Technology Analysis & Strategic Management

ISSN: 0953-7325 (Print) 1465-3990 (Online) Journal homepage: https://www.tandfonline.com/loi/ctas20

Analysing the dynamics of technological convergence using a co-classification approach: a case of healthcare services

Junghwan Yun & Youngjung Geum

To cite this article: Junghwan Yun & Youngjung Geum (2019) Analysing the dynamics of technological convergence using a co-classification approach: a case of healthcare services, Technology Analysis & Strategic Management, 31:12, 1412-1429, DOI: 10.1080/09537325.2019.1616082

To link to this article: https://doi.org/10.1080/09537325.2019.1616082

Published online: 10 May 2019.

TECHNOLOGY ANALYSIS & STRATEGIC MANAGEMENT
2019, VOL. 31, NO. 12, 1412–1429
https://doi.org/10.1080/09537325.2019.1616082

Analysing the dynamics of technological convergence using a co-classification approach: a case of healthcare services

Junghwan Yun and Youngjung Geum

Department of Industrial & Information Systems Engineering, Seoul National University of Science and Technology, Nowon-gu, Republic of Korea

ABSTRACT

Although the importance of technological convergence has increased, previous studies are highly dependent on static analysis. In response, this study suggests an index-based approach to identifying the dynamic trend of individual technologies, which enables the in-depth analysis for advances or declines of technological convergence. We suggest two types of indexes: fluctuation and continuity, and suggest eight sub-indexes to analyse the dynamic patterns of technological convergence for each international patent classification pair. As a result of case study, the frequency of technology convergence between data processing and diagnosis systems has highly increased over time. Treatment technologies and device-related technologies have experienced relatively high fluctuation. The frequency of convergence in water sterilising technology has continuously increased over time.

ARTICLE HISTORY
Received 27 November 2018
Revised 25 April 2019
Accepted 30 April 2019

KEYWORDS
Technology convergence; co-classification; healthcare; patent analysis

1. Introduction

With the rise of technological development and diversified customer demands, the body of literature has been almost unanimous in considering technological convergence as an important task for developing new products. Technological convergence is defined as the phenomenon of at least two discernible items moving toward union or uniformity or a blurring of boundaries between at least two hitherto disconnected areas (Geum et al. 2012). Recently, the importance of technological convergence has increased due to rapid technological advances and diverse customer needs (Tijssen 1992). This is especially true in current new product development (NPD) practice where a significant number of different technologies are used to develop a new product. Quite naturally, technological convergence has played a key role in developing such innovative products.

Thus, there have been many studies investigating technological convergence (Geum et al. 2012). Previous studies on technological convergence can be classified into two main categories. The first category mainly deals with defining, characterising, and analysing technological convergence based on empirical evidence or investigating the practical phenomena on convergence (Curran and Leker 2011; Jeong and Lee 2015). For example, Jeong and Lee (2015) conducted an empirical study and demonstrated that in the earlier stage of the technology life cycle, a lower technology readiness level, longer R&D timespan, or smaller R&D budget lead to the creation of technology convergence.

The second category focuses on a data-driven approach. Since data-driven approach can provide clear evidence for technological convergence, previous studies have employed several techniques to conduct a data-driven approach, such as patent bibliometric analysis (Karvonen and Kässi 2011), co-

CONTACT Youngjung Geum yjgeum@seoultech.ac.kr Department of Industrial & Information Systems Engineering, Seoul National University of Science and Technology, 232 Gongneung-ro, Nowon-gu, Seoul, 01811, Republic of Korea

citation analysis (Karvonen and Kässi 2011; Geum et al. 2012), co-classification analysis (Tijssen 1992; Curran and Leker 2011; Geum et al. 2012; Han and Sohn 2016), and network analysis (Geum et al. 2012; Kim, Kim, and Lee 2019). In particular, co-classification analysis has been employed as a good method to analyse technological convergence (Tijssen 1992; Geum et al. 2012; Park and Yoon 2014). Generally, a patent can be assigned to more than one patent class, which means it is developed and invented based on multiple technological backgrounds. For this reason, the increasing number of patents assigned in multiple technological fields is a good evidence of technological convergence (Geum et al. 2012; Karvonen and Kässi 2013; Caviggioli 2016). Especially, international patent classification (IPC) can provide flexible and diverse aggregation levels of analysis, which allows sufficient characterisation of technological convergence. Another advantage to employ co-classification is that there is no time-lag problem of patent co-citation analysis (Tijssen 1992; Geum et al. 2012; Park and Yoon 2014).

For this reason, several studies have employed co-classification analysis for analysing technological convergence (Kim, Cho, and Kim 2014; Jeong, Kim, and Choi 2015; Lee, Han, and Sohn 2015; Han and Sohn 2016). Geum et al. (2012) employed co-classification analysis and portfolio analysis to analyse technological convergence between information technology (IT) and biotechnology (BT). Jeong, Kim, and Choi (2015) used patent information to analyse technological convergence, and employed network analysis to visualise the occurrence of technology convergence. Lee, Han, and Sohn (2015) used association rule mining and link prediction, and applied topic modelling techniques to check the emerging areas for the predicted technological convergence.

Despite the numerous research streams in technology convergence, how to treat technology convergence considering the dynamic characteristics remains a void in the literature. Although some studies have tried dynamic analysis on technological convergence (Geum et al. 2012; Kim, Cho, and Kim 2014; Lee, Han, and Sohn 2015), these studies have employed simple analytics such as dividing the total period into several time slots and comparing the results. Even if Lee, Han, and Sohn (2015) tried to employ link prediction to predict future technological convergence, it is hard to monitor and capture the detailed changes of technology convergence in individual technology level. However, what is required in technology management practice is to identify the dynamic trend of individual technology for technology convergence. For this purpose, index-based approach is very helpful to track dynamics of technology convergence.

For this purpose, several studies employed index-based approach to analyse technological convergence. Kim et al. (2015) analysed industry convergence using a large volume of newspaper articles from 1989 to 2012 using industry convergence (IC) index. Kim, Kim, and Lee (2019) employed network analysis and link prediction method to predict future technological convergence using the Wikipedia database. However, previous studies have two limitations. First, they focused on broader spectrums such as industry convergence or technology groups, not treating individual technologies. What is necessary in practice is to analyse the dynamic characteristics of each converged technology, which can help firms to decide whether they have to develop certain technology convergence. For this purpose, the unit of analysis should be more specific, so it should be individual technology level. Second, even if previous studies have employed several indexes to analyse the trend of technology convergence, developing indexes to capture dynamic characteristics of convergence rather than static characteristics of convergence is still a void in the literatures. Therefore, indexes that properly capture the dynamics are in need.

In response, this study suggests a new index-based approach to identifying and capturing the dynamic trend of each individual technology, which enables the in-depth analysis for advances or declines of technological convergence. We suggest two types of indexes: fluctuation and continuity, and suggest eight sub-indexes to analyse the dynamic patterns of technological convergence for each IPC pair. To illustrate the working of the proposed approach, we conducted a case study for healthcare services.

