Convergence Technology Opportunity Discovery for Firms Based on Technology Portfolio Using the Stacked Denoising AutoEncoder (SDAE)

Deuksin Kwon and So Young Sohn

***Abstract*—Technology convergence, as a key driving force of innovation, has brought a burgeoning of research attention. Although numerous studies on technology convergence have been carried out, there were limitations in consideration of a firm's capability in technology convergence. This article proposes a framework for "Convergence Technology Opportunity Discovery" (CTOD) based on firms' technical convergence competence manifested in their patent portfolios, market competition, and technological growth potential. The present research, by employing a stacked denoising autoencoder, a deep neural network-based collaborative filtering method, provides reliable latent preference toward convergence technology for individual firms. Our CTOD framework is applied to three information technology and biotechnology firms to elaborately demonstrate its validity. Ultimately, the proposed framework is expected to provide practical assistance to organizations seeking technology convergence opportunities in various fields.**

***Index Terms*—Collaborative filtering (CF), stacked denoising autoencoder (SDAE), technical convergence competences, Technology Opportunity Discovery (TOD), technology recommendation.**

I. Introduction

THE emergence of innovative technologies that create high added value through technology convergence has led to much related research and investment activity to develop future markets at both the firm and country levels [1]. In order to preoccupy technological markets by developing convergence technology [2], it is necessary to identify potential areas for convergence first. Next, it is crucial to consider the firm's technological capabilities and R&D budgets, when setting up R&D investment goals and strategies with the resource-based perspective [3]. The competence-based view [4] suggests that the nature and portfolios of firms' technology and skill sets all have to be taken into account to make informed decisions to select the right areas of technology convergence. Also, drawing from a resource-based theory [5], one can assert that a firm's specific technological skills and capabilities may act as an important source of competitive advantage as long as they meet the criteria of rarity, inimitability, and nonsubstitutability.

Hence, with the requirements for myriads of resources, technology convergence involves a high cost and its successful implementation is indeed difficult [6], [7]. Moreover, the success of the technology does not guarantee economic benefits in the technology market. This is because there may already be a variety of competitors with similar convergence technologies in the market. Therefore, companies should use strategies of "Convergence Technology Opportunity Discovery" (CTOD) in consideration of not only the focal firm's capacity and competition but also marketability.

Admittedly, extant "Technology Opportunity Discovery" (TOD) methods can also contribute to discovering promising convergence technologies [8]. Kim et al. [9] suggested a method to find highly relevant convergence technology areas based on the analysis of patent citation networks through text mining and keyword analysis. However, their research gives no consideration on the resources that individual firms possess, such as individual firms' technology portfolio. Moreover, their study seemed to lack consideration on the competitiveness and growth of the discovered technology opportunities in the technology market. Meanwhile, Park and Yoon [10] proposed a method for discovering technology opportunities through the use of company technology portfolios by applying a collaborative filtering (CF) method. However, they were not able to accurately identify company technology convergence competences from the view of technology convergence because technology opportunities have been searched in terms of individual technologies. Moreover, the conventional CF method that they applied has a well-known data sparsity problem, which makes it difficult to obtain robust and satisfactory recommendation results. Therefore, the technology opportunities they discovered could not be regarded as optimal for technology convergence.

Given such limitations of the extant studies, our proposed framework has novelty and usefulness in two ways. First, as one of the first proposed frameworks for discovering technology opportunity in terms of technology convergence, it accurately reflects the convergence technology competence of individual firms by identifying an individual company's technology

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portfolio. Since technical characteristics of individual technologies lead to potentially varied technology convergence possibilities and categories of added value [11], companies with different technology portfolios should be seen as having different technology competencies, which can be used to measure the convergence technology competitiveness of a firm. Accordingly, identifying individual firms' convergence technology competence may provide a more profound understanding and guidance on promising convergence technologies at the firm level. Therefore, companies may enjoy reaping the benefits of creating a higher added value and preoccupying their technology markets through effectively concentrating their limited R&D expenditure on CTOD that aptly fits their unique firm conditions. Second, our CTOD framework introduces a deep neural network-based CF method, known as stacked denoising autoencoder (SDAE), which achieves an outstanding and robust performance with denoising techniques in dealing with large and sparse data sets, compared to conventional CF methods that suffer from the sparsity problem. Addressing this issue, our model employs SDAE to propose a way to effectively extract various latent factors among firms or convergence technology combinations inherent in the firm data of convergence technology, where the number of technology combination sets is very large and the data are sparse in nature. We apply our CTOD framework to actual firms in two high-tech industries [i.e., information technology (IT) and biotechnology (BT)] to test its applicability and usefulness in practice.

The rest of the article is organized as follows. Section II reviews previous research on technology convergence and TOD. Section III introduces a CTOD framework along with detailed methods utilized in the framework. Section IV presents empirical application. Finally, Section V concludes this article.

II. Theoretical Backgrounds

A. Technology Convergence and Technology Opportunity

1) Technology Convergence: Technology convergence is the process by which technologies in different application fields are transformed into a new integrated technology [12]. The precise definition of technology convergence varies from a narrow sense of convergence between different fields in the same sector to a broad sense of convergence between completely different sectors [13]. Technology convergence is regarded as a major source of new and innovative technologies and has been a primary driving force of technological development and economic growth [1]. Since technology convergence was first discussed in the context of the computer and communication sectors in the early 1970s, many separate technologies have converged into new technologies, products, and services in various fields, particularly in the IT and BT areas [14], [15].

Based on the importance of technology convergence for growth and innovation, convergence research has been carried out in various fields (e.g., R&D, technology roadmapping, the development of national policies and regulations, and business strategy development) to promote the convergence of technologies at both the company and country levels [16], [17], [18]. Hacklin et al. [16] developed a strategic commercializing tool for promoting technology convergence in the field of information and communications technology (ICT) and argued for a wider range of studies on technology management. Jeong [19] proposed the collaboration among different R&D entities to improve technology convergence by identifying how the organizational contexts of such institutions affect technology convergence and emphasized the benefit of using incentive systems for technology convergence. Yasunaga et al. [18] stressed the importance of creating and utilizing a technology roadmap to promote technology convergence, specifically highlighting the role of government in constructing technology roadmaps for the public sector.

While the above studies mainly focused on suggesting strategies to promote the convergence of technology at the country or firm level, the following line of research on technology convergence explores how specific technologies are converged. In particular, many studies highlight the current trends of convergence technology as well as predictions on future convergence technologies beyond the current horizons in specific industries or technology fields [20], [21]. They generally utilize patent information to identify the links between technologies in terms of technology convergence. Lee et al. [21] developed the International Patent Classification (IPC) co-occurrence network concept based on triadic patents and performed similarity-based link prediction. Shibata et al. [22] predicted future technologies citations from the perspective of convergence by constructing a technology citation network covering five technical fields including solar cells and nano-BT. Meanwhile, Kim and Lee [20] proposed a technology convergence map that can easily observe the trends and make predictions of technology convergence. The author applied the design structure matrix technique to patent citation information in order to reveal the direction and flow of technology convergence. Lee et al. [23] explored information on ICT technology convergence based on patent citation records.

However, most previous studies have either analyzed technologies that have converged or how technologies will converge in the future from a macrotechnical viewpoint, and there has been a lack of research on predicting specific convergences of technologies from the standpoint of the actors actually performing technology convergence and R&D. Even within industrial sectors, technical competence and resources can vary by company, whereas the feasibility of technology convergence can vary depending on technical characteristics. It is therefore difficult for individual firms to apply technology convergence patterns predicted from a macrotechnical perspective to their own technology development strategies. In particular, small- and medium-sized enterprises (SMEs) setting their R&D priorities with a small amount of resources face more risk in investing in technology development based on macrolevel information. To effectively utilize identified information on the patterns or future directions of technology convergence, it is necessary to make convergence technology recommendations based on the resources and technical competences of individual firms. It is also particularly important to understand companies' technology convergence capabilities from the perspective of convergence. If the level of growth of a specific convergence technology and its competition with other technologies within the technology market are considered together, convergence technology recommendations can lead to more effective opportunities that contribute to company growth and technological innovation.

2) Measurements of Convergence Technology With Patent Classification Information: A variety of sources, such as newspapers, research articles, government R&D database, and patents have been used for studying convergence technology [24]. Among these sources, patents, as a technology-related indicator containing a large amount of information on patented technologies, have been widely used as a common measure for technological convergence trend as well as firms' technological competence [25]. In particular, much research on technology convergence based on patents utilized information of 1) patent citation and 2) IPC co-occurrence of a patent [26], [27].

