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Technological opportunity discovery for technological convergence based on the prediction of technology knowledge flow in a citation network

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ABSTRACT

As technological convergence has recently become a mainstream innovation trend, technological opportunities need to be explored in heterogeneous technology fields. Most of the previous convergence studies have taken a retrospective view in measuring the degree of convergence and monitoring the converging trends. This paper proposes a quantitative future-oriented approach to technological opportunity discovery for convergence using patent information. In a future-oriented approach, technological opportunities for convergence are suggested by predicting potential technological knowledge flows (TKFs) between heterogeneous fields. The potential TKFs are predicted by a link prediction method in a directed network, which is suggested in this paper to represent the direction of the predicted TKFs by adapting the concept of bibliographic coupling and edge-betweenness centrality. Converging technological opportunities are proposed as incremental and radical technological opportunities by extracting the potential increased knowledge flow links and emerging knowledge flow links. Moreover, the direction and themes of the predicted potential TKFs are provided as technological opportunities for convergence. As an illustration of the proposed method, the technological opportunities between biotechnology (BT) and information technology (IT) are explored. Firms and researchers can use the proposed method to seek out new technological opportunities from various technologies so that R&D policymakers can plan new R&D projects on technological convergence.

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1. Introduction

It is critical to monitor technological trends and anticipate the direction of technological change under rapidly changing technological circumstances. Many attempts have been made for technological opportunity discovery (TOD) to identify technological opportunities and threats that could affect future growth and survival because they are considered some of the most crucial issues for companies (Cozzens et al., 2010). The studies on TOD have largely been conducted to anticipate promising technologies that have not yet been developed and to analyze potential new markets that can be created by utilizing existing technologies (Cho, Yoon, Coh, & Lee, 2016).

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Expert-based qualitative TOD approaches such as Delphi, questionnaire survey analysis, and TRIZ (Teoriya Resheniya Izobretatelskih Zadach) have the advantage of easy validation and the disadvantage of expensive costs and of being time-consuming. Quantitative approaches such as computer-based methods and bibliometric analysis can play a complementary role to the disadvantage of the qualitative approaches and propose objective results based on a large volume of data. As massive technological data have been accumulated and analytic techniques have advanced, it is possible to identify technological opportunities using a quantitative approach.

Patent analysis has been employed as a representative quantitative approach for TOD, and additional quantitative analytic techniques such as morphology analysis, text mining, network analysis, and novelty detection have been combined with patent analysis for TOD (Geum, Jeon, & Seol 2013; Lee, Kang, & Shin, 2015). The TOD studies based on patent analysis in the initial stage have focused on anticipating newly emerging technological opportunities. Recently, a few attempts have been made to identify technological opportunities via technological convergence (An, Kim, Mortara, & Lee, 2018). Thus, TOD research has been extended from technological opportunities in a specific technology area to those merged with heterogeneous technology fields, which are different from the existing technology domain.

Technological convergence is also a critical issue because it can be a technological breakthrough. Many quantitative approaches have been taken to tackle technology convergence using patent analysis. From the perspective of combining the research themes of TOD and technological convergence, the previous quantitative technological convergence studies have some limitations. First, most of the previous studies on technological convergence using patent analysis have analyzed patent data with a retrospective view by measuring the degree of convergence (Geum, Kim, Lee, & Kim, 2012; Takano, Mejia, & Kajikawa, 2016). However, it is necessary to identify technological opportunities for convergence in terms of technology planning for the future. This paper suggests a prospective TOD approach for technological convergence to overcome the limitation. Second, many convergence studies investigate industry- and macro-level technology fusion (Curran & Leker, 2011). It is insufficient to utilize the results at the stage of converging technology development because those studies analyze technological convergence at a high level. Third, from a methodological point of view, patent co-classification has been largely utilized to measure the degree of technological or industrial convergence in the previous convergence studies because patent classification is suitable to represent technologies as a proxy and to measure the overlap between technologies (Bongioanni, Daraio, & Ruocco, 2014). Although patent classification enables the monitoring status of convergence, it is difficult to suggest practical information in terms of a future-oriented perspective for converging technology development.

To overcome the aforementioned limitations, a concept of technological knowledge flows (TKFs) can be utilized because technological opportunities can be diversified by using the TKFs from the heterogeneous technology fields to detect signals of technological convergence for the future (Caviggioli, 2016). Patent co-classification analysis has been utilized in most of the previous convergence studies, whereas patent citation analysis can be utilized because the citation information on patents or scientific papers has been considered a reliable proxy for TKF (Jaffe, Trajtenberg, & Henderson, 1993). In addition, to emphasize the future-oriented view based on the TKF approach, link prediction, which is a technique used to detect missing links in the current networks and to predict new links in future networks, is utilized to identify technological opportunities for convergence.

This research contributes to existing literature in several ways by filling the research gap and overcoming previous studies' limitations. First, a TOD framework for converging technology opportunities is suggested as an extension of existing TOD studies. Second, a future-oriented TOD approach is proposed by overcoming the retrospective view. Third, technological opportunities are suggested at a micro level by subgrouping potential TKFs and suggesting promising technological themes. Finally, a link prediction method is utilized to identify technological opportunities to overcome the methodological limitation.

This paper aims to identify technological opportunities for convergence by predicting potential TKFs between heterogeneous fields using quantitative data analysis. Three research questions are suggested in the present study. First, what are the potential technological opportunities for convergence? Second, what are the characteristics of the predicted technological convergence areas? Third, what are the possible technological themes for technological convergence? To solve the research questions, a new approach to exploring the TOD for technological convergence is proposed by means of link prediction in patent-citation networks and TKF networks, as well as by investigation of knowledge flow properties and technological knowledge themes. In addition, technological opportunities for convergence are discussed with the direction and strength of the predicted potential TKFs.

2. Background

2.1. Patentometric analysis for technology opportunity discovery (TOD)

Technological opportunity is defined as the potential or possibility for technological progress in a general or particular field (Yang, Huang, & Su, 2018). Similar terms, such as technology intelligence (TI) and TOD, have been used to identify technological opportunities. Cho et al. (2016) elucidated the concept of TOD with TI, which was suggested by Kerr, Mortara, Phaal, and Probert (2006), in two perspectives: objects and activity. Although TI focuses on opportunities and threats in the perspective of objects and is interested in information management and an analysis process in the view of activity, TOD concentrates on opportunities and the strategic use of information in terms of objects and activity. In this paper, we used the concept of TOD to identify technological opportunities because we deal with future-oriented opportunities and the strategic use of technological information.
Although technological opportunity is generally discovered through qualitative approaches such as Delphi and scouting (Rohrbeck, Heuer, & Arnold, 2006), Porter and Detampel (1995) suggested technology opportunities analysis (TOA) as a start toward the quantitative TOD approach that identifies technological trends through bibliometric analysis and measurement of technological literature such as patents and publications. As data analytic techniques have advanced, technology opportunities have been identified mainly using patent information through many quantitative techniques such as keyword-based patent maps (Lee, Yoon, & Park, 2009; Yoon, Yoon, & Park, 2002), keyword-based morphology analysis (Yoon & Park, 2005), and novelty detection technique (Geum et al., 2013). The TOD studies initially focused on identifying the technological opportunity itself.

In previous TOD studies using patentometric analysis, technological opportunities are proposed as the patent vacancy in the patent map, the outlier patent, and the recombination of technological functions. First, the vacant area was suggested as technological opportunities by developing the patent map based on textual information using data mining techniques such as the self-organizing feature map (SOFM) (Yoon et al., 2002), principle component analysis (PCA) (Lee, Yoon et al., 2009), and generative topology mapping (GTM) (Son, Suh, Jeon, & Park, 2012). The vacant area in the patent map was proposed as technological opportunities because it indicated the area that is not yet developed when the patent information is visualized as a map. Second, outlier patents that were distinctive from existing technology were proposed using the outlier detection technique (Geum et al., 2013; Lee, Kang et al., 2015; Yoon et al., 2015), which can suggest more explicit potential technological opportunities by identifying a novel patent that is new and distinct from the existing technology rather than identifying a patent vacancy representing a set of keywords. Third, the recombination of technological functions was proposed as a technological opportunity by using keyword-based morphology analysis (Yoon & Park, 2005; Yoon, Park, & Coh, 2014) and the function-based TOD approach using the subject-action-object (SAO) structure (Yoon et al., 2015). This approach is based on the assumption that new knowledge or invention is the result of the recombination of the known components of knowledge (Abaronson & Schilling, 2016; Fleming, 2001; Funk & Owen-Smith, 2016; Notten, Mairesse, & Verspagen, 2017).

As TOD-relevant studies have progressed, the coverage of research on TOD has been extended by identifying potential opportunities from the convergence of various technological areas. Although existing studies have proposed the TOD methods for convergence based on patent citation analysis, they offered insufficient implications because they suggested patent pairs as potential technological opportunities. The coverage of recent TOD studies tends to be extended by identifying technological opportunities from external areas. This paper concentrates on the new subject by meeting the recently required TOD research trend, in that it proposes a TOD approach for technological convergence on the basis of TKF from the future-oriented perspective.

2.2. Technological convergence

The concept of technological convergence was first introduced by Rosenberg (1963) as a process commonly used by unrelated industry sectors and in various stages of tool production. Kodama (1986) used the term “technology fusion” to represent a type of breakthrough innovation created by merging more than two existing technologies as a similar concept. Although they have been used interchangeably in some cases to refer to a blurring of boundaries between more than two different areas, Curran and Leker (2011) differentiated between them in terms of loci where convergence and fusion take place. In this research, we conducted a literature survey on both as technological convergence research.

