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Exploring Suitable Technology for Small and Medium-Sized Enterprises (SMEs) Based on a Hidden Markov Model Using Patent Information and Value Chain Analysis

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Abstract: R&D cooperative efforts between large firms and small and medium-sized enterprises (SMEs) have been accelerated to develop innovative projects and deploy profitable businesses. In general, win-win alliances between large firms and SMEs for sustainable growth require the pre-evaluation of their capabilities to explore high potential partners for successful collaborations. Thus, this research proposes a systematic method that identifies SME-suitable technology where SMEs have a competitive edge in R&D collaborations. First, such technology fields are identified by various factors that influence successful R&D activities by applying the Hidden Markov Model (HMM) and using information on value chains of an industry. To identify these fields, innovation factors such as the current impact index and technology cycle time are composed using the bibliographic information of patents. Second, patent information is analyzed to obtain observation probability in terms of technical competitiveness, and value chain data is used to calculate transition probability in HMMs. Finally, the Viterbi algorithm is employed to formulate the aforementioned two types of probability as a tool for selecting appropriate fields for SMEs. This paper applies the proposed approach to the solar photovoltaic industry to explore SME-suitable technologies. This research can contribute to help develop successful R&D partnership between large firms and SMEs.

Keywords: Hidden Markov model; value chain; patent information; R&D collaboration; SME

1. Introduction

R&D collaborative efforts between large firms and small and medium-sized enterprises (SMEs) are increasingly recognized as central to innovation for sustainable growth. It is now commonly admitted that inter-firm collaboration can be beneficial to each firm due to the high possibility of accessing new knowledge, new markets, additional resources, and improving management skills [1,2]. In addition, to maintain the balance of the strength of SMEs and large firms, greater emphasis is placed on the differences between their strengths and weaknesses. Considering the importance of a win-win approach in the R&D collaboration of large firms and SMEs, it may be useful to investigate their characteristics. SMEs considerably differ from large firms in a variety of ways that effect fundamental organizational change [3–6]. In terms of firm size, while smaller firms have strengths in enabling rapid learning and development, as they have a narrow knowledge base, large firms have a wider knowledge base and focus on internal learning [7,8]. Furthermore, SMEs generally experience additional difficulties in managing R&D projects in comparison with large firms [9]. In particular, the effect of R&D collaboration for SMEs is greater than that for large firms [10]. Hence, new capitalism has recently emerged in the business environment, in which greed is controlled because of the deepening inequality and economic instability caused by the global financial crisis [11]. The aim of this study is therefore to determine whether technological collaboration can optimize the technological strengths of SMEs and large firms, and how this, in turn, could facilitate a successful R&D partnership between SMEs and large firms.

Several previous research works proposed the terminologies such as SME-oriented supply chain [12], SME-oriented innovation support [13] and SMEs-oriented technology [14] to define the specific capability of SMEs, considering their business environment. However, such terminologies have been barely utilized in practical fields of building strategies or policies. In general, the concept of SME-suitable industry has been suggested to identify industries that need to be protected from the indiscriminate business expansion of large companies [15,16]. Business expansion to new markets is influenced by firm size. In addition, incumbent firms could even have difficulty in competing with others even if they have all resources and advantages [17]. Since the notion of the SME-suitable industry focuses on the perspectives of products and services, the activities of technology development have been not considered on the table for discussing the protection of SMEs. Among others, SME-only areas that limit the entrance of large companies under the laws is a frequently used terminology [15]. In particular, appropriate technology for SMEs has been broadly utilized to elevate the technological capability of SMEs for the purpose of supporting undeveloped countries and disadvantaged social groups [18]. Since this paper deals with technology areas rather than business fields, the terminology SME-suitable technology will be selected to define specific technologies that SMEs have a considerable competence to develop in competition with large companies and which need to be protected from the invasion of them.

Concern about selecting the appropriate SME-suitable technology has surfaced as a serious issue in several countries because of the increasing conflicts between SMEs and large firms, in which knowledge embodied in the dynamic capabilities of SMEs can unintentionally flow to the larger partner [19]. It is essential that the knowledge of SMEs is not disclosed to the larger partner [20]. Curiously, despite the increase in the number of studies on the asymmetric relationship between large firms and SMEs, few have attempted to address a systematic method that identifies SME-suitable technology in R&D collaboration. In order to overcome the asymmetric nature of the partnership, the autonomous market penetration of large firms needs to be controlled by identifying SME-suitable technology as a public policy. In light of the important role played by SMEs in the economy, policy makers need to consider that the nature of the firm, especially its size, and the feature of technology should be simultaneously reflected for efficient R&D activities [21].

Recent studies have tended to deal with the effects of firm size on technological innovation. At a fundamental level, there is a similar consensus on the nature of related research, both in terms of theoretical arguments and empirical evidence. When opportunities are more uncertain, small-sized start-up firms have entrepreneurship to quickly respond to business opportunities for innovation with first mover advantages [22]. As Holgersson [23] points out, recent surveys have revealed different insights into the way that patenting is used in SMEs and large firms. In addition, many researchers have included firm size in their business innovation-related models [24].

However, minimal research has been carried out on the relation between fields of technology and size of company for win-win R&D collaboration. Previous studies conducted analyses of the relationship between R&D cooperative types and technology sectors without the consideration on the distinction between large enterprises and SMEs. In particular, the papers scarcely considered open innovation, although large firms and SMEs should be engaged in win-win collaboration. Although the relationship between firm size and innovation has been considerably examined in the earlier studies, theoretical frameworks and empirical evidence of this area remain far from a fully answered situation. Therefore, it will be necessary to relate company size to the characteristics of technology that influence the effectiveness of R&D partnerships between SMEs and large firms. Additionally, although existing studies concentrate on qualitative analysis based on business development, little research has been performed on quantitative analysis to classify a specific technology into large firms and/or SME-suitable categories.

