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Forecasting and identifying multi-technology convergence based on patent data: the case of IT and BT industries in 2020

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Abstract Having a new technology opportunity is a significant variable that can lead to dominance in a competitive market. In that context, accurately understanding the state of development of technology convergence and forecasting promising technology convergence can determine the success of a firm. However, previous studies have mainly focused on examining the convergence paths taken in the past or the current state of convergence rather than projecting the future trends of convergence. In addition, few studies have dealt with multi-technology convergence by taking a pairwise-analysis approach. Therefore, this research aimed to propose a forecasting methodology for multi-technology convergence, which is more realistic than pairwise convergence, based on a patent-citation analysis, a dependency-structure matrix, and a neural-network analysis. The suggested methodology enables both researchers and practitioners in the convergence field to plan their technology development by forecasting the technology combination that will occur in the future.

Keywords Technology convergence · Forecasting · Patent-citation analysis · Neural-network analysis · Dependency-structure matrix

Mathematical Subject Classification 68

JEL Classification O3

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Introduction

Convergence is an important keyword that explains the propensity and nature of current technology development in the technology-innovation field. Technological innovation has occurred through convergences in various fields, including the computer, semiconductor, mobile-telecommunication, and medical-healthcare fields, and the possibilities of generating future technological innovations through convergence are infinite. Thus, firms face the challenge of having to constantly develop new technological products through unceasing innovation (Cho and Kim 2014) and making the best use of opportunities (Geum et al. 2012). In this situation, understanding the state of development of technology convergence and forecasting the promising convergence area will enable a firm to perform more effective R&D activities and supply the market with a new technology or product that reflects the needs of customers at the right moment.

Patent analysis is one of the most widely used approaches for technology convergence monitoring. Patent documents are an ample source of technical and commercial knowledge and have been used to gain insight into technology dynamics (Ernst 2003). Patents contain up to 80% of all of the technological knowledge that is currently available (Blackman 1995). In addition, to become a patent, the technology needs to meet the condition "for industrial use" so that only a potentially commercializable invention is granted patent status. Therefore, it is worth analyzing patent documents, which are valuable sources of information about technologies available in a market. Thus, patent analysis has been used not only to monitor technologies over a short period of time but also to analyze technology-innovation patterns in order to develop a long-term technology strategy (Kim and Lee 2015). In this way, taking the patent as the objective and mature indicator of technology changes, patent analysis has been used as an analytical tool for technology convergence.

The research on technology convergence using patent information has been performed from various perspectives. From the research-purpose perspective, previous studies have attempted to identify technological convergence trends (Gauch and Blind 2015; Ko et al. 2014; Rizzi et al. 2014) or classify the types of convergence technologies based on the trends (Jeong and Kwon 2014; Kim et al. 2014). These studies applied two main methods, which included patent-citation analysis (No and Park 2010) and co-classification analysis (Kim et al. 2014; Kwon and Jeong 2014; Kim and Kim 2012). From the perspective of the analysis target, some studies focused on the convergence of a single technology (You et al. 2014; Cho and Kim 2014), while others investigated the convergence between a pair of technologies (Geum et al. 2012).

However, in spite of their invaluable implications, the previous research had several limitations. First, most of the previous works emphasized the past trends of technological convergence. Of course, investigating past trends can provide meaningful insights for the future, but the ability of the quantitative approach to objectively forecast the future was limited. Little effort has been made to forecast technology convergence using quantitative data. Second, many studies have focused on the convergence of technology pairs, asking such questions as, "What is a pair of converging technologies" or "What are a set of technologies converging with technology *A*," again by identifying a pair of converging technologies. Technology convergence is likely to happen not only within two technologies but also more than three technologies simultaneously, which should be traced. An analysis of the limited relationship of technologies does not provide a fair reflection of all of the changes in technology convergence.

To overcome those limitations, this paper proposes a forecasting methodology for multi-technology convergence. In this methodology, patent-citation analysis is first used to identify the convergence relationship. As the focus of this study is to forecast the future of technology convergence, we judged that it is more appropriate to adopt a citation-based approach, which shows the mechanism of convergence on the assumption that frequent knowledge that flows between different fields indicates a high probability of their convergence, rather than co-classification approach, which shows the current state of technology convergence with the promise that a large number of patents co-classified by different fields implies a great degree of their convergence. Second, neural-network (NN) analysis was applied to forecast the future data of the technology convergence. The citation relationships between technologies include large amounts of complicated data. NN is useful for extracting patterns and identifying trends that are too complex to be noticed by other techniques, thanks to its significant ability to derive meaning from complicated data. Thus, it is expected to be useful for this study. Finally, a dependency-structure matrix (DSM), which enables the modeling, visualization, and analysis of the dependencies among the entities of any systems (namely, the technologies in this study) is employed to present the multi-technology convergence. The proposed methodology is expected to help find promising converging technologies and prepare for them.

The paper is structured as follows. "Backgrounds" section outlines the theoretical and methodological backgrounds. "Methodology" section presents the proposed methodology for forecasting the state of future convergence. "Illustrative example" section gives an example to show the applicability of the proposed methodology, and finally, the study is concluded in "Conclusions" section.

Backgrounds

Theoretical background: patent-based studies of technology convergence

The previous studies on technology convergence based on patent information can generally be summarized from three different perspectives: the purpose, methodology, or object of the analysis. First, in terms of the purpose of the research, relevant studies can be divided into two categories: attempts to understand the trends of technology convergence and defining the types of technology convergence based on the trends. The studies in the first category investigated the evolution trajectory of the technology convergence, where developing a methodology for analyzing the evolution process with greater accuracy dominates the field. Rizzi et al. (2014) analyzed the worldwide convergence trends in hydrogen inventions. Ko et al. (2014) proposed a method to analyze the technology convergence trends by measuring the knowledge flows of patents. The studies in the second category analyzed the convergence patterns of technologies by measuring the degree of convergence among them. For example, Jeong and Kwon (2014) measured the degree of convergence in the green-technology field to consider which field of technology actually converged with it. Kim et al. (2014) identified the core technologies in printed electronics at particular time periods, along with the technologies that played a central role in the convergence of different core technologies with regard to printed e-technologies.