The evolutionary stages of the convergence phenomenon are defined as knowledge (or scientific disciplines), technological, application (or market), and industrial convergence (Curran, Bröning, & Leker, 2010). Research on the convergence of scientific disciplines has investigated the discovery of new knowledge through the exchange of knowledge. In this process, bibliometric analysis, such as co-word, co-citation, co-authorship, and journal subject category co-classification analysis, has been widely conducted using scientific article data (Leydesdorff, 2007; Porter & Rafols, 2009; Porter, Cohen, Roessner, & Perreault, 2007; Schummer, 2004; Sun, Ding, & Lin, 2016; Zhang, Zhang, Zhu, & Lu, 2017; Zitt, Ramanana-Rahary, & Bassecouard, 2005). Research on market-level convergence has analyzed product specifications using press release data (Lee, Lee, & Cho, 2009; Han, Chung, & Sohn, 2009). In this research, we focused on technological and industrial convergence using patent data. Research on the convergence of technology at the industry level used patent data because patents are considered an indicator of technological innovation (Curran & Leker, 2011; Lee, 2007). In particular, the research on industry convergence analyzes industry-patent concordance information, such as standard industry classification (SIC) and international patent classification (IPC) concordance (Curran et al., 2010), to link technology information to industry information.

Most of the previous studies on technological convergence using patent data have concentrated on measuring the degree of convergence or monitoring technological change. From a patent indicator perspective, most of the studies developed patent indicators based on a patent classification system to measure the degree of convergence and to monitor the phenomenon of technological convergence. Trajectory patterns of technology fusion were identified by measuring fusion degree indicators based on the citing-cited relationship between patent classification codes (No & Park, 2010). A fusion index (FI), which represented the degree of fusion, was identified to predict promising fusion technologies (Lee & Yoo, 2014). Furthermore, indicators for identifying technological convergence were suggested based on the IPC-level network using the concept of entropy and gravity (Han & Sohn, 2016). From the patent-citation analysis perspective, a few studies measured technological convergence and monitored the trends of convergence from knowledge flow based on patent citation with patent classification. Geum et al. (2012) measured convergence intensity and coverage by means of patent citation and
co-classification analysis. Ko, Yoon, and Seo (2014) analyzed the trends of industry-wide technology fusion by constructing a knowledge-flow matrix using the citation analysis between IPCs. Moreover, as a semantic analysis perspective, Moehrlie and Passing (2016) suggested the possibility of convergence by applying an anchor-based patent mapping approach based on the semantic similarity. Most of the previous research on technological convergence has utilized patent classification because it is appropriate to represent the technological area and to measure the overlap between technologies.

Although many previous studies on technological convergence have focused on analyzing the phenomena using a retrospective perspective, some researchers have attempted to identify technological convergence using a future-oriented perspective (Kim & Lee, 2017; Lee, Han, & Sohn, 2015; Song, Elvers, & Leker, 2017). Lee, Han et al. (2015) predicted the pattern of technological convergence by applying both an association rule and link prediction based on IPC co-occurrence. Song et al. (2017) and Kim and Lee (2017) anticipated technological convergence using the concept of TKF based on patent classification and patent citation, respectively. Patent citation analysis has been utilized in many studies on TKF diffusion and transfer (A.J. Nelson, 2009; R.R. Nelson, 2009; Park & Suh, 2013), technological trajectories and technological frontiers (Mina, Ramlogan, Tampubolon, & Metcalfe, 2007; Wong & Wang, 2015), technological knowledge domain (Weng & Daim, 2012), and so on.

2.3. Link prediction

Link prediction is utilized to identify a potential link in a TKF network based on patent citation information because this research aims to anticipate the future converging technological opportunity. Link prediction is a technique to detect missing links in current networks and to predict new links in future networks. Many algorithms are introduced to solve the link prediction problems from diverse types of networks (heterogeneous and bipartite) and links (multi-relational, active/inactive, and appearing/disappearing). It is categorized into (1) node-based metrics, (2) topology-based metrics, (3) social-theory-based metrics, and (4) learning-based methods (Wang, Xu, Wu, & Zhou, 2015). Below is a summary of a comprehensive review of the state-of-the-art link prediction in social networks by Wang et al. (2015). First, node-based link prediction metrics mainly calculate the similarities between node pairs by using attributes and actions that reflect node attributes and actions. Second, topology-based link prediction metrics are based on the topological information. Many topology-based metrics were proposed after Liben-Nowell and Kleinberg (2007) discussed several metrics based on structural graph features. The topology-based metrics can be divided into neighbor-, path-, and random-based metrics. Third, social theory-based metrics employ classical social theories, such as community, triadic closure, strong and weak ties, homophily, and structural balance. Finally, learning-based methods, as proposed in recent works, differ from the previous approaches by using link prediction metrics, internal attributes, and external information. These are divided into feature-based classification, probabilistic graph models, and matrix factorization. For more information on link prediction, several excellent survey papers used diverse perspectives (Liben-Nowell & Kleinberg, 2007; Wang et al., 2015).

Link prediction has been used for various applications within business areas, including recommendation systems to search for potential collaborators (Mori, Kajikawa, Kashima, & Sakata, 2012), patent partners in enterprise social networks (Wu, Sun, & Tang, 2013), and interesting items in online shopping (Ákkora, Carminati, & Ferrari, 2011). In academic social networks, a co-author relationship prediction is proposed in the heterogeneous bibliographic network in Sun, Barber, Gupta, Aggarwal, and Han (2011). In terms of technology forecasting, Lee, Han et al. (2015) proposed technological convergence pattern prediction using IPC. In this research, link prediction is used to predict TKFs between heterogeneous technology fields. The predicted TKFs between the fields can suggest the potential of technological convergence with strength and direction.

3. Research framework

3.1. Research concept and overall process

This research proposes a systematic method to investigate the current TKF between heterogeneous fields by using patent analysis and to identify technological opportunities for convergence by predicting the potential TKF. To this end, first, patent-level networks based on patent-citation relationships are generated by network analysis, which is widely used to comprehend knowledge flow. Two types of patent citation networks, patent citation networks, and potential patent citation networks are constructed. The patent citation network represents the current citation relationship, and the potential patent-citation network expresses the potential link between patents that do not have any citation relationship. The potential patent-citation network is generated by a link-prediction technique that predicts new links in future networks. In this paper, a link-prediction method based on edge-betweenness centrality is proposed to reflect the context of convergence and TKF between heterogeneous fields. Second, technology-level networks, TKF networks, and potential TKF networks are visualized by merging patents in the same technology group in the patent citation network. The types of change in TKF are identified based on the comparison of TKF networks and potential TKF networks. Third, a TKF property map is generated through the use of patent indicators that measure the property of TKF. The TKF property map represents the position of technology based on the property of knowledge flow and the direction of the predicted knowledge flow. Technological opportunities for convergence are identified by a comprehensive approach based on the types of change in TKF and the trends of the predicted TKF. Additionally, the themes of technological opportunities are suggested as a micro-level approach.
As shown in Fig. 1, our proposed approach consists of four steps: data collection and preprocessing, construction of TKF network, construction of potential TKF network, and TOD for convergence. The first step is to collect patent data and preprocess the data for analysis. The second step is to generate a patent-citation network, which is then merged into the TKF network. The third step is to predict the potential patent citation. In this step, the proposed edge-betweenness centrality-based link-prediction method is used. Thus, the potential patent-citation network and potential TKF network are generated by merging information on patent-level citations and the results of link prediction, and then the type of change in TKF is identified. Finally, in the fourth step, technological opportunities for convergence are identified by reflecting the knowledge-flow property of technology and the change in knowledge flow and by suggesting themes of technological opportunities for convergence. In the following section, the detailed procedures of step 3 and step 4 are explained as a proposed approach for the present research.

3.2. Edge-betweenness centrality-based link prediction

The potential TKF is predicted by link prediction from TKF based on the current citation relationships in the patent-citation network in step 3 of Fig. 1. In other words, the link prediction detects missing links that are likely to have citation relationships between patents even though patent citation actually does not occur. In the present study, a link-prediction method to anticipate knowledge flow between target technologies and heterogeneous technologies, which are different from the target technology, is proposed considering the context of technological convergence.

Most of the studies on link prediction methods have been focused on undirected networks (Yu & Wang, 2014). To solve this problem, Schall (2014) suggested a link-prediction method in a directed graph based on the probability that a given type of triad pattern will be closed. Jawed, Kaya, and Alhajj (2015) also proposed a time frame-based link prediction using the triad pattern. The link-prediction approach using a triad pattern is not appropriate for patent-citation networks, in that a citation cannot occur mutually between patents. That is, the patent citation network is a directed network because of the acyclic characteristic of patent citation (a patent never cites later patents). Yu and Wang (2014) proposed a different
approach for link prediction in directed networks by identifying three types of similar and candidate nodes for target nodes. In this research, the link-prediction technique suggested by Yu and Wang (2014) is adopted and revised to reflect the context of technological convergence opportunities.