The remainder of this study is organised as follows. A literature review illustrates how the research of technological convergence has been carried out. Then, the research framework shows the overall process and detailed procedures. A case study is provided for better comprehension using the healthcare industry. Finally, we summarise the contributions and limitations in the Conclusion.

2. Related studies

2.1. Technological convergence

Technological convergence generally occurs when innovations emerge at the intersection of different industry boundaries (Hacklin, Marxt, and Fahrni 2009). What is common in previous literature is that technological convergence mainly occurs in the information and communication technology (ICT) fields that cover telecommunications, broadcasting, information technologies, and entertainment (Han and Sohn 2016; Sick et al. 2018). No longer is innovation developed from single technology. Rather, it happens based on intensive recombination and collaboration among different technologies in different disciplines (Jeong and Lee 2015).

Some studies suggested that there is a close relationship among different types of convergence: market convergence, technology convergence, and industry convergence (Curran and Leker 2011). Xing, Ye, and Kui (2011) measured the industry convergence of China's ICT sector based on a 2002 input-output (IO) table, using an IO table cross-entropy updating technique. Kim, Cho, and Kim (2014) analysed the dynamic patterns of technological convergence using a patent citation network, and tried to identify key technologies by examining their dynamic role in technology convergence. Kim et al. (2015) showed two main processes of industry convergence: convergence of science and technology which is a supply-side convergence, and convergence of the market which is a demand-side convergence (Hacklin, Marxt, and Fahrni 2009; Curran and Leker 2011; Kim et al. 2015). Jeong and Lee (2015) analysed how technological and resource allocation contexts nourish technology convergence. In this work, theoretical framework was developed considering input, development, and output of technological convergence.

2.2. Patent analysis as a good method for measuring technological convergence

To measure technological convergence, many studies have tried to measure interconnectivity and interrelationships among different disciplines using citation analysis (Porter et al. 2007; Porter and Rafols 2009) and co-classification analysis (Pennings and Puranam 2001; Geum et al. 2012; Park and Yoon 2014; Caviggioli 2016). The data used in those studies are either academic journal articles or patent documents.

Patent analysis has been considered as a useful method for measuring technological convergence. Curran, Bröring, and Leker (2010) monitored the trend of technological convergence using co-authorship, citation, and co-citation analysis. Han and Sohn's (2016) work applies the concepts of entropy and gravity, social network analysis, and association rule analysis to patent IPC class. In particular, the use of patent co-classification analysis worth the effort. When the frequency with which two classification codes are jointly assigned to a patent document is high, it is considered that the knowledge relationships, in terms of knowledge links and spill-overs, are strong enough (Breschi, Lissoni, and Malerba 2003). Thus, patent co-classification has been considered to be the dominant method for measuring technological convergence (Pennings and Puranam 2001; Curran and Leker 2011; Geum et al. 2012; Park and Yoon 2014; Caviggioli 2016), since the increasing number of patents registered for multiple technical fields has been considered a good sign of a process of convergence (Caviggioli 2016).

Based on this assumption, Pennings and Puranam (2001) mentioned that convergence can be monitored by patents through growing overlaps among patent classification such as IPC and through an increase in patent citations between different classes (Pennings and Puranam 2001; Curran and Leker 2011). Curran and Leker (2011) conducted a co-classification analysis for patents to monitor technological convergence. Geum et al. (2012) also employed both citation analysis and co-classification analysis to measure technological convergence. Park and Yoon (2014) also suggested a co-classification-based method to measure the intermediarity of technology sectors using an analytic network process (ANP) and social network analysis. Caviggioli (2016) tried to identify new cases of convergence based on the patent IPC from 1991 to 2007, which identified the first occurrence of a patent incorporating a combination of IPC subclasses thereby signalling a new instance of fusion and convergence. Ko, Yoon, and Seo (2014) suggested a framework for analysing industry-wide technology fusion using patent-based knowledge flow matrix. Song et al. (2017) developed a patent landscape for personalised medicine industry using patent activity and patent citation information, and also employed a topic modelling to identify the emergence and institutionalisation of new technological fields.

2.3. Dynamic trend analysis

Even if there have been a substantial number of studies on measuring technological convergence, relatively few studies deal with dynamic analysis for analysing convergence. Some works have suggested methodological development for analysing and monitoring dynamic technological trends. Lee, Jeon, and Park (2011a) suggested a dynamic trend analysis using modified formal concept analysis. The technological similarities among patents are calculated using patent keywords and used for monitoring the technological trends over time. Lee, Lee, and Yoon (2011b) suggested a new methodology for analysing evolutionary patterns using an integrated approach of clustering analysis and Hidden Markov model. Kim et al. (2015) analysed dynamic patterns of industry convergence using text mining analysis for four million articles in the United States. They defined convergence patterns in two industries and measured convergence strength between two industries using industry convergence (IC) index. Niemann, Moehrle, and Frischkorn (2017) suggested a concept of patent lane analysis to visualise patenting patterns over time. In this study, they defined a concept 'patent lane' which can analyse patent clusters over time. Lim, Kwon, and Lee (2018) analysed technology convergence for Internet of Things (IoT) fields using network analysis.

Several studies employed link prediction technique to the prediction of technology convergence. Lee, Han, and Sohn (2015) jointly employed association rule mining and link prediction technique for the triadic patents. They identified possible technological convergences using co-occurrence similarity based on Adamic/Adar similarity. Kim, Kim, and Lee (2019) also employed a link prediction technique to predict future convergence. They developed a technological ecology network, and applied a link prediction technique using three predictive indicators.

3. Research process

The detailed procedure of the index-based approach is explained in Figure 1.

3.1. Plotting convergence frequency for each IPC pairs

A patent has several IPC classifications. Since IPC is defined as the international patent class that is the patent category that characterises patents' technological scope and characteristics, we consider IPC an important data source for analysing convergence. For examples, when investigating the patent 'Healthcare similarity engine' (Patent Number 'US10127359'), 4 IPCs are found: H04L 12/24; H04L 12/26; H04L 12/851; G16H 80/00. Basically, IPC system has a hierarchical meaning. In the IPC classification H04L 12/24, H denotes section, 04 denotes class, L denotes subclass, 12 denotes group, and 24 denotes subgroup. Since groups and subgroups are too specific, we used IPC information with subclass levels.

