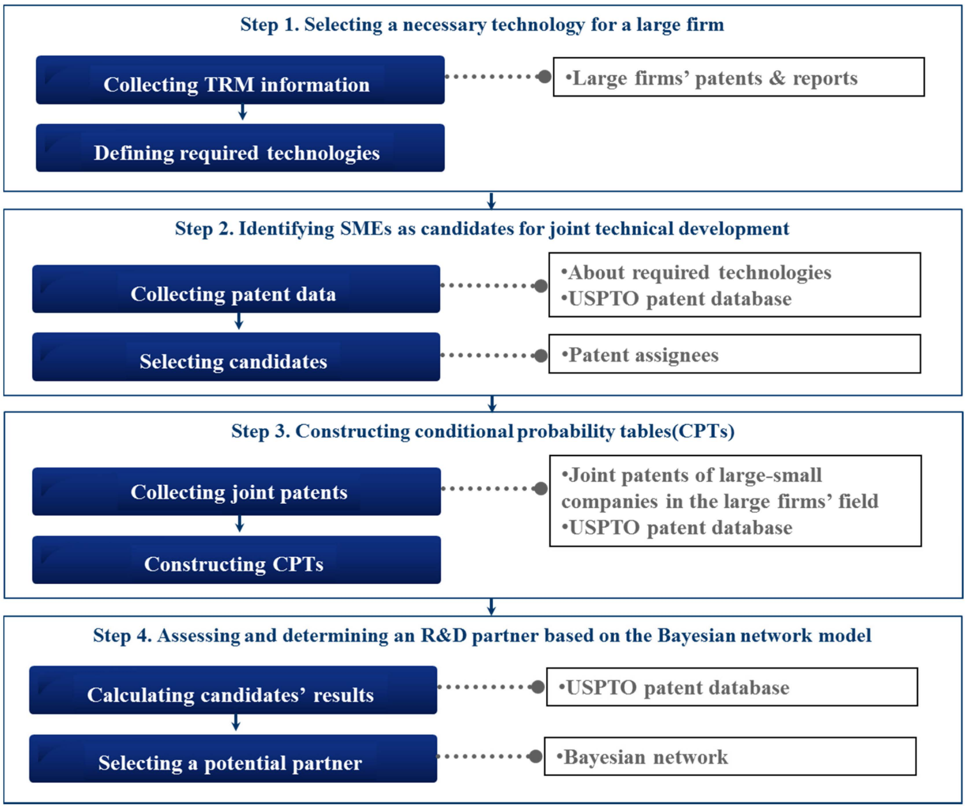

Figure 3. Proposed approach process.

3.5.1. Step 1: Selecting a Necessary Technology for a Large Firm

In this step, a prospective technology field is identified, as long as the multiple technology information is collected for a large firm which desires collaboration with other domains to create value. Especially, it is important to clarify that the large firm purchases or selects the necessary technologies that can affect complementarity for second movers. To this end, first, the firm needs to develop a technology roadmap (TRM) by collecting general technology information in a specific industry, as well as key technologies of the enterprise. In this paper, the definition of large firms is that the company has over 500 employees, in reference to the SBA's standard [39]. TRM is a primary technique and generally applied to various industries in the stage of technology planning [58]. It has a significant advantage of visualization to identify which technologies are profitable and necessary to advance markets. Second, the firm selects necessary technologies to establish an R&D alliance with SMEs by referring to the structured TRM. The prime technology, which is necessary to develop a new product in future markets, and sub-technologies, are defined based on the intended TRM. If the prime technology is a converging technology even though they are in a similar field by comparing the current technology and a sub-technology of prime technology, the R&D collaboration is necessary to develop the prime technology for the large firm.