Although the strength of the link is important in the patent citation network in terms of TF-IDF, many previous link prediction approaches have not focused on the strength of links but on the node-based metrics. In this research, the proposed method is to predict potential links using edge-betweenness centrality, as suggested by Girvan and Newman (2002). The concept of edge-betweenness centrality is adopted from the vertex-betweenness centrality proposed by Freeman (1977). The vertex-betweenness centrality of node i, which is the number of shortest paths between pairs of other vertices that run through node i, measures the influence of a node over the flow of information between other nodes. The edge-betweenness centrality of an edge is defined as the number of shortest paths between pairs of vertices that run alongside it. The edge with a high betweenness centrality value can be interpreted as a bridge connecting different communities. Although Liu, Hu, Haddadi, and Tian (2013) proposed a link-prediction model based on node centrality, it gave weight based on the node centrality of common neighbors. The proposed link-prediction method gives weight based on edge-betweenness centrality because the links with a high edge-betweenness centrality value can be considered important links connecting heterogeneous fields in terms of TF-IDF.

The concept of the proposed link-prediction method is shown in Fig. 2. The concept of similar and candidate nodes for target nodes from Yu and Wang (2014) is adopted, but with a difference in the method for selecting nodes. A directly linked node (called a 1-hop-out neighborhood) and an indirectly linked node (called a 2-hop-out neighborhood), among three types of similar nodes, as suggested by Yu and Wang (2014), are not considered similar nodes in this study because technological knowledge is transferred and accumulated by patent citation. In this research, bibliographic-coupled patents in heterogeneous technologies are considered similar nodes for target nodes in ways that Yu and Wang (2014) considered to be sharing nodes as a third type of similar nodes. After searching for similar nodes in different technology fields for a target node, the list of candidate nodes is identified based on the concept of edge-betweenness centrality in networks.

The proposed method consists of three steps: (1) locating similar nodes of a target node, (2) identifying candidate nodes, and (3) ranking candidate nodes. First of all, the nodes similar to target nodes are defined as bibliographic-coupled nodes, which are greater than a cut-off value, in a technology that is different from the target node’s.

\[
S(u) = \{ v \in V \mid B(u,v) > B_{\text{cut-off value}}(u,v), \text{Tech}(u) \neq \text{Tech}(v) \} .
\]  

(1)

A directed link, \( u \rightarrow v \), \( E \) exists between nodes \( u \) and \( v \) if \( u \) links to \( v \). According to Eq. (1), \( S(u) \) is a similar node to the target node \( u \). \( B(u,v) \) is a normalized bibliographic-coupling strength. \( B_{\text{cut-off value}}(u,v) \) is the cut-off value for the selection of a similar node. \( \text{Tech}(u) \) or \( \text{Tech}(v) \) is the technology field to which patent node \( u \) or \( v \) belongs. The bibliographic-coupling strength is defined as the number of common references, and the normalized bibliographic-coupling strength, which is shown by Glänzel and Czerwon (1995), is defined as the following:

\[
NBC_{uv} = \frac{n_{uv}}{\sqrt{n_u n_v}}
\]  

(2)

where \( NBC_{uv} \) is the normalized bibliographic-coupling strength between patent nodes \( u \) and \( v \), \( r_{uv} \) is the number of common references between patents \( u \) and \( v \), and \( n_u \) or \( n_v \) is the number of references in the reference list of patent \( u \) or \( v \).

Second, after selecting the list of similar nodes \( S(u) \) for target nodes \( u \), a list of candidate nodes \( C(u) \) is identified. It is assumed that a target node may link to nodes that its similar nodes also link to.

\[
C(u) = \bigcup_{v \in S(u)} \Gamma_{\text{out}}(v) - \Gamma_{\text{out}}(u).
\]  

(3)
Table 1
Type of Change in technology knowledge flow.

| Type of change | Type of Link in TKF network | Change of TKF in potential TKF network |
|----------------|------------------------------|---------------------------------------|
| Increased      | Unidirectional link (ex. A → B) | Identical-directional (ex. A → B) |
|                | Bidirectional link (ex. A → B)      | Unidirectional                        |
|                |                                | Bidirectional                         |
| Emerging       | Unidirectional link (ex. A → B)      | Different-unidirectional (ex. A → B) |
|                | Non-existence                   | Unidirectional                        |
|                |                                | Bidirectional                         |

According to Eq. (3), the set of out neighbors of node u is \( \Gamma_{\text{out}}(u) = \{ v \in V(\{u, v\} \in E) \} \). Similarly, \( \Gamma_{\text{out}}(v) \) is the set of out neighbors of node v.

Third, candidate nodes are ranked by scores composed of weight \( w(u, c, s) \) and edge-betweenness centrality \( EB(e_{sc}) \), which is the concept suggested by Girvan and Newman (2002):

\[
\text{Score}(u, c) = \sum_{s \in S(u)} w(u, c, s) EB(e_{sc}). \tag{4}
\]

According to Eq. (4), \( \text{Score}(u, c) \) is the score that links target node u to candidate node c reflecting weight \( w(u, c, s) \) and edge-betweenness centrality \( EB(e_{sc}) \). \( w(u, c, s) \) and \( EB(e_{sc}) \) are the weight scores that link target node u to candidate node c through similar node s, and \( EB(e_{sc}) \) is an edge-betweenness centrality that links similar node s to candidate node c. As shown in Eq. (5), weight score \( w(u, c, s) \) is calculated by the score of a similar node \( s \in S(u) \) for each candidate \( c \in C(u) \), if s follows c:

\[
w(u, c, s) = \begin{cases} 1 & c \in (C(u) \cap \Gamma_{\text{out}}(s)) \wedge s \in S(u) \\ 0 & \text{otherwise} \end{cases} \tag{5}
\]

\[
EB(e_{sc}) = \sum_{i \neq j} \sum_{v_i} \left( \frac{\sigma_{v_i v_j}(e_{sc})}{\sigma_{v_i v_j}} \right) \tag{6}
\]

According to Eq. (6), \( \sigma_{v_i v_j} \) is the number of shortest paths between vertices \( v_i \) and \( v_j \), and \( \sigma_{v_i v_j}(e_{sc}) \) is the number of shortest paths between vertices \( v_i \) and \( v_j \) that run through the edge between vertices \( s \) and \( c \).

For example, patent u2 in Fig. 2, which belongs to technology B, is selected as a similar node to target patent u1, which belongs to technology A because both patents are bibliographically coupled and have a normalized bibliographic-coupling strength of 2/3 when the cut-off value is 1/3 and belong to heterogeneous technology fields. The candidate nodes are identified as u3, u4, and u5 because the similar node, u2, is connected to those nodes in the patent-citation network. Finally, the candidate nodes u3 and u4 are predicted to link to target node u1 even though u1 belongs to technology A, whereas u3 and u5 belong to Technologies B and C, respectively, after the candidate nodes are ranked using a score based on edge-betweenness centrality when using an appropriate cut-off value.
Based on the patent-citation relationship, a potential patent-citation link is predicted by the proposed link-prediction method, which is described above in detail. Potential patent-citation links are derived as a potential patent-citation network through link prediction based on the bibliographic coupling relationship and edge-betweenness centrality. Then the potential TKF networks are visualized by integrating the patent nodes by technology level. The predicted link indicates the direction of the potential patent citation and the linked patent information that is positioned in a different technology field. Thus, the purpose of step 3 is to recommend the patents that might be cited and that are positioned in heterogeneous technology fields by using a systematic link prediction method.

3.3. Technology opportunities discovery (TOD) for convergence

The change in direction and strength of the predicted links is categorized in Table 1 through comparison of the TKF network and potential TKF network. The TKFs increase when the predicted links are added from the TKF network to the potential TKF network; otherwise, those newly predicted links emerge from the TKF network. Two types of links can exist as unidirectional and bidirectional links; otherwise, the link does not exist in the TKF network.

In terms of increased change, first, TKF can increase in an identical-directional way when unidirectional links exist between technologies in the TKF network and when the identical-directional links are predicted in the potential TKF network. For example, patent-citation links are predicted from technology A to B in the potential TKF network when patent citation occurred from technology A to B, and then the knowledge flow increased identical-directionally. Second, the TKF can increase unidirectionally when bidirectional links exist between technologies in the TKF network and the links are only predicted to be one-way in the potential TKF network. For example, patent-citation links are predicted only from technology A to B in the potential TKF network when patent citation occurred from technology A to B and vice versa; then the knowledge flow is unidirectionally increased. Third, TKF can become bidirectional when bidirectional links exist between technologies in the TKF network and the links are predicted to be two-way in the potential TKF network. For example, patent-citation links are predicted from technology A to B and vice versa in the potential TKF network when patent citation occurred from technology A to B and vice versa; then the knowledge flow became bidirectional.

From the perspective of emerging change, first, TKF can emerge as different-directional when unidirectional links exist between technologies in the TKF network and the different-unidirectional links are predicted in the potential TKF network. For example, patent-citation links are predicted from technology B to A in the potential TKF network when patent citation occurred from technology A to B; then the knowledge flow emerges different-directionally. Second, TKF can emerge as unidirectional when the link does not exist between technologies in the TKF network and the unidirectional links are predicted in the potential TKF network. For example, patent-citation links are predicted from technology A to B in the potential TKF network when patent citation did not occur between technologies A and B; then the knowledge flow emerges unidirectionally. Third, TKF can emerge as bidirectional when the link does not exist between technologies in the TKF network and the bidirectional links are predicted in the potential TKF network. For example, patent-citation links are predicted from technology A to B and vice versa in the potential TKF network when patent citation did not occur between technologies A and B; then the knowledge flow emerged bidirectionally.