With regard to patent citation information, although they may be helpful in identifying the technical sources and fields of the patent, suffer from several limitations on apprehending the recent technological trends. One of the causes is that once a patent is registered, sufficient time is required to be cited. In particular, the more recent patents are registered, the shorter time it takes to be cited. Another cause to blame is on firms that tend to cite as few of other patents as possible in order to emphasize the novelty of their own patented technology [28]. Therefore, some of the significant information related to convergence technology may be absent in the citation information. Given the rapidly changing nature of technological fields, it is thus, not enough to use exclusively the patent citation information to fully capture the recent trends of convergence technologies.

Aside from patent citation information, more research on convergence technology has used IPC information of a patent. Since technological classes of patent can be regarded as a proxy of technological knowledge elements [29], information of patent classification systems, such as IPC, Cooperative Patent Classification (CPC), and US Patent Classification (USPC) allows the identification of technological knowledge and competence of a firm by providing more detailed classification information of specific technology. Since each IPC code presents a specific technology, a combination of IPC codes can be understood as a convergence of technologies. From the perspective of technology convergence, through many combinations of IPCs in a patent, firms' convergence technology capabilities can also be measured. Also, despite the limitations of citation information stated above, combined information of citations and IPC of patents enables us to analyze how various technologies are combined and which prior technologies are referred to in detail, from a technology competence standpoint.

Patent IPC information has been employed by numerous studies on convergence technology [1], [24], [26], [30]. For instance, Curran and Leker [1] analyzed technology convergence patterns between heterogeneous industries using information on co-IPC codes in patents. Han and Sohn [30] identified the convergence patterns of ICT-related standard technologies using network analysis of co-IPC information. In addition, the sharing of citation information in patents and research papers has been used to study the changing characteristics of convergence technology in specific industries [31]. Citation networks have also been used to analyze key technologies and convergence patterns across time [28]. Moreover, Ko et al. [32] identified trends of interindustry technology convergence using knowledge flows based on USPC codes and citation information in patents. Son and Cho [27] analyzed technology fusion characteristics in the Solar Photovoltaic Industry with IPC coutterance networks.

In line with these prior studies, our research identifies firms' convergence technology competences by using CPC information of patents that each firm owns. Furthermore, since innovation takes place by combining a variety of knowledge components [29], the present research proposes a framework for discovering technological opportunities based on different combinations of CPCs corresponding to knowledge components, thereby sparking innovation. In particular, the use of different combinations of CPC subclasses in this study also provides a more comprehensive apprehension toward the heterogeneity of technology in patents.

3) Technology Opportunity Discovery: Technology opportunities are defined as the set of potentials and possibilities for technical progress and development within a general context or a specific industry sector [33]. TOD also incorporates different activities, such as discovering or investing in innovative or promising technology opportunities and setting up a roadmap of profit-making technologies. Finding technology opportunities in rapidly changing and intensely competitive technology markets has become an important issue directly linked to the survival of companies [34]. Correspondingly, many firms are putting much effort into finding suitable technology opportunities considering their own respective technical and economic factors.

TOD involves the discovery of new, unoccupied fields or promising technologies with technological potential [35], and TOD research has been conducted in various technology-related applications involving trend analysis, prediction, roadmapping, and opportunity development. A number of TOD studies have used methods based on experience and expertise developed using techniques, such as the Delphi method or the analytic hierarchy process (AHP) rating method [8], [34], [36]. Yu and Lee [36] utilized the AHP rating method based on experts' ratings along with other methods for identifying optimal emerging technologies. However, such methods can be time-consuming and costly and might be limited in how well they reflect relevant information in various technical fields.

Due to the shortcomings of the previous studies, quantitative TOD analysis methods have been developed based on the data that provide objective insights from information, such as patent documents [37], [38]. Daim et al. [37] performed technology forecasting for three specific technologies using a combination of technology forecasting methods, quantitative surveys, and patent analysis. Yoon [39] applied a morphology analysis to patent data and proposed a method for discovering promising technology opportunities and prioritizing based on conjoint analysis. Choi et al. [40] analyzed fuel cell patents using the subject-action-object networks in conjunction with a natural language process technique to identify technology trends and provide application planning for TOD. However, these extant quantified TOD studies have focused on predicting new technologies at the macrolevel without considering the specific situations and technological capabilities of individual firms. Therefore, studies to find more appropriate technology opportunities for individual firms were also conducted, taking into account the technical capabilities and resources of individual firms [10], [41].

As such, the scope of TOD research has been continuously expanding, and research interests in discovering technological opportunities for convergence technologies have also been growing. Since new technologies are usually developed by the convergence of several technologies, discovering and investing in technologies to be converged has become more important for firms to survive and grow. Kim et al. [9] suggested a method to find highly relevant convergence technology areas based on centrality measures derived from the analysis of patent citation networks and to propose concrete convergence directions through text mining and keyword analysis. Park and Yoon [42] proposed a TOD method for technology convergence identifying technology knowledge flow through a patent citation network and a link prediction. Recently, research has been conducted to recommend convergence technology opportunities based on each firm's technology portfolio through a deep neural network [43].

Although such extended stream of recent TOD research has significantly contributed to the convergence technology fields, there still exist limitations. First, it shows a lack of grasp of company technology convergence capabilities based on technology portfolios. A discovered technology opportunity for technology convergence may not be adequate for individual firms, depending on their specific situations, such as technical competence and resources. Second, there is a lack of consideration on the position of the discovered technology opportunities in the technology market. Even if it is an appropriate convergence technology opportunity for a target company, it cannot be an attractive opportunity in the real business environment if the technology is already saturated in the market or it belongs to a technology area that is not growing.

Complementing such limitations, our framework proposes CTOD that considers the technical convergence capability of a firm based on combinations of technologies in terms of convergence, as well as the growth and competition of the technology in the market. As to date, few CTOD studies based on convergence technology capability at a firm level have been carried out; this article fills this gap by proposing a framework for discovering the optimal convergence technology opportunities of individual firms using a combination of patent technical classification analysis and convergence capabilities.

B. CF and SDAE

Recommendation systems are actively utilized in many fields to suggest products and services that are likely to meet the individual tastes and preferences of customers. A well-established recommendation system can provide customers with benefits by reducing the time and energy invested in item selection. In particular, CF remains the most popular recommendation method and has inspired a number of recommendation system studies related owing to its capability to produce successful recommendations with high accuracy based on the accumulated information on products and customers [44].

Among CF methodologies, memory-based CF is the most commonly used for recommendation algorithms. Memory-based CF calculates similarities or weights between customers or items and makes recommendations accordingly. The technique is widely used in a variety of fields because it is easy to implement and highly effective in product recommendation [45]; however, it calculates the similarity between customers based on commonly evaluated items, which can result in poor predictive performance when data are sparse. To overcome these shortcomings, many model-based CF methods that learn or presume models for prediction have been proposed [46]. Among the best-known model-based CFs are the Bayesian belief nets CF model [47], which is widely used in machine learning, the clustering CF model [48], the latent semantic CF model [49], and the Markov decision process based CF model. The most successful approach using the CF method involves finding and using latent variables in a customer-item matrix of rating scores. In turn, the most commonly used method for finding latent factors is to apply singular value decomposition (SVD) to low-rank rating matrices using the gradient descent method or a regulated alternating least square algorithm [50], [51]. However, these linear methods are unable to capture complex and subtle latent factors.

Hence, complementing these methods in application to recommendation systems, neural networks that find latent factors through multiple hidden nodes, hidden layers, and nonlinear activation functions have been introduced [52]. Although the use of sparse data for which ratings and preferences exist for only a few items is not easily compatible with the application of artificial neural network models, artificial neural networks have been applied to CF methods because they are excellent at extracting features of the relationships among nonlinear latent factors [53]. Salakhutdinov et al. [53] proposed a system for recommending movies according to customers' preferences based on the application of a restricted Boltzmann machine to Netflix data that proved superior to existing SVD-based models. To solve the data sparsity problem, research has also been conducted on the use of autoencoders (AEs) to predict customers' optimal preferences and form recommendation models [54], [55]. AEs have been widely used to reduce the dimensionality of data while extracting features through hidden layers with lower dimensionality than the input dimension. However, classical AEs often suffer from degenerating into identity networks, resulting in poor training of relationships within data. To address these problems and further enhance the restoration ability of the existing AE models, Vincent et al. [56], [57] proposed a "denoising autoencoder" (DAE) that corrupts the input but finally denoises the output. With the denoising method, Strub et al. [55] developed a CF based on an SDAE for movie recommendation that could be used in conjunction with sparse customer-movie rating vectors.

