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Monitoring trends of technological changes based on the dynamic patent lattice: A modified formal concept analysis approach

Changyong Lee, Jeonghwan Jeon, Yongtae Park *

Department of Industrial Engineering, School of Engineering, Seoul National University, San 56-1, Shillim-Dong, Kwanak-Gu, Seoul 151-742, Republic of Korea

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ABSTRACT

The strategic importance of monitoring technological changes is highlighted given the ever faster pace and increasing complexity of technological innovation. In this respect, patent citation analysis has been the most frequently adopted tool among others. However, patent citation analysis is subject to certain drawbacks that stem from only consideration of citing-cited information and time lags between citing and cited patents. This study proposes a formal concept analysis (FCA)-based approach to developing a dynamic patent lattice that can analyze complex relations among patents and monitor trends of technological changes. The FCA is a mathematical tool for grouping objects with shared properties based on the lattice theory. The distinct strengths of FCA, *vis-á-vis* other methods, lie in structuring and displaying the relations among objects from a massive amount of data. For the purpose of technology monitoring, the FCA is modified to take into account time periods and changes of patent keywords. A patent context is first constructed with the aid of domain experts and text mining technique. Two types of dynamic patent lattices are then developed by executing the modified FCA algorithm. A case study of laser technology in lithography for semiconductor manufacturing shows that the suggested dynamic patent lattice has considerable advantages over conventional patent citation maps in terms of visualization and informative power.

1. Introduction

The ever faster pace and increasing complexity of technological innovation places more emphasis on strategic importance of monitoring technological changes. In this situation, firms are focusing increasing attention on technology monitoring – efforts to observe and assess technologies – to gain and maintain a competitive edge [1,2]. Technology monitoring is a general term that concerns acquisition, assessment, and communication of information on technology, and has been defined in many different ways. According to the European Industrial Research Management Association, it was referred to as identification and assessment of technological changes that are critical to the firm's competitive position [3]. It was defined as scanning the environment to obtain historical information on technology's development, current information of the state of art today, and information pointing directly to future prospects [4]. Although variations may exist among researchers regarding to the definition and scope of technology monitoring, the literature commonly views technology monitoring as an indispensible task in defending against the potential threats and exploiting the promising opportunities [5].

Technological changes and the process of innovation have been regarded as an evolutionary process having a certain inner logic of its own and depending on manifold factors of selection environment [6–8]. A variety of concepts, such as technological regime, technological trajectory, Abernathy and Utterback (AU) model, reverse salient, lock-in, dominant design, etc., have been put forward to capture the common features of technological changes. While previous studies are useful for understanding important aspects of technological changes, a lacuna still remains in the literature as to how to monitor trends of technological changes in a

* Corresponding author. Tel.: +82 2 880 8358; fax: +82 2 889 8560.
E-mail address: parkyt@cybernet.snu.ac.kr (Y. Park).

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systematic and quantitative manner for the following reasons. First of all, previous models cannot provide objective information about technological changes based on objective technological data since most research has focused on case-based conceptual framework [9]. Even though many methods such as statistical analysis and trend extrapolation have been applied to indirect measures of technological changes to enhance the objectivity of analysis results, it can only describe overall directions and processes of technological changes. To provide more detailed guidelines for trends of technological changes, it is critical to secure the applicable quantitative data and provide the objective information. Second, despite of idiosyncratic nature of technological changes and difficulties in generalization thereof, most previous studies have attempted to analyze the technological changes at the macro level. As a result, the explanatory power of framework lies mainly in the general patterns of technological changes, and less in the trends of changes within a particular technology field [10]. Consequently, recent years have seen major increases in attempts to develop models, methods, and tools to overcome the limitations mentioned above.

In this respect, patent analysis has long been considered as a useful analytic tool, and significantly benefited from the use of computerized methods such as text mining and bibliometric analysis. An analysis of technological information in patent documents is visualized as a patent map, allowing the complex information to be understood easily and effectively [11]. Patent maps can highlight the crucial pieces of knowledge about technological details and relationship, novel industrial solutions [12], business trends [13], competitive positions [14,15], and infringement risk [16]. Among the various methods and visualization techniques for analyzing patent information, patent citation analysis has been the most frequently adopted tool. The citation information has been utilized to investigate knowledge flows at various levels, such as national [17], industry [18], firm [19], and technology level [20]. In addition to simple frequency of citations, such quantitative indexes as citing-cited intensity and linkage, technological prominence, technological coverage, and technology cycle time have been developed for this purpose. However, albeit easy to understand and simple to use, the salient problems and deficiencies of patent citation analysis for technology monitoring have been pointed out, as clarified next [21]. First and foremost, the scope of analysis and richness of potential information are limited because it only takes into account citing-cited information. Although the citing-cited information has been employed as a proxy for technological knowledge flow and technological prominence, it cannot consider the internal technological relationships among patents. Thus, what has been technologically changed among patents cannot be fully captured from patent citation analysis. Second, it is difficult to grasp up-to-date trends of technological changes since the time lags between citing and cited patents are more than ten years on average [22]. For this reason, patent citation analysis is forced to face a serious challenge in monitoring the recent trends of technological changes, especially as for fast changing and complex technology fields. To overcome the limitations mentioned above, the keyword-based patent analysis has been suggested as a remedy of patent citation analysis. However, despite all the possibilities offered by the keyword-based patent analysis, it is still subject to some limitations that need to be further addressed. Initially, only simple and static methods have been utilized such as cluster and co-word analysis incapable of investigating trends of technological changes over time. Secondly, regarding to the first problem, the keyword-based patent map only shows the relations of technologies without time considerations. Finally, it is difficult to interpret and understand the detailed changes in technology due to large and complex structures of patent maps. Both the limitations of patent citation analysis and keyword-based patent analysis will be fully addressed in our proposed analysis model.

The primary purpose of this study is to propose a formal concept analysis (FCA)-based approach to developing a dynamic patent lattice that can analyze the complex relations among patents and monitor the trends of technological changes over time. The FCA is a promising mathematical tool for grouping objects with shared properties based on the lattice theory. The distinct strengths of FCA, *vis-á-vis* other methods, lie in structuring and displaying the relations among objects in voluminous data. For the purpose of technology monitoring, the FCA is extended to take into account time periods and changes keywords of patents. A patent context is first constructed with the aid of domain experts and text mining technique. Two types of dynamic patent lattices are then developed by executing the modified FCA algorithm. Based on the dynamic patent lattice, in-depth analysis is carried out to obtain richer information on technological changes. It has been recognized that the cornerstone of technology monitoring process is to identify historical information on technology's development [23]. In this regard, we believe that the suggested approach can improve the efficiency of technology monitoring process by systemizing experts' manual work and complement other technology monitoring methods.