3.5.2. Step 2: Identifying SMEs as Candidates for Joint Technical Development

This step aims to identify SMEs as candidates for R&D collaboration on the predefined necessary technology in the previous step. To this end, the relevant patents of needed technology are collected. Then, the patents which are assigned by SMEs are selected, considering the number of employees which is fewer than 500, which is the criteria based on the U.S. Small Business Administration [39]. Since it is hard to grasp the size of companies with a bibliography of patents, other information resources should be utilized to decide which companies can be included as SMEs or not. In this stage, patent information is still an important source in that it is the only way to determine technology and innovation capabilities of SMEs. The patent information is useful for partner selection for R&D collaboration because it can explain promising technologies that large firms want to explore as alternatives of existing technologies

3.5.3. Step 3: Constructing Conditional Probability Tables

This step was used during the application of the Bayesian network methodology. Joint patents of large-small companies were collected, which represent collaborative cases between large and small companies. In particular, conditional probability tables (CPTs) were created based on the large firm's industrial field. The type of CPTs is the histogram to determine probability estimates, after dividing the parameter space into several sections, because of the discrete variable type in this paper.

3.5.4. Step 4: Assessing and Determining an R&D Partner Based on the Bayesian Network Model

Information of the large firm and candidates was collected and the X1 to X5 criteria information is necessary to enter the data using bibliographic information. On the other hand, the prior information on X6 to X8 is not essential to provide at this stage. Since these indexes are related to joint patents between two companies, they are omitted because of the difficulty of calculation. The forth step is to calculate the posterior probability of X8 using the Bayesian model. During this step, the final probability of each candidate is generated, based on the CPTs, which were constructed in the third step. Finally, candidates were ranked based on the final probability, and the candidate with the largest probability was considered as the best candidate for collaboration.

4. Case study

4.1. Background

The largest company of the semiconductor industry in Korea is selected in that the firm is proper to deploy the proposed method since it has had considerable collaboration experience with SMEs through win-win collaboration programs and implemented open innovation strategies in various ways. Semiconductor businesses accounted for over 50% of business profit and memory was the main field among several fields of semiconductors. The firm tried to commercialize bio-sensors in order to extend the semiconductor business to systems. In addition, it concentrated on the business of system semiconductors by focusing on image sensors, mobile SoC (system on chip), and nano-sensors according to the trends of smartphones. The total number of employees are 98,295 and the employees of semiconductor business departments are 42,104, which is a greater number of other departments. The USPTO patents and reports, which are registered and published from 1976 to 2013, are collected to select and analyze the large firm's necessary technologies. After selecting the large firm's necessary technology, relevant patents from 1976s to 2012s are collected from the USPTO database. 658 patents were related to selected technology for R&D collaboration, and 80 joint application patents, which are collaborations between large and small firms, were singled out from among 10,000 patents in the field of the semiconductor industry.

4.2. Selecting a Necessary Technology for a Large Firm

A technology roadmap in Figure 4 is analyzed in order to determine the firm's necessary technology. The technology roadmap is developed on the basis of the corporation's technologies and public technology roadmaps in the semiconductor industry. A company in the semiconductor industry should develop Internet of Things (IoT) semiconductors to obtain competitiveness due to market trend changes from mobile to IoT, according to the technology roadmap. Under the situation that a large firm already has relevant semiconductor technology, the firm should develop sensor technologies, such as nano-biosensors and intelligent sensors, in order for the corporation to advance the development of nano/mcro-electro mechanical (NEMS/MEMS) sensors, which are essential to develop IoT semiconductors. The firm tries to collaborate with SMEs to develop IoT semiconductors despite it having many strategic alternatives, such as in-house R&D, outsourcing, licensing, and so on, because SMEs are actively developing nano-sensor technology and they have focused on product differentiation and niche market strategies.