The TKF property is determined whether the technology is mainly absorptive or diffusive between heterogeneous technologies by using a patent classification code, which is assigned to patents in focal technologies. Degree centrality and the ratio of patent classification in technology are used to measure the TKF property as Eqs. (7) and (8). To this end, a citation network whose node is a patent classification is generated when the patents whose citations occur between heterogeneous fields are used. The inflow and outflow properties are defined as the following:

\[ P_{IF,t} = \sum_{i} IF_i R_{i,t} \]  \hspace{1cm} (7)

\[ P_{OF,t} = \sum_{i} OF_i R_{i,t} \]  \hspace{1cm} (8)

where \( P_{IF,t} \) and \( P_{OF,t} \) are the inflow and outflow properties for technology \( t \), respectively; \( IF_i \) and \( OF_i \) are the inflow and outflow properties for patent classification \( i \) by using in-degree centrality and out-degree centrality, respectively; and \( R_{i,t} \) is the ratio for patent classification \( i \) in technology \( t \).

The in-degree and out-degree centrality are measured as follows (Freeman, 1978):

\[ IF_i = \sum_{i=1}^{N} C_{ij} \]  \hspace{1cm} (9)

\[ OF_i = \sum_{j=1}^{N} C_{ij} \]  \hspace{1cm} (10)

where \( IF_i \) and \( OF_i \) are the in-degree and out-degree centrality for patent classification \( i \) respectively; \( C_{ij} \) represents the relation from patent class \( i \) to \( j \) in the network.
The technologies are mapped in the TKF property map with the x-axis representing the inflow property and the y-axis the outflow property, as shown in Fig. 3. The TKF property is categorized into the technology knowledge absorption and diffusion active group (A&D), TKF absorption-oriented group (AO), TKF diffusion-oriented group (DO), TKF absorption and diffusion neutral group (A&DN), and TKF absorption and diffusion passive group (A&DP), using proper cut-off values. The TKF property map shows the position of technology property and the direction and type of change (increased or emerging) for predicted knowledge flows. The position can indicate which technologies are active, passive, or biased between the heterogeneous fields in terms of TKF absorption and diffusion. In the context of convergence, the TKF property (absorption or diffusion) represents which technologies already technologically converged between two fields in the status quo, in that technology convergence may come from technological interaction. Technologies in the TKF A&D (or A&DP) group have actively (or passively) interacted with each other between the heterogeneous fields, because the technologies in the A&D (or A&DP) group have both high (or low) in- and out-flow property values. Technologies in TKF AO (or DO) that have a high (or low) inflow but low (or high) outflow property value serve as knowledge absorbers (or diffusers), largely in terms of the TKF bias between the fields in the current situation. Technologies in TKF A&DN that have a middle inflow and outflow property value or have a middle inflow (or outflow) but a low outflow (or inflow) property value interacted neutrally with each other between the fields. The predicted TKFs that are represented as dashed and solid lines show the directions of the potential TKFs in the future. The increased knowledge flows are considered incremental converging technology opportunities, and the emerging knowledge flows are considered radical converging technology opportunities. In the context of convergence, the predicted TKF is able to suggest which technologies have the potential to converge with each other with in terms of direction, strength, and type. Technological opportunities for convergence are identified by suggesting technological themes for predicted knowledge flows.

4. Illustration: predicting technology opportunities for convergence between BT and IT

Many studies have conducted exemplary case studies on the convergence between BT and IT because IT provides tools and platforms for the investigation and transformation of biological systems (Geum et al., 2012). To illustrate the proposed approach, we also conducted a case study of BT-IT convergence and adopted the technology field classification of BT and IT proposed by Geum et al. (2012), which measured the convergence of BT and IT at the technology level because the classification was the accumulated results based on the technology classification of research in IT (Lee, Kim, & Park, 2009) and in BT (No & Park, 2010), and it was derived systematically using information such as the US patent classification (USPC) and USPC to IPC concordance. The technology fields BT and IT were split, as shown in Table 2, into 8 BT-related technologies and 9 IT-related technologies.

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1 We used the terms “incremental” and “radical” converging technological opportunities adapted from the concept of incremental and radical innovation. Incremental innovation provides the present technical potential and has smaller changes in the existing products, whereas radical innovation possesses the characteristics of unprecedented performance and brings new market opportunities (Dewar & Dutton, 1986; R.R. Nelson, 2009).

2 Geum et al. (2013) firstly categorized US patent classification (USPC) classes related to IT and BT. Then they combined 27 USPC classes of BT-related patents into 8 BT technology categories and 33 classes of IT-related patents into 9 IT technology categories, as shown in Table 2.
Table 2
Data collection.

| Technology Sector | Technology field                  | Patent # |
|-------------------|-----------------------------------|----------|
| BT                | 1. Nano technology (NNT)          | 4,310    |
|                   | 2. Biomedical devices (BMD)       | 7,545    |
|                   | 3. Molecular bioengineering (MBE)| 70,672   |
|                   | 4. Organic compound (ORC)         | 19,390   |
|                   | 5. Surgery (SGY)                  | 10,903   |
|                   | 6. Biomedical imaging and processing (BIP) | 11,134 |
|                   | 7. Healthcare technology (HITE)   | 7,696    |
|                   | 8. Chemical processing (CHP)      | 29,854   |
| IT                | 9. Mobile telecommunications, telematics (MOT) | 16,595 |
|                   | 10. Broadband, home network (NET) | 52,045   |
|                   | 11. Signal processing (SIG)       | 54,159   |
|                   | 12. Electrical computing (ELC)    | 66,101   |
|                   | 13. Intelligent robot (ROB)       | 1,444    |
|                   | 14. Radio frequency identification, ubiquitous sensor network (RFID) | 3,288 |
|                   | 15. Information technology system on chip, united parts (SOC) | 23,753 |
|                   | 16. Embedded software (ESW)       | 1,743    |
|                   | 17. Digital contents, software solutions (SOL) | 33,573 |
| Total             |                                   | 414,205  |

**Fig. 4.** Patent citation and technology knowledge flow network.

4.1. Step 1: data collection and preprocessing

The granted patent data that were registered between January 2006 and December 2015 were collected from the USPTO online database, as shown in Table 2, using searching queries combining relevant USPCs by technology field, as proposed by Geum et al. (2012), and keywords in abstracts that represent the technology's title. The collected granted patent data from 2006 to 2012 were used for the proposed approach, and the data registered between 2013 and 2015 were used to validate the proposed method. The 414,205 collected patents, registered between 2006 and 2012, among 664,367 patents registered between 2006 and 2015, were preprocessed by removing noisy and duplicated data in multiple technological fields. The data were transformed to the cited-citing format, with the patent number, assigned focal technology, registration year, and patent classification code for further steps.

4.2. Step 2: construction of technology knowledge flow network

The patent-citation network was generated based on the 1,439,432 cited-citing pairs, as shown (a) in Fig. 4, using NodeXL, a free and open-source network analysis and visualization software package. The TKF network was developed, as shown (b) in Fig. 4, by merging patents in the same technology group in (a) in Fig. 4. The TKF network still shows a complex relationship between technologies, and the widths of the links in the network indicate the number of citations between technologies. The TKF between technologies in homogeneous technology sectors (i.e., IT to IT or BT to BT) account for approximately 66% (951,713 patent-citation pairs), and the TKF between technologies in heterogeneous technology sectors (i.e., IT to BT or BT to IT) account for approximately 34% (487,719 patent-citation pairs). In this research, we focused on the TKF between BT and IT because the purpose of the research is to identify technological opportunities for convergence.

4.3. Step 3: construction of potential knowledge flow network

The potential patent-citation network was developed through link prediction, and the potential TKF networks were visualized by merging the patent nodes by technology level, as shown in Fig. 5, after conducting link prediction and selecting
cut-off value for the TKF network. The black solid line and gray dashed line in the potential TKF network in Fig. 5 denote emerging links and increased links in comparison with the TKF network. To conduct the proposed link prediction, cut-off values for bibliographic-coupling strength and edge-betweenness centrality should be selected. The distribution of the respective value on normalized bibliographic coupling strength and the edge-betweenness centrality for the method is shown in Appendixes A and B. The x-axis represents the intervals of continuous numerical value, the bar represents the rate of each interval, and the curve represents the cumulative rate as the y-axis. Both values follow long-tail distributions that have few very large events and many very small events. Most of the links have low normalized bibliographic-coupling strength values as shown in Appendix A because few sharing references exist between the patents in heterogeneous fields. Moreover, many zero values are found in the edge-betweenness centrality in the patent citation graph as shown in Appendix B. It is assumed that the distributions roughly follow the Pareto principle (also known as the 80/20 rule), in that 80% of the effects come from 20% of the causes. Most of the normalized bibliographic coupling strengths had a low value because we searched for similar patents in different technological fields, and most of the edge-betweenness centrality had zero value in the patent citation network. We focused on the long tail in the distribution because the link prediction for converging TOD is intended to detect weak signals from the knowledge flow between heterogeneous fields. In other words, we chose the threshold value to catch weak signals by removing 80% of the general results. Thus, link prediction was conducted with the cut-off value for the normalized bibliographic-coupling strength as 0.262, which is in the top 20%, and for the edge-betweenness centrality of 360,000, which is also in the top 20%. The bibliographic-coupling value is calculated from the data assigned in heterogeneous technology sectors (i.e., the patents between BT and IT). The edge-betweenness centrality value was calculated for the patent-citation graph using the “igraph” package in R.