The rest of this paper is organized as follows. As an introductory statement, the general background of patent analysis and FCA is reviewed in Section 2. The proposed FCA-based approach is explained in Section 3, and illustrated with a case study of the laser technology in lithography for semiconductor manufacturing in Section 4. Finally, this paper ends with conclusions in Section 5.

2. Background

Put theoretically, our attempt is to integrate the modified FCA algorithm together with patent analysis under a systematic framework. They are used together only rarely, and thus most readers will be comfortable with one or some, but perhaps not all of them. We therefore touch briefly on what they are and how they are combined in this study.

2.1. Patent analysis

Patents are regarded as an ample source of technological and commercial knowledge for the following reasons. First, an extensive volume of patents holding specific technology information has been accumulated for a long period of time. Over 6,000,000 patents have been applied to the United States Patent and Trademark Office (USPTO), and an average of 150,000 patents are steadily being issued every year. Almost 80% of all technological information can be found in patent publications [24]. Second, each patent employs detailed information on the developed technology, technological domain, inventor, etc. Patents are also applied across various fields, covering inventors and applicants from a wide scope such as universities, governments, corporations, and they predicate the inventors' nationalities, regional information, references, etc. Third, patents can also be seen as valuable inventions that leap over all expenses and create profits because acquiring the rights to patents takes time and investment. Using patents in analysis therefore reduces the inclusion of useless data. Finally, patents are public documents in which all related information is standardized and released, and they can be easily accessed through public and commercial databases [25].

Hence, patent analysis has long been considered as a useful analytic tool for technology monitoring. The patent analysis provides a unique opportunity to satisfy the need for conceptual or qualitative analyses of technological change [26] and empirically explains most aspects of technological innovation [27]. Recent years thus have seen a huge increase in the use of patent analysis. It has been employed in various problems such as identification of economic effects of technological innovation [28], assessment of technological competitiveness [29–31], investigation of effects of technological change on performance [32], and prioritization of R&D activities [33], and exploration of technological opportunity [25].

Patents contain dozens of items for analyses, which can be grouped into two categories: structured and unstructured items [34]. The structured items are consistent in semantics and formats across patents (e.g. patent number, filing date, inventors, and assignees) while the unstructured items are text of contents having different structures and styles (e.g. descriptions and claims). At first, the structured data analysis has been major interests [35,36]. In the structured data analysis, the bibliographic fields of patents are utilized to explore, organize, and analyze a large amount of historical data in order that researchers can find hidden patterns to support their decision making. However, the scope of analysis and the richness of information are limited since only bibliographic fields are employed, despite the potential utility of unstructured items [37]. Recognizing the shortcomings of structured data analysis, the unstructured data analysis has emerged as an alternative or a complement to structured data analysis [38]. In this regards, there have been growing interests in application of data mining techniques to patent analysis, especially text mining technique [21,39]. The primary advantages of text mining in patent analysis lie in extracting and analyzing valuable information from voluminous textual data [40,41]. In addition, it can considerably reduce time and human efforts required to analyze unstructured, lengthy, and rich textual data of patent documents [42].

An analysis of technological information in the patent documents is visualized as a patent map generally presented in the form of chart, table, graph, and network. The patent map allows the complex information to be understood easily and effectively by assisting analysts to grasp diverse features of individual patents and identifying complex relationship among them [11]. A crucial piece of knowledge can be found in the patent map, for instance, technological details and relationship, novel industrial solutions [12], business trends [13], competitive positions [14,15], and infringement risk [16].

2.2. Formal concept analysis

Formal concept analysis (FCA), first proposed by Wille [43] based on the lattice theory of Birkoff [44], is a mathematical tool for analyzing the relations among objects with shared properties. Based on the historical cases, it provides a hierarchy of cases to be understood easily and effectively [45]. The distinct strengths of FCA, *vis-á-vis* other methods, lie in structuring and displaying the relations among objects in an amount of data. Recent years thus have seen a huge increase in the use of FCA for various research areas such as ontology engineering [46], knowledge discovery [47], service engineering [48], collaborative recommendation [49], case-based reasoning [50], and software engineering [51].

The basic notions of FCA are formal context and formal concept denoted as context and concept, respectively. First, a context (O, A, I) consists of a set of objects O, a set of attributes A, and relations I between O and A. A formal context is represented by a cross table as depicted in Fig. 1(a). The elements on the left side o_i ($\in O$) are objects and the elements at the top a_j ($\in$A) are attributes. If an object o_i has an attribute a_j, the relation between them is represented by the cross. For instance, object o_1 has attributes a_1 and a_2 while object o_2 has another attributes a_3 together with a_1 and a_2 in the context shown in Fig. 1(a).

(a) Context

	f_1	f_2	f_3
e_1	×	×	
e_2			×
e_3	×		
e_4			×

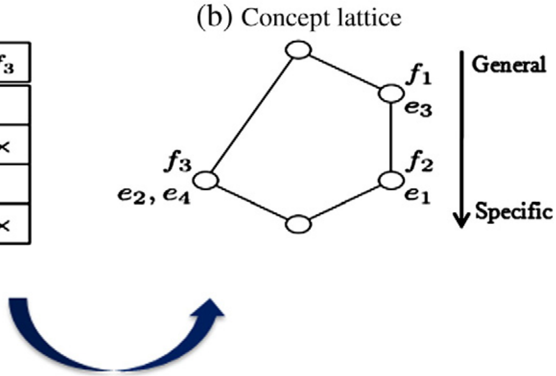

Fig. 1. Basic notions of FCA.