Within the field of company convergence technologies addressed by this study, the number of technology combination sets is very large but the data are sparse because the technology convergence competence of a company will be limited to a specific convergence technology. Moreover, it is necessary to accurately capture the complex and subtle latent factors between companies and their technology combination set. To obtain improved results, it is preferable to use deep artificial neural networks to find various latent factors among customers or items than it is to apply the general CF method of measuring the similarity between customers based on a distance index. Thus,

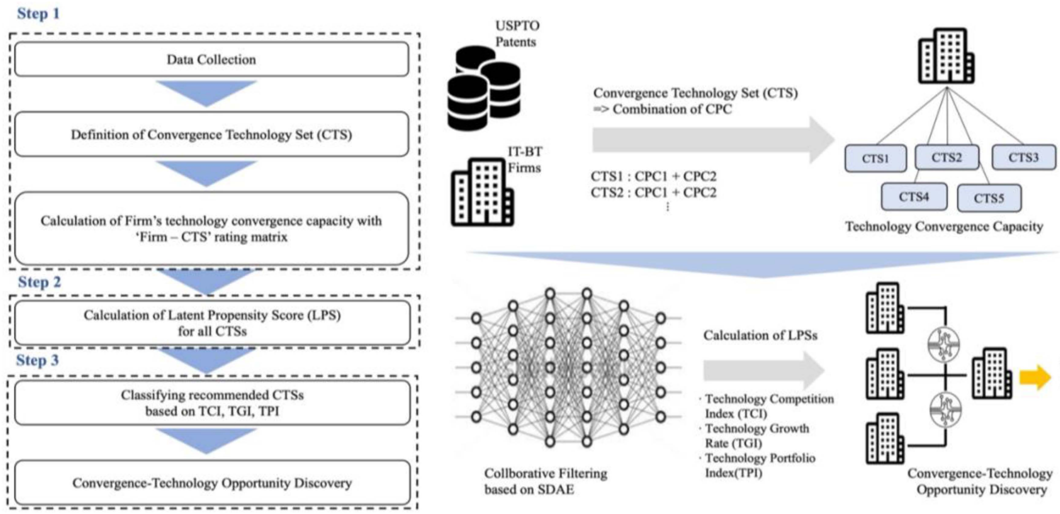

Fig. 1. Proposed framework for discovery of convergence technology opportunities.

our method performs CF based on an SDAE model to discover convergence technology opportunities.

III. Methodology

In this article, we propose a method for finding the most suitable opportunity for the convergence technology for a given firm by assessing its technical convergence capability using company's patent portfolio. To assess firms' technical convergence capability, a collection of pairs of combination of technologies is first defined as "convergence technology sets" (CTSs) based on the CPC system. With CTSs, individual firms' technical convergence capability is measured in our study.

The proposed framework for CTOD for a firm can be traced through the following three steps, as shown in Fig. 1.

1) Step 1 consists of three substeps, namely a) data collection, b) definition of CTSs, and c) derivation of firm's technological capability for convergence technology. First, we collect patents for target firms and then define CPC pairs based on patents owned by individual companies as CTSs. Then, with the defined CTSs, we derive companies' technological capability for convergence technology. The method of utilizing combinations of technologies as a company's technological convergence capability in our study is a new approach that has not been taken in any TOD studies, which can produce different results from those obtained by analyzing technology convergence by simply identifying a company's portfolio on an individual CPC basis.
2) Step 2 involves applying SDAE-based CF to the set of technical convergence capabilities of each firm to obtain adequate CTSs for them. With SDAE-based CF that has strength in solving data sparsity problems, more robust and reliable recommendation scores, so called the latent preference scores (LPSs), can be derived for all CTSs that the target company does not have.
3) Step 3 is to classify the recommended CTSs in light of the competitiveness of the technology market, the technology growth rate, and the firm's existing technology portfolio, and to finally obtain optimal CTODs for the target firm.

A. Convergence Technology Competences of Firms

The CTOD process produces recommendations of practical convergence technologies for specific companies. To do this, it is necessary to consider the convergence technology capability of the company. Although patent information would not cover all aspects of individual firms' technology, since it has been regarded as the most widely used index that represents an overall technological capability of a firm [58], we refer to patent information for CTOD process. Each patent held by the company can be regarded as a component of technology portfolio of the company and, according to CPC classification, the plurality of technology areas belonging to that patent can be recognized as technical capabilities possessed by the company. However, rather than assessing technology areas based on CPC classification as individual technologies, we seek to understand the convergence capability of the company, as the goal is to recommend convergence technologies. Based on a company's patents we can obtain its respective CTS frequencies, which are recognized as the degree of technical convergence competences of the company. As for copatents, technological spillover has been found to take place among coapplicants in the process of technology development [59], we presumed that coapplicants of an identical copatent possess the same convergence technological capabilities. These factors can also be expressed in a recommendation system as the technical preference of the company for a particular convergence technology. Based on this definition, a company's own technical convergence competences are defined as follows:

$$U_i = [CTS_{i,1},\ CTS_{i,2}, \cdots,\ CTS_{i,j}\ ],\quad (i \in \{1, 2, \ldots,\ N\}\ \ j \in \{1, 2, \ldots,\ M\}) \tag{1}$$

where $CTS_{i,j}$ denotes the frequency of the *j*th CTS in the patents owned by company *i*. *N* and *M* stand for the total number of companies and the total number of CTSs, respectively.

Through this process, convergence technology competence vectors are derived for all companies. Prior to deriving those vectors, a preprocessing was executed for a notable case. There are some patents where CPCs lied across an excessively broad range of other domains and industries even if they are related to a specific technology area, such as IT or BT. For example, there is a patent with more than 30 CPC four-digit subclasses for different technical fields. Due to some technologies that were combined with a variety of other fields, the scope of technologies to be recommended for convergence may become excessively large, which hinders an optimal recommendation of technologies to many SMEs with technology resources concentrated in a specific field. For this reason, the patents where the number of four-digit CPCs is over 30 were removed from the technology portfolio vectors of each company as they may hamper in recommending a specific field's convergence technology. This was to ensure that the scope for the convergence technological opportunity is limited to the extent that does not encompass substantially distant or irrelevant technical fields.

$CTS_{i,j}$, the preference by company *i* for a combination of convergence technology *j*, is converted into a five-point scale value between one and five for use in CF. By considering the frequency of patent applications for a specific CTS, it is possible to infer the level of technical competence of a given firm; however, the relationship between frequency and firm's technical capacity is not linear. Park and Yoon [10] assumed nonlinearity between the frequency of a specific technology field and the technological capability of a firm and converted the IPC frequency of companies to technology competencies on a five-point scale using fuzzy logic. In this study, we applied a modified form of the fuzzy logic used in previous studies to convert the frequency of technology convergence to the competence or preference for a specific convergence technology of an individual company [10]. Our fuzzy logic conversion equation is given as

$$FCTS_{i,j} = \begin{cases} 5 \times \left(1 + CTS_{i,j}^{-a}\right)^{-b}, & \text{if } CTS_{i,j} > 0 \\ 0, & \text{if } CTS_{i,j} = 0 \end{cases} \tag{2}$$

where $FCTS_{i,j}$ denotes the technology convergence preference for firm *i* for convergence technology *j* converted to the fuzzy logic scale, and *a* and *b* are the fuzzy logic scale parameters. Depending on the values of *a* and *b*, the five-point conversion level of the company's technology capability varies. A fuzzy logic-scale technology capability portfolio vector for the *M* CTSs of firm *i* can be written as follows:

$$FCTP_i = [FCTS_{i,1},\ FCTS_{i,2},\ \cdots,\ FCTS_{i,j}, \cdots, FCTS_{i,M}]. \tag{3}$$

B. Derivation of LPS of CTS With SDAE-Based CF

Our CTOD framework applies an SDAE-based CF, which achieves outstanding and robust performance with denoising techniques by accurately capturing various latent factors among firms or convergence technology combinations inherent in the firm data of convergence technology, where the number of technology combination sets is very large and the data are sparse in nature. As shown in Fig. 2, fuzzy logic-scaled technology capability portfolio vectors of individual firms, called as FCTP, are feedforwarded to SDAE as inputs, and then through decoder, we can obtain dense vectors as output, which are LPS of all CTSs. The LPS of undeveloped items for the target firm is finally calculated by using $FCTP_i$ as follows:

$$LPS_j = SDAE(FCTP_i)_j \tag{4}$$

where LPS_j denotes a latent preference score for *j*th CTS, and $SDAE(x)_j$ denotes the *j*th decoder output of SDAE given input *x*.