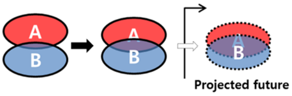
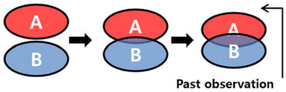
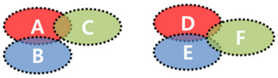
Second, the previous studies can be divided into two categories according to the methodology used for the technology convergence: The first group applied patent-citation analysis, and the other applied patent co-classification analysis. Of course, these two methodologies have often been used in conjunction with another methodology, and other methodologies, such as IO analysis (Xing et al. 2011; Choi and Hwang 2014) or co-word analysis (Wu and Leu 2014), have also been applied to technology-convergence analysis. Nevertheless, the most frequently used methodologies include patent-citation analysis and patent co-classification analysis. In studies that use patent-citation analysis, the goal is to identify the flow among different pieces of knowledge (technologies) and reveal the convergence mechanism from the knowledge flows. For example, No and Park (2010) developed a citation-based index that measures the degree of convergence of cross-disciplinary technologies. Then, this citation analysis was combined with social network analysis to classify the trajectory patterns of the technology convergence. On the other hand, the previous studies using patent co-classification analysis attempted to analyze the phenomena occurring in technology convergence. Kim et al. (2014) studied the degree of mergers and the relationships between different technology domains through the association rule mining of patent co-classification. Kwon and Jeong (2014) analyzed the associative relationship between green technologies through patent co-classification and relevance analyses. Some studies have used both patent-citation analysis and patent co-classification analysis. Kim and Kim (2012) proposed two approaches using patent data to examine technological convergence. After a patent-network analysis using patent citations, which could be considered a knowledge flow among technological fields, they carried out a co-classification analysis of technologies to measure the convergence intensity, rate, and coverage.

Third, depending on the object of the technology-convergence analysis, the existing studies can be divided into single technology studies and technology pair studies. The study type varies with the number of technologies for analysis, where most of the current emphasis lies in a single technology (You et al. 2014; Cho and Kim 2014) or a technology pair (Geum et al. 2012).

The previous studies had some limitations. First, most efforts were made to investigate and interpret the past trends of convergence, while forecasting future trends is vital to gain the preoccupancy of a promising technology. There has been relatively little interest in forecasting technology convergence. Of course, there have been several attempts to forecast the future status of technology convergence, mostly through qualitative approaches such as through expert-based forecasting (Bengisu and Nekhili 2006) or using the comprehensive results of past technological characteristics to identify promising technology fields (Lee and Yoo 2014). While these qualitative approaches to technology foresight focus on expert opinions, the incorporation of quantitative data, along with a qualitative approach, will enable greater reliability and accuracy in the analysis results. To forecast the future trends of convergence, we not only investigate the past data in an attempt to understand past trends, but we also extrapolate the data in an attempt systematically to forecast future trends. For this purpose, this study developed a neural network model, which produced a reliable future citation matrix that performed relatively well. Based on such forecasting results, more patent analyses could be conducted to develop more insights into future technology characteristics.

Second, numerous studies have focused on the convergence of a single technology or a pair of technologies to observe how a particular technology has converged with other technologies or how a particular pair of technologies shows remarkable convergence trends. However, a technology has boundless opportunities to converge with multiple other technologies simultaneously. For example, during the 90 s, convergence was mainly discussed in the context of the convergence of the IT, telecommunications, media, and entertainment industries into a giant “infocom” sector (Lind 2004). Now, more and more

Table 1 The difference of the approach in this study and its advantages

	The approach in this study	The existing approaches
Focus	Forecasting the future trends on convergence - projecting the future trends based on the past data - identifying emerging core-converging areas 	Monitoring the past trends of convergence - observing the past trends based on the past data - defining the types of convergence patterns 
Object	Modeling, visualizing, and analyzing the convergence among more than two technologies 	Identifying the convergence between a pair of technologies 
Advantages	1. The projected future derived from the past trends helps identify the technology areas expected to converge in the future, which supports future-oriented perspectives and also increases the forecasting accuracy, especially when combined with a qualitative approach, compared to the existing approaches that are solely based on experts' opinion 2. The modeling of convergence among more than three technologies enables more realistic visualization and interpretation of convergence phenomena	

industries are experiencing convergence with other industries, and technological innovation no longer occurs within the previously existing industrial silos but rather between them (Hacklin et al. 2009). As a result, sticking to a pair of technologies in investigating convergence may limit the possibilities to identify the overall trends of multi-technology convergence in multiple industries. There are limitations in presenting the whole technology convergence using limited perspectives. To overcome the limitations, this paper proposes a methodology for multi-technology convergence, projecting the future trends of convergence based on past trends. In the multi-technology convergence approach, we look at pairs of technologies, but these pairs may converge at one point, which enables the relationships between multiple technologies to be investigated. Table 1 shows the difference between the existing approach to technology-convergence analysis and the approach taken in this study.

Methodological background

Patent-citation analysis

Patent-citation analysis has been adopted for conceptual and qualitative investigation (Ernst 1998), along with quantitative and empirical analyses of technological innovation (Trajtenberg 1990). Its strategic importance becomes more apparent as the process of innovation becomes more complex, the cycle of innovation becomes shorter, and the market demand becomes more volatile (Lee et al. 2012). Accordingly, patent-citation analysis has been used with a variety of objectives. The basic concept of patent-citation analysis is that there exists a technological link between patents if one patent cites another (Lee et al. 2012). Once the link is created, new knowledge comes from combinations of existing knowledge (Érdi et al. 2013). In particular, it enables an investigation of the knowledge flows (Duguet and MacGarvie 2005; Fleming et al. 2007) and links between innovations and their technological "antecedents" and "descendants" (Jaffe et al 2000), as well as the multiple linkages among inventors, firms, regions, and so on (MacGarvie 2005; Gomes-Casseres et al. 2006). Therefore, measuring technological knowledge flows can be a good start to analyzing the trends of technology convergence (Ko et al. 2014).