To overcome these limitations, this paper aims to propose a method for identifying SME-suitable technology in a win-win innovation for SMEs and large firms through empirical analysis. To accomplish this, this research first identifies the types of enterprises and constructs a value chain model using patent data in the United States Patent and Trademark Office (USPTO) and descriptive statistics of enterprises. Second, the collected data of technology and value chain is analyzed using the Hidden Markov Model (HMM). Finally, all technologies in a value chain are classified into two areas (large firms and SMEs), determining the field of technology that is well fitted for core competence of SMEs. From the results of this paper, useful implications can be offered for managers in the R&D collaboration, as well as for policy makers. It is understood that using objective data and methodology can extract a competitive advantage on technology sectors of SMEs from a neutral standpoint without political bias.

The remainder of this paper is structured as follows. In Section 2, the theoretical background behind the promising fields for the small business, called an SME-suitable area in this research, and a win-win cooperation strategy between SMEs and large firms is described. Section 3 explains the methodological aspects of this study for empirical analysis. In Section 4, the results and implications of the statistical analysis are discussed. The concluding remarks and future research are presented in Section 5.

2. Theoretical Background

2.1. Successful Cooperation between Large Firms and SMEs

Many researchers have studied the differences between the properties of large and small firms. Large firms are capable of utilizing a variety of resources, power, and capabilities; on the other hand, smaller firms have a stronger capacity for innovation and are generally characterized as being more flexible, responding faster to changing needs and environments [19]. However, large firms are more likely to possess complementary assets as a source of competitive advantage, which allows them to have a strong brand name or access to distribution channels; thus, they tend to integrate new technologies with a broad array of other specific technologies, while small firms are better fitted to respond to new specific technologies faster [7]. The different processes can be sources of competitive advantage to each firm size; in particular, small firms have effective processes based on so-called dynamic capabilities, depending on the properties of the firm such as its portfolio of knowledge [25]. This is important because innovating firms without appropriate capacities and capabilities necessarily will fail regardless of innovation [26].

Much discussion concentrated on the determinants of success in collaborative R&D in the market place. Collaboration between large and small firms can be beneficial to small firms because it provides opportunities to access new technology with new knowledge, experts, markets, and additional funds, providing opportunities to improve management skills [1]. Arranz and de Arroyabe [27] emphasized two types of the most common cooperation networks: (i) cooperation to seek synergies or complementariness between large and small firms and (ii) the cooperation to seek growth effects or market power.

Collaborative efforts can be profitable for both large and small firms, but the distinctive processes need to be considered. Blomqvist et al. [28] argue that collaborative R&D partnerships among asymmetric partners are becoming increasingly common, but given the asymmetry, they involve inherent challenges in terms of the R&D context and the dynamic environment. The effect of industry possibly needs to be investigated when analyzing the relation between innovation performance and firm size. Until now, an optimal firm size model for effective collaboration has not been available. Lin and Ho [29] describe an example drawn from an empirical study on firm size of the warehousing and transportation of companies in China. In addition, the growth of a small firm is significantly influenced by the impact of the external environment and by internal resources of the firm; thus, the collaborative

R&D can ultimately determine the fate of firms [30]. Optimal firm size may have a strong impact on collaborative R&D activities.

2.2. Exploring Technology Fields Appropriate to SMEs

Discovering technology opportunities can affect performance of SMEs [31] and SMEs are aware of the importance of technology innovation to survive because the market is under increasing competition. The topic of technology opportunity appropriate to a firm's characteristics has assumed increasing significance not only in governments or large firms, but also in SMEs. Furthermore, transaction costs of multinational firms are also based on the nature of technology [26]. Recently, selecting SME-suitable technology has been a critical issue in even developing countries such as South Korea. Cho et al. [32] argues that identifying the appropriate technology fields for SMEs will provide useful information for strategic planning. While many attempts have been made to systematically discover technology opportunity for large firms [33], there is surprisingly little literature on SME-suitable technology [34]. Given that they possess relatively higher levels of flexibility and R&D productivity levels than larger firms [35], SMEs need to identify SME-suitable technology for market success.

When considering technology fields that are appropriate to a firm's characteristics, prior studies on the technology opportunity usually rely on a number of factors that represent the principal aspects, including markets and business models. The general tendency has been to emphasize factors based on attributes of the market and technology. When partner firms are competing for identical or similar technologies in end product or strategic resource markets, they are facing the hazards of R&D cooperation because partners are concerned about unintended leakage of valuable technology [36]. According to criteria to identify promising items for SMEs, the assessment can be made by measuring factors concerning market, technology, and spillovers [37]. None of these factors under consideration provides satisfactory criteria for identifying the SME-suitable technology, but, in general, most assessments are based on market size, investment scale, and competition situations [38]. In a more recent study, Cho et al. [32] extended this further by suggesting factors using the business drivers and business models that affect the technology opportunities for SMEs.

Two main approaches are currently taken in identifying technology opportunities for SMEs. Drawing from the quantitative and qualitative methods, most studies explore various fields of technology for firms, and efforts have been made to combine expert-based methods and data-based methods. Many studies in this research subject propose diverse methods fields such as text mining [39], Delphi [40], and morphology analysis [41]. In recent years, the methods used to select a field of technology for SMEs have enabled them to move toward discussing empirical analysis on SME-suitable technology, and have been used to evaluate promising technology, including subject-object-action analysis [42,43], patent analysis [44,45], and document mining [46]. Given the lack of methods on SME-suitable technology, while there has been a great deal of studies at national, industry, and firm levels, little is known of the studies that reflect the characteristics of SMEs.

2.3. Patent Bibliographic Information

Patents, which are outputs of innovations, are vital for R&D and provide useful information of novel technology. They can provide abundant data for analyzing the innovation and technological change of a firm. In particular, as patent protection is strong, start-up firms create more innovation and generate markets for ideas. Moreover, competitive interaction between large and start-up firms depends on whether the market for ideas is present or not [47]. Yoon and Song [48] utilized patents to investigate innovation activities and Abbas et al. [49] analyzed new opportunities, competitiveness, and trends of technology. Patent information has some advantages in providing R&D information over the other data sources. The advantage of patent information is that it is accessible through the internet and its unified procedure and form make it easy to conduct a lot of useful analyses [38]. In particular, since the patent specification requires a detailed description of technologies in the patent document, it enables analyzers to understand the technology. Moreover, it helps companies to perform research activities, comprehend the technical trends, and establish a business strategy by facilitating such information. In particular, the most significant advantage could be the ability to show information on R&D capability of companies.