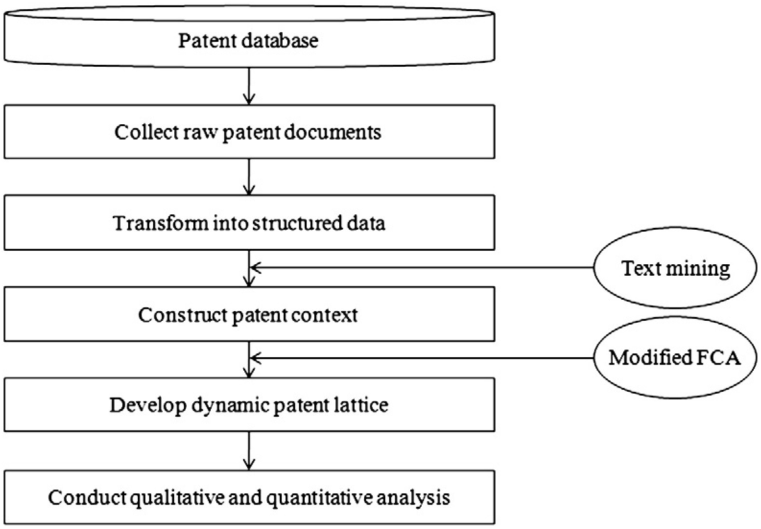

Fig. 2. Overall process.

Suppose that a subset of objects $O_S \subseteq O$ with a set of common attributes $A_S \subseteq A$. It means that every object in O_S has all attributes in A_S. In such a case, a formal concept for the formal context (O, A, I) is defined as a pair of (O_S, A_S). Here, O_S is the extent and A_S is the intent of the formal concept (O_S, A_S). The extent covers all objects belonging to the formal concept while the intent comprises attributes shared by all those objects. In Fig. 1(a), the objects o_1 and o_2 have attributes a_1 and a_2 in common. Thus, $(\{o_1, o_2\}, \{a_1, a_2\})$ is a concept of the context; the subset of objects $\{o_1, o_2\}$ is the extent and the subset of attributes $\{a_1, a_2\}$ is the intent of the concept.

The set of all concepts of a context is ordered by inclusion relations between the extents (or intents) of the concepts. If the objects in the extents of a concept c_1 include all objects in the extents of concept c_2, c_1 is defined as a super-concept of c_2, and c_2 is denoted as a sub-concept of c_1.[1] As can be seen Fig. 1(a), $(\{o_1, o_2\}, \{a_1, a_2\})$ is a super-concept of $(\{o_2\}, \{a_1, a_2, a_3\})$ while $(\{o_2\}, \{a_1, a_2, a_3\})$ is a sub-concept of $(\{o_1, o_2\}, \{a_1, a_2\})$. Based on the hierarchical orders of all concepts in the context, a *concept lattice*, which is a graphical representation of inclusion relations between concepts, can be generated as exemplified in Fig. 1(b). Each node corresponds to a concept. Nodes are placed and connected to each other to represent their order relations. Specifically, it shows a hierarchical clustering of objects and attributes, where super-concepts display unique objects and common attributes with sub-concepts, while sub-concepts display common objects with super-concepts and unique attributes.

3. Proposed approach

In this section, we examine the overall process of proposed approach, giving a brief explanation of each stage at the same time. The proposed approach is composed of five stages, as depicted in Fig. 2. First of all, data collection and data preprocessing are the preliminary step. A technology field of interests is selected and related patents are collected in electronic text format. Second, a patent database is constructed by parsing the patent documents. The original documents are expressed in natural language format, so they should be transformed into structured data to be analyzed and utilized. Third, a patent context is constructed with the aid of domain experts and text mining technique. The patent context consists of three parts: issued date, patent number, and occurrence of keywords. Fourth, a modified FCA algorithm is executed to develop the dynamic patent lattice. Finally, based on the dynamic patent lattice, in-depth analysis is carried out to aid decision making in technology monitoring.

3.1. Data collection and transformation

Patent documents in a technology field of interests are collected based on various search conditions from USPTO. The patent documents need to be preprocessed since they are semi-structured data, which are merely expressed in text format. For this reason, the patent documents are parsed based on the structure of document, and then transformed into a structured patent database for further analyses. The patent database includes not only structured items but also unstructured ones for structured and unstructured data analyses.

[1] Mathematically, a super- and sub-concept relation is represented by $\leq$ and defined as: $(O_{S1}, A_{S1}) \leq (O_{S2}, A_{S2})$ *if* $O_{S1} \subseteq O_{S2}$, where (O_{S1}, A_{S1}) is a sub-concept of (O_{S2}, A_{S2}), and vice versa.

3.2. Construction of patent context

A patent context is constructed to be utilized as an input of modified FCA. It consists of three parts: issued date, patent number, and keyword vector. A field of issued date is added to the original context to take time periods into account. The patent number and keyword vector correspond to the object and attributes in the original context. Using only a keyword list extracted by text mining technique is difficult to describe the technological characteristics. Thus, the repetitive trials between experts and computer-based approach are required to define the form and elements of keyword vector in the patent context. The detailed procedure is depicted in Fig. 3. As a screening process, the text mining technique is first conducted to find words with high frequency from the patent database, and then they are refined based on experts' judgments. Finally, the keyword list is derived and rearranged to consider the abbreviation, synonyms, singular, and plural forms of words.

A patent context constructed is exemplified in Table 1. The issued date and patent number are represented in the text format, and the keyword vectors are derived from the frequencies of keywords extracted by text mining technique. The frequencies are transformed into a binary value based on the pre-determined cut-off; '1' means that the patent is related to the corresponding keywords, while '0' means the patent does not. For instance, P5 was issued in 2008 and related to K1 and K2.

3.3. Development of dynamic patent lattice

The conventional concept lattice only shows the order relations among concepts without time considerations and changes of attributes; thus, simply applying the FCA to technology monitoring problem is not appropriate because it is difficult to structure and analyze the dynamic nature of technological changes. For this reason, the FCA is extended to take into account time periods and changes of keywords of patents.