There are two types of citations. The first is a backward citation, which is used to measure the inflow of knowledge from other technologies. The second is a forward citation, which is used to measure the inventive quality in terms of the technological or economic value (Henderson et al. 1998; Jaffe et al. 2000). These unique linking properties of citations provide useful information on what is vital in studying technology fusion, which is greatly influenced by the relationships among other technologies (No and Park 2010). The studies on technology convergence using patent-citation analysis take advantage of the previously mentioned citation characteristics because these provide a better understanding of the overlapping technology areas and trajectory changes with the emergence of citations (Karvonen and Kässi 2013). If one patent cites another (i.e., a new technology is created by combining existing technologies), this is regarded as a convergence. If intensive patent citations are observed in different industries, technologies in the industries are likely to be converged. In this respect, convergence can be observed from the citation information that reflects the knowledge flows at the technology level. Technologies that have higher citation counts with other technologies have a higher possibility of convergence.

As a result, patent-citation analysis has been used as a main approach in technology convergence studies to identify the convergence trends, analyze the convergence evolution trajectories, and determine the newly converged technologies. No and Lim (2009) analyzed "the degree of technological convergence and diffusion" and "the influence and potential of a technology" using backward-citation information. Lee et al. (2012) proposed a stochastic patent-citation-analysis method to assess future technological impacts. Ju and Sohn (2015) proposed a hierarchical quality function deployment (QFD) framework that makes it possible to set R&D priorities and then develop corresponding business models to meet future societal needs. In this research, we also adopted a backward-citation approach to identify converging technologies, but unlike the previous studies, we firstly developed a future-citation matrix based on past citation information and then analyzed the converging areas based on the "projected future."

Neural-network analysis

The objective of an NN is to obtain meaningful outputs by controlling the weights on the relationships between inputs and outputs. There are various NN techniques, including a multilayer feed-forward NN, recurrent NN, and time delay NN. Among these techniques, a multilayer feed-forward NN trained by a back-propagation algorithm is most commonly used for forecasting (Gutierrez et al. 2008). One major application area of an NN is forecasting multivariate, nonlinear, nonparametric statistics (Sharda 1994). Many studies have established that an NN's forecast is more accurate than those of forecasting methods such as the moving average (MA), autoregressive integrated moving average (ARIMA), linear regression, and exponential smoothing methods (Mitrea et al. 2009). An NN offers better forecasting performance than traditional methods.

Thus, an NN has also been applied to patent analysis, though not quite frequently or for various purposes. For example, Trappey et al. (2011) used an ontology-based NN algorithm to automatically classify and search knowledge documents. Zhang et al. (2012) used it to explore the nonlinear relationship between the patent performance and corporate performance of pharmaceutical companies. Lai and Che (2009) proposed a revolutionary valuation model for the monetary legal value of patents, and Zang and Niu (2011) suggested a forecast model for the patents granted in colleges. In this research, an NN was applied to produce expected future-citation values for a citation matrix. Considering the complexity of our data and the forecasting accuracy of NN, it would be appropriate to apply the NN to the patent data for this study. In addition, since the purpose of this study is to produce accurate results rather than to gain implications from parameter estimation, the use of the non-parametric analysis method is justified.

Dependency-structure matrix

A DSM, which is also known as a design-structure matrix or dependency-source matrix, is a network-modeling tool that is used to represent the elements comprising a system and the interactions between the elements. It is particularly well suited for analyzing complex systems and thus has previously been used actively in the areas of engineering management. This method is powerful for engineering management, especially due to its advantages in terms of compact format, visual nature, intuitive representation, powerful analytical capacity, and flexibility (Eppinger and Browning 2012). More in detail, it provides a simple and concise way to present a complex system. Second, it is amenable to a powerful analysis, such as clustering (e.g., to facilitate modularity) and sequencing (e.g., to minimize the cost and schedule risk in processes).

A DSM is an N by N matrix that has an equal number of rows and columns. It shows the relationship among the system's elements. In the matrix, the off-diagonal cells are used to present relationships between the elements. That is, a marking of the cell indicates a link between two elements. In Fig. 1, The X symbol relating to C and D indicates that Technology D is dependent on Technology C. If intensive knowledge flows from Technology C to Technology D are observed, innovation of Technology D is likely to be affected greatly by that of Technology C. In other words, the advances in Technology D require knowledge in Technology C, while Technology C transfers knowledge to Technology D. If Technology C affects Technology D, and vice versa, it is likely that convergence between the two technologies occurs.

In this research, instead of adopting a clustering algorithm, which finds subsets of DSM elements that are mutually exclusive or minimally interacting subsets, we applied the sequencing algorithm of DSM to the matrix to show the relationships between technologies. Sequencing is the reordering of the DSM rows and columns such that the new DSM arrangement contains the fewest iterations (feedback marks), thus transforming the DSM into an upper triangular form. If any iterations exist, they indicate the possibilities of

Fig. 1 DSM matrix

	A	B	C	D	E	F
A				X	X	X
B						X
C				x		
D						X
E						x
F					x	

technology convergence. We assume that technology convergence is realized only through bi-directional knowledge flows rather than one-directional knowledge flows. The sequencing algorithm identifying iterations is more suitable for our assumption than the clustering algorithm, considering both bi-directional and one-directional relationships between technologies.