When it comes to the denoising technique, there are three ways widely used to corrupt inputs: 1) add Gaussian noise to an input value; 2) set the value of a randomly selected specific input to "0"; or 3) give a maximum/minimum value of input to a randomly selected input value. Corrupting the input provides two advantages: it can serve as a powerful regularizer to prevent over-fitting of neural networks, and it allows the AE to predict missing values. We use the second method for input corruption and set the loss function of the DAE modified to emphasize a denoising part of the network. Two hyperparameters (α and β) are added to the loss function to determine whether the network will focus more on denoising (α) or reconstructing the input (β). The formula for the loss function is (5) shown as the bottom of the next page, where $x_{i,j}$ denotes the *j*th input of the *i*th firm (i.e., $FCTS_{ij}$), $SDAE(\tilde{x} \text{ or } x)_j$ denotes the *j*th output of the decoder of SDAE, $\tilde{x}$ denotes the corrupted input, $K(x)$ is the set of location indices for known values of *x*, which are the firm-owned CTSs, and $H(\tilde{x})$ is the set of location indices for $\tilde{x}$.

As shown in Fig. 2, in the process of minimizing the loss function for training SDAE, missing value corresponds to CTS not owned by the company, and the input edge is inhibited in the network by setting it to "0" in the input and output layers (i.e., $FCTS_{ij} = 0$) as in FCTS definition (3). Then, the related weights of missing values are not updated in backpropagation [55]. In addition, the loss of the missing values is ignored in the total loss (empirical loss), that is, as error backpropagation proceeds only for known values, missing values cannot affect the weight update of the network. In this manner, we optimally train SDAE-based CF models and obtain an LPS of a target firm for untapped CTSs by forwarding its convergence competency into our SDAE-based CF model.

C. Indices for CTOD

Considering the technology convergence competence of firms with SDAE-based CF, we can derive LPSs for CTSs that a target firm does not have but other firms have. A high LPS for a CTS indicates a convergence technology that is adequate for development by the firm in consideration of its technology convergence competence compared to all other companies. However, even a CTS with high preference may not represent a CTOD for the firm in practice, as the proposed convergence technology might already be saturated with many competitors in the technology market and thus might not be as promising as it would be in a slower growth phase. However, given low competition in the technology market and the high growth rate of

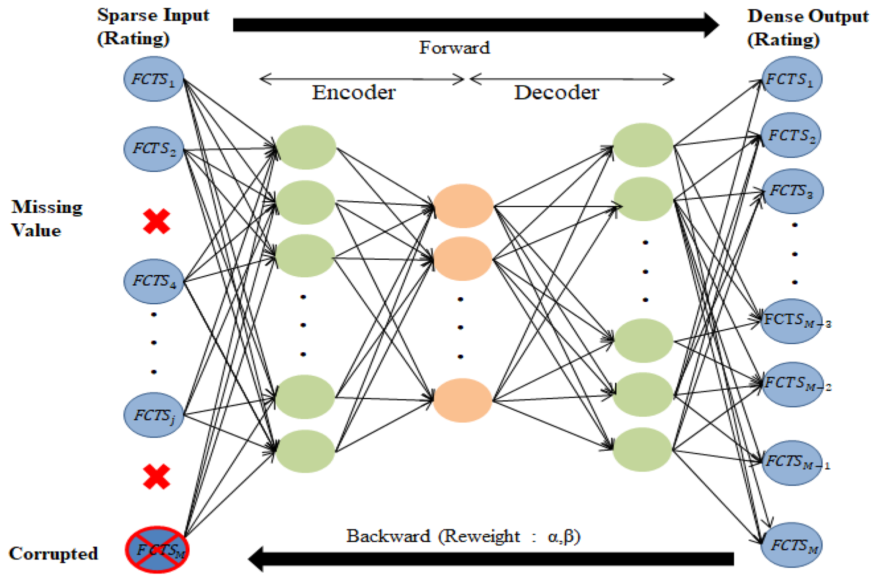

Fig. 2. SDAE with FCT.

convergence technologies with high preference scores, the CTS might be a practical CTOD for a specific company. In addition, for more practical and immediate technology convergence it is necessary to reconsider technical competences with respect to the technologies comprising a proposed CTS. To do this, the proposed CTOD framework uses the following three indices: competitiveness in the technology market, the growth rate of the convergence technology, and the technical competence of the recommended CTS.

The technology competition index (*TCI*) is an index indicating the degree of competition in the technology market. The proposed *TCI* can be measured by the number of patents with a specific CTS. Even though a specific convergence technology field might be growing rapidly, many patents might have already been applied in the field, indicating many competitors in the market. Because a specific technology field will be already saturated if there are many applied patents in the field [37], in this study the number of patents with specific CTS was used as a measure of the level of competition in the market. *TCI* is measured using the following equation:

$$TCI(CTS_j) = \sum_{t=1}^{T} NoP\left(CTS_j, t\right) \tag{6}$$

where $NoP(CTS_j, t)$ denotes the number of patents in year t with CTS_j in the CPC and *TCI* is the sum of the *NoP*s in the analysis target period ($t = 1, \ldots, T$).

Moreover, to distinguish whether a particular CTS was highly competitive in the technology market with *TCI*, the *TCI*s were derived for all CTSs and sorted in ascending order. The bottom 40% of the *TCI*s were all lower than 21, and therefore CTSs with *TCI* values lower than 21 could be considered to be less competitive in the technology market.

It is also important to consider the growth rate of the convergence technology to measure the growth potential of the convergence technology. The technology growth rate index (*TGI*) is an indicator of the growth potential of a recommended CTS, which can be measured as the average of the annual change in the number of patents with that CTS during the analysis period. As technology fields with high growth rates are considered to be promising, many companies will continuously apply for patents related to the field. A positive *TGI* for a specific CTS indicates that it was growing during the analysis period. Therefore, CTSs with positive and negative *TGI*s can be classified as high (H) and low (L), respectively. *TGI* can be measured using the following equation:

$$TGI(CTS_j) = \frac{1}{T}\sum_{t=1}^{T} \frac{NoP\left(CTS_j, t+1\right) - NoP\left(CTS_j, t\right)}{NoP\left(CTS_j, t\right)} \tag{7}$$

where $NoP(CTS_j, t)$ denotes the number of patents in year t with CTS_j in the CPC and *TGI* is the average growth rate during the analysis period.

To develop practical convergence technologies according to the recommended CTS, the company's technological competence for one or more individual technologies containing the CTS must be known. For example, if a CTS containing A61F-G06C is recommended and the company already has the technical capability for one of the A61F or G06C technologies, it would be relatively easy to develop the other technologies that the firm does not have. However, if the company does not have

$$L_{\alpha,\beta}\ (x, \tilde{x}) = \sum_{i=1}^{M}\left(\alpha\left(\sum_{j\,\in\, H(\tilde{x})\cap K(x)}\left[SDAE(\tilde{x})_{i,j} - x_{i,j}\right]^2\right) + \beta\left(\sum_{j\,\notin\, H(\tilde{x})\cap K(x)}\left[SDAE(x)_{i,j} - x_{i,j}\right]^2\right)\right) \tag{5}$$

any current competences for the technologies that make up the recommended CTS, it will be difficult in practice to promote technology convergence. In this study, we define the technology portfolio index (*TPI*) of a company as follows and recommend the CTS corresponding to "1": unnumbered Equation shown at the bottom of this page, where Techs. means technologies and Rec. means recommended.

The final selection of the CTS to be proposed to the target company as the CTOD is based on the above three indices and uses the LPSs derived from the SDAE CF based on the following criteria: high LPS and *TGI*, low *TCI*, and *TPI* = "1."

IV. Empirical Study

A. Data

In this study, a recommendation model was constructed using patent information to confirm whether the proposed framework could be actually applied for CTOD. IT- and BT-related industries were selected as technology fields for empirical study as convergence has been very active in and between these fields. Patents relating, respectively, to mobile telecommunication and biomedical devices in the IT and BT fields were extracted from the PATSTAT database based on the CPC standard. The relevant CPCs are shown in the Appendix.

We collected all granted patents that have at least one IT- or BT-related CPC (i.e., mobile telecommunication or biomedical devices) at the USPTO from 2008 to 2015 for our CTOD framework and validation analysis. However, to ensure that the scope for the convergence technological opportunity is limited to the extent that does not encompass substantially distant or irrelevant technical fields, patents where the number of four-digit CPCs is over 30, were removed from the collected patents as they may hamper in recommending a specific field's convergence technology.