The modified FCA algorithm is summarized as follows. First, in contrast to the conventional FCA, it is an iterative process which generates the dynamic patent lattice based on the issued date. Only patents issued earlier than the target patent are taken into account in constructing the dynamic patent lattice. In other words, two different patents having the same keywords, but issued at different time periods, generate two different concepts. Second, the order relations among concepts are derived by index of the cosine similarity instead of a concept of subsets. The cosine similarity is the most frequently adopted similarity indicator in calculating similarities of documents [52] and defined as:

$$\cos\theta = \frac{A \cdot B}{|A|\,|B|}$$

where A and B are keyword vectors of documents. Specifically, when the target patent is composed of all new keywords (similarity = 0), a new concept is generated without linkages. In the case of the target patent containing new and existing keywords (0 < similarity < 1), a new concept is generated with linkages to concepts whose similarities are greater than a pre-defined threshold. As for the target patent including only existing keywords (similarity = 1), if the dynamic patent lattice has the concept whose attributes are the same with those of target patent, the property of corresponding concept is updated. If the dynamic patent lattice does not have the concept, a new concept is generated with linkages to concepts whose similarities are greater than a pre-defined threshold. Finally, nodes and arcs differ from one another in the dynamic patent lattice according to the number of patents in a concept and types of changes of keyword. The size of nodes is proportional to the number of patents in the

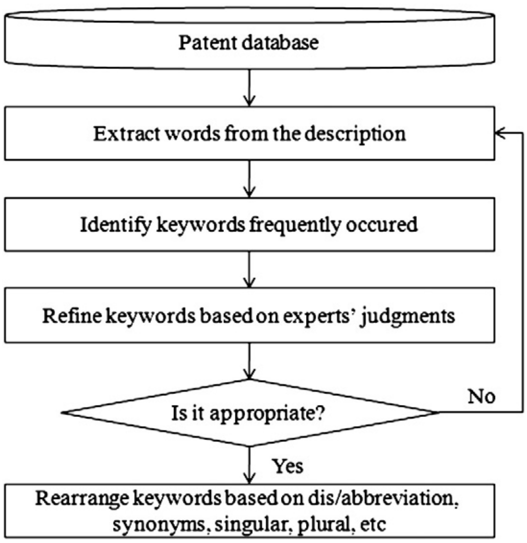

Fig. 3. Procedure for definition of keyword list.

Table 1
Example of patent context.

Year	Patent #	K1	K2	K3	K4
2007	P1	1	0	0	0
	P2	1	1	0	0
	P3	1	0	0	0
2008	P4	0	1	1	0
	P5	1	1	0	0
	P6	0	0	1	0
2009	P7	0	0	1	0
	P8	1	1	1	1

concept. In terms of arcs, a thick solid line shows that there is no difference of keywords between super- and sub-concept where the similarity is equal to one. In the case of two concepts having different keywords, the case where the differences are induced from a new keyword that previous concepts do not have is represented with dotted lines while the other case where the differences are induced from existing keywords is depicted with thin solid lines. The pseudo-code of modified FCA algorithm is shown in Appendix A.

Based on the modified FCA algorithm, two types of dynamic patent lattice are proposed according to the visualization format: horizontal and radial dynamic patent lattice. They can be utilized for different purposes. First, the horizontal dynamic patent lattice emphasizes the technological trends with the information such as horizontal time frame, category of patents, number of keywords that can be used as a proxy measure for the complexities of patents, etc. The horizontal dynamic patent lattice is effective in

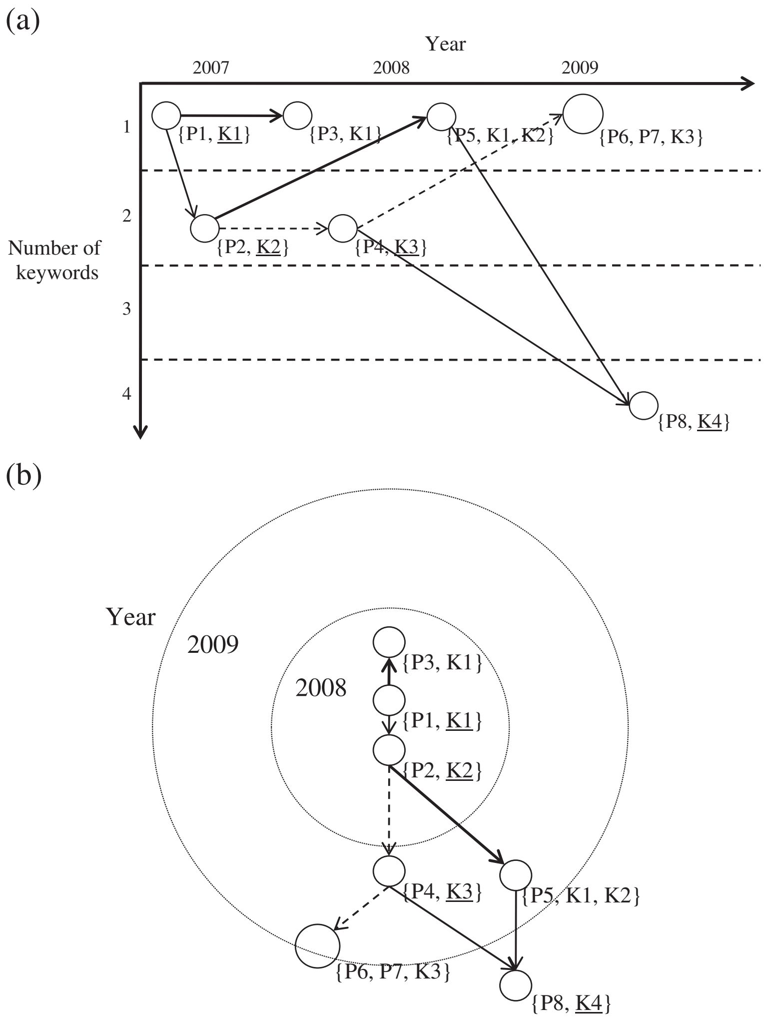

Fig. 4. Two types of dynamic patent lattice. (a) Horizontal dynamic patent lattice and (b) radial dynamic patent lattice.

visualizing the evolution process of technologies over time but has some difficulties in visualizing the structure of technological changes due to complex and twisted arcs. Second, the radial dynamic patent lattice overcomes the abovementioned limitation of horizontal dynamic patent lattice. It is developed by transforming the horizontal time frame into concentric rings, allowing the complex and twisted arcs to be distinguishable. Consequently it is more appropriate to grasp the detailed structure of technological changes. Fig. 4(a) and (b) exemplifies the horizontal and radial dynamic patent lattice of patent context described in Table 1.