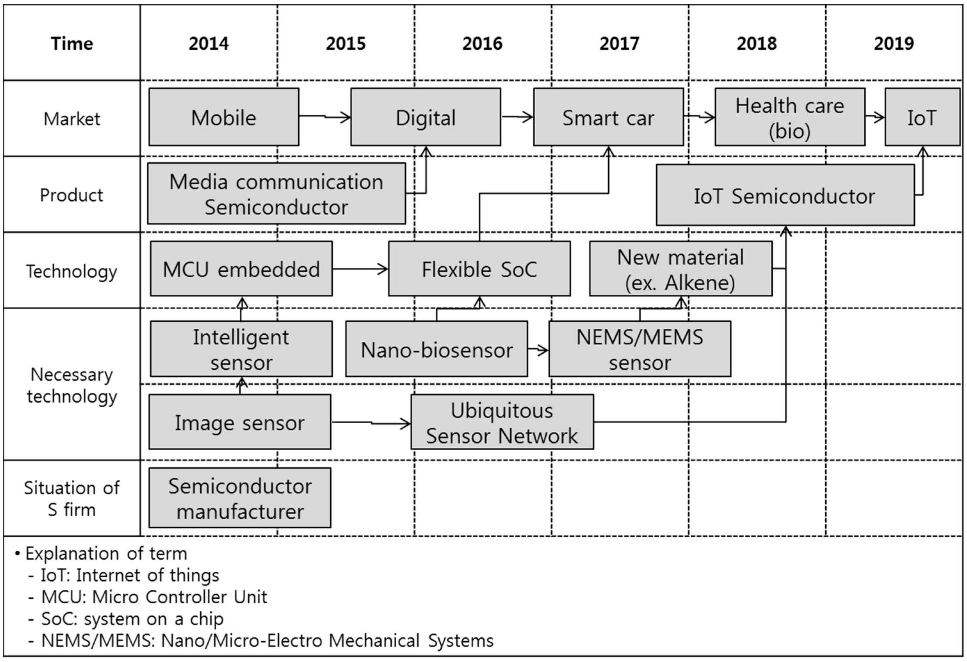

Figure 4. Technology roadmap of the large firm to unite semiconductor and sensor technology.

4.3. Identifying SMEs as Candidates for Joint Technical Development

SMEs which already have nano sensor technology are selected to conduct collaborative R&D. Four SMEs, which are professional manufacturers in the nano sensor technology field, were selected as R&D collaboration partner candidates by using 658 patents from USPTO database. However, many large and global firm candidates are excluded, such as Matsushita, Sumitomo, Abbott, and Genentech.

4.4. Constructing Conditional Probability Tables

In this step, in order to determine probability estimates in the semiconductor industry, patent data for joint applicants were collected. For example, Sinfonia Technology Co., Ltd. formed R&D collaboration with a small firm, while Ulvac collaborated with a large company. 70 collaborative cases were selected, and the conditional probability tables for technical skills and cooperation relationship information were built in Tables 3–5. The 70 collaborate cases are joint patents between large and small companies from 1976 to 2012 in the semiconductor industry. A data sample is displayed in Table 6, and a descriptive statistic is provided in Table 7.

Table 3. Conditional probability tables about technical skills.

X1	X2	X3	X6	Probability
1	1	1	1	66.6
1	2	1	1	44.4
1	2	2	1	33.3
1	3	2	1	22.5
1	3	3	1	41
2	1	3	1	100
2	3	2	2	100
3	1	2	1	80
3	2	2	1	35

Table 4. Conditional probability tables about correlation.

X4	X5	X7	Probability
1	1	1	42
1	2	1	50
1	3	1	100
2	1	1	69
2	2	1	25
2	3	1	95.45
2	3	2	4.54

Table 5. Conditional probability tables of P(X8 | X6,X7).

X6	X7	X8	Probability
1	1	1	70
1	2	1	30
2	1	1	55
2	2	1	45

Table 6. Data sample.

	TE	AC	TL	CE	GD	TS	CR	S
Small firm	128	17	0.74	2	-	-	-	-
Large and small firm	-	-	-	-	N	-	-	-
Joint patents	-	-	-	-	-	1	0.03	0

Table 7. Descriptive statistics.