The sequencing results are expected to provide insights into how convergence happens, highlighting knowledge flows and the roles of technologies. From the rearrangement, three types of relationships can be represented in a DSM: parallel, sequential, and coupled. Parallel means that the system elements do not interact with each other (e.g., A and B in Fig. 1). A sequential relationship shows that one element influences the behavior or decision of another element in a unidirectional fashion (e.g., C and D in Fig. 1). Coupled indicates that the flow of influence or information is intertwined (e.g., E and F in Fig. 1). Convergence happens through coupled technologies, which are the focus on this research. In addition to the identification of converging areas, the matrix visualizes the role of technologies (system elements) in the technology areas (elements). If a technology has a relatively large number of marks in its row, it is regarded as a knowledge provider (e.g., A in Fig. 1), whereas a technology with a large number of marks in its column is considered a knowledge absorber (e.g., F in Fig. 1).

The DSMs in existing studies were mainly used as tools to project scheduling, work division, design-process management, and software-architecture management. Danilovic and Browning (2007) attempted to reduce the risk arising from the product-development phase by handling the dynamics of project development using a DSM and domain-mapping matrix. Austin et al. (2000) established DSM tools to suit the building-design process based on the existing DSM techniques and tools and validated these matrixes by testing the analytical design-planning technique on historical and current building projects. Sangal et al. (2005) described an approach to managing software systems using dependencies. Now, DSM is increasingly extending its application to deal with complex issues in healthcare management, financial systems, public policy, natural sciences, and social systems (Eppinger and Browning 2012).

To summarize, the DSM concept may be applied to our study as follows. First, each row (or column) in the DSM represents a technology. Second, the interaction between system elements represents a citation between technologies (i.e., convergence). When a coupled relationship occurs, it is considered to be a convergence between technologies, and a block that occurs as a result of a conversion is called a convergence cluster. A convergence cluster becomes a newly introduced convergence technology because of the coupling between the existing technologies. This is one of the earliest but most meaningful attempts to apply the DSM concept to innovation studies.

Methodology

Proposed approach

Figure 2 shows the overall framework for the proposed methodology. For multi-technology convergence forecasting, the technology field for the forecast is first selected. The technology field under consideration may vary with the purpose of the researcher's analysis, and two or more fields may be selected. Second, the patent data related to the target technology field are collected. The selected patent data are taken from the registered

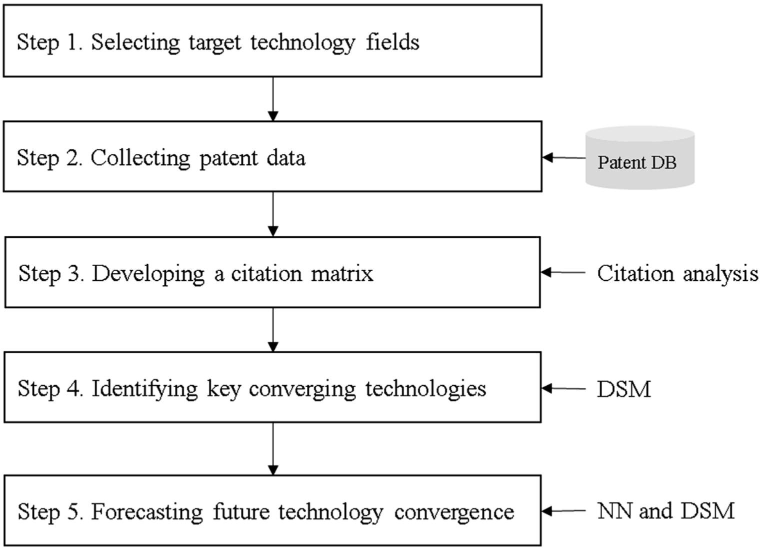


Fig. 2 Proposed process to forecast future technology convergence

patents, and the sub-technologies belonging to the target technology field may be coded by a patent-classification coding system for technology, such as International Patent Classification (IPC) or United States Patent Classification (USPC). For example, USPC 700, which denotes "data processing: generic systems or specific applications" is considered a single technology in the information technology (IT) field. Third, the flow of knowledge among technologies is identified by analyzing the citation relationships among the collected patents and then presented in the DSM matrix to analyze existing convergence trends. Fourth, the value of a future patent-citation matrix is forecasted through the NN analysis, and the results are used to construct a DSM matrix for forecasting the status of technology convergence among future technologies in the final step. Steps 3–5 are explained in detail in "Detailed process" section.

Detailed process

Developing a patent-citation matrix

To identify the technology convergence, a patent-citation matrix is first developed. Figure 3 shows the structure of this matrix. The matrix takes an N by N structure containing the technology classes and number of citations. In this matrix, groups of technologies are

Fig. 3 Structure of a patent-citation matrix

t	T1	T2	T3	T4	T5
T1					
T2			X_{32}		
T3					
T4					
T5					

classified according to technology classification codes, such as A01 (when adopting IPC) and 700 (when adopting USPC), which are selected by the researcher. The technology classes in the columns cite the technology classes in the rows. If T2 is cited by T3, cell X_{32} indicates the number of citations from T2 (patents on T2) to T3 (patents on T3).

Identifying key converging technologies

Before applying the DSM to the forecasted citation matrix, it is worth using it on past data divided into several periods, which helps understand the past trends of convergence. Thus, the DSM is constructed using the values of the patent-citation matrix. In this study, we adopted a binary DSM, which is simple to use but provides enough information for our research purpose. To convert the citation matrix into a matrix with binary values, cut-off values are applied: A value of *one* is assigned when at least a certain amount of citation occurs within the patent-citation matrix and *zero* when no or few citations occur (see Fig. 4). Because of the characteristic of the DSM, the citation relationship between the same technologies is excluded. Here, a DSM was constructed using the "Macros for Partitioning and Simulation" provided for research at www.dsmweb.org.