4. Case study

A case study of patents related to the laser technology in lithography for semiconductor manufacturing is presented to illustrate the suggested approach. We consider this case example appropriate for the following reasons. First, the laser technology is one of the most critical technologies in the lithography process for semiconductor manufacturing. Second, the performance improvement has been continuously introduced to keep pace with shrinking feature sizes as well as light sources, as depicted in Fig. 5. Finally, the number of patents is a convenient size for illustrating the proposed approach. For more details on the laser technology in lithography, see the text by Smith [53] and Levinson [54].

4.1. Data collection and transformation

The U.S. Patent and Trademark Office (USPTO: www.uspto.gov) database served as the source for collection of patent documents. In all, a total of 80 patent documents about laser technology in lithography for semiconductor manufacturing were obtained with the reference period from 1984 to 2009. MS Access database was utilized to construct the patent database. The constructed database included a variety of information such as assignee, issued date, classification, citation, etc. In this study, the data fields of patent number, issued date, and description were employed to develop the dynamic patent lattice while citation information was used for comparative analysis.

4.2. Construction of patent context

With the aid of three domain experts and text mining program developed by JAVA, a total of 23 keywords, which can describe the technological characteristics, were selected. Based on the patent database and keyword list, the patent context was automatically constructed by text mining program.

4.3. Development of dynamic patent lattice

The dynamic patent lattices were developed by executing the modified FCA algorithm, as shown in Fig. 6(a) and (b). The keywords changed are omitted due to the space constraints. In this section, two types of dynamic patent lattice are further investigated to identify directions and structures of technological changes.

4.3.1. Horizontal dynamic patent lattice

According to the International Technology Roadmap for Semiconductors (ITRS), the recent technologies of computer chip fabrication have been developed in the order of krypton fluoride (KrF, 248 nm), argon fluoride (ArF, 193 nm), and immersion ArF lasers. Extreme ultraviolet (EUV, 13 nm) and other technologies such as X-ray and E-beam are followed as the candidate technologies for the next generation lithography. Although there were differences across the technological capabilities of nations or firms, the wavelength of laser technology was competent enough for chip manufacturing until the late 1990s. In other words, the feature size had been longer than the wavelength of laser technology, as shown in Fig. 5. However, the feature size for chip manufacturing has been becoming shorter to manufacture the next-generation products. In this context, an extensive volume of R&D activities has been carried out to overcome the problems that stem from marginal limit; such history of technological changes

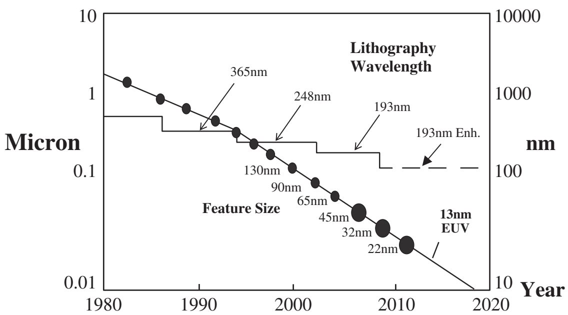

Fig. 5. Performance improvement of laser technology.

appears in the horizontal dynamic patent lattice shown in Fig. 6(a). The number of patents on laser technology in lithography has radically increased by the late 1990s. Moreover, the number of patents on the KrF and ArF has increased until 2004, but has decreased since then. By contrast, the increase of number of patents on EUV shows that an extensive body of research has been conducted since the year of 2004.

From the proposed horizontal dynamic patent lattice, it can be found that the technological changes of laser technology are from KrF to EUV via ArF. It can also be said that EUV is the most predominant one among several candidate technologies for next generation lithography, and many efforts would be invested for the development of EUV lithography in the future. In practice, world-leading stepper manufacturers such as AMSL, NIKON, and Canon are increasing their investment in the development of EUV infrastructure and the integration of EUV for fabrication of working devices. To conduct a more detailed analysis and obtain richer information, quantitative indexes need to be defined and gauged. Although various indexes can be developed to this end, we proposed two major indexes related to trends of technological changes: intensity of patenting activity (IPA) changes in intensity of patenting activity (CIPA). IPA is defined as the number of issued patents for a specific technology in a given period while CIPA is referred to as the increasing and decreasing ratio of IPA. IPA and CIPA can provide the insight into technological trends at present and in the future, respectively. In other words, if IPA and CIPA of a subject technology are greater than those of another, it means that the subject technology is being intensively investigated and this trend is expected to be more deepened in the future. The IPA and CIPA for KrF, ArF, and EUV, as can be seen in Fig. 7(a) and (b), also represent that the trends of laser technology in lithography have been changed from KrF to EUV through ArF.

The development paths at the individual patent level are also meaningful. The representative examples that are highlighted by circles in Fig. 6(a) are summarized as follows. Firstly, patent 6480518 has improved the performance of internal transmittance and resistance that could be achieved by patent 6266978. The internal transmittance of patent 6480518 is 99.8% superior to that of patent 6266978. Secondly, patent 5790574 has developed a technology on the short pulse duration at low energy per pulse to deal with the gas breakdown problem of patent 5491707. It can adjust the focus of beam in the helium and atmospheric environment. As a result, no vacuum chamber was necessary in patent 5790574. Finally, patent 7006547 produced a higher repetition rate of gas discharge laser system in MOPA that could be achieved by patent 6693939. This invention offered the possibility of substitution of KrF and ArF to EUV.

4.3.2. Radial dynamic patent lattice

Five types of technology groups were identified from the radial dynamic patent lattice. The names and descriptions of technology groups are summarized in Table 2. Firstly, group 1 is composed of the excimer laser apparatus technologies using a bandwidth-narrowing optical system. The beam diameter-enlarging optical system and optical bandwidth monitor systems are examples of this technology group. Secondly, group 2 includes patents related to the light source for EUV lithography. For instance, the patent 6377651 implemented a laser produced EUV source based on water droplet target. Thirdly, group 3 describes the features and characteristics of EUV optical systems to improve the accuracy of wavefront characterization. The hybrid spatial/