The appropriate cut-off value should be selected to categorize the change of TKF to remove noise because patent citations occurred in 136 pairs among 144 possible pairs between BT and IT. The number of patent citations follows a long-tail distribution, as shown in Appendix C. The x-axis of the graph represents TKF combinations as discrete categories that are sorted in descending order of patent-citation frequency, the bar represents the rate of each category, and the curve represents the cumulative rate as the y-axis. For instance, the pair with the most patent citations among the 136 pairs is the pair from SGY (Surgery) to SIG (Signal processing), labeled as “Tech5_Tech11” in Appendix C. We selected the top 67 pairs, those whose frequency of citation between technologies was larger than 100, to include around the top 96% (95.72%) of all pairs based on the statistical significance level of 0.05, and we removed the rest of the pairs (around 4.27%) in the technology knowledge flow.

4.4. Step 4: technology opportunities discovery (TOD) for convergence

The change of TKF resulting from the link prediction with the cutoff value mentioned in step 3, is shown in Appendix D and is compared with the original citation links. Among the 96 potential TKFs, 61 increased from the TKF network, and 35 had newly emerged. Most of the increased potential links were predicted to increase TKF bidirectionally; however, three TKF pairs (BMD→NET, SGY→NET, SGY→ROB) were predicted to be unidirectional although the TKFs were bidirectional in their network. The six unidirectional TKFs in the TKF network increased identical-directionally, and the five pairs (except BIP→NET) newly emerged in a different unidirectional way. The TKFs that had not existed in the network emerged unidirectionally for 14 pairs and bidirectionally for 16 pairs.

The property of TKFs between heterogeneous fields was analyzed using IPC codes assigned in patents and in Eqs. (7) and (8) in Section 3.3. As suggested in Fig. 3, the technologies were categorized into the four types shown in Appendix E, with the inflow and outflow property values using cut-off points that divide the maximum values of inflow and outflow into three equal parts. A TKF property map was developed in Fig. 6. The width of a link represents the number of predicted patents between technologies as knowledge flow, and the black solid line and gray dashed line denote emerging links and increased links, respectively, in the map. The degree centralities for IPCs were calculated, and the percentage of IPC in the respective technologies was calculated to measure the technology inflow and outflow.
The top 10 potential TKFs were proposed as technological opportunities for convergence between BT and IT fields among 96 potential TKFs in the increased links and emerging links groups. Appendix F shows the technological opportunities for convergence between BT and IT with type, the predicted TKF’s direction, and the TKF property type. To identify the technological opportunities in the respective potential TKFs, patents were grouped according to the Girvan-Newman clustering method (Girvan & Newman, 2002). The number of clusters was selected based on the results of modularity value, which is often used to detect an optimal number of clusters. The number of clusters in Appendix G was chosen when the network had a high modularity value through repeated calculations because networks with high modularity have dense connections between the nodes within clusters but sparse connections between nodes in different clusters. After the clustering method was conducted, technological themes of the respective groups were proposed, as shown in Appendix G, by reviewing patents’ titles and abstracts in groups. Several groups in the potential TKFs presented incremental technological opportunities for convergence, but only one group presented radical technological opportunities for convergence because many predicted patent-citation links for increased links, and only a few patent citation links in the emerging link group existed.

4.5. Validation

To sum up the data between 2006 and 2012, 136 TKFs appeared among 144 possible TKFs (8 BT and 9 IT fields in a direct network). In order to delete noise, we adopted 67 pairs among 136 TKFs, which account for approximately 95% in terms of patent citation distribution as shown in Appendix C. After performing link prediction with data between 2006 and 2012, 96 pairs are predicted. To validate the results, 250,162 patents registered between 2013 and 2015 were used as a future point data. In the data between 2013 and 2015, 109 TKFs appeared among 144 possible TKFs. Under the situation, we calculated precision and recall indices to validate the proposed method. First, the precision is the fraction of predicted pairs that are correctly predicted. It is calculated by dividing the number of correct results by the number of all predicted pairs. The 86 pairs in future point data occurred among the 96 predicted TKFs. Thus, the value of precision is 86/96 = 0.89. Second, the recall is the fraction of correctly predicted pairs to actual pairs that should be correctly predicted. It can be calculated by dividing the number of correct predicted results by the number of actual TKFs in future point. To calculate this, we took 57 pairs among 109 TKFs as the actual results in future point data by adopting the same cut-off rule selecting 95% pairs among all pairs in terms of patent citation distribution. The 55 pairs in future point data occurred among 96 predicted TKFs. Thus, the recall value is 55/57 = 0.96.

Under the link prediction power, the additional validation was conducted specifically by conducting correlation analysis between the predicted results and the future actual data with the correctly predicted 86 TKFs. We performed the correlation analysis using Spearman’s rank correlation coefficient on the rate of knowledge flow that each pair has in the predicted and actual data. It was conducted from two perspectives, knowledge flow prediction and degree of convergence, because TKFs were predicted to detect the signals of technological convergence. Therefore, we investigated whether the knowledge flows and whether two technological fields derived from the predicted knowledge flows could converge in the future. More specifically, the first investigation determined whether the distribution of correctly predicted knowledge flows was similar to future distribution of actual knowledge flows. The second investigation determined whether the distribution of correctly
predicted knowledge flows was similar to the future distribution of the degree of convergence. First, the rate of the correctly predicted 86 TKFs based on the patent data registered between 2006 and 2012 was compared to the rate of the correctly predicted 86 TKFs based on the patent data registered between 2013 and 2015 using correlation analysis. We suggested a correlation between predicted results of knowledge flows based on the data at the present point (2006–2012) and the future real knowledge flows (2013–2015). The Spearman’s rank correlation coefficient was 0.707. Second, the degree of convergence in the future real knowledge flows was measured by using co-classification analysis based on a 4-digit IPC, which represented a subclass, as co-classification analysis was widely used to calculate the degree of convergence. The rate of the correctly predicted 86 TKFs based on the patent data registered between 2006 and 2012 was compared to the degree of convergence in the correctly predicted 86 TKFs based on the patent data registered between 2013 and 2015 using correlation analysis. The Spearman’s rank correlation coefficient was 0.743. It has strong correlation in both perspectives when we measure Spearman’s rho, which was calculated to reflect the difference between the present and future in terms of components of knowledge flow and the difference between the rate of knowledge flow and degree of convergence. Therefore, the technological opportunities for convergence can be discussed based on the results of proposed TKF prediction because the proposed link prediction power is high and the correctly predicted TKFs have roughly strong positive correlation with future point data.

5. Results and discussions

5.1. Results and interpretation

Overall, all the technologies in BT and IT were balanced in terms of TKF without bias toward absorption or diffusion, as shown in Fig. 6, against the expectation that some technologies play an absorption-oriented or diffusion-oriented role under the circumstance of BT–IT convergence. That is, no technologies took the definite absorptive–or diffusive-oriented roles in circumstances of TKF between BT and IT. Consequently, technological knowledge had been exchanged between BT and IT fields through equal reciprocal cooperation, and technological convergence between BT and IT has been in progress. These results are similar to those suggested by Hur (2017) showing that technological sectors coevolve with reciprocal knowledge exchange with each other. The properties of TKF between BT and IT could be divided into active, neutral, and passive properties, as suggested in Appendix E. The IT fields tended to actively absorb and diffuse technological knowledge compared to BT because three technologies (11(SIG), 13(ROB), and 17(SOL)) in IT fields were located only in TKF absorption and diffusion active groups (A&D), but almost all technologies in the BT fields (except for two technologies, 5(SGY) and 2(BMD)) were located in the TKF absorption and diffusion passive group (A&D'). Although some technologies such as 2(BMD), 12(ELC), and 15(SOC) belonged to the TKF absorption and diffusion neutral group (A&DN) and 5(SGY) belonged to the TKF diffusion oriented group (DO), six BTs and four ITs were assigned to TKF A&D in the current situation. One can interpret that some TKFs between BT and IT have been exchanged, but the TKFs rarely interacted with each other in over half of the technological areas. In the context of the convergence status quo, technological convergence has proceeded between BT and IT through reciprocal TKFs. However, several IT-relevant technologies tend to technologically converge more with some BT technologies because the TKF property (absorption or diffusion) represents the technologies that have already technologically converged between two fields in the status quo.

Appendix D shows that TKFs were predicted equally because the 48 TKFs from BT to IT and from IT to BT were predicted among 96 potential knowledge flows. There were 33 knowledge flows from BT to IT, which accounted for approximately 54% in terms of increased link prediction, and there were 20 knowledge flows from IT to BT, which accounted for approximately 57% in terms of emerging link prediction. In Appendix F, 6 knowledge flows from IT to BT and 7 knowledge flows from IT to BT were in the top 10 predicted increased knowledge flows. Although TKFs were predicted to be at a similar level from BT to IT and vice versa in all potential technological flows, technological flows from IT to BT accounted for 60 to 70 percent of the increased links and emerging links in terms of the top 10 TKFs, which we considered incremental or radical technological opportunities for convergence between BT and IT. Therefore, IT can play more of a leading role in terms of technological convergence between BT and IT because it provides technological tools and platforms for analysis to BT (Geum et al., 2012). The TKFs from IT to BT tend to be predicted for the future in the context of direction and strength for technological convergence.