The first disadvantage of patent information is that not all inventions are given patent rights, since not all inventions satisfy the standards established by the Patent and Trademark Office. Second, the inventor has to make strategic decisions about whether or not the invention should undergo patent registration or be kept confidential. This strategic decision depends on the types of corporations or industry, so the patent analysis might not be in accordance with the areas of industry or technology. Third, the change of patent law over time makes it difficult to conduct a correct analysis about patents.

However, such limitations should not be the cause of a complete abolition of patent data as a means of developing statistical indices. Many studies on patents rely on the descriptive statistics, such as the number of patents, year of registration, country of registration, or the applicant information. Therefore, collective information about patents could be used to analyze the technological value, influence, or proliferation of a patent. For example, Seol et al. [50] measured quality of the firm's patents to identify new business areas by applying some patent indicators, such as backward citations and forward citations.

3. Proposed Approach

3.1. Basic Concepts

This study explores SME-suitable technology using patent information. Two types of companies are considered for large firms and SMEs in a value chain using the concept of HMM based on collaboration synergy, as shown in Figure 1. The SME-suitable fields are explored in a level of technology that can be identified in a value chain because it is difficult to apply technology classification codes such as International Patent Classification (IPC) and F-term, the patent classification used in Japan. The technology fields of a company are incompletely identified without detailed information on the technology because the IPC codes do not specifically indicate details of patents, and the F-term codes of patents are difficult to collect in USPTO. When a process of collaboration is involved in R&D projects, selecting a large firm or SME-suitable technology in the value chain can facilitate a win-win collaboration between two types of firms.

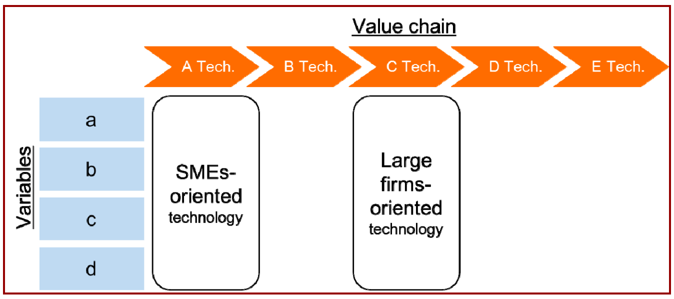

Figure 1. Research concept.

3.2. Research Process

Most of the existing processes to select an appropriate business field for SMEs in Korea are as follows. Firstly, SMEs apply a specific field that should be protected in a competition with large companies to the government, and the Korean Commission for Corporate Partnership (KCCP) then examines the applied document. Second, after the investigation on demands for appropriate businesses suggested by SMEs, the KCCP designates items for the appropriate business for SMEs. In the traditional selection process, controversial fields, in which there are conflicts between large firms and SMEs, are selected as appropriate business fields for SMEs. Four criteria are used to identify the appropriate businesses: (1) the efficiency of operation (the size of market and the number of SMEs), (2) the fitness for SMEs (the productivity and the ratio of employees in SMEs), (3) the protection of results (the satisfaction for customer and the damage due to collaboration), and (4) the competitiveness of SMEs (the level of R&D intensity). Based on these criteria in the traditional process, Korea government identified some manufacturing industries such as corrugated cardboard box, plastic envelope, and anti-freezing liquid as appropriate businesses for SMEs [51]. In addition, the Korean government announced in 2014 that large firms should refrain from entering and expanding these selected industries.

The definition of an 'appropriate business' differs depending on the purpose of research. This study defines an appropriate business, the called SME-suitable technology, as that in which SMEs can be competitive to pursue technology development not with assistances from large firms, but partnership for technological development. Figure 2 illustrates the proposal of a 7-stage framework to help policy makers select an appropriate technology for large firms and SMEs using patent information. The process used to identify SME-suitable technology is explained below and described in Figure 2. (1) This paper collects research information about the difference in R&D between SMEs and large firms. (2) Variables are defined as innovation factors. (3) This study analyzes the characteristics of both SMEs and large firms using the USPTO patent database. (4) The patents related to a value chain are collected and are considered the technologies of each structured value chain. (5) An appropriate business field is defined using the HMM and database of the value chain. (6) The prediction model is verified by experts' model assessment and gives insight into selection of appropriate fields. The technical process of HMM for identifying SME-suitable technology is described in detail in the process section.

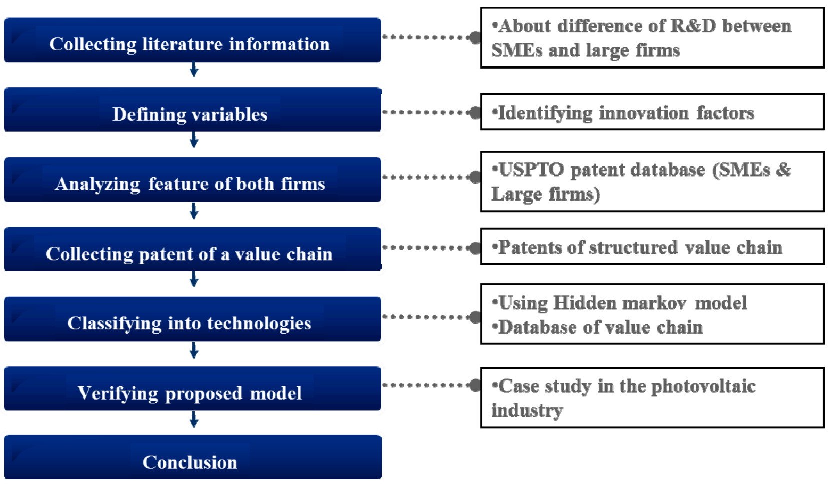

Figure 2. Research process.