	Mean	Standard Deviation	Minimum	Maximum
Technical experience	58.41	42.99	1.00	161.00
Absorptive capacity	10.22	13.48	1.75	62.5
Technology lifecycle	0.54	0.27	0	1
Collaboration experience	2.47	7.89	0	34
Geographical distance	1.23	0.57	1	3
Technological skills (TS)	4.97	12.81	1.00	81.00
Cooperation relation (CR)	0.04	0.07	0.00	0.71
Success (S)	3.76	11.99	0.00	47.76
The number of small firms' patents	58.41	42.99	1.00	161.00
The number of large firms' patents	5875.10	12,327.95	1.00	50,572.00
The number of joint patents	4.97	12.81	1.00	81.00

Table 3 is the CPT of technical skills of SMEs information, and Table 4 is the CPT of collaborative cases between large and small companies. If a company belongs to the case of X1 = 1, X2 = 1, X3 = 1, the company has 66.6% high technology skill (X6 = 1) in Table 3. By reference to Table 4, a company has 50% high cooperation skill (X7 = 1), when the company is affiliated to X4 = 1, X5 = 2. Finally, Table 5 is made, to obtain the probability for the candidate of whether to collaborate with large firms or not. For example, the combination of high technology skill (X6 = 1) and high cooperation skill (X7 = 1) causes a success in R&D collaboration (X8 = 1) of 70%. The omitted cases, which did not appear in the semiconductor industry, have 0% probability to belong to the cases of X6, X7, and X8 in Tables 3–5. A large number of classifications means higher skills, for example, X7 has low cooperation skill (1) and high cooperative skill (2).

4.5. Assessing and Determining an R&D Partner Based on the Bayesian Network Model

This paper used the conditional probability table to assess the probability of collaborating with each SME. In addition, the comparison between considering only technical skills, and considering combined technology capabilities and the correlation with large firms, is in Table 8. The probabilities of considering only technical skills are 35%, 41%, 80%, and 44%, respectively, and the probabilities of considering only cooperate relation are 69%, 42%, 25%, and 42%, respectively. The number of the large firms' granted patents is 7289, and there are different characteristics for each candidate. These results made it difficult to determine which company would be selected.

Table 8. Candidates' data.

No.	Criteria	Candidate A	Candidate B	Candidate C	Candidate D
X1	Technical experience	16 (3)	3 (1)	14 (3)	5 (1)
X2	Absorptive capacity	10 (2)	19 (3)	7 (1)	20 (2)
X3	Technology lifecycle	0.75 (2)	1 (3)	0.21 (2)	0 (1)
X4	Collaboration experience	2 (2)	0 (1)	3 (2)	0 (1)
X5	Geographical distance	1 (1)	1 (1)	2 (2)	1 (1)

Table 9 is the results of calculating the posterior probability, using the Bayesian model and conditional probability table. The probabilities generated by the Bayesian model and their correlation with large firms were 53.8%, 48.2%, 41.5%, and 48.1%, respectively. Therefore, company "A" was selected as the final SME. In other words, company "A" had the highest possibility among the candidates, for collaborating with the large firm. This approach could impact the large firm in its decision-making, regarding partner selection.

Table 9. Comparison of success probabilities.

Criteria	Candidate A	Candidate B	Candidate C	Candidate D
High technological skill (1)	35%	41%	80%	44%
High cooperation skill (1)	69%	42%	25%	42%
Success R&D collaboration (1)	53.8%	48.2%	41.5%	48.1%

5. Results and Discussion

In this paper, the small company labelled "A" was selected through the use of the proposed methodology as the best company for collaborating with the large company. The case study used the case of the semiconductor industry to generate conditional probability tables, and company "A" had the largest posterior probability. Since "A" has low technological skills and a high cooperation relationship, it means that the conditional probability table shows high similarity and little importance of the large company's patents do not cause success of collaboration. On the other hand, the "C" candidate has lowest success probability, 41.5%, even though it has high technology skills, 80%. Likewise, the semiconductor industry regards social value more important than technological value.