5.2. Discussions

In this research, Biotechnology (BT) and Information technology (IT) were illustrated for application of the proposed method. IT supports other technologies as an enabling technology. If the proposed approach applied to other technologies, they could have various characteristics. However, the proposed method can be generalized because it is a prediction methodology based on TKF in patent citation networks between various technological areas if knowledge flows occur between distinct technology fields. Fortunately, we could define technologies in BT and IT using predefined technological classification based on IPC and USPC. An issue of reliability may arise for the classification defining technology with combinations of patent classification. If this method was applied to other technology fields, defining technology using patents could be one of the tricky issues. IPC at a high level can be used as a proxy for technology if a proper way to define technologies is not found. Although an argument can be made for using IPC to represent technologies, patent classifications such as IPC
and USPC are utilized as proxies for technology in some research because the IPC-classification system’s granularity varies greatly between various technology areas.

In the proposed method, cut-off selection steps arose in several phases. These cut-off values should be carefully chosen because these are a sensitive factor. To choose the cut-off value in respective phase, first of all, data distribution should be observed. Then, the cut-off value should be selected by considering the objective of cut-off value with sensitive analysis. We mentioned three types of cutoff values in terms of link prediction, TKF network, and TKF property maps. First, the goal of using cutoff values in the link prediction is the detection of weak signals between two distinct heterogeneous technology fields. In our case, we used the Pareto rule and focused on the long tail in the distribution. We selected the threshold with top 20% to catch weak signals by removing 80% of general results in the distribution. The cutoff value in the link prediction process can be chosen with high values of bibliographic coupling and edge-betweenness centrality between two heterogeneous fields using sensitive analysis. This criterion can be utilized when applying this method between other distinct technology fields. It is expected that most of the bibliographic coupling strength and edge-betweenness centrality may have low value or zero value because this approach searches for similar patents between two distinct technological fields. Second, the cut-off value in the TKF network was selected to remove patent citation links, which can be considered noise because a technology-level network is merged with a patent network. In our case, we took 95.75% of patent citations and removed the rest based on the statistical significance level of 0.05 because the significant level indicates a 5% of risk of conclusion statistically. This cut-off value that selects a strategy using significance level can be applied to other cases, however, the distribution should be firstly checked and an analyst’s review was also necessary with sensitive analysis because the distribution of patent citation between technology fields can be dependent on the technology fields. Finally, the cutoff point in the TKF property map was selected by dividing the inflow and outflow maximum values evenly to define the TKF property type in order to identify types of TKF property. It can be generally used when applying this method to other technological fields. When the proposed approach is applied to other cases, the cut-off value should be selected by considering the objective in each step. Qualitative approaches using sensitive analysis as well as quantitative criterion are necessary to determine a cut-off value because two types of cut-off value can be sensitively affected by the criterion.

We adopted the concept of link prediction in a direct network, which is suggested by Yu and Wang (2014). In the previous research, a unified weighting approach was taken with three voting strategies, which is termed as \( V_1 \), \( V_{ta} \), and \( V_{sim} \) to compute \( w(u, c, s) \). \( V_1 \) is the weight strategy as a binary value that we are taking in this research, \( V_{ta} \) strategy is the way weighting the similar nodes by applying the inverse of its out-degree, and \( V_{sim} \) strategy is the way weighting a candidate by measuring Pearson’s correlation coefficients between a target node and similar nodes according to overlap of their out neighbors. These three voting strategies can be weighted by using unified algorithm with \( \alpha \), \( \beta \), and \( \gamma \). It is suggested that the \( \alpha \), \( \beta \), and \( \gamma \) can be determined in order to obtain practical outcome in the research. The current study adopts only \( V_1 \) strategy by simplifying the model because the parameters (\( \alpha \), \( \beta \), and \( \gamma \)) vary with settings and objectives and moreover, this research concentrates on predicting knowledge flow by merging predicted links between patents. More information on retrieving crucial links can be offered by applying other weighting schemes in further research.

6. Implications and conclusions

6.1. Implications

This paper addresses three research questions on identifying opportunities for technological convergence as presented in the introduction. Appendix F shows the results of the first and second research questions, determining potential technological opportunities and their characteristics. In the context of potential types of technological convergence, the type of technological opportunity is suggested as incremental or radical technological opportunities for convergence. In terms of increased link prediction, half of the knowledge flows go from the A&DN group to the A&DP group; for the emerging link predictions, half of the knowledge flows go from the A&DP group to the A&DP group, and two knowledge flows go from the A&DA group to the A&DP group, as shown in Appendix F. The potential increased TKFs can be considered incremental technological opportunities for convergence because many TKFs already existed between BT and IT. Furthermore, many links were predicted to increase the existing TKFs. However, the potential emerging TKFs can be considered radical technological opportunities for convergence because the knowledge flows had not existed in the TKF network, and the TKFs that had passive properties in terms of knowledge flow between BT and IT accounted for half of all emerging TKFs. It can be interpreted that the potential TKFs that have both passive properties signify a more radical change than TKFs that have the active property because they are predicted to be technological opportunities for convergence although the property of technologies is presently passive. Moreover, bidirectional emerging TKFs tended to be more active than the unidirectional emerging TKFs because they included the A&DA, A&DN, and DO groups. Unidirectional emerging TKFs can be considered an incremental change among emerging TKFs. Therefore, the emerging TKFs as radical technological opportunities for convergence can be weak signals for technological convergence because all emerging TKFs had fewer predicted citation links than the increased TKFs, and the flows’ properties tended to be more passive than the increased flows. The information on potential emerging TKFs can be riskier than the information on potential increased TKFs.

The third research question in this paper is what technological themes on technological convergence exist at the micro level. Appendix G presents the list of potential technological themes as the results of the third research question by dividing them into two groups (incremental and radical opportunities). The TKFs for incremental technological opportunities were
all predicted as bidirectional increased links. Only two bidirectional TKFs (11(SIG) → 5(SGY) and 5(SGY) → 11(SIG)) were included in the top 10 potential TKFs for incremental technological opportunities. The two technological flows have some difference in technological themes. The potential technological flow from signal processing (SIG) to surgery (SGY) showed knowledge flows (1) from touch detection to blood glucose level control, analysis of eating habits, and gastric stimulation; (2) from display for medical procedures to surgical navigation, brain stimulation, and neuron signal analysis; (3) from imaging an interior surface of a cavity to endoscopy and visualization systems; and (4) from x-ray images and methods for bone diseases to endoscopy and 3-D bone organic matrix density. However, the potential technological flow from surgery (SGY) to signal processing (SIG) showed knowledge flows (1) from data processing for use in tissue characterization to image processing and pattern recognition of images, (2) from cochlear implant sound processors to audio signal processing, (3) from surgical instruments to user interfaces and 3-D pointing devices, (4) from illustration methods to handheld devices as visual indicators and portable media devices, (5) from hearing aid appliances to optical waveguide vibration sensors and noise cancellation systems, (6) from biopsy devices to touch screens, and (7) from analytic sensors to video data recording. Although two TKFs are predicted as bidirectional increased knowledge flows and as incremental technological opportunities, their themes are rather different. The technological contents on SIG, which are mainly about image processing, flow to technological contents on SCY, which are related to surgical systems. In terms of the flows from SCY to SIG, not only image technological themes but also audio signal processing and biopsy-relevant technology flows to technological themes on user interfaces, such as 3-D pointers and touch screens. The potential emerging TKFs can also provide weak signals for radical convergence although the number of patents in the potential knowledge flows is small compared to those in the potential increased knowledge flows. Therefore, the directions of potential knowledge flows and technological themes can provide useful micro-level information when one builds a plan for technological convergence and conducts technology cooperation between heterogeneous fields. It can identify target technology fields for technological convergence, micro-level contents for technological convergence, and the role of knowledge diffuser or receiver on a cooperative R&D for convergence. For example, when one conducts technology cooperation for technological convergence between the technology fields of SIG and SCY, image processing techniques for medical procedures in SIG should be primarily used in collaboration with the techniques for surgical navigation and neuron signal analysis in SGY, and technology on hearing aid appliances in SGY should take the leadership with the noise cancellation system in SIG.

The proposed method adds to the existing knowledge base in three ways. First, the predicted results are derived through a future-oriented approach based on link prediction that overcomes the retrospective perspective of previous convergence research. Second, patent citation information that traces TKF direction is utilized to overcome the prior approach to measuring the degree of convergence using patent classification overlap that does not include the direction of information flow. Third, technological themes are suggested with direction information by clusters in the predicted TKF, which can be considered micro-level technological convergence as the way of overcoming the macro-level approach.

6.2. Conclusions

This paper suggested technological opportunities for convergence by predicting TKFs based on patent citations between BT and IT. Several findings emerge from this research. First of all, TKFs between BT and IT were balanced based on patent data registered from 2006 to 2012 in terms of absorption and diffusion of knowledge flow without bias; consequently, technological convergence had already been in progress across many technologies in BT and IT. Therefore, many TKFs were predicted to increase, and some TKFs had recently emerged. Second, TKFs from BT to IT and from IT to BT were equally predicted in general. In terms of increased knowledge flow prediction, more knowledge flows occurred from BT to IT than from IT to BT, and more knowledge flows occurred from IT to BT than from BT to IT in terms of emerging knowledge flow prediction. Many TKFs moved from IT to BT when we extracted the top 10 potential TKFs as technological opportunities for convergence. Therefore, TKFs from IT to BT were mainly predicted because IT was a knowledge diffuser in knowledge flow between them although several knowledge flows that had already proceeded at a higher level than a certain standard moved from BT to IT. Third, the emerging TKFs can be considered radical opportunities for convergence because they were predicted as technological opportunities although they presently exhibited passivity.