Forecasting future technology convergence

The target for analysis in this study is future convergence, and hence, a future-citation matrix is developed using an NN. The NN is frequently used as a time-series analysis method to estimate the lag dependence in the data. The first step to forecast the convergence status using the NN is defining the inputs and outputs. In general, the value of a given time, t (month, year or term), is correlated with the past values of precedent times, $t-1$, $t-2$, … and $t-n$. Therefore, instead of using only a single value, the sum of the past n time-series data was used. The number of data that shows the best performance is chosen to calculate the values for an input variable. The overall forecasting accuracy can be measured by the mean absolute percentage error (MAPE). The formula for the MAPE is

$$\mathrm{MAPE} = \frac{100}{n}\sum\nolimits_{t=1}^{n}\frac{|A_t - F_t|}{A_t} \tag{1}$$

where A_t is the actual value at period t and F_t is the forecast value at period t.

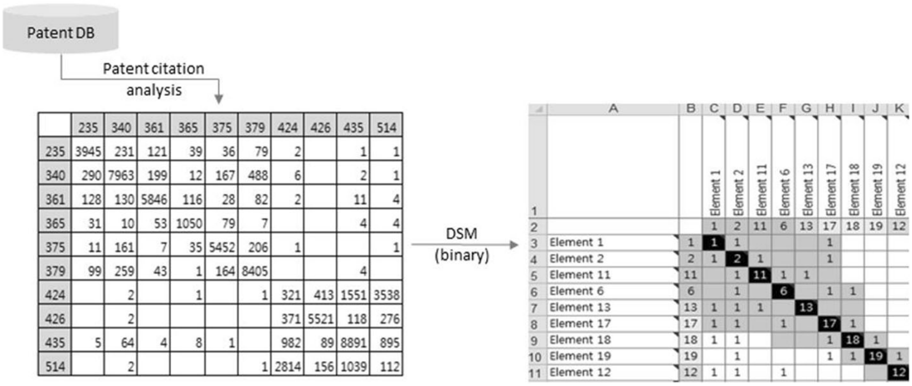


Fig. 4 Transforming a citation matrix to a binary DSM

Table 2 MAPE values under different input variable conditions

Input	Individual performance			Overall performance	
	365-235	435-424	705-379	Average	Standard deviation
1 year	38.62	25.23	51.90	38.58	10.89
2-year sum	49.87	22.01	0.53	24.14	20.20
3-year sum	46.00	24.00	17.02	29.01	12.35
4-year sum	37.45	20.63	41.49	33.19	9.03
5-year sum	9.68	19.24	33.46	20.79	9.77
6-year sum	*18.33*	*21.08*	*12.31*	*17.24*	*3.66*
7-year sum	4.06	20.85	48.26	24.39	18.22
8-year sum	9.32	20.33	22.52	17.39	5.78
9-year sum	6.71	20.02	28.64	18.45	9.02
10-year sum	9.24	20.04	35.38	21.55	10.73

Accordingly, the number of data sets was set to six. The experiment was conducted on the randomly selected variables in the 2006 citation matrix—the number of citations from 365 to 235, from 435 to 424, and from 705 to 379—and the real citation values were compared with the estimation results. The experiment results shown in Table 2 revealed that we could expect the greatest performance—minimum average and standard deviation values—by training the NN with the sum of the lasted six years' data as an input (see the Italics).

Let us assume that we forecast the value of a specific year in the future (here, 2006) using the data for the past 10 years (1996–2005). In the NN matrix, t is 1996, and the X_{32} value of 1997 is X_{32_t+1}. The X_{32} value of 2006 ($t + n$) that we are trying to forecast is the output value of 2005 ($t + (n - 1)$). If a value is to be forecast for 2016, the NN training can be performed 10 more times.

Illustrative example

Selecting target technology fields

To illustrate the analysis method, the fields of IT and biotechnology (BT) were selected. IT–BT convergence is a representative technology field for technology convergence, which is a technology field in which an existing IT is converged with a biological phenomenon to produce new IT products/services (i.e., hardware, software, and an application field) using biological principles and characteristics. We used these as an example to forecast the future status of convergence because they both have the potential to grow into a driving force for the development of a nation's economy, and their convergence with various fields is currently being promoted. To classify the technology, this paper uses USPC, which is partially referenced from the research of Geum et al. (2012). Table 3 lists the technology fields and USPC codes used in this paper. The IT fields consist of three sub-fields: "mobile telecommunications, telematics (USPC 340, 375, 379, 701)," "electrical computing (USPC 235, 361, 365)" and "digital contents, software solutions (USPC 705, 707, 715)." The BT fields also have three sub-fields: "biomedical devices (USPC 623, 702),"

Table 3 The definition of USPCs used in this research (Geum et al. 2012)

Technology field	USPC code	Notes[a]
IT		
Mobile telecommunications, telematics	340	Communications: Electrical
	375	Pulse or digital communications
	379	Telephonic communications
	701	Data processing: Vehicles, navigation, and relative location
Electrical computing	235	Registers
	361	Electricity: Electrical systems and devices
	365	Static information storage and retrieval
Digital contents, software solutions	705	Data processing: Financial, business practice, or management arrangement
	707	Data processing: Database and file management or data structures
	715	Data processing: Presentation processing of document, operator interface processing, and screen-saver display processing
BT		
Biomedical devices	623	Prosthesis (i.e., artificial body parts), parts thereof, or aids and accessories therefore
	702	Data processing: Measuring, calibrating, or testing
Molecular bioengineering	424, 514	Drug, bio-affecting, and body-treating compositions
	426	Food or edible material: processes, composition, and products
	435	Chemistry: Molecular biology and microbiology
	800	Multicellular living organization and unmodified parts thereof and related processes
Surgery	600	Surgery
	602	Surgery: Splint, brace, or bandage
	607	Surgery: Light, thermal, and electrical application

[a] *Source*: Wipson, version 2014.02 (www.wipson.com)

"molecular bioengineering (USPC 424, 426, 514, 435, 800)," and "surgery (USPC 600, 602, 607)."

Collecting patent data

The United States Patent and Trademark Office's (USPTO) patent data registered from 1996 to 2005 in the IT and BT fields were collected from the National Bureau of Economic Research (NBER) database. The database has information about the number of patent citations, the patent number of the citation, the registered date of the cited patent, the USPC of the cited patent, and the USPC of the patent doing the citing. As a result, the information from 387,703 patents and 353,785 citations between them was used for this research.