Although the CPC standard is based on the IPC system, it provides a more detailed classification of the technology than the IPC and enables the collection of more accurate information related to the IT-BT fields [60]. The CPCs of the collected patent data were refined to four-digit codes. Although from the perspective of convergence the CPC seven-digit group level is sufficiently detailed to explain specific products and mechanisms, it contains parts that might not credibly reflect convergence between two different technologies. By contrast, the CPC four-digit subclass level does not provide very detailed information from the technical field perspective but it has been used in many related studies as a representative class level for different technical fields [21], [26]. Therefore, in this study, the analysis was conducted at the CPC subclass level. A total of 12 887 CTSs were defined by combining the CPC four-digit subclasses of individual patents.

As the purpose of the CTOD is to discover new or promising technology areas, it is important that it grasps recent technology developments and convergence patterns. With the consideration of data availability (until 2015) and the period (2013–2015) for validation of result of recommendation, we conducted an analysis assuming 2012 as the present. As mentioned above, a total of 72 865 patents at the USPTO, in the field of mobile telecommunication and biomedical devices published from the preceding five years, 2008–2012, were used for analysis.

Because the same applicants are marked differently in some patents, it was necessary to refine the applicant names in accurately assessing the patent portfolios of individual firms. In this study, instead of manual refinement we used the automatic refinement name provided by EEE-PPAT.[1] Applicants with less than five different CPC four-digit subclasses in their patents were excluded from the analysis [10]. We believe that these companies can be regarded as lacking basic technology capabilities for convergence as well as the persistence of applicant technology development, and that their technology portfolios are limited in providing good technology opportunities to other target firms through our framework. In sum, 8453 applicants were selected for analysis.

B. Target Firms

We applied the proposed framework in this study to target firms to validate its practicality and value. Target firms were selected in consideration of the company's technology portfolio based on CPC subclass, i.e., 1) the main technology field and 2) the technology spectrum to validate whether the discovered technology opportunities for convergence are suitable for them. Moreover, we also considered 3) the amount of the technical resource that firms possessed for technology convergence, measured by the number of their owned granted patents. Finally, the following three target firms were selected.

1) *Cook Biotech*, which has the main technology in the IT field and has a relatively little technology resource and a narrow technology spectrum, respectively.
2) *InvenSense* with a wider technology spectrum and more technology resource compared to Cook Biotech while having the main technology in the BT technology field.
3) Second Sight Medical Products, which has main technical capabilities in both IT and BT fields and has a wide technical spectrum and a large amount of technical resource.

First, as a firm with major technical competence in BT we selected "*Cook Biotech*," which was established in the United States in 1995 and has developed innovative technology related to tissue transplantation in the field of regenerative medicine. Cook Biotech has produced products that have been used in more than 1.5 million soft-tissue-repair treatments and have excellent efficacy in tissue transplantation and cell regeneration. By 2012 it had registered 42 patents with the USPTO, with patented technologies covering various implants and artificial

[1] [Online]. Available: http://www.ecoom.be/en/EEE-PPAT

$$\text{TPI} = \begin{cases} 0, & if\ Firm\ already\ has\ Techs.\ in\ both\ CPC\ classes\ of\ Rec.CTS \\ 1, & if\ Firm\ already\ has\ Techs.\ in\ one\ CPC\ class\ of\ Rec.CTS \\ 2, & if\ Firm\ does\ not\ have\ any\ Techs.\ in\ CPC\ class\ of\ Rec.CTS \end{cases}$$

TABLE I
CPC SUBCLASSES OF THREE TARGET FIRMS

Firms	# of granted patents in USPTO (until 2012)	Top 15 CPC sub-class of granted patents (2008–2012)
Cook Biotech	42	A61B A61L A61K A61F B29C C12N Y10S
InvenSense	55	H04R G06F G01C G01P H03F A63F B81C B81B H01L H04M G03B G01R H03G Y10T B60R
Second Sight Medical Products	122	A61N H05K H01L Y10T A61F C25D G06K G06T A61B G09B C23C C23F G01N G02C H04N

TABLE II
TECHNOLOGY CONVERGENCE CAPACITY OF TARGET FIRMS

Cook Biotech			InvenSense			Second Sight Medical Products		
CTS	Freq.	Capacity	CTS	Freq.	Capacity	CTS	Freq.	Capacity
A61F-A61L	9	4.94	A63F-G06F	5	4.81	A61F-A61N	12	4.97
A61F-Y10S	8	4.92	G06F-H04M	3	4.5	A61F-G02C	3	4.5
A61B-A61F	7	4.9	G03B-G06F	3	4.5	A61F-H04N	3	4.5
A61L-Y10S	6	4.86	G03B-H04M	3	4.5	A61N-H04N	3	4.5
A61K-A61L	4	4.71	A63F-H04M	3	4.5	G02C-H04N	3	4.5
A61B-A61L	4	4.71	A63F-G03B	3	4.5	A61N-G02C	3	4.5
A61B-A61K	2	4.0	G01C-G01P	2	4	A61N-G09B	2	4.0
A61L-A61M	1	2.5	B60R-G01P	2	4	A61B-A61F	1	2.5
A61B-Y10S	1	2.5	G01P-G06F	1	2.5	A61B-A61N	1	2.5
A61B-A61M	1	2.5	A61B-G01C	1	2.5	A61F-H05K	1	2.5
A61F-A61K	1	2.5	G06F-G09G	1	2.5	A61N-H05K	1	2.5
A61K-Y10S	1	2.5	A63F-G09G	1	2.5	A61N-G06K	1	2.5
			A63F-G01P	1	2.5	G06K-G09B	1	2.5
			G01P-G09G	1	2.5			

*This table was formed based on patents having two or more different CPC subclasses.

insertion technologies, including extracellular matrix material related technologies. As shown in Table I, the analysis of the technologies developed by the firm during the analysis period (2008–2012) reveals that it has primary technical competences in the BT field as follows: A61B (diagnosis, surgery, personal identification); A61F (sterilizing or deodorizing of air, bandages, articles of clothing, absorbent pads, etc.); A61L (method or apparatus for sterilizing materials or articles in general, disinfecting, sterilizing or deodorizing air, or materials for surgical articles); A61K (medical, dental, or cosmetic formulations). In addition, it also has cell transplantation and regeneration-related technologies, such as C12N (microorganisms or enzymes; composition, preservation, maintenance, proliferation, mutation or gene engineering), B29C (molding or joining of plastics), and Y10S (prostheses, i.e., artificial body parts, parts thereof, and accessories and accessories therefor). The company's convergence technology competence was then evaluated based on these CTSs. The results, shown in Table II, indicate that Cook Biotech has a high technology convergence capability that fuses the technologies of the A61 lines of the hygiene, biological, and medical fields with the technologies of the Y10S, which implement physical implants and components.

As the next target company, "*InvenSense*," a firm with major technology competence in the IT field was selected. *InvenSense* was founded in the United States in 2003 and is a supplier of MEMS sensor platforms used in mobile, wearable, smart-home, industrial, and automotive applications. By 2012, *InvenSense* had registered 55 patents with the USPTO and had produced highly innovative solutions and products for audio and motion detection. The company has excellent developmental capabilities for producing sensors, which are one of the core technologies of Internet of Things. CPC subclass analysis of the technology portfolio developed by *InvenSense* during the analysis period revealed that the majority of its technologies were in H04R (loudspeaker, microphone, phonograph pickup, or similar acoustic electromechanical transducers, hearing aid, public address system), which is generally related to music. Its other technologies were related to sensor technology, including G06F (digital data processing by electricity), G01C (gyroscope; rotation-sensitive device with vibration mass; rotation-sensitive device without motion mass; angular velocity measurement using the gyroscope effect), G01P (linear velocity, angular velocity, acceleration, deceleration or shock impact measurement, motion presence; suggestion of motion direction), and H03F (amplifier). In addition, there were a number of video and image technologies, including (A63F), microstructure technologies (B81B, B81C), electrical devices (H01L), and telephony (H04M) technologies. In terms of technology convergence, *InvenSense* has an excellent capability for converging electronically generated images (A63F) and digital processing technology (G06F) and for converging technologies that use waves other than light (G03B) and telephone communication technology (H04M).