The results derived by Vasudeva *et al.* [59] correspond that the increasing social value of potential partners raises the probabilities of collaboration between firms.

The reasons for this results are referenced by the conditional probability table of P(X8 | X6,X7), which is the posterior probability of successfull R&D collaboration between large and small companies. Table 5 specifies that the high cooperation relationship (X7 = 1) will obtain a high probability of successful R&D collaboration, a high X8 index. This means a lot of large companies in the semiconductor industry prefer the SMEs, which have high cooperation relationships, especially near their geographical location, and various collaboration experiences. This result can be changed according to the industry and large firms, although using the same SME candidates. By this one-time analysis, both the collaboration trend in a specific industry and the results of partner selection are discovered. The industry is appropriate for vertical coordination since many firms in the industry put emphasis on collaboration capabilities rather than technological capabilities despite firms collaborating for R&D. These results are supported by a study of Nieto and Santamaría [7] contending manufacturing SMEs are more productive when conducting vertical coordination.

However, there is some reason for uncertainty about the result. First, it was not verified that company "A" was the best choice and it is necessary to do so. Second, the opinion of experts is necessary to produce a conditional probability table section, such as a cut-off in the Bayesian network process, even though the probabilities were generated based on patent information. Third, if there were not enough cases, there may be an error in the calculation of the probability, and it is difficult to make conditional probability tables. In spite of these limitations, this process contributes to partner selection, because it works systematically, by using patent data that is easy to access and use, and it makes use of quantitative data. Since the method reflects features of industry and target companies, it is more reasonable than a consistent process, which cannot apply new trends. For these reasons, one can have more confidence in the proposed method than in prior methods for partner selection.

In addition, this research compares results of the proposed methodology and a traditional approach, Fuzzy-set/Qualitative Comparative Analysis (FsQCA). The FsQCA is generally utilized to understand causal relationships among determinants because it is an alternative method which overcomes the limitation of analyzing small cases [60]. This paper analyzes the degree of correct prediction results using extracted 10-test data to compare the reliability of each methodology. Table 10 describes the analytical model and three types of configuration solutions which affect success on the R&D collaboration between large firms and SMEs. This research shows that results (the consistency is over 0.8) provide sufficient solutions, because there is substantial inconsistency when the consistency value is lower than 0.75, according to Ragin [61]. The first solution among the three types of configuration solutions is the case that SMEs have high technology experience, high absorptive capacity, and high geographical proximity, but low collaboration experience. The second solution is the case that SMEs have lowtechnology experience, low absorptive capacity, low collaboration experience, high geographical proximity, and the technologies positioned in the initial stages of the technology life cycle. The last solution is the case that SMEs have lowtechnology experience, low absorptive capacity, and low geographical proximity, but high collaboration experience and the technologies positioned in the initial stage of the technology life cycle.

Table 10. Sufficient configuration solutions.

Category		Output	Coverage	Consistency
Model		X8 = f(X1, X2, X3, X4, X5)		
Solution	1	X1*X2*~X4*X5	0.47	0.86
	2	~X1*~X2*~X3*~X4*~X5		
	3	~X1*~X2*~X3*X4*X5		
	→ X1*X2*~X4*X5 + ~X1*~X2*~X3*~X4*~X5 + ~X1*~X2*~X3*X4*X5			

The success probabilities of collaboration between large firms and SMEs are, respectively, estimated by using the proposed method and FsQCA, calculating the variables (X1 to X5) of ten cases. The evaluation results are shown as Table 11. Ten cases are collected as results of collaborative R&D in a situation where there are jointly applied patents between a large firm and SME. The respective variables have categories that are denoted as H when fuzzy set value is greater than 0.5, otherwise L. The number in brackets represents the particular case of the conditional probability table. The proposed method reflects 80% of explanatory power, while FsQCA reflects 50% of explanatory power, since the coverage of the FsQCA solution has a low value of 0.47. Furthermore, the Bayesian network model is able to show the results in detail since the variables are constructed as a hierarchical structure and the number of intervals is set to three, while the FsQCA method suggests output as a high or low and explains configurations among the variables to predict the results using only five variables. Thus, the proposed method is appropriate to use for a quantitative approach using current cases and patent information since the explanatory power is greater than that of FsQCA, which is appropriate for qualitative approaches, such as surveys.