We use patent data with at least two IPCs, since patents with a single IPC are related to only one technological field. To analyse the IPC pair, we conducted a preprocessing step, which transforms the

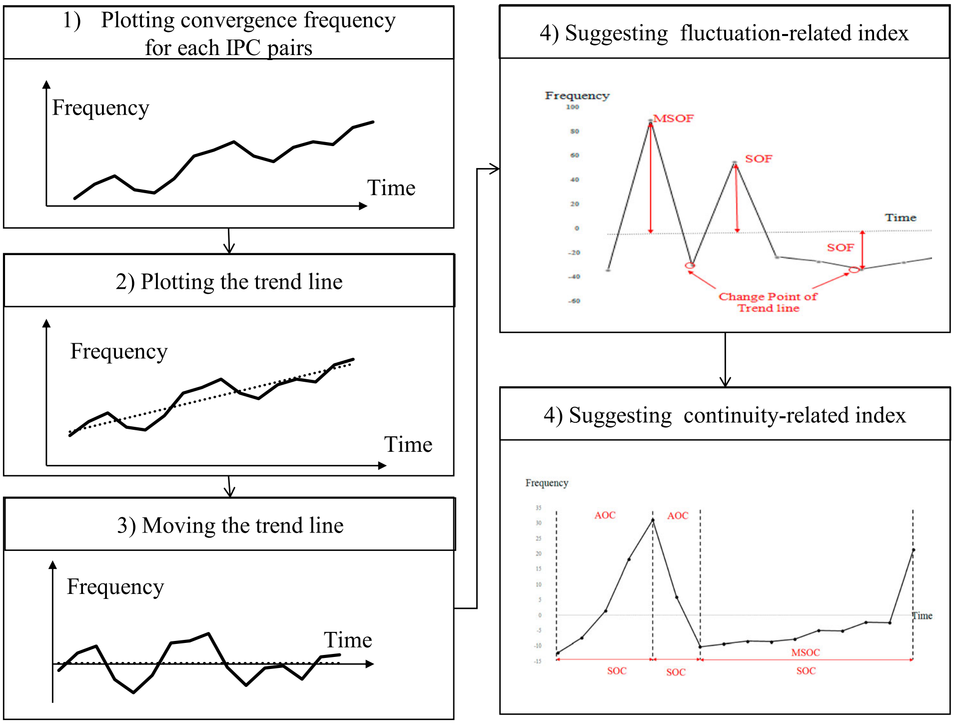


Figure 1. Detailed procedures for index-based approach.

multiple IPCs for a certain patent to IPC pairs, as follows.

$$ {}_nC_2 = k $$

where n represents the number of IPCs a patent has, and k represents the number of generated IPC pairs.

Then, the frequency of each IPC pair is calculated according to the time, and their frequencies are plotted in a two-dimensional matrix where the y-axis represents the frequency and the x-axis represents the time.

3.2. Finding the trend line

After plotting the frequency of each IPC pair, we draw the trend lines and measure the slope of each line. Since our focus is to develop indexes to explain dynamics of technology convergence, not to predict exact value of technology convergence, we used a simple linear regression model for finding the trend line.

$$ y_t = \beta_0 + \beta_1 t + \varepsilon $$

To estimate the coefficient of this model, method of least squares is used. Therefore, the slope of the trend line is obtained as follows.

$$ \beta_1 = \frac{\sum (t_i - \bar{t})(y_i - \overline{y})}{\sum (t_i - \bar{t})^2} $$

When this step is finalised, the dynamic patterns of IPC pairs are investigated. To compare each dynamic pattern, we suggested eight possible types of dynamic patterns of IPC pairs, as shown in Table 1 and Figure 2.

Table 1. Types of convergence patterns.

Convergence type	Direction	Speed of increase/decrease	Aperiodic peak
Rapid increase	Increase	High	No
Rapid increase with exceptional peak	Increase	High	Yes
Continuous increase	Increase	Low	No
Continuous increase with exceptional peak	Increase	Low	Yes
Rapid decrease	Decrease	High	No
Rapid decrease with exceptional peak	Decrease	High	Yes
Continuous decrease	Decrease	Low	No
Continuous decrease with exceptional peak	Decrease	Low	Yes

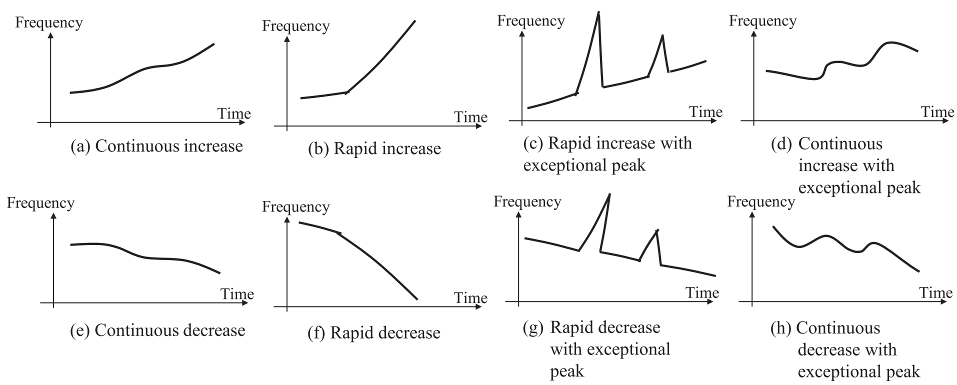


Figure 2. Possible types of dynamic patterns.

3.3. Moving the trend line

When the trend line is prepared, the trend line is moved towards the x-axis to compare the trend with other IPC pairs. When the trend line is moved toward x-axis, the revised value is calculated as follows.

$$y_{moved} = y - (\beta_0 + \beta_1 t)$$

where y is the actual frequency of technology convergence, β_0, β_1 is the coefficient of regression model, t is the timeframe

3.4. Analysing dynamic trend using two types of index

Based on this moved trend line, two types of indexes are suggested: a fluctuation-related index and a continuity-related index. We define fluctuation and continuity as two important criteria for measuring the dynamic pattern. First, the first criteria 'fluctuation' measures how much the trend has changed over time. Technology fluctuation happens when the increasing patterns or decreasing patterns are changing toward the opposite direction over time. This indicates whether the technological convergence increases or decreases over time. Second, the second criteria – continuity – measures how long specific technological convergence continues without any changes in its direction. If the trend continues longer, this means this change is meaningful and trustworthy.

3.4.1. Analysis of fluctuation

To measure fluctuation, this paper suggests four types of indexes, as represented in Table 2 and Figure 3. To measure this, we define the function that represents the convergence pattern for each IPC pair over time as $f(t)$. First, NOF (number of fluctuations) measures the number of inflection

Table 2. Definition and explanation of fluctuation-related index.