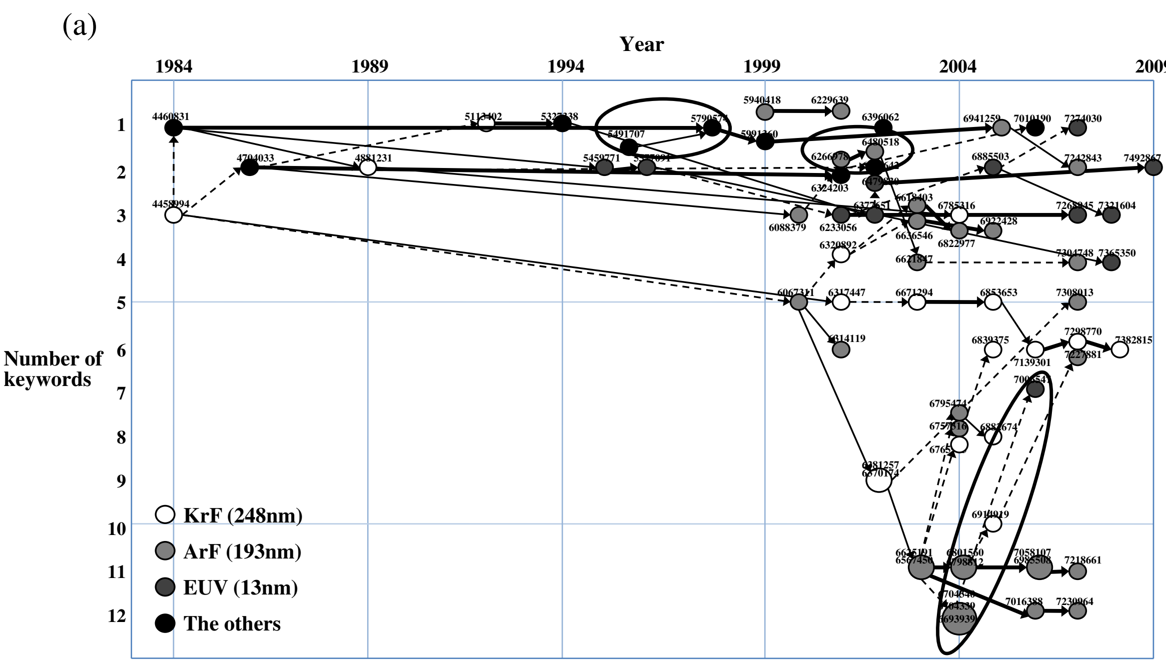

Fig. 6. Dynamic patent lattice for laser technology in lithography. (a) Horizontal dynamic patent lattice and (b) radial dynamic patent lattice.

(b)

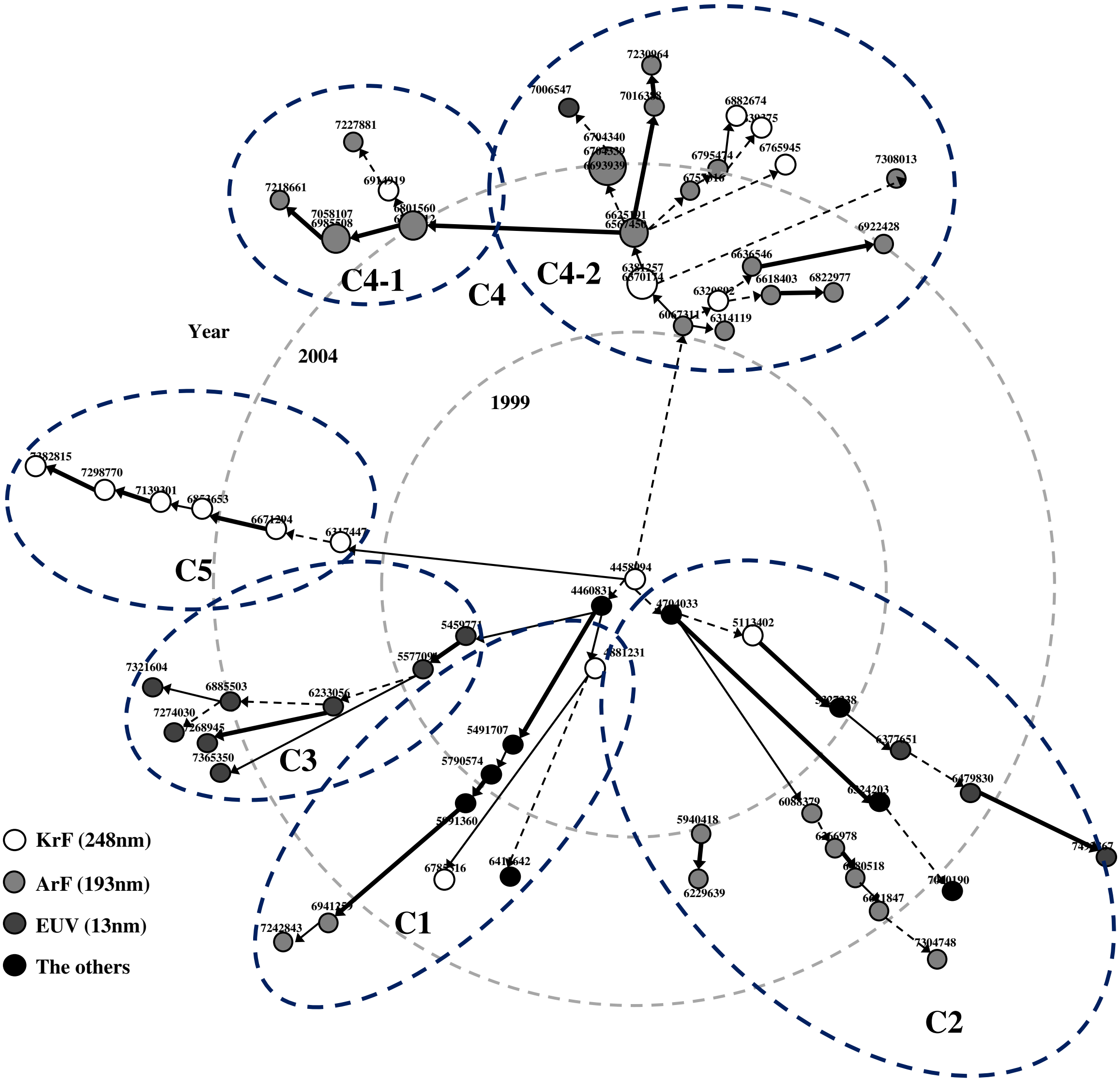

Fig. 6 (*continued*).

temporal-domain point diffraction interferometer and achromatic Fresnel objective are belonging to this sub-technology. Fourthly, group 4 deals with the converged technology, and all patents in this group were issued since the year of 2000. They can be divided into two sub-groups: one related to the lithography laser with beam delivery and beam pointing control and the other about the excimer laser with optical pulse multiplication and discharge chamber. Finally, group 5 has patents related to the technique for bandwidth control of an electric discharge laser.