As a firm with both BT and IT competences, we selected "*Second Sight Medical Products*," a vision-related healthcare company founded in Switzerland in 1998. *Second Sight Medical Products* had 122 patents registered with the USPTO in 2012 and had been continuously developing eye care aids and treatments for people suffering from retinal degeneration conditions such as retinal pigmentation. The technical portfolio it developed during the analysis period had excellent technologies related to both vision therapy, such as A61N (electrotherapy) and A61F (implantable filter; prosthesis), and electricity, such as H05K (printed circuit, printed circuit board, etc.), C25D (electrolytic or electrophoretic means; devices for it), and H01L (semiconductor devices, electrical solid devices not belonging elsewhere). In addition, it developed the types of technologies in the data recognition and processing fields (G06K, G06T, H04N) that are characteristically held by IT companies. As evidenced by its sight-related BT and IT-related technology capabilities, the firm was converging biotechnologies (A61N, A61F) and electrical devices and technologies (H04N, H05K).

C. Validation of SDAE CF

As the second step of the proposed framework, we constructed a CF system based on SDAE that recommends CTSs based on the technology convergence competencies of each firm. The SDAE-based CF can address the problem of sparse data better than traditional CF methods and can capture complex relationships among firms with different convergence technologies. To confirm this, the analysis period (2008–2012) was divided into two periods (2008–2010 and 2011–2012) and the technology convergence capabilities of IT and BT companies corresponding to each period were used as training and test data. Even if a firm had applied for a patent in 2008–2010, the validity of the constructed model could not be verified unless the firm applied a patent during the test period (2011–2012); therefore, we were limited to 3136 firms that applied at least one patent with two or more different CPCs (four-digit criteria) during the test period. As the goal was to measure the recommendation accuracy of each model for the CTSs that a firm had newly developed in the test period, we reselected 1978 firms that had developed the technical capability for new CTSs in the test period. Based on the patent applications in the 2008–2010 period, the convergence capabilities of individual companies were measured and used as input for a traditional CF based on cosine similarity and to the SDAE-based CF for calculating LPSs for the new CTSs in the test period. Using the patent activity in the test period, the actual preference scores of individual firms for specific CTSs were obtained and the differences between the actual preference scores and the LPSs in the test period were calculated as means square errors (MSEs). The results showed that the recommendation error of SDAE-based CF (MSE $= 0.501$) was lower than that of conventional CF (MSE $= 0.628$).

To construct an SDAE-based CF system for CTOD, SDAE was trained based on the patents and technology convergence competences of companies in the IT and BT subfields mentioned in the data section. Two hidden layers, comprising 600 and 100 hidden nodes, respectively, were stacked as encoders. The learning rate was set to 0.005 and the β (denoising parameter) was set to 0.3.

D. Results

As the first step in the CTOD process, we identified technology convergence capabilities based on company patents and converted them into a five-point scale. In the second stage, SDAE-based CF was performed using the technology convergence capability information of each company. Based on the SDAE-based CF, LPSs for all of the CTSs of the three target companies were derived. We then selected 100 CTSs with the top LPS for each firm as CTOD candidates and finally discovered convergence technology opportunities by the company based on the respective market competitiveness (*TCI*), technology growth (*TGI*), and company's portfolio (*TPI*) indices.

As elaborated in Section III about the CTOD indices, with consideration of the distributions of *TCI*s for all CTSs, we set the threshold for high (*H*) or low (*L*) classes of *TCI* as 21. In addition, according to a sign of *TGI*, it is classified as either high (*H*) or low (*L*). CTSs with positive and negative *TGI*s were denoted as "*H*" and "*L*," respectively. Finally, based on the "*H*" and "*L*" levels of *TCI* and *TGI*, we have classified the groups of recommended CTSs into classes of "*A*," "*B*," "*C*," and "*D*," with class "*A*" being the most preferable option and "*D*" the least, i.e., recommended CTS with both *TCI* and *TGI* of "*H*" levels is classified as "*A*" class, and CTS with both *TCI* and *TGI* of "*L*" levels as "*D*" class.

Table III shows the top 100 recommended CTSs, as determined by the three indicators, sorted by class and LPS. The LPSs were derived by considering the technology convergence competence of the target company and its complex relationship with those of other companies so that a CTS with a higher LPS would be given a higher priority in recommendation. Finally, we selected the top CTSs that also combined low *TCI*s, high *TGI*s, and *TPI*s with a "1" as the CTOD.

In the case of *Cook Biotech*, which had major technological capability related to BT, a CTS (G01N-B41F) between the company's own "investigating or analyzing materials technology" and "printing technology" and a CTS (A61N–A62C) between its own "electrotherapy and surgical instruments BT technology" and "fire-fighting technology" were recommended as the CTOD in class *C*, in which the corresponding CTSs are less competitive and growing in the market. Specifically, a BT-IT CTS between "electrotherapy and surgical instruments technology" and "pictorial communication technology" was recommended. In addition, because *Cook Biotech* has an edge in technologies related to tissue transplantation and regeneration, a CTS that merges the company's own "shaping and joining of plastics technology" with "special design technology" was intriguingly suggested.

In class *A*, in which both the *TGI* and *TCI* are high, indicating already saturated development, CTSs merging technologies related to "measuring specific variable" (G01D) and "pump device" (F04D) with the firm's own BT technology of "sleeping and anesthesia device" (A61M) were suggested. Additionally, various CTSs between BT technologies and IT-BT technologies

TABLE III
RECOMMENDED CTSs FOR TARGET FIRMS

Firms	Class	TCI	TGI	Recommended CTS (LPS)
Cook Biotech	A	H	H	B29C-B60K(5) A61M-G01D(4.97) F03D-Y10T(4.87) E21B-Y10T(4.85) F02D-G01N(4.81) G06T-Y10T(4.76) A61N-H04R(4.69) A61M-F04D(4.44) A61K-C12P(4.43) C12Q-G06F(4.42)
	B	H	L	A43B-A61F(5) B29C-A44B(5) B29C-B31D(5) A62B-Y10T(5) A43B-A61B(4.92) C07F-C08F(4.71) A61M-F16L(4.71) G01N-H01J(4.67) A61M-A62B(4.57) B60N-Y10S(4.57) Y10T-B44F(4.56)
	C	L	H	B41F-G01N(5) B29C-B44F(4.96) A61N-A62C(4.92) C07K-D01F(4.91) A23L-B29C(4.78) B29C-B25C(4.42) A61N-H04N(4.418)
	D	L	L	A61M-G01M(4.71) A61F-H01Q(4.67) A61M-B21F(4.46) A41D-A61N(4.43) A61L-G11C(4.403)
InvenSense	A	H	H	E21B-G06F(5) F03D-Y10T(5) G01V-G06F(4.89) F41G-G02B(4.74) F41H-G02B(4.72) A61N-H04R(4.66) E21B-Y10T(4.65) G06N-H03K(4.64) C12Q-G06F(4.63) A61M-G01D(4.63)
				B60R-A44B(4.55) A01K-G06Q(4.50) B64D-G01C(4.49) B64D-G01S(4.43) A63F-A63H(4.42) B60B-G01L(4.38) B60B-G01P(4.37) A61B-H01R(4.365)
	B	H	L	F16C-G01L(4.87) Y10T-B44F(4.82) B60K-G01D(4.73) A62B-Y10T(4.719) A61L-G02B(4.58) B01J-G06F(4.4)
	C	L	H	B60R-H04K(5) G02C-G06F(4.99) D21F-G01B(4.95) B64D-G01P(4.88) A63H-G08C(4.85) E05B-G01B(4.80) G01L-G05D(4.77) G08B-F21K(4.68) F41G-G03B(4.61) G01V-G08C(4.52) G03F-Y02B(4.44) Y10T-A24D(4.43) H02P-H03M(4.37) G01R-G06J(4.37)
	D	L	L	G01B-H04Q(4.527)
Second Sight Medical Products	A	H	H	A61M-F04D(4.98) E21B-Y10T(4.80) A61N-H04R(4.78) F03D-Y10T(4.65) A63B-G06K(4.54) A61B-H01R(4.47) G01J-Y02E(4.47) F04D-Y10T(4.46) B41M-G06K(4.45) G01P-H01L(4.37) A61C-A61F(4.37) G01R-H02P(4.34)
	B	H	L	A43B-A61F(4.92) A61M-A62B(4.91) G01Q-G03F(4.80) A62B-Y10T(4.80) A61M-F16L(4.79) A61L-G02B(4.74) H03H-H03M(4.73) G01N-H01J(4.72) B60N-Y10S(4.57) F02K-Y02T(4.56) A61M-F16C(4.49) Y10T-B44F(4.48) A61C-A61L(4.44)
	C	L	H	B41F-G01N(4.95) A61N-A62C(4.77) G02C-G06F(4.72) A61M-G01D(4.70) G01R-G08C(4.52) G01R-G06J(4.44) F16K-G05B(4.43) A62C-H04N(4.43) G06J-H03M(4.34)
	D	L	L	A61F-H01Q(4.88) H04R-Y02E(4.34)

***This table is based on the recommended CTSs with TPI "1."**

were also suggested, as the firm had a variety of BT technologies, such as "preparations for medical purpose" (A61K), "electrotherapy" (A61N), and "microbiological or enzymological process" (C12Q). Based on these BT technologies, CTSs that merged them with other BT technologies, such as "fermentation and enzyme-based chemical synthesis" (C12P) or with other IT technologies, such as "digital data processing" (G06F) and "acoustic conversion" (H04R) were recommended. Also, as the company had "hardware-related" technology (Y10T), convergence combinations that converged it with various machinery technologies related to "motor" or "excavation" (F03D, E21B) or "image data processing IT technology" (G06T) were also recommended. However, the CTSs in class *A* could not be prioritized over those in class *C* because other firms had already developed related technologies. Nevertheless, if the company intends to develop convergence technologies in the BT field and considers the growth potential of specific CTSs to be higher in the future, they could be considered CTOD.