Index	Definition	Usage
NOF	Number of inflection points for the function f(t)	Analysing fluctuation frequency of technology convergence
SOF	Absolute value of y_{moved} at each Inflection point of each IPC pair	Analysing changes of market popularity of technology convergence over time
ASOF	Average of every SOF	Analysing changes of market popularity of technology convergence over time
MSOF	Maximum value for all SOFs	Analysing market & technological event to trigger radical changes at the certain period

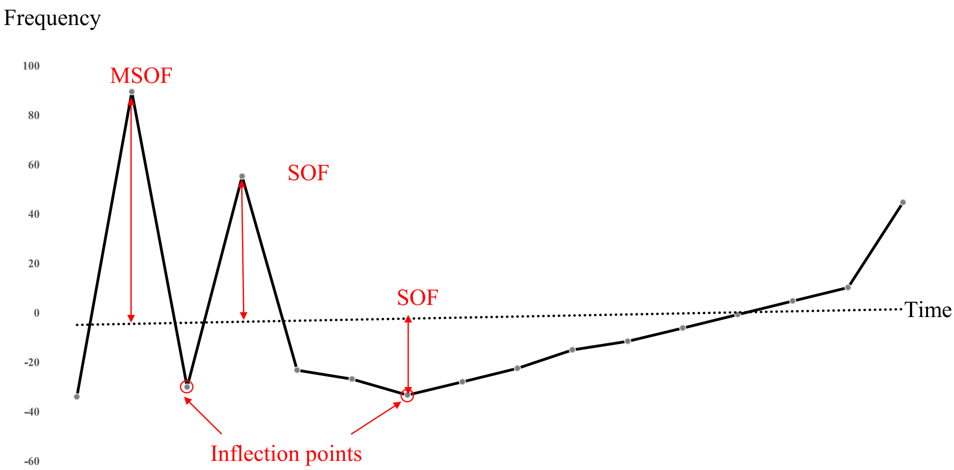


Figure 3. The fluctuation index.

points for the function $f(t)$.

$$\mathrm{NoF} = \mathrm{count}\left(\frac{\mathrm{d}}{\mathrm{dt}}f(t) = 0\right)$$

If the NOF is high, the convergence frequency of the IPC pair has been highly fluctuated, i.e. frequently increased and decreased over time. Since this IPC pair experienced a lot of fluctuation over time, this convergence is highly influenced by business and market trend.

Second, SOF (strength of fluctuation) measures the actual frequency (y-value of the moved trend line, i.e. y_{moved}) at the inflection point of each IPC pair. Since this measures the frequency in an inflection point t, this can be interpreted as the SOF. The high SOF indicates high amplitude in the graph, which means the market popularity of technology convergence highly varies over time.

$$\mathrm{SoF} = \left| y_{\mathrm{moved}}\left(\frac{\mathrm{d}}{\mathrm{dt}}f(t) = 0\right)\right|$$

Finally, ASOF (average size of fluctuation) is defined as the average of every SOF, whereas MSOF (maximum size of fluctuation) is defined as the maximum value of all SOFs. If the ASOF and MSOF are high, this means that this IPC pair shows high-level technological convergence as well as high-level fluctuation.

$$\mathrm{ASOF} = \mathrm{average(SOF)}$$

$$\mathrm{MSOF} = \mathrm{max(SOF)}$$

The comparison of ASOF and MSOF can provide significant implications for technology development. When MSOF is much higher than ASOF, this means there has been a significant technological event, which means examination on market & technological event to trigger radical changes of technological convergence is required. However, the difference of MSOF and ASOF is not big enough, the fluctuation seems trivial, so the changes of technology convergence can be understood as a general trend.

3.4.2. Analysis of continuity

Although fluctuation can be considered to be an important measure for investigating convergence dynamics, how long a certain pattern continues is another important research question. Therefore, we employ several continuity-related indexes to measure how long a certain pattern continues.

To measure continuity, we define the AOC (area of continuity) first. This AOC is defined as the area between a certain inflection point and the next inflection point. Therefore, wherever an inflection point occurs, we can define the AOC. The AOC is defined as the area that increasing or decreasing pattern continues, so it can be considered as continuity. When the increasing pattern continues over time, technology convergence is practically understood as genuine innovation pattern, and its popularity is guaranteed in the market. Based on the AOC, we measure the NOC (number of continuity), SOC (size of continuity), and ASOC (average size of continuity), and MSOC (maximum size of continuity), as shown in Table 3 and Figure 4.

First, the NOC measures the number of AOCs. Therefore, higher NOC implies less stability in technology convergence. On the contrary, lower NOC denotes that certain technology convergence (IPC pair) continues for a long time, which guarantees certain technology convergence pattern is confirmed as the major trend.

$$\mathrm{NOC} = \mathrm{count(AOC)}$$

Second, the SOC measures the size of continuous areas. SOC can imply the length of stable patterns of technology convergence, which means higher SOC denotes the higher stability of technology convergence.

$$\mathrm{SOC} = \mathrm{length(AOC)}$$

The ASOC and MSOC also measure the average and maximum value of every SOC, respectively. Note that analysing differences between ASOC and MSOC can provide a good implication, as did in fluctuation-related indexes. When MSOC is much higher than ASOC, it means certain convergence pattern continues in a long time. More in-depth investigation for identifying the time point of MSOC in the entire timeframe is required in this case, since the interpretation of technology convergence is different according to whether the area with MSOC happens recently or long time ago. When the area with MSOC is located at the front of entire period, this means that this technology convergence has experienced a stable increase or decrease for a long time, but its pattern tends to change and fluctuated recently.

$$\mathrm{ASOC} = \mathrm{average(SOC)}$$

$$\mathrm{MSOC} = \max(\mathrm{SOC})$$

In some cases, the minor fluctuation cannot affect the direction of the continuity. For example, when the slope at a certain inflection point is low, and at the same time, the slope at the next inflection point is also low, the continuity seems so minor even if the increasing pattern is changed to the

Table 3. Definition and explanation of continuity-related index.

Index	Definition	Usage
NOC	Number of AOCs.	Analysing stability in technology convergence
SOC	Length of every AOC.	Analysing continuity of each technology convergence
ASOC	Average of every SOC.	Analysing continuity of each technology convergence
MSOC	Maximum value for all SOCs.	Analysing market & technological event to trigger radical changes at the certain period

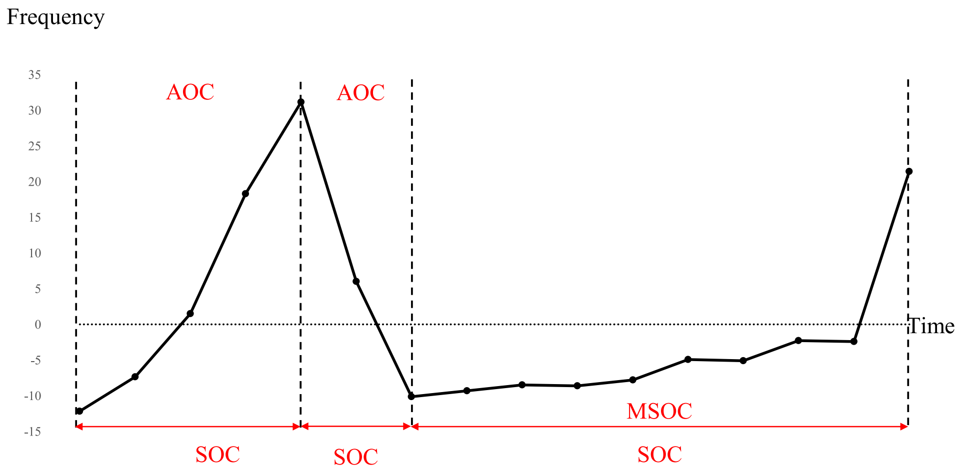


Figure 4. The continuity index

decreasing pattern. Therefore, several options can be used for considering inflection points for calculating continuity-related index.