Developing a patent-citation matrix

For analysis, a patent-citation matrix needs to be developed. Figure 5 shows a patent-citation matrix for 2004. The most number of citations was observed within 600 and 514.

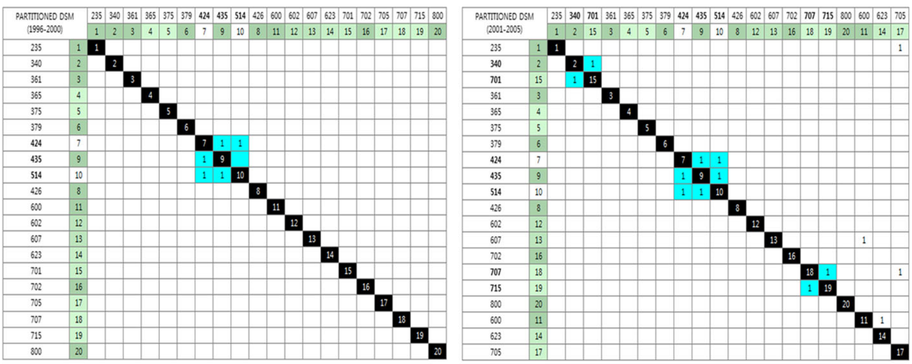
2004	235	340	361	365	375	379	424	426	435	514	600	602	607	623	701	702	705	707	715	800
235	5,234	618	146	78	38	194	4	6	7	0	39	0	3	0	58	36	1,363	112	87	0
340	351	8,996	170	15	276	217	4	1	12	0	392	0	60	2	1,284	263	267	33	53	0
361	49	137	8,716	134	13	50	3	1	15	4	7	1	72	2	13	44	1	0	5	1
365	14	20	70	12,795	58	2	2	0	4	2	2	0	0	0	6	20	0	11	1	0
375	43	163	19	46	6,838	457	0	0	0	1	10	0	5	0	81	88	23	26	62	0
379	103	330	106	8	358	10,611	1	0	1	1	42	0	4	0	51	38	790	461	211	0
424	0	1	3	0	1	0	13,014	644	2,061	4,205	215	50	28	257	0	4	0	0	0	96
426	0	4	0	0	0	0	310	4,735	88	178	5	1	2	1	0	0	1	0	0	27
435	4	21	11	6	0	0	1,296	116	11,731	1,204	114	6	20	52	0	40	1	6	1	403
514	1	1	0	1	2	0	3,404	140	1,371	14,326	64	9	25	62	1	4	0	0	0	31
600	16	207	27	7	27	36	343	7	139	83	18,933	33	1,351	500	14	123	115	16	39	3
602	0	2	0	0	0	0	77	1	2	16	14	1,426	24	18	0	0	0	0	0	0
607	0	51	196	3	21	4	100	3	37	110	2,271	37	8,279	92	1	9	20	3	2	0
623	0	4	1	0	0	0	531	1	109	192	801	25	148	13,353	0	0	3	0	1	10
701	20	1,627	28	6	64	322	0	0	1	3	8	0	1	0	5,259	213	117	90	27	1
702	53	562	257	100	155	76	8	12	201	3	317	0	71	6	511	2,418	192	181	91	4
705	339	103	18	2	9	241	0	0	1	1	24	0	4	0	44	48	2,950	243	177	0
707	138	148	7	33	42	254	4	2	34	4	104	0	1	1	114	126	1,403	9,562	1,329	0
715	48	56	13	0	16	123	0	0	5	0	55	0	10	0	67	32	285	796	2,931	0
800	0	0	0	0	0	0	61	25	483	49	3	0	1	0	0	0	0	0	0	1,327

Fig. 5 Patent-citation matrix of 2004

When a forecast is made with 10 years of data, 10 patent-citation matrixes are constructed, which are used as inputs for NN analysis and also to investigate the past trends of convergence.

Identifying key converging areas

A DSM sequencing algorithm was applied to the citation matrixes on each of the 1996 to 2005 data sets to examine the past trends of convergence. Then, for ease of visualization, the convergence trends over 10 years, split into five-year units are presented in Fig. 6. The cut-off value of the DSM was set to the average citation frequencies for all patents published over the past 10 years, which corresponded to 4134.4. If a citation frequency of a particular cell is greater than the cut-off value, a value of one was assigned to the relevant cell to develop a DSM. Figure 6a shows that DSM built one cluster consisting of USPC 424, USPC 435, and USPC 514 during the period from 1996 to 2000. This convergence cluster was formed within the same technology field, molecular bioengineering in BT. Here, it should be noted that USPC 514 is an integral part of USPC 424, and thus, it is the convergence between USPC 514 (drug, bio-affecting, and body-treating compositions) and USPC 435 (chemistry: molecular biology and microbiology). Nevertheless, the analysis results showed that not only the convergence between two technologies but also among



(a) 1996–2000 **(b)** 2001–2005

Fig. 6 Key converging areas identified three technologies could be identified with the suggested approach, which is one of its advantages over other approaches. On the other hand, two more convergence clusters were identified in the other unit, 2001–2005 (see Fig. 6b). One of them consists of USPC 340 (mobile telecommunications) and USPC 701 (telematics) within the IT sector, while the other consists of USPC 707 (digital contents) and USPC 715 (software solutions), again in the IT sector. The analysis results uncovered that technology convergence within the same industry field was dominant by 2005.

Forecasting future technology convergence

It is more significant to forecast the future trends of IT–BT convergence based on the past data than to investigate the past trends for technology planning. The past 10-year citation data from 1996 to 2005 were used to project the data for 2006. SPSS 18 was used for NN training. The dependent variable was the normalized values at time t, and the independent variables were the normalized values at time $t-1$. The training parameters are listed in Table 4.