Group 5 was further investigated for more detailed explanation of development path. Taking the bandwidth technology as an example, a lithographic exposure process was developed for bandwidth control in 2001 (patent 6671294). In 2003, the multi-mode illumination spectrum of the lithographic exposure process was improved by illuminating a more narrowband wavelengths (patent 6671294). In the year 2005, an advanced tuning mechanism was developed to provide a plurality of incremental adjustments by spectral energy distribution in the lithographic exposure process (patent 6853653). This tuning mechanism was further advanced by patent 7298770. The newly suggested mechanism was able to determine the bandwidth of individual laser output pulses and broaden the effective bandwidth of the series of pulses. Finally, these technological improvements were integrated in 2008 (patent 7382815). Based on this development path, it is expected that improvement of tuning mechanism for narrowing bandwidth and developing a more accurate and reliable control system has been at the core of technological changes, and this trend would be more deepened in the future.

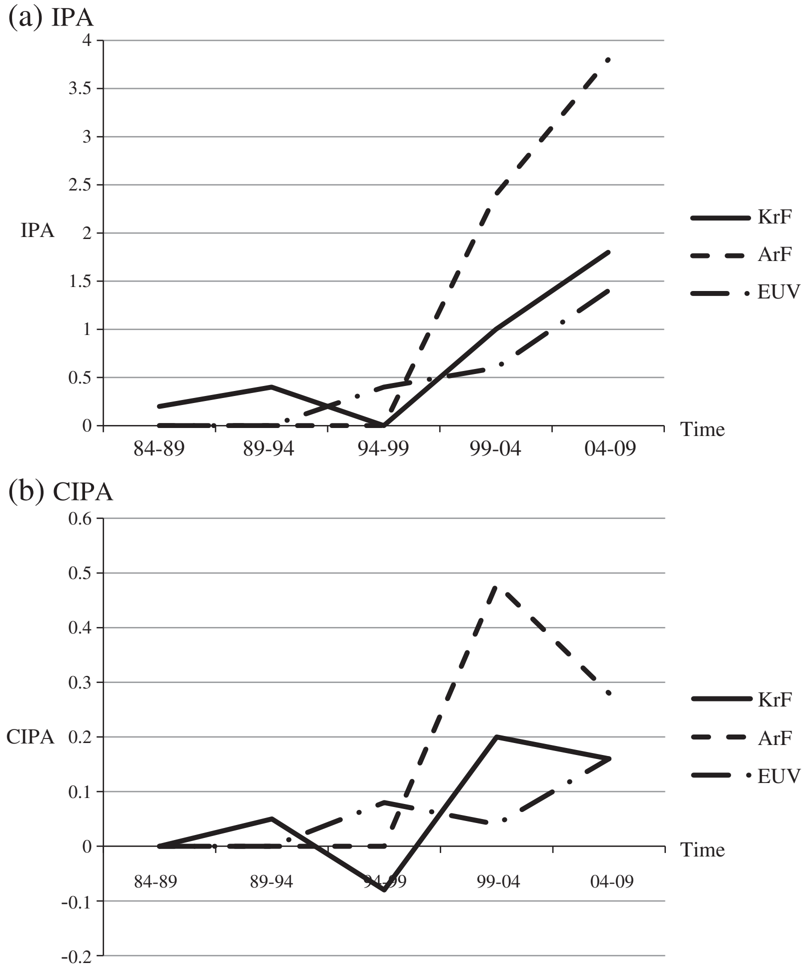

Fig. 7. IPA and CIPA for laser technology in lithography.

4.4. Comparison with patent citation map

The conventional patent citation map was also developed for comparative analysis, as shown in Fig. 8. The form of patent citation map was conformed to the suggested dynamic patent lattice for effective comparison. The distinct strengths of the suggested dynamic patent lattice, *vis-à-vis* conventional patent citation map, are summarized as follows. First of all, in terms of the richness of information, the dynamic patent lattice delivers more information than patent citation map since the suggested approach takes into account the meanings of patents based on keywords. Specifically, whereas the patent citation map only represents the citing-cited relationships among patents, the dynamic patent lattice contains further information about technological changes, such as what the patents are related to and what are changed over time, based on the keywords of patents. This information can extend and diversify the scope of analysis. In this study, it was used to make a linkage between patents, derive the IPA and CIPA of KrF, ArF, and EUV, and explain the structure of technological changes. Secondly, in terms of trends of technological changes, the patent citation map is unable to fully capture the detailed changes of technology due to the time lags of more than 10 years between citing and cited patents. As shown in Fig. 8, the developed patent citation map is too sparse and the citation relationship is focused on specific patents (e.g. patent 7218661). Moreover, there exist some development paths in the dynamic patent lattice, which are meaningful but cannot be found in the patent citation map. On the contrary to this, the dynamic patent lattice explains detailed changes from KrF to EUV through ArF together with two quantitative indexes such as IPA and CIPA. Lastly, in terms of the form of visualization, most previous studies have generated patent citation maps as a series of snapshots by aggregating the citation counts of pre-defined time periods. Although these are useful to describe the characteristics of technological changes at the macro level, they cannot explain the detailed history of technology development at the micro level. By contrast, the dynamic patent lattice explains and visualizes the detailed technological changes along a timeline, thereby allowing analysts to grasp the big picture of the trends of technological changes as well as associations among patents easily and effectively.

Table 2
Name and description of sub-technologies.

Group	Name	Description
C1	Excimer laser apparatus	Excimer laser apparatus using a bandwidth narrowing optical system
C2	Light source	Light source for EUV lithography
C3	EUV system	Characteristics and application of EUV optical systems
C4-1	Beam	Lithography laser with beam delivery and beam pointing control
C4-2	Pulse and chamber	Excimer laser with optical pulse multiplication and discharge chamber
C5	Bandwidth control	Technique for bandwidth control of an electric discharge laser

5. Conclusions

This article presents a modified FCA-based dynamic patent lattice that can analyze the complex relations among patents and monitor trends of technological changes. The FCA is extended to take time periods and changes of patent keywords into account for the purpose of technology monitoring. A patent context is first constructed with the aid of domain experts and text mining technique. Two types of dynamic patent lattice are then developed by executing a modified FCA algorithm. The proposed dynamic patent lattice provides insights into the trends of technological changes by identifying and visualizing the development history of individual patents. The comparative study shows that it has considerable advantages in terms of visualization and informative power, compared to conventional patent citation map.