(1) Considering all inflection points

When considering all inflection points, one can check basic patterns, i.e. whether the increasing pattern of convergence frequency continues for a long time or not. This aims to check all patterns.

(2) Considering inflection points

When one wants to ignore minor fluctuation to calculate the continuity, there are several options to select the inflection points as follows.

- Minor change: When the ratio of slope at the next inflection point compared to the original inflection point is less than 0.1 (Less than 10% increase/decrease)
- Major change: When the ratio of slope at the next inflection point compared to the original inflection point is more than 0.5 (More than 50% increase/decrease)
- Tremendous change: When the ratio of slope at the next inflection point compared to the original inflection point is more than 1 (More than 100% increase/decrease)

4. Case study

To illustrate the working of the proposed approach, a case study was conducted. The target industry is the healthcare industry where a significant number of technologies are aggregated together to provide the desired value for the customers. Since many different technologies are integrated together to provide healthcare services, the healthcare industry is considered to be a good target industry for analysing the convergence dynamics.

4.1. Data collection and preprocessing

To analyse the dynamics of technological convergence in the healthcare industry, patent data is collected from the USPTO website (https://www.uspto.gov/). To collect meaningful patents for healthcare, we used this formula for keyword searching in abstract fields: (Health OR Medical) AND (Information OR Care OR Monitoring OR Apparatus OR Communication OR Service OR System OR Management).

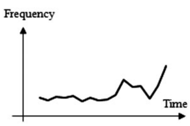
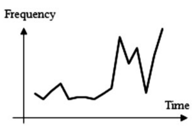
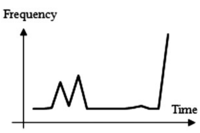
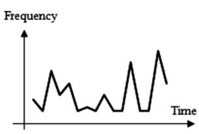
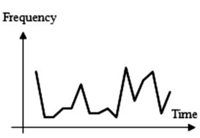
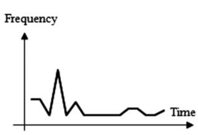
A total of 9594 patents are downloaded from January 2000 to December 2015 for their publication dates, which satisfies the keyword searching condition. After collecting patents, we only extracted patents that contained at least two or more IPCs, which amounted to 4678 patents. For the 4678 patents, we extracted IPC pairs to analyse the convergence phenomenon for each IPC pair. To prepare IPC pairs from multiple IPCs in the original patent documents, function 'combination' is used in R software. As a result, 36,825 IPC pairs were extracted and used for the case study.

4.2. Index-based approach

4.2.1. Trend line fitting

For 36,825 IPC pairs, we fitted the trend line and measured the general patterns and slope of each trend line to characterise the dynamic pattern of industrial convergence, as shown in Table 4. The time unit of dynamic pattern is year.

Table 4. Dynamic patterns of technological convergence for representative IPC pairs.

IPC Pair	Convergence curve	Slope of trend line	Converged technologies	Pattern
G06F-G06Q		3.56	Data processing system	Continuous increase
A61B-G06Q		2.30	Data processing and forecasting systems for medical purposes	Rapid increase
A61B-H04L		0.64	Telemedicine, personalised healthcare system	Rapid increase with exceptional peak
A61K-C12N		0.21	Preparation of health-related chemicals (microorganisms or enzymes)	Continuous increase with exceptional peak
G05B-G06F		0.23	Data processing and control/regulation systems	Continuous increase with exceptional peak
A61L-B05C		-0.68	Technology for sterilising materials	Continuous decrease with exceptional peak

Technologies that show a continuous increase generally emerge from the early 2000s, and the convergence frequency continuously increases until the recent period. These technologies include (1) methods for processing medical records and (2) systems for managing and processing the data. This is quite natural in the current healthcare industry where new technologies accelerate the digitalisation of medical records. The representative IPC pair for this case is G06F-G06 K/G06Q.

Technologies that show a rapid increase tend to have no special changes in the early 2000s, but show a radical increase after 2010, especially in 2014. The representative convergence type is the integration of communication technology and data processing technology, which includes communication of medical records via a wireless communication environment, systems for processing and analysing the medical image records, telemedicine systems, and a personalised health management system. This convergence pattern shows rapid technological improvement due to the growth of big data analytics. The representative IPC pairs are A61B-H04L (telemedicine, personalised healthcare system) and A61B-G06T (medical processing technologies).

Periodical fluctuation with a decrease shows a periodical increase and decrease after the 2000s, but eventually shows decreasing patterns. Technological convergence with this pattern shows relatively small numbers, compared to periodical fluctuation with an increase. This is because both people and firms tend to innovate, and technology tends to grow and improve. The representative IPC pairs for this trend are B05C-B05D (medical coating agent) and G05B-G06F (control for digital data processing).

Continuous decrease (with exceptional peak) is a pattern that shows the decrease of the frequency after the early 2000s, whose IPC pair is A61L-C08G (materials for medication). Finally, the convergence pattern with a rapid decrease is not found in the representative IPC pair with more than 60 frequencies.

4.2.2. Analysis of fluctuation

To analyse fluctuation, NOF, SOF, ASOF, and MSOF were calculated for 36,825 IPC pairs. Table 5 shows the convergence pattern of IPC pairs with the top 10 ASOF values. The pair that fluctuates most is the IPC pair A61B-A61N, which is the medical technology for electrotherapy, magnetotherapy, and radiation. The IPC pairs A61B-A61M, G06F-G06Q, and A61B-G01S also show high fluctuation for their convergence. This means that technologies with body-interpolated medical devices show fluctuated patterns for their convergence occurrence. Please note that the pattern in Table 5 is not the original frequency patterns, but the results of moving trend line into the *x*-axis.

4.2.3. Analysis of continuity

For the continuity-related index, we also conducted a case study. However, when we derive the IPC pairs with the top 10 ASOC value, we find all top 10 IPC pairs show the same ASOC, which is 14 years. Therefore, we analyse the distribution for ASOC, as shown in Table 6. As a result, about 27% of all IPC pairs show seven years of ASOC, and the second largest ASOC is 13 years, which is 22%.

The IPC pairs with the largest ASOC (14 years) comprise 5% of total IPC pairs, whereas the IPC pairs with the smallest ASOC (3 years) account for only 2% of all IPC pairs. (Note that the minimum number of ASOCs is 3, since we believe that there is no continuity when the ASOC is less than 2).