This study contributes to several perspectives. First, from an academic perspective, three research questions from the introduction are answered. To answer the first research question, the top ten potential TKFs are suggested as incremental and radical technological opportunities for convergence by the proposed methodology. To answer the second research question, the characteristics of the predicted technological convergence are proposed by analysis of the TKF’s property and by prediction of the TKF’s direction and strength between the BT and IT fields with a future-oriented approach. To answer the third research question, technological themes are suggested at the micro level by grouping potential TKFs together. Second, from a research methodological perspective, a novel link-prediction approach is proposed by applying the concept of edge-betweenness centrality to a link-prediction method for a directed network to reflect the importance of links between heterogeneous fields in terms of TKF. Third, from the perspective of research policy, this research can offer improved processes and systems related to technological collaboration between heterogeneous fields for technological convergence.

The proposed method and results can be used in various ways. First, it helps firms seek technological themes for convergence, considering their own technological capability, which enables them to prepare strategic technology development for the future based on the results of quantitative analysis. Second, R&D policymakers can plan new research projects on technological convergence that act as a bridge in terms of technology collaboration for convergence. Third, the results
help research institutions and universities improve interior systems to develop converging technology and professional technology manpower training systems across disciplines effectively.

This research has several limitations. First, we suggested the results of correlation with perspectives of knowledge flow and degree of convergence because the causality between the results of prediction and the future cannot be analyzed. It can, however, be validated by applying the proposed predicting methodology with patent data and comparing the actual cases of technological convergence quantitatively. In addition, the proposed method could be more reliable if the qualitative evaluation was conducted by domain experts. Second, non-patent references were not considered for analysis because we focused on technological convergence. The addition of non-patent data could provide many more implications in terms of scientific discipline convergence and evolution between science and technology. Third, analyst’s subjectivity and a sensitive analysis are required when one selects cut-off values in several steps of the proposed method. Finally, we focused on technological opportunities for convergence between only BT and IT. In future research, to surmount the above limitations, technological opportunities for convergence based on data in multiple technologies can be identified with improved massive data processing techniques.

Author contribution

Inchae Park: Collected the data; Contributed data or analysis tools; Performed the analysis; Wrote the paper.
Byungun Yoon: Conceived and designed the analysis; Performed the analysis; Wrote the paper.

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Appendix A

See Fig. A1.
Appendix B

See Fig. B1.

**Fig. B1.** Distribution of edge-betweenness centrality.
Appendix C

See Fig. C1.

Fig. C1. Distribution of technology knowledge flow network.
Appendix D

See Table D1.

Table D1  
The change of technology knowledge flow.

| Type of link in TKF network | Predicted link | No. of predicted Tech. pair | Predicted Tech. pairs (No. of predicted links) |
|-----------------------------|----------------|----------------------------|-----------------------------------------------|
| Unidirectional link         |                |                           |                                               |
| Identical-directional       |                | 6                         | ELC→HTE(177), BIP→NET(26), SIG→HTE(16), SGY→RFID(14), CHP→MOT(12), MBE→MOT(4), BMD→NET(59), SGY→NET(42), SGY→ROB(10), ELC→ELC(348), SIG→SGY(393), ELC→MBE(374), BIP→MOT(142), SGY→SIG(310), SOC→MOT(31), ELC→CHP(230), BIP→SIG(211), SIG→MOT(186), NNT→ELC(177), SOL→SGY(167), SIG→SOL(162), SIG→MBE(149), SOC→CHP(142), ELC→SIG(136), BMD→SIG(131), BMD→SOL(124), SIG→BIP(123), SIG→MBE(120), BIP→ELC(118), CHP→ELC(113), CHP→SIG(85), SIG→NNT(80), MOT→SGY(76), BMD→MOT(74), MBE→SIG(74), SOL→BMD(70), ELC→BMD(67), BIP→MOT(66), SOC→BMD(62), SOL→MBE(62), NNT→SOC(60), SOC→BIP(59), SIG→CHP(57), BIP→SOC(56), SOL→BIP(53), ELC→BIP(38), MOT→BMD(33), MBE→ELC(30), SOL→CHP(29), MOT→BIP(26), BIP→SOL(26), CHP→SOL(24), MBE→SOL(16), NNT→SIG(14), MBE→SOC(12), CHP→SOC(9), BMD→ROB(8), BMD→SOC(3), ROB→BMD(2), MOT→MBE(21), RFID→SIG(15), MOT→CHP(9), HTE→SIG(4), HTE→ELC(4), CHP→NET(13), NNT→MOT(9), SOC→HTE(7), ELC→ORC(6), BMD→ESW(4), SIG→ORC(4), SOL→ORC(3), MOT→ORC(3), BIP→ESW(3), SOC→ORC(2), NET→ORC(1), RFID→BIP(1), RFID→HTE(1), NNT→NET(1), ROB→MBE(21), ROB→NNT(15), SOC→SGY(14), MBE→NET(8), SGY→SOC(6), HTE→MOT(6), BMD→RFID(5), ROB→MOT(4), HTE→SOL(4), CHP→ROB(4), NET→MBE(3), MBE→ROB(3), RFID→BMD(1), SOL→HTE(1), MOT→HTE(1), NNT→ROB(1) |
| Bidirectional link           |                | 54                        |                                               |
| Unidirectional               |                | 3                         | BMD→NET(59), SIG→SIG(310), SOC→MOT(31), ELC→CHP(230), BIP→SIG(211), SIG→MOT(186), NNT→ELC(177), SOL→SGY(167), SIG→SOL(162), SIG→MBE(149), SOC→CHP(142), ELC→SIG(136), BMD→SIG(131), BMD→SOL(124), SIG→BIP(123), SIG→MBE(120), BIP→ELC(118), CHP→ELC(113), CHP→SIG(85), SIG→NNT(80), MOT→SGY(76), BMD→MOT(74), MBE→SIG(74), SOL→BMD(70), ELC→BMD(67), BIP→MOT(66), SOC→BMD(62), SOL→MBE(62), NNT→SOC(60), SOC→BIP(59), SIG→CHP(57), BIP→SOC(56), SOL→BIP(53), ELC→BIP(38), MOT→BMD(33), MBE→ELC(30), SOL→CHP(29), MOT→BIP(26), BIP→SOL(26), CHP→SOL(24), MBE→SOL(16), NNT→SIG(14), MBE→SOC(12), CHP→SOC(9), BMD→ROB(8), BMD→SOC(3), ROB→BMD(2), MOT→MBE(21), RFID→SIG(15), MOT→CHP(9), HTE→SIG(4), HTE→ELC(4), CHP→NET(13), NNT→MOT(9), SOC→HTE(7), ELC→ORC(6), BMD→ESW(4), SIG→ORC(4), SOL→ORC(3), MOT→ORC(3), BIP→ESW(3), SOC→ORC(2), NET→ORC(1), RFID→BIP(1), RFID→HTE(1), NNT→NET(1), ROB→MBE(21), ROB→NNT(15), SOC→SGY(14), MBE→NET(8), SGY→SOC(6), HTE→MOT(6), BMD→RFID(5), ROB→MOT(4), HTE→SOL(4), CHP→ROB(4), NET→MBE(3), MBE→ROB(3), RFID→BMD(1), SOL→HTE(1), MOT→HTE(1), NNT→ROB(1) |
| Bidirectional                |                | 52                        |                                               |
| Unidirectional               |                | 3                         | BMD→NET(59), SIG→SIG(310), SOC→MOT(31), ELC→CHP(230), BIP→SIG(211), SIG→MOT(186), NNT→ELC(177), SOL→SGY(167), SIG→SOL(162), SIG→MBE(149), SOC→CHP(142), ELC→SIG(136), BMD→SIG(131), BMD→SOL(124), SIG→BIP(123), SIG→MBE(120), BIP→ELC(118), CHP→ELC(113), CHP→SIG(85), SIG→NNT(80), MOT→SGY(76), BMD→MOT(74), MBE→SIG(74), SOL→BMD(70), ELC→BMD(67), BIP→MOT(66), SOC→BMD(62), SOL→MBE(62), NNT→SOC(60), SOC→BIP(59), SIG→CHP(57), BIP→SOC(56), SOL→BIP(53), ELC→BIP(38), MOT→BMD(33), MBE→ELC(30), SOL→CHP(29), MOT→BIP(26), BIP→SOL(26), CHP→SOL(24), MBE→SOL(16), NNT→SIG(14), MBE→SOC(12), CHP→SOC(9), BMD→ROB(8), BMD→SOC(3), ROB→BMD(2), MOT→MBE(21), RFID→SIG(15), MOT→CHP(9), HTE→SIG(4), HTE→ELC(4), CHP→NET(13), NNT→MOT(9), SOC→HTE(7), ELC→ORC(6), BMD→ESW(4), SIG→ORC(4), SOL→ORC(3), MOT→ORC(3), BIP→ESW(3), SOC→ORC(2), NET→ORC(1), RFID→BIP(1), RFID→HTE(1), NNT→NET(1), ROB→MBE(21), ROB→NNT(15), SOC→SGY(14), MBE→NET(8), SGY→SOC(6), HTE→MOT(6), BMD→RFID(5), ROB→MOT(4), HTE→SOL(4), CHP→ROB(4), NET→MBE(3), MBE→ROB(3), RFID→BMD(1), SOL→HTE(1), MOT→HTE(1), NNT→ROB(1) |
| Bidirectional                |                | 16                        |                                               |
| Unidirectional               |                | 14                        |                                               |
| Bidirectional                |                | 16                        |                                               |
Appendix E

See Table E1.