3.3. Data

In this research, the process of collecting data is divided into two parts: the level of technology skill and the marketability. Marketability is a predominant factor for commercialization of technology [52] in R&D projects, which should consider both markets and technology skills. In this study, patent data and business transaction information are collected to cover two types of data. The technology skill and marketability factors are typically used for technology and market evaluation, where the technology skill determines the technical suitability, and the marketability helps in the analysis of the current market share. In general, the technology skill factors include backward citation index (BCI), the current impact index (CII), the citations performance ratio (CPR), and the technology cycle time (TCT), based on the collected U.S. patent data. The marketability factor measures the market share of a company by collecting information on value chains and calculating the ratios with respect to the types of companies (large firms and SMEs) regarding certain technology.

Thus, the data are categorized into two types: patent information for calculating observation probability and business transaction data on the SMEs and large firms in each value chain. The existing technologies, which large firms and SMEs possess, can be identified by using the applicant information of patent data. The collected patent data is used to create a formula that calculates the probability of success in technology development by collecting values of successful firms and unsuccessful firms. Then, the raw data is also used to measure the probability of success, depending on the type of firm in a specific technology.

3.4. Methodology

The main methodology in the proposed approach is Hidden Markov Model (HMM), which uses a finite set of states, each of which is associated with a generally multidimensional probability distribution using time series data consisting of states, observation, and time [53]. In addition, this model expresses specific time based on the sequential data to recognize patterns and infers the desired information from the order of items in the data. The purpose of HMM in this study is to determine the appropriate SME-suitable technology and then change the optimal arrangement of large and small firms in the technology of the value chain. The application of HMM is suitable because the form of value chains has a sequential step among the technologies and each step means the flow of time. If the features shown at orders are changed, the physical properties of the pattern in the sequential data will distort the meaning. The previous classification method such as Euclidean distance in clustering considers a fixed length of time among technologies; otherwise, this study performs the categorization, using the results of observation in the value chain. HMM has some benefits in this research; for example, it can determine the state transition probability using time series data and obtain the likelihood of the sequence of observations. Therefore, it can predict the next observation based on models of observed data, and HMM consists of state, observation, and time.

The applied HMM is designed as shown in Figure 3. The number of states are two: SMEs and large firms in t. Observations on success, failure, and time refer to the technological step of the value chain ($T = t_1, t_2, t_3, \ldots, t_j$), from i to j ($i \rightarrow j$).

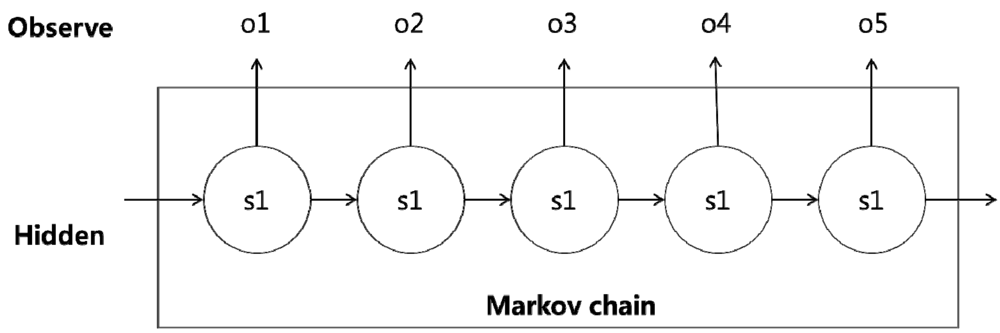

Figure 3. Hidden Markov model.

The Viterbi algorithm finds the optimal state line $Q = (q_1, q_2, \ldots, q_t)$ with the observation vector $O = (o_1, o_2, o_3, \ldots, o_{t-1}, o_t)$ in the fixed model. It is suitable in the optimal problem to extract a high probability state row among a number of candidates. This study uses the Viterbi algorithm to detect the prime arrangement for success of each value chain, as shown in Figure 4.

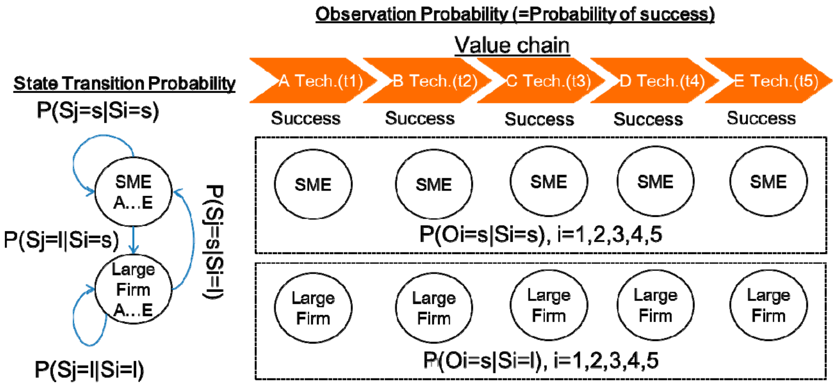

Figure 4. Proposed methodology concept.

Logistic regression can be used when a dependent variable is the qualitative factor, such as binary data, and predicts the event generation probability. Because the occurrence (1) or non-occurrence (2) is not clearly classified, this study determines the probability of success for large firms and SMEs in each value chain component. Various methodologies have been used for detecting the success probability of candidates; however, they have a critical difficulty to apply in this study for the following reasons. In the Bayesian network, it is difficult to build the structure of a cause-and-effect relationship, while the in case of linear regression analysis, it is difficult to measure the probability of occurrence even though the expected y-score is calculated. Although the back propagation technique in a neural network method can be used to judge the type of company, it is not easy to determine the success in SMEs.

An expectation-maximization (EM) algorithm is an iterative method used to measure probability distribution for maximizing functional possibility and consists of the expectation (E) step and maximization (M) step [54]. The EM algorithm is generally used to learn parameters because the HMM has complexity to decide parameters by analytic methods. The probability of belonging in the K Gaussian distribution is predicted in the E step and then the parameter in the M step is estimated using the probability of belonging, which is calculated in the E step. The use of this method in this study aims at detecting the transition probability from SMEs to large firms in each stage of the value chain.

3.5. Processes

The approach taken in this paper consists of four steps, as shown in Figure 5. First, the technology field and value chain models are selected. In the second step and third steps, the probability of success and transition probability are calculated. Finally, using the Viterbi algorithm, the optimized combination in the value chain is determined. The expected result is the best state sequence in the value chain, for example, 'SME—SME—large firm—SME—large firm' in each value chain technology. From these results, A, B, and D technologies are selected as being appropriate for SMEs.