As shown in Table 7, the IPC pairs with the largest ASOC, which means the highest level of continuity of convergence, are A21D-A23L and A61L-C02F. These technologies have been developed continuously, regardless of recent advances in technology-based healthcare services.

5. Discussion

5.1. Summary and implication for case study

We investigate the dynamic convergence pattern using two different types of index: fluctuation index and continuity index. To summarise, the dominant IPC pairs with their graph pattern and fluctuation/

Table 5. Fluctuation-related index for IPC pairs with high ASOF values.

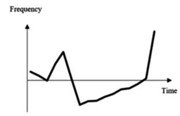
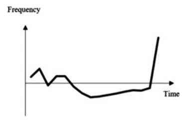
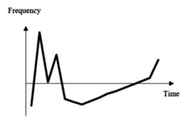
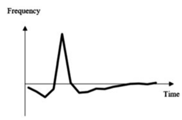
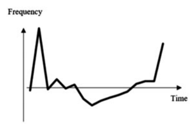
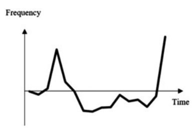
IPC pair	Pattern	NOF	ASOF	MSOF	Name
A61B-A61N		3	78.37	127.89	Medical technology for electrotherapy, magnetotherapy, and radiation
A61B-A61M		6	54.70	98.47	Devices for introducing media into the body
A61B-G01S		4	51.31	102.62	Radio navigation technology for medical purposes
A61L-B05D		7	37.85	164.28	Methods and processes for applying liquid to the body
A61B- A61F		6	29.07	104.11	Chemicals and treatment for body-injection media
A61B-G06F		7	28.89	86.07	Electric digital data processing for diagnosis and surgery
A61N-H01G		4	25.74	67.01	Switching device for electrotherapy, magnetotherapy, and radiation therapy

Table 6. Distribution for ASOC.

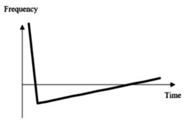
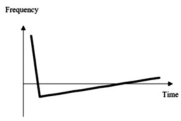
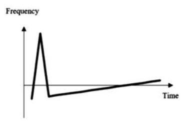
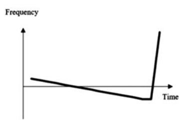
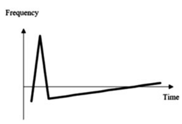
ASOC	3	4	5	6	7	8	9	10	11	12	13	14
Ratio	2%	5%	4%	6%	27%	1%	3%	3%	12%	9%	22%	5%

ASOC: Average size of continuity.

continuity index are listed in Table 8. The convergence of A61B-A61N, A61B-G06F and A61B-A61F show similar patterns, which increase initially and then decrease rapidly, and then continuously increase slowly, and finally show a rapid increasing pattern. This type shows a relatively higher fluctuation index than the other convergence types.

From the perspective of the fluctuation, technologies that are related to treatment and device have experienced relatively high fluctuation. This is in line with practice, where many different types of technologies related to electro- and radiated-devices have been developed so far. From the perspective of the continuity, traditional and casual technologies such as food and beverages

Table 7 Several IPC pairs with the highest ASOC.

IPC pair	Pattern	NOC	ASOC)	MSOC	Technology Definition
A21D-A23L		1	14	14	Food and beverages for physical treatment
A61L-C02F		1	14	14	Sterilising treatment for water
A61M-B32B		1	13	13	Layered Products for medical devices
A61M-F04B		1	13	13	Positive-displacement machines
A61M-B67D		1	13	13	Medical devices for transferring liquids medicines

turned out to be continuously improved. This is the same in technology related to water sterilising technology. However, IT-related convergence such as data transmitting and processing systems shows a low level of continuity, due to its rapid changes and fluctuation over time.

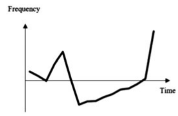
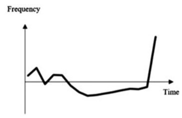
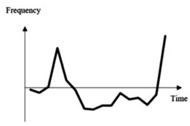
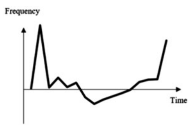
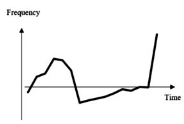
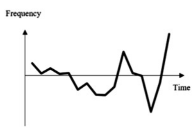
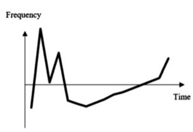
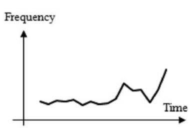
In general, technologies related to data processing for medical records and medical devices have played key roles. It should be noted that political issues including regulations, laws, and even social trends can affect to ICT-related technological convergences. For example, technology related with the transmission of customers' medical record, or technology for telemedicine requires social consensus as well as the legal basis. For this reason, companies that want to develop those technologies have to check the socio-economical and legal backgrounds underlying technology development.

5.2. Integration of two types of indexes

To derive more meaningful implication, we developed an integrated matrix, as shown in Figure 5. To illustrate, we develop a 2 by 2 scatter-plot for technology convergences whose convergence frequency is more than 160, as shown in Figure 6.

(1) **Stable and settled**: The technology convergence can be said to stable and settled when its frequency fluctuation is low but continuity is high. This means technology convergence happens without significant changes. Since less fluctuation happens over time, the dynamic trend of technology convergence is stable and settled. Thus, companies can invest enough R&D budgets continuously for this technology convergence. The representative convergence pairs include A61N-H01G (capacitors for bioelectric medical devices), and A61B-A61F (chemical and treatment for body-injection media) which are actually settled in practice.

Table 8. Dynamic convergence patterns of dominant IPC pairs with fluctuation and continuity index.

Combination	Pattern	Freq.	NOF	ASOF	MSOF	NOC	ASOC	MSOC	Technology definition
A61B-A61N		1538	3	78.37	127.89	1	9	9	Medical technology for electrotherapy, magnetotherapy, and radiation
A61B-A61M		1427	6	54.70	98.47	2	4.5	5	Devices for introducing media into the body
A61B-G06F		668	7	28.89	86.07	2	3.5	4	Electric digital data processing for diagnosis and surgery
A61B-A61F		623	6	29.07	104.11	1	8	8	Chemicals and treatment for body-injection media
A61F-A61L		496	6	19.86	39.77	2	4	5	Chemicals for electrotherapy, magneto therapy, and radiation therapy
A61B-G01S		465	4	51.31	102.62	2	6	9	Radio navigation technology for medical purposes
G06F-G06Q		412	4	51.31	102.62	2	6	9	Data processing and prediction system for medical purpose
A61L-B05D		364	5	16.83	39.92	2	4	5	Chemical aspects of surgical articles

(2) **Leading Fluctuated**: This type of convergence got attention from the market for certain technological issue, and its attention has lasted for a long time. This can happen when there are continuous market needs due to the sound technological background and solid business models. The representative convergence is A61B-A61N (bioelectric/ electro/ magneto/radiation devices for surgical purpose), and G06F-G06Q (Electric digital data processing for medical purpose). Such technology convergences are generally related with ICT technologies.