We believe that with the suggested algorithm it is possible to understand the trends of technological changes. The main contributions and potential utilities of this study are twofold. First, this study theoretically contributes to technology monitoring research, proposing an intelligent approach that can structure, analyze, and visualize the trends of technological changes. As the comparative study shows, the dynamic patent lattice is advantageous over conventional patent citation map in terms of visualization and informative power. It overcomes the drawbacks of patent citation analysis that stem from only consideration of citing-cited information and time lags between citing and cited patents by extending the conventional keyword-based patent analysis. Second, this study is exploratory in that a modified FCA algorithm is first proposed. The focus of this study is not limited to the development of dynamic patent lattice. Rather, this research emphasizes on the details of modified FCA algorithm and its strengths for monitoring the trends of technological changes. Also, the modified FCA algorithm can be applied in many real world problems. The procedures can be used in monitoring and assessing new business opportunities instead of technological changes. Although more business models and software solutions are patented, they have not been yet analyzed actively. Those patents can be good sources of new business creation and should be addressed in the future research.

By its nature, this study is an exploratory one, and needs more extension and/or elaboration in terms of methodology and application. Firstly, information loss occurs during analysis since the dynamic patent lattice is developed based on the index of similarity. This is why one of main objectives of our algorithm is to effectively structure and visualize the trends technological

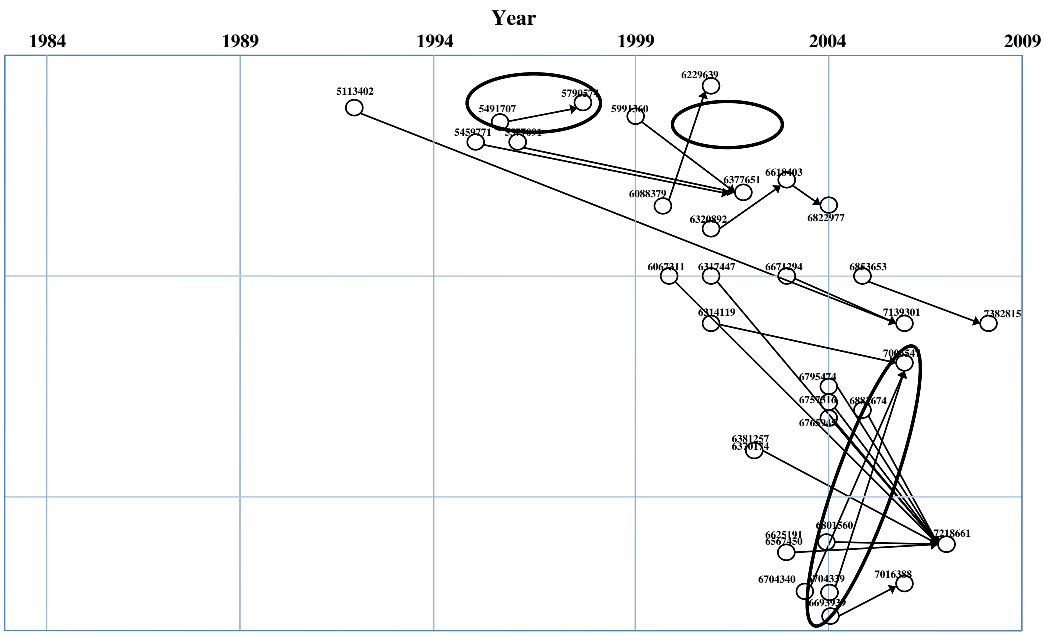

Fig. 8. Patent citation map for laser technology in lithography.

changes. Trade-offs between readability and information are inevitable. Secondly, the validity of this approach necessitates more testing work by employing patent documents from a wider range of technologies, which is indispensable for gaining external validity. In addition, real case studies in the company setting will be required in the future and we are planning to continue the research. Thirdly, various algorithms and indexes need to be devised to extend and diversify the scope of analysis. Moreover, other factors such as organizational capability and selection environment should be incorporated to fully understand the nature of technological development. Finally, the whole process needs to be systemized and automated. Although an automated supporting system has been developed, there is still considerable scope for further work to enhance operational efficiency. These topics can be fruitful areas for future research.

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Appendix A. Pseudo-code of modified FCA algorithm

```
RPC=Sort (patentContext, issuedDate)
for i=1 to # of patent{
        tempList=Read(RPC, i)
        if ( tempList consists of all new keywords )
                Make_Node(tempList)
                // Make a node for ith patent without linkage
        else if ( tempList consists of new and existing keywords ){
                Make_Node( Find_New_Key(tempList) )
                Link( Find_Related_Node(tempList) )
        }       // Make a node for ith patent and link up with related patents
        else
                if ( there exists nodes with same property in the same year )
                        Update_Property(existingNode)
                        // Add the patent to existing nodes
                else{
                        Make_Node( tempList)
                        Link( Find_Related_Node(tempList) )
                } // Make a node for ith patent and link up with related patents
        }
}
```

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Changyong Lee is a Ph.D. candidate in the Department of Industrial Engineering at Seoul National University (SNU). He holds a BS in computer science from Korea Advanced Institute of Science and Technology (KAIST). His research interests are in the areas of technology intelligence, patent analysis, business and technology planning, and service engineering.

Jeonghwan Jeon is a Ph.D. candidate in the Department of Industrial Engineering of SNU. He holds BS and MS in mechanical engineering from KAIST. He has nine years of experience as a senior engineer at semiconductor division of Samsung Electronics, Korea. His research interests include technology roadmap, technology planning, and performance evaluation.

Yongtae Park is a professor in the Department of Industrial Engineering at SNU. He holds a BS in industrial engineering from SNU, and an MS and PhD in operations management, both from the University of Wisconsin-Madison. His research topics cover a wide variety of areas including technology management, technological innovation, knowledge management, and service engineering.