To validate the use NN for the purpose of forecasting, we compared the MAPE values obtained by NN and growth curves. Table 5 shows the forecasting performance of the NN and growth curves, with the focus restricted to the three randomly selected variables. As in Table 2, a training data set included the values from the 1996 to 2005 citation matrixes, and a test data set was collected from the 2006 citation matrix. The MAPE value obtained from the NN was from 12.31 to 21.08%, which indicates that the forecasting performance is quite good, being greater than the performance of other growth curve models (see Table 5). Here, it should be noted that there exist various forecasting models (e.g., linear, exponential and logistic) but we chose the growth curve model, $Y = e\text{^}(b\_0 + b\_1t))$, for comparative analysis, which shows the greatest forecasting performance in terms of R square values among them.

Table 4 Parameters for training

Parameters	Notes
Type	Feed-forward (back-propagation)
Number of hidden layers	2
Number of units	Hidden layer(1):50, Hidden layer(2):50
Activation function	Hyperbolic tangent
Epochs	10,000
Initial learning rate	0.4
Momentum	0.9
Interval center	0
Interval offset	±0.5

Table 5 Comparative analysis of forecasting performance

Forecasting method	MAPE		
	365–235	435–424	705–379
Neural network	18.33	21.08	12.31
Growth curve (R^2)	64.44 (0.43)	3013.79 (0.66)	904.25 (0.87)

2020	235	340	361	365	375	379	424	426	435	514	600	602	607	623	701	702	705	707	715	800
235	6800.11	933.97	389.64	230.31	91.05	390.19	3.89	12.57	53.92	2.90	75.79	0.40	1.22	1.20	149.85	107.10	2783.52	117.51	78.60	0.00
340	666.40	12976.15	366.31	19.44	503.14	566.46	9.51	2.11	14.03	5.02	508.46	6.24	115.62	9.40	2954.18	636.62	509.34	153.18	119.77	0.18
361	74.88	224.93	16979.39	78.47	14.12	61.85	4.81	0.72	14.38	4.48	23.09	1.15	445.25	2.97	13.51	88.24	5.32	5.91	9.51	1.16
365	23.08	15.77	252.38	19356.84	83.64	12.34	1.30	0.17	6.24	1.96	2.00	0.23	2.58	0.19	4.70	56.10	2.52	16.62	0.00	0.23
375	116.12	340.13	39.89	255.59	19903.88	504.52	0.30	0.00	1.08	0.49	23.71	0.17	55.54	0.00	102.92	76.03	86.83	26.94	130.61	0.00
379	97.52	298.08	213.00	5.23	349.75	10615.33	1.61	0.15	0.99	0.00	98.53	0.00	58.77	3.72	101.67	57.29	491.97	316.75	163.06	0.00
424	0.66	4.66	2.55	2.33	2.98	0.49	13627.62	641.20	2561.26	4369.37	316.26	31.92	37.03	1146.85	0.00	10.97	2.22	1.33	0.00	150.85
426	0.04	12.05	0.33	0.68	0.32	0.00	373.45	5057.36	103.86	312.76	3.58	0.08	0.23	0.63	0.00	0.00	0.20	0.00	0.00	63.69
435	4.68	29.42	6.80	9.09	0.92	3.33	2715.17	213.48	12878.11	2203.14	220.16	3.57	70.96	115.74	3.76	133.44	0.00	6.86	1.18	715.74
514	1.11	1.18	2.05	1.02	0.00	0.35	3400.42	172.89	1797.88	16471.83	63.45	7.28	28.30	51.81	0.69	7.10	0.41	0.48	0.32	136.63
600	21.87	174.59	21.59	8.69	50.68	108.64	673.51	12.48	367.78	126.39	17623.46	67.22	1758.19	506.77	9.02	136.19	83.83	36.20	27.89	14.18
602	0.00	1.13	7.38	0.00	0.00	0.00	141.90	0.98	14.29	42.14	14.64	2198.63	56.08	24.07	0.00	0.00	0.00	0.00	0.00	0.00
607	0.31	85.46	253.65	6.99	50.19	6.81	147.90	2.39	138.59	168.92	2696.91	49.60	14189.56	235.18	2.46	12.13	22.00	9.05	7.19	0.01
623	0.00	3.85	1.94	0.45	0.05	0.16	816.80	1.27	105.77	139.98	731.09	25.72	147.08	14603.50	1.11	3.43	5.60	0.12	5.52	7.95
701	26.45	1372.24	57.03	4.59	68.67	126.33	0.43	0.09	10.82	0.00	14.16	0.00	7.13	0.18	6459.40	374.82	101.78	129.36	39.84	0.00
702	163.61	892.20	179.13	91.73	177.15	133.24	26.94	7.62	669.17	51.44	588.24	0.28	137.84	5.63	383.27	2305.48	185.07	185.03	139.01	5.00
705	780.14	1485.63	20.56	21.12	23.68	657.87	0.00	7.70	7.24	0.95	141.62	0.75	10.06	1.67	267.38	10204.60	165.02	1487.93	516.74	0.00
707	145.02	333.77	26.92	29.81	72.77	213.28	3.66	0.97	29.40	9.45	58.61	0.16	6.10	1.41	627.57	199.24	2132.10	11942.52	2784.19	0.14
715	165.19	167.76	65.90	6.63	27.33	406.52	0.95	3.25	3.09	1.42	131.54	0.00	7.59	0.86	149.67	75.73	697.61	1639.37	5179.35	0.00
800	0.00	0.35	0.00	0.00	0.00	0.00	109.19	13.13	564.93	54.17	1.70	0.18	0.16	3.27	0.00	0.00	0.00	0.00	0.00	1389.62

Fig. 7 Patent-citation matrix of 2020 (projected data)

Therefore, the NN was applied to forecast the citation matrix of 2020, and the projected values in the matrix (see Fig. 7) were transformed to a binary value by using the cut-off value. As we used the total number of citations made in the past 10 years as a cut-off value for the five-year-period citation matrix in Fig. 6, we divided the cut-off value by five to generate a new cut-off value for the one-year-period citation matrix, which corresponded to 826.9.