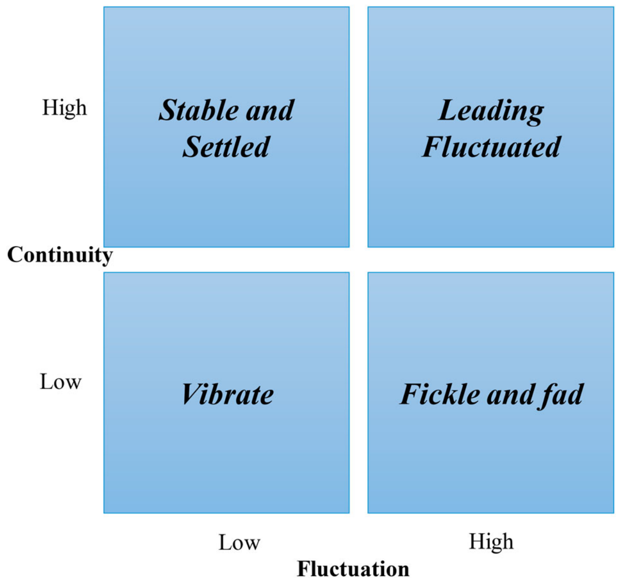


Figure 5. Integrated matrix using fluctuation and continuity.

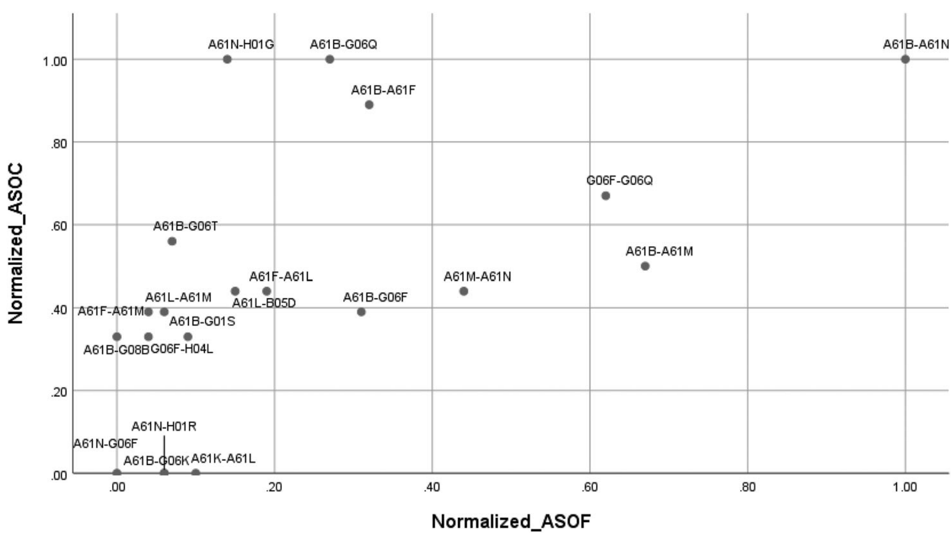
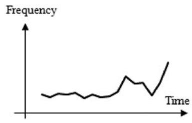
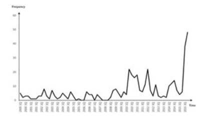
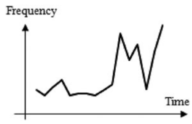
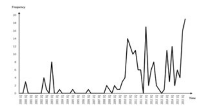
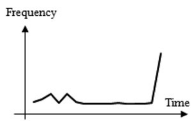
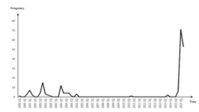


Figure 6. Integrated matrix for representative convergence pairs.

(3) **Vibrate:** This type of convergence shows low fluctuation and low continuity, which means convergence patterns vibrate with minor changes. This can happen in many technological convergences whose main patterns are not determined. The representative examples include A61N-G06F (Data processing from bioelectric medical devices), A61N-H01R (Electrically conductive connections for bioelectric devices (electro/magneto/radiation devices)), and A61B-G06K (Data recognition and representation for medical diagnosis and surgery).

(4) **Fickle and fad:** This type shows high fluctuation but low continuity, thus very fickle. This type of convergence is not stable for its convergence frequency, and the pattern does not last. Since this type is very unstable and has to be convinced from the technological market, continuous R&D

Table 9. Sensitivity analysis according to the different timeframe.

Technology convergence	Timeframe: Year (Current)	Timeframe: Quarter
G06F-G06Q		
A61B-G06Q		
A61B-G06T		

investment should be re-considered. In our healthcare case study, convergence that is classified into fickle and fad is only A61B-A61M (Surgical devices for introducing/transducing media into the body).

5.3. Sensitivity analysis for different timeframe

Currently, our time unit for dynamic analysis is the year. However, dynamic patterns can be different according to the timeframe. If the timeframe of our study is semesters or quarters, the results might be different. Therefore, sensitivity analysis that compares the result according to the timeframe is required. For this reason, we compared the graph of different timeframe in order to check the differences between timeframe. We conducted an experiment for three convergence patterns: G06F-G06Q, A61B-G06Q, and A61B-G06T, as shown in Table 9. The result shows that general patterns are almost same even if the timeframe changes. The graph for year shows similar but more aggregated results compared to the quarter.

However, even our experiment shows similar graph pattern regardless of the timeframe, it does not mean that timeframe is unimportant. What kinds of time unit is the most preferred to analyse the dynamic change is another important future work, since the most preferred time unit can be different according to the technological domains due to the different technology lifecycle and different industry characteristics.

6. Conclusion

This paper suggests a data-driven approach for analysing dynamic patterns of technological convergence using co-classification analysis. Addressing the limitations of previous dynamic analysis, which is generally based on a time slot-based dynamic study, this paper focuses on identifying dynamic trends of individual technologies for certain technology convergence, and analysing the trends of the advances and declines in each technological factor. For this purpose, this paper suggests an index-based approach to characterise the dynamic of technological convergence: fluctuation and continuity.

From an academic perspective, this paper contributes to the field in that it suggests how to analyse the dynamic changes in technological convergence, using IPC-based indexes which illustrate the fluctuation and continuity of technological convergence. Our approach to analyse dynamic technological convergence is index-based approach which is domain-neutral, so it can be applied to many different domains with the current format. In addition, this study can be further applied to analysing and comparing technological convergence in multiple industries. From a practical perspective, this study can help practitioners or managers by providing new indexes for analyse technological convergence. Firms can understand how a certain technological convergence changes, identifying whether the technological convergence is rising or declining, whether the technological convergence is changing or not, and whether the technological convergence can continue stably or not.