Table E1
The types of technology knowledge flow property.

| Technology field | Technology in-flow | Technology out-flow | Type of TKF property                           |
|------------------|--------------------|---------------------|-----------------------------------------------|
| 1(NNT)           | 157.05             | 161.91              | TKF Absorption & Diffusion Passive Group (A&DP) |
| 3(MBE)           | 123.58             | 196.40              |                                               |
| 4(ORC)           | 98.52              | 181.85              |                                               |
| 6(BIP)           | 259.27             | 265.92              |                                               |
| 7(HTE)           | 15.5               | 15.58               |                                               |
| 8(CHP)           | 142.91             | 186.36              |                                               |
| 9(MOT)           | 293.98             | 233.47              |                                               |
| 10(NET)          | 210.19             | 169.18              |                                               |
| 14(RFID)         | 249.61             | 223.18              |                                               |
| 16(ESW)          | 285.53             | 277.98              |                                               |
| 2(BMD)           | 652.00             | 692.86              | TKF Absorption & Diffusion Neutral Group (A&DN) |
| 12(ELC)          | 565.11             | 511.05              |                                               |
| 15(SOC)          | 456.60             | 455.86              |                                               |
| 5(SGY)           | 540.00             | 753.81              | TKF Diffusion Oriented Group (DO)             |
| 11(SIG)          | 1212.59            | 1090.60             | TKF Absorption &                              |
| 13(ROB)          | 1138.73            | 1084.24             |                                               |
| 17(SOL)          | 861.95             | 756.50              | (A&DA)                                        |

Appendix F

See Table F1.

Table F1
Technological opportunities for convergence between BT and IT.

| Type of Tech. opportunities for convergence | Predicted link Type | Direction | Type of TKF property | Potential TKF Predicted Tech. pairs (From → To) | Freq. |
|-------------------------------------------|---------------------|-----------|----------------------|-----------------------------------------------|-------|
| Incremental technological opportunities for convergence | A&DN A&DP           | Bidirectional | 12(ELC)→1(NNT)      |                                               | 597   |
|                                              | A&DN A&DP           | Bidirectional | 15(SOC)→1(NNT)      |                                               | 592   |
|                                              | A&DN A&DP           | Bidirectional | 15(SOC)→3(MBE)      |                                               | 374   |
|                                              | A&DN A&DP           | Bidirectional | 12(ELC)→3(MBE)      |                                               | 287   |
|                                              | A&DN A&DP           | Bidirectional | 12(ELC)→8(CHP)      |                                               | 230   |
|                                              | A&DN A&DP           | Bidirectional | 2(BMD)→12(ELC)      |                                               | 339   |
|                                              | A&DN A&DP           | Bidirectional | 5(SGY)→12(ELC)      |                                               | 438   |
|                                              | A&DN A&DP           | Bidirectional | 11(SIG)→5(SGY)      |                                               | 310   |
|                                              | A&DN A&DP           | Bidirectional | 6(BIP)→11(SIG)      |                                               | 211   |
|                                              | A&DN A&DP           | Bidirectional | 14(RFID)→5(SGY)     |                                               | 15    |
|                                              | A&DN A&DP           | Bidirectional | 9(MOT)→3(MBE)       |                                               | 21    |
|                                              | A&DN A&DP           | Bidirectional | 9(MOT)→8(CHP)       |                                               | 9     |
|                                              | A&DN A&DP           | Bidirectional | 8(CHP)→10(NET)      |                                               | 13    |
|                                              | A&DN A&DP           | Bidirectional | 1(NNT)→9(MOT)       |                                               | 9     |
|                                              | A&DN A&DP           | Bidirectional | 15(SOC)→7(HTE)      |                                               | 7     |
|                                              | A&DN A&DP           | Bidirectional | 13(ROB)→3(MBE)      |                                               | 21    |
|                                              | A&DN A&DP           | Bidirectional | 13(ROB)→1(NNT)      |                                               | 15    |
|                                              | A&DN A&DP           | Bidirectional | 15(SOC)→5(SGY)      |                                               | 14    |
|                                              | A&DN A&DP           | Bidirectional | 3(MBE)→10(NET)      |                                               | 8     |

Appendix G

See Table G1.
### Table G1
Themes of technological opportunities for convergence between BT and IT.

| Type of Tech. opportunities for convergence | Potential TKF | Group | Technological themes (From) | Technological themes (To) |
|--------------------------------------------|---------------|-------|-----------------------------|---------------------------|
| Incremental                              | 12(ELC) − 1(NNT) | G1    | Non-volatile RAM cell, memory cells, memory system, nanotube–based switching elements, electrostatic discharge (ESD) protection circuit | Carbon nanotube, CNTs (carbon nanotubes), microscale vacuum tube, switching elements, patternning nanocarbon material |
| Incremental                              | 15(SOC) − 1(NNT) | G1    | Bit selectable device, Electromechanical circuits, memory cell, static ram (SRAM) | Nanotube semiconductor, molecular nanowires, nanoparticles, nanoscale wires |
| Incremental                              | 5(SGY) − 12(ELC) | G1    | Indicator, sensor, capture system | Light management system, media device |
| Incremental                              | 11(SIG) − 5(SGY) | G1    | Touch detection for a digitizer | Reconfigurable digital processing system |
| Incremental                              | 12(ELC) − 3(MBE) | G1    | Data processing and control in a medical communication system | Communication station and software, smart tag activation, processing wirelessly communicated information apparatus |
| Incremental                              | 2(BMD) − 12(ELC) | G1    | Tracing thermal data | Thermal monitoring and response apparatus |
| Incremental                              | 5(SGY) − 11(SIG) | G1    | Processing spectral data for use in tissue characterization | Automatic object identification, image processing, pattern recognition of image contents |
| Incremental                              |                | G2    | Cochlear implant sound processors, bionic ear programming system | Audio signal processing, automatic magnetic detection |
| Type of Tech. opportunities for convergence | Potential TKF | Group | Technological themes (From) | Technological themes (To) |
|------------------------------------------|--------------|-------|-----------------------------|---------------------------|
| Radical technological opportunities for convergence | G3 | G1 | Surgical instrument, instantaneous ultrasonic measurement | Simulation interface, image processing device, user interface device, 3D pointing device |
| | G4 | G1 | Illumination methods and systems | Handhelded devices as visual indicators, portable media devices, system for transferring images between devices |
| | G5 | G1 | Hearing aid appliance | Optical waveguide vibration sensor, robust and reliable acoustic echo and noise cancellation system |
| | G6 | G1 | Biopsy device | Reflection resistant touch screens |
| | G7 | G1 | Analyte sensor | Video data recording |
| | G8 | G1 | Microfluidic design automation | Microfabricated cell sorter, real-time PCR, diagnosis of fetal abnormalities |
| | G9 | G1 | Photonic crystal biosensor structure and fabrication method | Detecting biomolecular or biochemical interactions, fusion proteins and assays for molecular binding |
| | G10 | G1 | Measuring analytes using large scale FET arrays | Sequencing polynucleotides, microfluidic sequencing, sequencing nucleic acids |
| | G11 | G1 | Control of microfluidic devices | Performing chemical reactions, signal measuring system, nanoparticles for manipulation of biopolymers |
| | G12 | G1 | Providing bacterial bioagent characterizing information | Genetic analysis, detection of nucleic acid polymorphism |
| | G13 | G1 | Automated pre-treatment and processing of biological samples | Facilitating biological reactions, automated rapid immunohistochemistry |
| | G14 | G1 | Macroelectronic substrate materials, nanofiber surface based capacitors | Nanoparticle delivery system, nano-chem-FET based biosensors |
| | G15 | G1 | Dispensing of defined volumes of solid particles | Identification of sepsis-causing bacteria, pathogens and coronaviruses etc. |
| | G16 | G1 | Encoded variable filter spectrometer | Finger motion tracking, fingerprint sensor |
| | G17 | G1 | Auto focus for a flow imaging system | Pattern noise correction, detecting poor quality images, segmentation of images of objects |
| | G18 | G1 | Integrated proximity sensor and light sensor | Multipoint touchscreen, graphical user interfaces for touch sensitive input devices |
| | G19 | G1 | Glucose measuring device for use in personal area network | Implantable analyte sensor, analyte monitoring and drug delivery |
| | G20 | G1 | Protein design automation for protein libraries | Process for purifying antibody, regulating neural cell proliferation or differentiation |
| | G21 | G1 | Detection of transponder tagged objects | Capsule tracking system, invasive medical device with position sensing and display, portable surgical implement detector |
| | G22 | G1 | Control displacement of a body spaced-apart from a surface | Imprint lithography templates, patterning substrates |
| | G23 | G1 | Miniaturized imaging device, printable semiconductor | Fiberscope, tissue visualization, Optical Coherence Tomography (OCT) |
| | G24 | G1 | Automated treating tissue samples | Gateway for controlling call routing |
| | G25 | G1 | Glucose measuring device for use in personal area network | Biosensor, blood glucose sensing, sensing electrochemical reactions |
| | G26 | G1 | Electrically erasable programmable read only memory (EEPROM), One-time programmable; non-volatile field effect devices | Image processing |
| | G27 | G1 | Automated pre-treatment and processing of biological samples | Gateway for controlling call routing |
| | G28 | G1 | Producing structures for electron beam | Portable patient monitor, compound charged particle beam device |
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