Figure 8 presents the results of applying a DSM technique to the projected patent-citation matrix of 2020, which helps identify the expected future convergence. The convergence of USPCs 340 (mobile telecommunications)—701 (telematics), USPCs 707 (digital contents)—715 (software solutions), and USPCs 424 (drug, bio-affecting, and body-treating compositions)—435 (chemistry: molecular biology and microbiology)—514 (drug, bio-affecting and body treating compositions) is expected to continue until 2020. In addition to the three convergence clusters, we could also expect that two more convergence clusters will be created in 2020 between USPCs 600 (surgery)—607 (surgery: light, thermal, and electrical application) and UPSCs 705 (data processing: financial, business practice, or management arrangement)—707 (digital contents). Until 2020, the convergence of IT and BT fields is observable within the same fields on the assumption that the convergence defined in this study is the knowledge *exchanges* among technologies. Moreover, in the convergence between the two fields, it is expected that USPCs 424 (drug,

PARTITIONED DSM (2020)		235	361	365	375	379	424	435	514	426	600	607	602	623	705	707	715	800	702	340	701
		1	3	4	5	6	7	9	10	8	11	13	12	14	17	18	19	20	16	2	15
235	1	1													1					1	
361	3		3																		
365	4			4																	
375	5				5																
379	6					6															
424	7						7	1	1					1							
435	9						1	9	1												
514	10						1	1	10												
426	8									8											
600	11										11	1									
607	13										1	13									
602	12												12								
623	14													14							
705	17														17	1			1	1	
707	18														1	18	1				
715	19															1	19				
800	20																	20			
702	16																		16	1	
340	2																			2	1
701	15																			1	15

Fig. 8 Expected technology convergence areas in 2020

bio-affecting, and body-treating compositions) and 705 (data processing: financial, business practice, or management arrangement) will act as a knowledge provider in general, while USPC 340 (communications: electrical) will act as a knowledge absorber.

The forecasting results suggested that the number and size of the convergence clusters would continue to increase over the past 10 years in terms of convergence trends. We can observe that the cluster whose number was 1 in 1996–2000 increases to 4 in 2020. In addition, IT and BT used for this analysis are proven to be converged with sub-technologies significantly. In terms of the convergence fields, the cluster of USPC 424, USPC 435, and USPC 514; the cluster of USPC 340 and USPC 701; the cluster of USPC 600 and USPC 607; and the cluster of USPC 707 and USPC 715 are core convergence technologies, which are noticeable for IT and BT. In terms of the continuity of the convergence, each cluster appeared continuously until 2020 from since they were built. Especially, cluster 424, 435, and 514 is believed to contain core convergence technologies for BT, regardless of time. Though our analysis was restricted to the citation matrix for 2020 using data from 1996 to 2005, the continued projection of the forecasted results will enable us to obtain the citation matrixes in the following years and identify the converging technologies in the distant future.

Types of technology convergence

From the matrix in Fig. 8, several types of technology convergence could be identified. Some of them are based on bi-directional knowledge flows. The simplest type is a coupled convergence between two technologies (e.g., USPC 600 and USPC 607, USPC 340 and USPC 701) where both the knowledge in-flow and out-flow between the two technologies are active. On the other hand, the number of converging technologies can be extended to more than three, which is called as an interrelated convergence, where all technologies in the converging cluster are closely related to each other with extensive knowledge exchanges (e.g., USPC 424, USPC 435 and USPC 514). Another interesting type is an intermediated convergence, where pairs of technologies are linked together through the mediation of a particular technology (e.g., USPC 705, USPC 707 and USPC 715, though the mediation of USPC 707).

There are also some other technology pairs worth noting. Although this study assumed that bi-directional knowledge flow was a requirement for technology convergence and thus that converging areas were identified based on this requirement, one-directional knowledge flow also needs to be considered if a substantial amount of knowledge flow is observed (e.g., from USPC 235 to USPC705; from USPC 235 to USPC 340; from USPC 424 to USPC 623; from USPC 705 to UPSC 702; and from USPC 705 to USPC 340); such one-directional knowledge flow can be an early signal of technology convergence, or it can be regarded as another type of technology convergence.

Conclusions

This paper proposed a future-oriented forecasting methodology for multi-technology convergence. First, we selected the fields for analysis and collected patent data for each field. Then, we analyzed the citation relationships among the technologies in each field, constructed a patent-citation matrix and DSM, and analyzed the status of the existing convergences. Then, using an NN, we forecasted the status of future technology convergences.

The proposed methodology provides the following contributions for studies of technology convergence. First, this methodology enables a quantitative forecast of "the status of future technology convergence." By providing quantitative forecast values related to whether instances of convergence would increase or decrease between technologies in the future, we attempted to overcome the limitations of an expert-based forecast method or a convergence analysis focusing on the past trends. Second, the proposed methodology forecasts a future technology convergence from "a multi-technology perspective." By considering the convergence potentials among all of the technologies in a field for a forecast, our methodology attempts to overcome the limitations of the existing studies of convergence with limited technologies. This proposed methodology generates convergence clusters through a DSM to enhance the visibility of convergence patterns among multiple technologies.

Despite these contributions, this study has some limitations. First, the elaboration of NN is required in order to determine the input variables or cut-off values. Instead of using a single input variable with the sum of several time-series values, it will be possible to adopt several input variables. Determining cut-off values is also worth considering. A smaller cut-off value will generate a greater number of converging areas and vice versa. Finding the most appropriate cut-off values should be addressed as a future research topic. Second, we defined converging areas as the technologies showing active knowledge inflows and outflows. However, convergence between Technologies T1 and T2 can happen via one-directional knowledge flows. Future research needs to define several types of convergence and suggest an approach suitable for each of the types.

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