Despite the contribution, however, this study is subject to some limitations. First, we only investigate IPC pairs composed of two IPCs. However, it is still true that technological convergence can happen with more than two technologies, so future studies can deal with this problem. Second, more indexes which can indicate variation should be developed. For example, growth rate per period, increasing rate of growth rate, or changes of standard deviation over time can indicate how the convergence patterns change. Third, we applied the simple linear regression for all trend line fitting. However, since the most preferable trend is different according to the technology, different methods can be applied for different kinds of technology. Finally, since our case study is conducted for illustrative purpose, the number of target patents is relatively small. Therefore, future work should include in-depth case study that deals with a large number of patents.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by National Research Foundation of Korea (NRF). Grant funded by the Korea government (MSIP) [grant number NRF-2017R1E1A1A01077324].

Notes on contributors

Junghwan Yun is a data scientist in OP.GG. He received the M.S degree in the Department of Data Science, Seoul National University. His research interests include data mining and big data analytics.

Youngjung Geum is an assistant professor in the Dept. of Industrial and Information Systems Engineering, Seoul National University of Science and Technology. She has authored several papers in leading journals of technology management. Her main research interests include technology planning, product–service integration, and new product/service development.

References

Breschi, S., F. Lissoni, and F. Malerba. 2003. "Knowledge-Relatedness in Firm Technological Diversification." *Research Policy* 32 (1): 69–87.

Caviggioli, F. 2016. "Technology Fusion: Identification and Analysis of the Drivers of Technology Convergence Using Patent Data." *Technovation* 55-56: 22–32.

Curran, C. S., S. Bröring, and J. Leker. 2010. "Anticipating Converging Industries Using Publicly Available Data." *Technological Forecasting and Social Change* 77 (3): 385–395.

Curran, C. S., and J. Leker. 2011. "Patent Indicators for Monitoring Convergence–Examples from NFF and ICT." *Technological Forecasting and Social Change* 78 (2): 256–273.

Geum, Y., C. Kim, S. Lee, and M. S. Kim. 2012. "Technological Convergence of IT and BT: Evidence from Patent Analysis." *ETRI Journal* 34 (3): 439–449.

Hacklin, F., C. Marxt, and F. Fahrni. 2009. "Coevolutionary Cycles of Convergence: An Extrapolation From the ICT Industry." *Technological Forecasting and Social Change* 76 (6): 723–736.

Han, E. J., and S. Y. Sohn. 2016. "Technological Convergence in Standards for Information and Communication Technologies." *Technological Forecasting and Social Change* 106: 1–10.

Jeong, S., J. C. Kim, and J. Y. Choi. 2015. "Technology Convergence: What Developmental Stage Are We In?" *Scientometrics* 104 (3): 841–871.

Jeong, S., and S. Lee. 2015. "What Drives Technology Convergence? Exploring the Influence of Technological and Resource Allocation Contexts." *Journal of Engineering and Technology Management* 36: 78–96.

Karvonen, M., and T. Kässi. 2011. "Patent Citation Analysis as a Tool for Analysing Industry Convergence." In *Technology Management in the Energy Smart World (PICMET), 2011 Proceedings of PICMET'11, Portland, OR, USA*, 1–13. IEEE.

Karvonen, M., and T. Kässi. 2013. "Patent Citations As a Tool for Analysing the Early Stages of Convergence." *Technological Forecasting and Social Change* 80 (6): 1094–1107.

Kim, E., Y. Cho, and W. Kim. 2014. "Dynamic Patterns of Technological Convergence in Printed Electronics Technologies: Patent Citation Network." *Scientometrics* 98 (2): 975–998.

Kim, J., S. Kim, and C. Lee. 2019. "Anticipating Technological Convergence: Link Prediction Using Wikipedia Hyperlinks." *Technovation* 79: 25–34.

Kim, N., H. Lee, W. Kim, H. Lee, and J. H. Suh. 2015. "Dynamic Patterns of Industry Convergence: Evidence from a Large Amount of Unstructured Data." *Research Policy* 44 (9): 1734–1748.

Ko, N., J. Yoon, and W. Seo. 2014. "Analyzing Interdisciplinarity of Technology Fusion Using Knowledge Flows of Patents." *Expert Systems with Applications* 41 (4): 1955–1963.

Lee, W. S., E. J. Han, and S. Y. Sohn. 2015. "Predicting the Pattern of Technology Convergence Using big-Data Technology on Large-Scale Triadic Patents." *Technological Forecasting and Social Change* 100: 317–329.

Lee, C., J. Jeon, and Y. Park. 2011a. "Monitoring Trends of Technological Changes Based on the Dynamic Patent Lattice: A Modified Formal Concept Analysis Approach." *Technological Forecasting and Social Change* 78 (4): 690–702.

Lee, H. J., S. Lee, and B. Yoon. 2011b. "Technology Clustering Based on Evolutionary Patterns: The Case of Information and Communications Technologies." *Technological Forecasting and Social Change* 78 (6): 953–967.

Lim, S., O. Kwon, and D. H. Lee. 2018. "Technology Convergence in the Internet of Things (IoT) Startup Ecosystem: A Network Analysis." *Telematics and Informatics* 35 (7): 1887–1899.

Niemann, H., M. G. Moehrle, and J. Frischkorn. 2017. "Use of a New Patent Text-Mining and Visualization Method for Identifying Patenting Patterns Over Time: Concept, Method and Test Application." *Technological Forecasting and Social Change* 115: 210–220.

Park, H., and J. Yoon. 2014. "Assessing Coreness and Intermediarity of Technology Sectors Using Patent Co-Classification Analysis: The Case of Korean National R&D." *Scientometrics* 98 (2): 853–890.

Pennings, J. M., and P. Puranam. 2001. "Market Convergence & Firm Strategy: New Directions for Theory and Research." In *ECIS Conference, the Future of Innovation Studies*. Eindhoven. 20 (23.09).

Porter, A. L., A. S. Cohen, J. D. Roessner, and M. Perreault. 2007. "Measuring Researcher Interdisciplinarity." *Scientometrics* 72 (1): 117–147.

Porter, A. L., and L. Rafols. 2009. "Is Science Becoming More Interdisciplinary? Measuring and Mapping Six Research Fields Over Time." *Scientometrics* 81 (3): 719–745.

Sick, N., N. Preschitschek, J. Leker, and S. Bröring. 2018. "A New Framework to Assess Industry Convergence in High Technology Environments." *Technovation*. doi:10.1016/j.technovation.2018.08.001.

Song, C. H., J. W. Han, B. Jeong, and J. Yoon. 2017. "Mapping the Patent Landscape in the Field of Personalized Medicine." *Journal of Pharmaceutical Innovation* 12 (3): 238–248.

Tijssen, R. J. 1992. "A Quantitative Assessment of Interdisciplinary Structures in Science and Technology: Co-Classification Analysis of Energy Research." *Research Policy* 21 (1): 27–44.

Xing, W., X. Ye, and L. Kui. 2011. "Measuring Convergence of China's ICT Industry: An Input–Output Analysis." *Telecommunications Policy* 35 (4): 301–313.