Of the CTSs for which the company had no technical capability of ($TPI = 2$) in class *C*, a CTS between "detection of object technology" (G01V) and "electrical signal selection IT technology" (H04Q) was a top recommendation. In addition, technology convergence between "sanitary facilities BT technology" (A47K) and "display and recording device technology" (G07C) was also suggested. Although in these cases it might be difficult for the firm to develop the relevant convergence technology because of its limitations in terms of technical capability, to attain convergence between BT-related technologies and other technical fields the company can refer to these CTSs in setting the direction of future convergence and development.

In the case of *InvenSense*, which had its main convergence capability in IT technology, for class *C*, a CTS between the firm's own "vehicle parts technology" (B60R) and technology related to "confidential transmission by wire and wireless system" (H04K) was recommended for CTOD. In addition, it was recommended that the company combine its excellent "measurement" related technologies (G01B, G01L) with "aircraft power and propulsion technology" (B64D) or "nonelectric variable control technology" (G05D). In particular, based on the IT technical capabilities of the firm exemplified by "measurement of electrical variables" (G01R) and "decryption and code conversion of electronic circuits" (H03M), convergence combinations between IT technologies with "electricity generation and energy conversion technology" (H02P) or "hybrid computer technology" (G06J) were also recommended.

Class *A* recommendations were made for converging the company's "digital signal generation pulse technology" (H03K) and "digital data processing technology" (G06F) with IT technologies, such as "computer system" (G01V), "electrical connecting device" (H01R), and "object detection and measurement" (G01V). In addition, unlike in Class C, IT-BT CTSs that converged the company's "data processing IT technology" (G06F) with either "measuring and preparing enzymes or microorganisms BT technology" (C12Q) or "sleep and anesthetic device BT technology" (A61M) were recommended. If this IT-based firm intends to attempt convergence with BT technology and place more weight on technological growth potential than on competition level in market, then the recommended CTSs in Class *A* can be considered as the CTOD.

Of the CTSs for which the company had no technical capability ($TPI = 2$) in class C, a CTS between "blood vessel implant filter technology" (A61F) and "electron tube technology" (H01J) and a CTS between "electrical variable measurement technology" (G01R) and "signal control and measurement technology" (G08C) had the highest recommendation scores. In other words, convergences between BT and IT or between IT technologies were top recommendations. Owing to the company's lack of relevant technical competence, immediate technology development for the suggested CTSs might be difficult; however, in light of the company's IT technology capabilities, these results can be used to study the technology convergence direction of other IT firms or to set a future technology convergence and development direction.

Of the class *C* competences for *Second Sight Medical Products*, which has BT and IT convergence technology competences, a CTS (G01N-B41F) between the company's own "investigating or analyzing materials technology" and "printing technology" and a CTS (A61N–A62C) between the company's own "electrotherapy and surgical instruments BT technology" and "fire-fighting technology" were recommended, as they were for Cook Biotech. This might have been a result of the target firm sharing many BT technical competences (A61B, A61F, A61N) in the medical-related A61 line with Cook Biotech. On the other hand, as the target firm possessed many IT-related technology capabilities, CTSs were recommended between IT technologies, such as its own "electric variable measurement technology" (G01R), "control signal transmission technology" (G08C), and "control signal transmission technology" (G08C). A CTS between "hybrid computer technology" (G06J) and "circuit decoding and code conversion technology" (H03M) was highly recommended for CTOD. As an optical therapy healthcare company, the convergence of "glasses-related technology" (G02C) and "digital data processing IT technology" (G06F) was recommended. In addition, unlike the other two companies, a class *C* IT-BT CTS between "sleep and anesthesia device BT technology" (A61M) and "measurement of specific variable IT technology" (G01D) was recommended.

Even in the case of Class *A*, in which both *TCI* and *TGI* are high, BT-IT convergences, such as a CTS between its own "electrotherapy technology" (A61N) and "acoustic electric machine technology" (H04R) and between "surgery related technology" (A61B) and "electrical connecting technology" (H01R) were recommended. Convergences between BT technologies, such as (A61C–A61F) and between IT technologies (G01R–H02P, G01P–H01L) were also recommended. In particular, based on the firm's excellent "hardware related technology" (Y10T), convergences with technologies related to "motor" and "excavation" (F04D, F03D, E21B) were recommended.

Looking at CTSs for which the company had no technical capability ($TPI = 2$) in class *C*, CTSs converging the firm's IT technologies, such as "control signal transmission technology" (G08C) and "confidential communication" (H04K) with "toys production technology" (A63H) and "vehicle parts technology" (B60R) were intriguingly recommended instead of IT-BT, IT-IT, or BT-BT convergences. In addition, a CTS between "motion and impact measurement IT technology" (G01P) and "aircraft related technology" (B64D) was also recommended.

E. Discussion

In the proposed framework, it is necessary to verify whether proposed CTSs are convergence technologies applicable to a target company. To validate this applicability, the Second Sight Medical Products, a firm with both IT and BT technical competences compared to other target firms, was selected as a target for validation of TOD and a qualitative analysis of the recommended CTSs was conducted. To do this, we searched firms with CTSs suggested as CTOD for the Second Sight Medical Products and evaluated the feasibility of the selected CTODs by comparing the technological fields and convergence technology capabilities of searched firms with those of the target company. As a result of the three-step CTOD process, the number of companies that actually had technical competences for the selected CTSs was small, as CTSs for which the competition level in the technology market is low and the growth potential is high were suggested.

First, as firms with the convergence technology competences "material detection and investigation technology" (G01N) and "printing device and press technology" (B41F), "Ricoh Company," "Theta System," and "Heidelberger Druckmaschinen" were searched. These companies generally manufacture products or sell solutions based on innovative digital imaging, optical, and printing technologies. Such technologies are related to the visual therapies and assistive technologies that the target company develops, and all of the companies including the target firm have measurement-related and IT technologies, which led to the recommendation of printing-related technologies for CTOD. Companies with convergence technologies (A61M–G01D) between "sleep and anesthesia device technology" and "specific variables measurement technology" included "BAXTER HEALTHCARE," "CELLNOVO," "TRUDELL MEDICAL INTERNATIONAL," "DEKA PRODUCTS LIMITED PARTNERSHIP," and "VALENCELL," which provide various healthcare and medical devices based on software and IT technology. In particular, VALENCELL manufactures wearable or hearable healthcare devices that use high-level biometric sensor technology, whereas DEKA PRODUCTS manufactures mobile devices that help patients move and wearable robotic arms for various applications. Pharmaceutical companies, such as "ELI LILLY and COMPANY" and "NOVO NORDISK" also have relevant convergence technology. In the case of convergence technologies (G02C–G06F) between "eyeglass-related technology" and "electrical-variable measurement technology," companies that produce optical products based on lens technology were searched; these included "Hoya corporation," "HOYA LENS MANUFACTURING Philippines," "CARL ZEISS VISION Australia HOLDINGS," and "ADLENS BEACON." "Digital Vision," which has excellent technology in the digital video field based on IT technology, also had convergence capability for the corresponding CTS.

As a company with convergence technologies (G01R–G06J, H03M–G06J) employing decoding technology (G01R), "electric variable measurement technology" (H03M), and "hybrid computer technology" (G06J), "National Semiconductor" was selected. This firm is a semiconductor manufacturer specializing in "analog devices and base systems" and has various IT technologies related to "power management, circuit, and communication." In particular, as it provides solutions related to display, medical devices, and measurement equipment, a technical correlation with the target firm based on IT technology related to visual therapy could be identified. Companies possessing convergence technologies (H04N–A62C) between "image communication technology" and "fire-fighting" included "DRAEGER SAFETY AG and CO" and "En-Gauge," which manufacture medical devices, such as patient defibrillators and anesthesia equipment as well as "fire-fighting" related products based on "medical and safety related technology." In particular, as En-Gauge was the only company with convergence technology between "electrotherapy technology" and "fire-fighting technology" (A61N–A62C), we could find technical similarities with the target company in terms of producing medical devices based on IT technology.