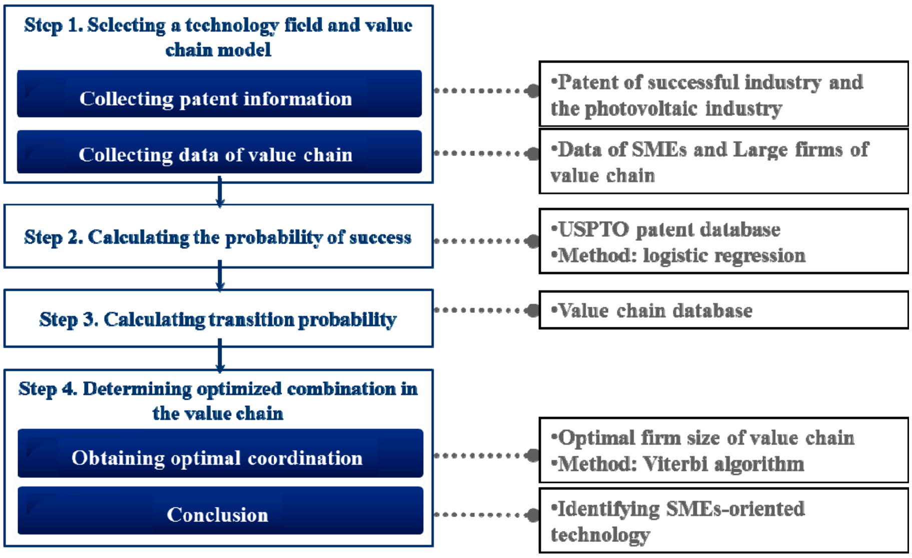

Figure 5. Defining SME-oriented technology process.

3.5.1. Step 1. Selecting a Technology Field and Value Chain Model

The purpose of this step is to identify a technology field to analyze and make a value chain structure of the field. This step involves preparation for the patents, creates a value chain data, and defines a patent for large or small firms based on the applicants. According to the U.S. Small Business Administration, if the number of workers in a company of a patent applicant is smaller than 500, the applicant belongs to the group of SMEs [55]. Thus, according to the number of workers, the patent can be categorized into a large company, small company, laboratory, or individual. In addition, only a large company and small company patent is allowed because the aim of this research is to determine the cooperative relationship between large and small companies. In addition, this research constructs a sequential value chain model.

In this study, the value chain is determined to be a field in which small and medium-sized companies and large companies coexist, and the level of technology is determined at the level of the hierarchical classification method. The traditional value chain analysis [56] has become widely used to check the process of generating value added in enterprise activities including primary activities (inbound logistics, operations, and marketing) and support activities (human resource management and technology development). Value chain analysis can be leveraged not only in terms of corporate perspectives but also in an industrial view. From an industry standpoint, the value chain analysis indicates the process of the final product in the industry to the consumer. For example, the value chain of the telecommunications industry is referred to as CPNT, which consists of contents, platform, network, and terminal [57]. In this study, analyses are carried out in the context of the value chain of the industry to analyze the technologies of large enterprises and SMEs, rather than one company. In particular, a serially structured value chain is established for the analysis. The value chain is selected as the appropriate field for three reasons. First, in the case of using a technical categorization code, such as IPC, F-term, etc., it is difficult to collect the data of F-term, and it is also difficult to name such fields because the technical fields of a company for an IPC do not specifically define techniques. Since currently most techniques are fusion technologies, no technology field is available that can represent the IPC. Second, since this research focuses on the technical cooperation between large and small companies, it seems appropriate to select techniques inside the value chain that can be viewed as part of a process of cooperation. Lastly, each technology is sequentially developed to make one product. It is appropriate to regard the value chain as representing the characteristic of cooperation between large and small companies because it is not microscopic R&D collaboration for development of a product between large and small companies, but a macroscopic one between them in a whole industry.

3.5.2. Step 2. Calculating the Probability of Success

The purpose of this step is to identify the regression equation for calculating the probability of success, which is used to determine the optimized combination in the value chain in the following step 4.

First, the patent bibliographic information of successful firms and unsuccessful firms in a field is collected from the patent database. The successful firms have market power in the field and have conducted R&D activities for more than 15 years. The unsuccessful firms register patents in the field and the firms have not carried out R&D for 10 years. Second, structuring a logistic regression model is necessary. The dependent variable for a successful firm is 1 and for an unsuccessful firm is 0. Independent variables are the backward citation index (BCI), the current impact index (CII), the citations performance ratio (CPR), and the technology cycle time (TCT), as shown in Table 1. The BCI refers to the level of learning of external knowledge and the high number of this index means a high probability to develop improved technology. When the technology matures, the backward citation score increases [58], and the high backward-citation patent-content score influences the higher returns of sales [59]. Based on this, it can be determined that the information on backward citation can affect a successful enterprise. The other independent variables are associated with the technology effect. The CII represents how often patents are cited in other patents referring to the latest five years [60]. The larger the value, the more recent technology will continue to affect subsequent technology, and it is possible that studies in the field are continuously being conducted. This indicator is used to elect a highly skilled M&A candidate in technology [61] and as a measure of the degree of innovation [62]. The CPR is calculated using the top 20% of the patent portfolio and identifies the usefulness and application of the central patent in the portfolio. By comparing with the CII, the level of dependence in the corresponding patent portfolio can be identified. If the values of the CII and CPR are similar, the patents contained in the portfolio are not dependent on the core patents and develop in balance. On the other hand, if CPR is relatively much higher than CII, the patent portfolio means that it is highly dependent on the essential patents. The TCT, which is the median age of patents cited in the company's patents [60], describes the evolution rate of the technology. This indicator is used to predict the performance of stocks [63], and to forecast the current technological situation [64]. Other variables, which are not selected as variables in this analysis, are the growth rate, the number of IPC codes, and the number of granted patents by one applicant. These variables have some limitations to be included in the model; for example, large firms always have more patents than small firms or there is no causal relationship with success. Several control variables that could have confounding effects on success of companies were used. First, the size of R&D in a company was selected as large R&D employees are likely to have high possibility of success. The size of R&D was calculated by counting the number of scientists in the company's patents, referred from McFadyen and Cannella [65]. Second, the age of company is included as a control variable because the older the company is, the more knowledge and experience is obtained for developing technology.