Table 11. The evaluation results of the proposed method and FsQCA.

Case	X1	X2	X3	X4	X5	Actual Results	Prediction Results	
							Proposed Method	FsQCA
1	H (3)	H (2)	H (2)	H (2)	H (2)	Fail	Fail	Fail
2	H (3)	H (2)	H (2)	L (1)	L (1)	Fail	Fail	Success
3	L (1)	L (1)	L (1)	H (2)	H (2)	Success	Fail	Success
4	H (3)	H (2)	H (2)	L (1)	H (2)	Success	Success	Fail
5	L (1)	L (1)	L (1)	L (1)	L (1)	Fail	Fail	Success
6	L (1)	L (1)	H (2)	H (2)	H (2)	Fail	Fail	Fail
7	L (1)	L (1)	L (1)	L (1)	H (2)	Success	Success	Fail
8	L (1)	H (3)	L (1)	H (2)	H (2)	Fail	Fail	Fail
9	L (1)	L (1)	L (1)	L (1)	H (2)	Success	Success	Fail
10	L (1)	L (1)	H (2)	H (2)	L (1)	Fail	Success	Fail
Prediction probability							80%	50%

6. Conclusions

This study has focused on the enhanced R&D cooperative efforts that are being made, especially between large firms, and small and medium-sized enterprises (SMEs). In order to promote win-win alliances beginning at the planning stage, it is necessary to consider the capabilities of both large firms and SMEs. For these reasons, the purpose of this paper has been to explore forecasting methodologies and measureable factors, in order to develop a method for pairing large firms and SMEs, so as to collaborate on R&D. To develop this method, this paper suggested technology roadmapping, and a Bayesian network model that uses patent information, as a tool for selecting an SME among potential R&D candidates with a large firm.

The present research is differentiated from the two important points of view. First, patent information and TRM are utilized to select the technologies for R&D collaboration and potential collaborative partner candidates. Second, patent information and a Bayesian network model is used to select appropriate SMEs and overcome the prior approach, which is based on the opinions of experts. The unique characteristics of collaboration between large firms and SMEs makes a different R&D partner selection method from traditional methods. Understanding industrial environments is a vital stage to select faithful and successful partners in light of firm size. In addition, collaboration with ventures, which retains new and niche technology, has advantages for large firms and any firms cannot avoid alliance with SMEs. This paper explores and analyzes which methodology fits on partner selection between the two types of enterprises. The proposed methodology helps calculate success probability between them using quantitative data to overcome the limitation of an expert's opinion. Likewise, the proposed model has high prediction probability when it is compared with other traditional models, which are valuable when the number of cases is small.

This research includes several limitations. First, the expert's opinion is somewhat necessary to select necessary technologies of large firms and build TRM. Second, the probability information for constructing a Bayesian network model is difficult to obtain since the empirical survey data is insufficient. Third, although patent information is very helpful in analyzing R&D activities of several high-medium technology sectors, it is normally an irrelevant source to low technology sectors or knowledge-intensive business service sectors. Thus, the proposed approach might be unable to support the decision-making process in those sectors. However, this research contributes to suggest a quantitative partner selection approach based on technology capability in the perspective of overcoming previous approaches focused on experts' opinion. In addition, the results will encourage R&D alliance partners between large firms and SMEs because successful partnership can be implemented by the proposed systematic process. However, further research needs to construct the more systematic partner selection process with a minimum of expert intervention. In particular, an advanced Bayesian network model for partner selection can be developed under insufficient data. Moreover, the proposed method can be extended to low-technology sectors and knowledge-intensive business sectors by using other technological information sources, such as academic papers or business data.

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