We identified companies with the recommended CTSs as CTODs based on their respective corporate information and technological capabilities. By assessing the technical relevance of this information to that of the target company, we could validate the feasibility of the recommended CTSs and the actual application of the proposed framework.

V. Conclusion

Technology convergence to create high added value and establish R&D investment direction is an extremely important factor in achieving sustained company growth. However, simply exploring which technologies are converging in the technology market without consideration of a company's own technology convergence competences will not provide practical information on the convergence technology opportunities available to the company. Most of the previous studies on technology convergence or TOD also have limitations in not sufficiently considering the technological capabilities of individual companies or the competitiveness and the growth of their technologies in the market. To address this gap, the framework proposed in this article suggested suitable convergence technology opportunities by considering the relevant convergence capabilities of individual companies, thereby enhancing the possibility of actual implementation and success in technology development and R&D planning. To achieve this, we defined a technology convergence combination based on company bibliographic information and used this as a measure of company's technical convergence competences. The proposed method applies SDAE-based CF models to the technical convergence capabilities of individual firms and discovers convergence technology opportunities based on the indices related to the technology market and growth potential. In addition, although many TOD-related studies were conducted, TOD for technology convergence was understudied. Therefore, this article greatly contributed to the expansion of TOD research. Moreover, we applied the neural network-based CF model that can well-capture the complex relationship between companies and technologies to the field of TOD research for the first time, contributing to the development of the TOD literature methodologically.

The convergence technology opportunities revealed by the proposed framework can help firms strategically preoccupy specific technology markets to gain competitive advantage. As misdirected technological investments threaten the competitive position of firms and, in cases of firms with limited resources, their very survival, CTOD can also contribute significantly to sustained company growth and competitiveness [2]. In particular, the proposed method can provide vital assistance to SMEs with limited resources. Furthermore, the promotion of technology convergence through the proposed framework is expected to contribute to continuous economic growth and technological development at both the firm and country levels.

Despite these contributions, this research has limitations that will require further study. First, since this study discovers convergence technology opportunities mainly from a technical point of view with patent data, nontechnical areas, such as size, resource and competitive position of the target firm in the market, and R&D investment costs were not fully taken into account. In our SDAE recommendation model, convergence technology opportunities were discovered by considering the forms and the amounts of technology resources of individual firms based on their patents. Hence, this indirectly signifies the technology resource and size of the firm. Nonetheless, future research may provide more insightful findings if the aforementioned, nontechnical aspects of firms were directly taken into considerations. Second, in this study, CPCs were combined at the level of the CPC subclass (four digits) in defining CTSs. If more detailed information is required to set the direction of technology development in an individual business unit, CTSs can be defined at the level of the CPC group (five to seven digits) even if this causes the number of CTSs to increase disproportionately. In addition, extending to three or more CPC combinations will enable the definition of more varied technology combinations in terms of technology convergence. It is also possible to build a more practical and reliable recommendation system using a more advanced SDAE-based CF that, for instance, incorporates side information related to the company into the modeling process. Meanwhile, time lags between patent application and registration limit the indices used in our study in terms of measuring the competitiveness of the market or the growth potential of the recommended technology at the time of recommendation. These indicators could therefore be supplemented by using information other than the patent to identify the technology market condition. Finally, in this article, we limited the scope to IT-BT specific subfields in constructing the model and selecting target firms. It is possible to extend the proposed framework to a wider range of technologies or to build a model employing the technology competences of a more diverse set of firms to further enhance the applicability and recommendation accuracy of the proposed framework. These efforts will be left as a follow-up study.

APPENDIX

CPC FOR BT AND IT SECTORS

SECTOR	CPC
BT	A41B/9 A43B/3 A61B/1 A61B/10 A61B/13 A61B/17 A61B/18 A61B/19 A61B/3 A61B/5 A61B/6 A61B/7 A61B/8 A61B/9 A61B2010 A61B2017 A61C/19 A61D/15 A61D/19 A61F/13 A61F/15 A61F/2 A61F/5 A61F/7 A61F2007 A61F2013 A61G/10 A61G/11 A61H/1 A61H/33 A61H/35 A61H/39 A61K/31 A61L/15 A61L/26 A61M/1 A61M/13 A61M/21 A61M/25 A61M/5 A61M2001 A61N/1 A61N/2 A61N/5 A61N2005 A63B/21 A63B/71 B64D/10 G01J/5 G01N/27 G01N/33 G01R/33 G01S/15 G01S/7 G01T/1 G02B/23 G06T/7 G10K/11 H04N2005 H04R/25
IT	A01C/0 A01K/1 A01K/8 A01M/2 A01M/3 A23J/0 A24F/1 A45B/0 A45C/1 A47F/1 A47G/2 A47G/3 A47J/3 A61B/0 A61B2562 A61F/0 A61F/1 A61G/0 A61G/1 A61J/0 A61M/0 A62B/0 A62C/3 A63B/6 A63B/7 A63B2055 A63D/0 A63H/0 A63H/1 A63H/3 A63J/1 B01D/4 B01D/6 B06B/0 B25B/2 B29C/4 B41F/3 B60C/1 B60C/2 B60D/0 B60G/1 B60G2400 B60K/0 B60K/2 B60K/3 B60K2741 B60L/0 B60N/0 B60Q/0 B60Q/1 B60R/0 B60R/1 B60R/2 B60R2300 B60S/0 B60T/0 B60T/1 B60W/1 B60W/2 B60W/5 B60W2050 B61B/1 B61L/0 B61L/1 B61L/2 B61L2205 B62B/0 B62D/0 B62H/0 B62J/9 B63B/2 B63B2201 B63H/2 B64C/2 B64D/1 B64D/4 B64D2700 B64F/0 B64G/0 B65G/4 B65H2701 B66C/2 B82Y/1 E01F/1 E02F/0 E03F/0 E04H/0 E05B/3 E05B/4 E05B/7 E05F/1 E06B/0 E21B/0 E21B/1 E21B/4 F01M/0 F01M/1 F01M2011 F01P/1 F02C/0 F02D/1 F02D/4
	F04B/4 F16C/1 F16D/4 F16D/6 F16H/5 F16H/6 F16H2061 F16L/5 F16N/2 F16P/0 F21L/0 F21S/0 F21V/0 F21W2111 F23N/0 F25D/2 F41G/0 G01B/0 G01C/0 G01C/1 G01C/2 G01D/0 G01D/1 G01D/2 G01F/0 G01F/1 G01F/2 G01H/0 G01K/0 G01M/0 G01M/1 G01N/1 G01N/2 G01P/0 G01P/1 G01R/1 G01R/2 G01R/3 G01S/0 G01S/1 G01V/0 G01V/1 G01W/0 G02B/2 G04C/1 G04C/2 G04G/1 G05B/1 G05B/2 G05D/0 G05D2201 G05F/0 G06F/0 G06F/1 G06F/2 G06G/0 G06K/0 G06K/1 G06Q/1 G06Q/2 G06Q/3 G06Q/5 G07B/1 G07C/0 G07C/1 G07C2009 G07D/0 G07F/0 G07F/1 G07G/0 G08B/0 G08B/1 G08B/2 G08C/1 G08C/2 G08G/0 G09B/2 G09F/0 G09F/1 G09F/2 G09G/0 G10K/0 G10L/2 G11B/1 G11B/2 G11C/0 H01F/2 H01H/0 H01H/1 H01H/4 H01H/6 H01H/8 H01L/2 H01M/1 H01R/1 H01R/2 H01R/3 H02G/1 H02H/0 H02J/0 H02J/1 H03D/0 H03F/0 H03G/0 H03J/0 H03K/0 H03K/1 H03L/0 H03M/0 H04B/0 H04B/1 H04B2001 H04B2203 H04H/2 H04H/6 H04J/0 H04L/0 H04L/1 H04L/2 H04L2012 H04L2027 H04M/0 H04M/1 H04M2201 H04M2203 H04M2242 H04N/0 H04N/2 H04N2201 H04Q/0 H04Q/1 H04Q2213 H04R/0 H04W/1 H04W/6 H04W/8 H05B/3 Y02E/6 Y04S/4

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