Table 1. Independent variables of logistic regression.

Variables	Operational Definition
Backward citation index (BCI)	BCI = the number of backward citation/the number of patents
Current impact index (CII)	CII = sum of annual forward citation X annual number of patents/the number of patents
Citations performance ratio (CPR)	CPR = The number of top 20% forward citations/the number of top 20% citation patents
Technology cycle time (TCT)	The median age of the patents cited on the front page of a patent document

The methodology to examine the relationship between independent variables and dependent variables is logistic regression, which is a statistical method to analyze a dataset in which one or more independent variables determine an outcome. In addition, it estimates the probability of an event occurring. In this study, the function is given by:

$$\mathrm{E(Y)} = \frac{\exp(\beta_0 + \beta_1 \mathrm{x})}{1 + \exp(\beta_0 + \beta_1 \mathrm{x})}$$

where E(Y) is the probability that Y is 1, β is the regression coefficient, and x is an independent variable.

3.5.3. Step 3. Calculating Transition Probability

This chapter aims to measure transition probability, which is the probability of transitioning from one state to another. In this paper, the one-step transition probability means the probability of having business with large companies or SMEs and examines frequency of transaction between companies in t_i and t_{i-1} technologies. The measured transition probabilities are applied to identify SME-suitable technology by the Viterbi algorithm. Technology transaction relations among companies in the value chain are collected, and the companies are classified into two groups: large company and SMEs. With this, technological cooperation data between large companies and SMEs in each value chain is constructed, which is called the value chain data.

The value chain data is composed by two data sources such as 'main materials' and 'the amounts of orders received' of Dart Analysis, Retrieval and Transfer System (DART). The value chain is used to distinguish a company's strategic activities. In addition, it indicates the actions that have a structural linkage with each other; it is not merely a simple combination of independent action components. The purpose of the value chain is to determine the strengths and weaknesses of a company and find a valuable source of production. Value chain analysis includes research on the business process and activities of a company, finding ways to allocate costs for assigned processes, determining the value of products due to each different process, and confirming whether each part is operating at its best performance in terms of price, speed, and efficiency. In other words, value chain analysis is used to investigate the key activities that closely influence the creation of added value of each phase and to determine the cost drivers of each action phrase in order to make it a tool for building competitive advantage. While most value chains are utilized to confirm the competency of the method, especially in microscopic perspective, this study identifies the value chain as a method of competition in macroscopic terms and as a way to investigate the roles of major and small companies regarding major actions.

3.5.4. Step 4. Determining Optimized Combination in the Value Chain

The purpose of this step is to identify which field is the best matched for a large or small firm in the value chain. The applied methodology is the Viterbi algorithm in the HMM. The Viterbi algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states. In addition, it identifies an optimal coordination, which has the greatest amount of success, from observation results, using the probability of both transition and success after calculating the probability of success using the patent data of each value chain.

The key methodology is the Viterbi algorithm, which spans the lattice of N states and T times and retains the probability. The path comes to each state i at time t and path selection is determined by path probability and path node. The transition probability a_{ij} stores the transition probability of transiting from state i to state j, $a_{ij} = P(q_t = j | q_{t-1} = i), 1 \leq i, j \leq N$ and the observation probability $b_j(k)$ contains observation sequence $O = (o_1, o_2, o_3, \ldots, o_{t-1}, o_t)$. Let $\delta_t(j)$ be the probability of the most probable path that has j as its final states in t time:

$$\delta_{t+i}(j) = \max_{1 \leq i \leq N} \left[\delta_t(i) a_{ij}\right] \cdot b_j(o_{t+1})$$

4. Case Study

4.1. Background

The types of manufactured solar cells include thin film type and crystal type; especially, the crystal type represents 80% of the world market. The value chain of the solar cell for the crystal type consists of five technologies: (1) material (polysilicon), (2) components (wafer), (3) cell, (4) module, and (5) system, as shown in Figure 6. The thin film type has easier manufacturing processes than the crystal type and it involves only one procedure, apart from making the material.

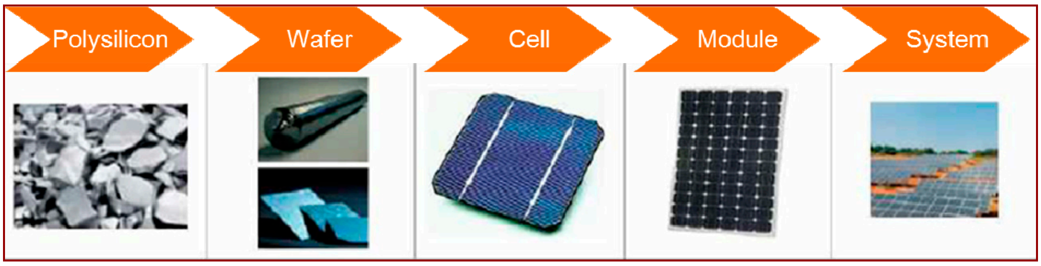

Figure 6. Value chain of the solar photovoltaic industry.

The value chain of the crystal solar cell has more complex processes than the thin film type and is used in various industries. Upstream groups include the polysilicon and wafer and downstream groups include the cell, module, and system. In particular, upstream groups require detailed technology capability and have a severe entry barrier because of the high investment cost in facilities, while it can involve a high operating income. The ratio of SMEs producing copper indium selenide (CIS) thin film solar cell systems is (50%) in the first item (end goods), board (0%), CIS thin film solar cell module (10%), and power converter (48%) in the second item, process equipment for the solar cell (63%), process material for the solar cell (10%), and equipment for modular (100%), and modular material and components (33%) in the value chain of thin film type. These percentages are based on the volume of manufacture and the ratio of SMEs is similar to that of large firms. Especially, small firms produce 100% of equipment for modular systems and large and small firms manufacture 50%. This means that SMEs are in the competition with large firms in this industry, and it is important to detect SME-suitable technology for training small firms.

4.2. Step 1. Selecting a Technology Field and Value Chain Model

In this study, the solar cell industry was selected as a case study and information was collected from the value chain in series. This case is based on the solar photovoltaic industry, including five technologies: polysilicon, wafer, cell, module, and system. The case is suitable for analysis because the solar photovoltaic industry is a key emerging industry, as it provides energy that is clean, safe, convenient, and highly efficient. In addition, large and small firms exist in all value chains and intense competition between firms is shown in some technologies.

The search keywords for solar photovoltaic technology are based on the analysis of the patent-based technology of report-alternative energy. If the applicant has more than 500 employees, their company is classified as a large firm. This study examines a number of granted patents in large or small firms using quantitative analysis and citation analysis is used in terms of qualitative analysis.

4.3. Step 2. Calculating the Probability of Success

The data include patent portfolios of 80 firms in the USPTO database, 40 of which are successful firms and 40 are unsuccessful firms. The successful firm refers to a company that is 1st to 2nd market share in each field of the world and has R&D activities for more than 15 years until over 2010 years to identify innovative SMEs. In order to distinguish between successful firms and unsuccessful firms, the successful SMEs were selected by domain experts and patent analysis to define duration of R&D activities. In addition, the unsuccessful companies have relatively low global market share in the same type of IPC code, and a short period of R&D activities. For example, Baader, a successful company, applied the first patents in 1974 and the final application in 2011 at the area of cutting fish (IPC code = A22C – 025/16), and has 35 years in innovation. Meanwhile, Systemate Holland has patent applications from 1984 to 1999, and is currently defined as an unsuccessful corporation in this study. For another example, Gallagher is a successful firm and Dare Products is an unsuccessful firm in the electric fence manufacturing industry. This is because Dare Products have not undertaken R&D activity since 1988 and Gallagher has performed R&D activities since 1983, for more than 20 years. The descriptive statistic and correlation matrix for our criterion is shown in Table 2.

Table 2. Descriptive statistic and correlation matrix.

	Variable	N	Min.	Max.	Mean	S.D.	1	2	3	4
1	BCI	80	0.00	5.51	0.44	0.90	1			
2	CII	80	1.92	60.0	27.39	16.17	−0.00	1		
3	CPR	80	2.00	50.00	24.38	14.24	0.07	0.01	1	
4	TCT	80	8.50	24.00	14.63	5.25	0.12	0.06	0.37	1

Note: BCI is the backward citation index, CII is the current impact index, CPR is the citations performance ratio, and TCT is the technology cycle time.

Prior to conducting a logistic regression, the tolerance was used to examine the correlation analysis between independent variables to measure multicollinearity. High multicollinearity refers to a problem that causes the coefficients to be unreliable in the regression analysis, since the relationship between the input variables exists and the variance of regression coefficients increases. As a result, the tolerance was found to be higher than 0.8 in the maximum 1 value and the multicollinearity was low. The results of logistic regression are shown in Table 3. Model 1 in Table 3 is the baseline model with only control variables and Model 2 adds independent variables to the analysis. The variables are significant for success of the company and while BCI, CRP, and TCT have a positive effect on the dependent variable, CII appears to have a negative impact. From the results of logistic regression, the probability of success formula is measured.

Table 3. Results of logistic regression.

Variable	Model 1		Model 2	
BCI			10.68 **	(0.02)
CII			−0.28 **	(0.03)
CRP			0.25 *	(0.06)
TCT			0.78 ***	(0.00)
R&D size	0.25 *	(0.09)	−0.02	(0.12)
Age of company	−0.10 ***	(0.00)	−0.0.6 ***	(0.01)
Constant	−12.57	(0.23)	−10.01 ***	(0.00)
Number of company	80		80	
χ^2 test	0.00		0.00	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Applying the formula to the solar photovoltaic industry, the data include 6018 patents in the USPTO dataset. The probability of success in the value chain is identified in Table 4.

Table 4. Observation probability of success in the value chain.

Type	Polysilicon	Wafer	Cell	Module	System
Small firms	53%	82%	81%	72%	86%
Large firms	70%	81%	74%	67%	87%

4.4. Step 3. Calculating Transition Probability

One hundred and twenty-four cases of value chains were collected by searching information on materials and contracts in reports and news. For example, the first case of small enterprises is in all of the value chains and the second case consists of large firms in polysilicon and cell manufacturing.

The results of transition probability are explained below. Initially, small companies moved 1% to polysilicon while major companies had a 99% difference. This means that the technology of polysilicon is monopolized by major companies, rendering access by small companies challenging. The probability of transition from polysilicon to wafer shows that 80% of major companies manufacturing polysilicon deal with small companies in wafer manufacturing, while 20% of major companies deal with major companies of wafer manufacturing. This demonstrates that small companies have access to wafer technology and that they have developed sufficient techniques to run their business. Meanwhile, small and large companies of wafer technology deal with major companies of cell technology, each comprising 89% and 92%. While cell technology can be judged as a difficult field for small companies without large capital, small companies need to identify success probability using the data. The probability of cooperation between major cell companies and small companies possessing module technology is 53%. In addition, the probability of cooperation between major companies, each possessing cell and module technology, is 47%. Considering that most of the cell technologies are owned by major companies, almost half of the cooperation in the module is performed between small companies and major companies. At this point, this statistic cannot be used to determine whether small or major companies have strengths in the module fields; in order to examine success probability further, finding and selecting proper fields is necessary. Finally, the cooperative probability between small companies of module fields and system fields is 56% and the probability for cooperation between major companies of module fields and major companies of system fields is also 50%. As well as module fields, system fields need additional analysis to determine the size of company that is apt to develop this type of technology.

4.5. Step 4. Determining Optimized Combination in the Value Chain

The best combination is large–small–large–small–small and the optimal arrangement is wafer, module, and system technologies that are appropriate for SMEs to support R&D as shown in Figure 7. The technological success probability for a major company in the polysilicon field is 70% and the transition probability is 99%. Thus, we can say that major companies that are currently monopolizing the value chain are fit for approaching this technology. Overall, transition probability for small companies in wafer technology is 80% and success probability is 82%. Thus, in terms of technological consideration and current businesses, it seems that small companies are suitable to follow this field. Since major companies in cell fields have 89% of transition probability and 74% of success probability, major companies seem more appropriate than small firms. In module fields, the transition probability of small companies is 53% and the probability of transition to major companies is also 47%, making a 50 to 50 situation. However, the technological skills of small companies are 72% higher than those of major companies, which makes it probable for small corporates to lead technology successfully in the module industry. Lastly, in system fields, similar to module fields, the transition probability for small companies is 56%, while the success probability is 86%; thus, it seems that SMEs are fit to survive the system fields.

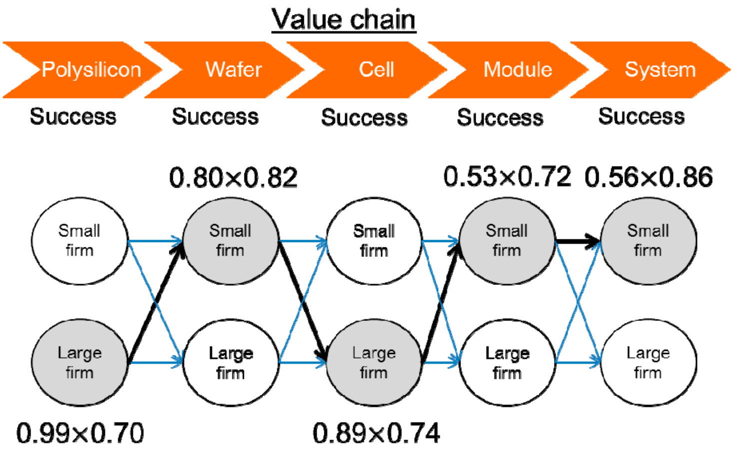

Figure 7. The results of optimal arrangement.

5. Results and Discussion

Depending on the complexity of technology, role allocation and strategic collaboration are important to improve the coexistence between large and small firms. This study shows the SME-suitable technology in the solar industry, including the manufacturing of wafers, modules, and systems. Otherwise, large firms are suitable for developing the technology of polysilicon and cells, of which SMEs find it difficult to enter. The selected optimal arrangement has a high impact of transition probability because of the probability gap. The sum of transition probability regardless of prior state is shown in Table 5. The transition probabilities of SMEs is 180%, 122%, and 106% for wafer, module, and system technology, respectively, which are higher than the transition probabilities of large firms of 20%, 78%, and 94%, respectively.

Table 5. Sum of transition probability.

Type	Polysilicon	Wafer	Cell	Module	System
Small firms	1%	180%	19%	122%	106%
Large firms	99%	20%	181%	78%	94%

However, in technology within similar transition probability of such a system, it is confirmed that the appropriate company type for corresponding technology is different, depending on the observation probability. In Table 6, rankings 1 through 6 are all large firms in polysilicon and cell manufacturing because these companies produce these items already. This means that, in this technology, it is difficult to enter a new market according to the minimum efficient scale. The minimum efficient scale is the level of minimum costs for entry to a new market. Thus, low minimum efficient scale in a technology field means that SMEs can enter easily in the field. Even if SMEs produce most of the wafers, the entry of large companies needs to be regulated in order to protect SMEs because the minimum efficient scale is low. Otherwise, module and system manufacturing are in competition because the capability of SMEs is similar to large firms' technology in modules and systems. If a government establishes a policy to support SMEs, it is necessary to encourage firms to manufacture modules and systems to improve their advantage.

Table 6. Ranking of optimal arrangement.

Ranking	Polysilicon	Wafer	Cell	Module	System
No. 1	Large	Small	Large	Small	Small
No. 2	Large	Small	Large	Large	Large
No. 3	Large	Small	Large	Large	Small
No. 4	Large	Small	Large	Small	Large
No. 5	Large	Large	Large	Small	Small

6. Conclusions

This study tackles suggesting a methodology and measureable factors to determine the appropriate SME-suitable technology. In order to overcome the limitations of prior research, in which the opinions of experts were employed, it is more reasonable to use patent information and the HMM. To calculate transition probability, the information for the value chain is collected and logistic regression is used to measure the coefficient of observation probability in components of HMM. This study differs from previous research in reflecting reality using value chain analysis. In the last step, this paper verified the proposed method by applying it to technologies related to solar cells. The proposed method would show remarkable performance to identify appropriate technologies in the framework of R&D ambidexterity, technology and commercialization. The findings suggest that some technologies—wafer, module, and system—in the solar industry are SME-suitable technology from the case study. In the case of technology in the field of system, large companies and SMEs have a similar probability of success. From these results, SMEs can compete successfully with large enterprises by developing their technology in specific fields.

Despite several contributions, this research has some limitations. First, even though many types of companies were examined, firm size is considered as a factor for classification. Second, this study did not detect detailed technology because the parallel value chain was not considered. This is because the value chain, consisting of primary, secondary, third steps, etc., needs not only one technology but also two or more technologies at each step concurrently. For example, in the case of a value chain for a thin film solar cell, the end goods are copper indium gallium selenide (CIGS) thin film solar cell systems, and it requires equipment and material for modularization as well as for the solar cell in the previous step, having a parallel relation. Third, there is a lack of more reasonable variables in logistic regression, and it is difficult to determine whether or not the assignee is an SME.

Even though this research has some limitations, it also makes key contributions to support strategic decision-making for large and small firms. This research helps strategic businesses of SMEs and government policy by discovering the appropriate technology for SMEs. In addition, in previous study, SME-suitable industries were selected utilizing a survey method, which is limited by a lack of objectivity. However, this research uses the value chain and the SMEs' relative technological competitiveness over large firms by patent analysis to overcome the aforementioned limitations. To promote the selected SME-suitable technology, considerable assistance is necessary in developing a sound corporate ecosystem and a win-win company culture. Since the concept of competition changes from inter-enterprise competition to inter-network competition, the SME-suitable technology simultaneously increases the large firm's competitiveness by improving small business.

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