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A PATENT MINING APPROACH FOR TECHNOLOGICAL OPPORTUNITY ANALYSIS IN THE TELEHEALTH INDUSTRY

Abstract:

Early identification of emerging technological opportunities is crucial for companies to formulate technology strategies that can provide a core competitive advantage over competitors in the future. This research develops a dynamic patent citation analysis methodology based on the theory of social network evolution to analyze patent documents for technological opportunity discovery in the telehealth industry. We found several technological opportunities, including healthcare administration, vital sign detection methods, transaction-based healthcare network management, movement disorder therapeutic system, health related services for IOT devices, alarm management for vital signs, and teleconference among medical practitioners. The research findings are useful for telehealth firms to understand the technological trend and explore potential technological opportunities, while formulating technology strategies to provide a core competitive advantage over competitors in the future.

Keywords:

Patent mining, technology opportunity analysis, technology strategy, telehealth.

JEL Classification: O31, O32, O33

1 Introduction

Technological opportunity is referred to a set of possibilities or potentials for technological progress in general or within a particular field (Klevorick et al., 1995). In the competitive industrial environment, early identification of technological opportunities is crucial for companies to formulate technology strategies that can provide a core competitive advantage over competitors in the future. Despite the importance of technology opportunities, technological opportunity discovery is ill-defined and poorly-structured problems in nature and thus there has been little effort to systematize practice. New opportunities may come from many different internal or external sources (Chesbrough, 2003). Companies often organize technology scouting teams with networks of experts to monitor and assess recent developments of technologies as well as their applications and focus their attention on future key technologies. Several tools or methodologies such as brainstorming, industrial/market analysis, benchmarking, technology forecasting, technology roadmapping, TRIZ, creative thinking, scenario analysis, morphology analysis, or Delphi surveys have been used in practice (Martino, 2003). However, due to reducing innovation cycles, increasing competitive volatility, fast-changing market needs, and ever-growing volumes of technical data, the expert-centric approach may not be able to fast respond to dynamic changing technologies and markets.

Another is the computer-based approach, which can well handle ever-growing amounts of information, and it is expected to complement the expert-centric approach. Meanwhile, there is an increasing number of studies to discover emerging research domains and technological opportunities (Porter, 2005). Several methodologies based on patent analysis integrated with other tools have been developed for technological opportunity analysis (Zhu & Porter, 2002; Abbas et al., 2014). A patent represents an invention in a particular field of technology and also previous studies revealed that patents constitute reliable information reflecting advances in technological development (Ernst, 2003). It contains two types of technical information: bibliographical information which is structured such as inventor, owner, application date and country, and the description of the technology and application which is unstructured such as claims and description. Since the patents are objective measure of R&D or technology development activities of companies and industries, it has been employed as an important method for technology monitoring (Porter & Detampel, 1995). According to the paper by Teichert and Mittermayer (2002), up to 80% of all technological knowledge can be assumed to be entailed in patents. Using this patent information can be regarded as a solid basis for monitoring technology evolution. Therefore it may be possible to identify the patterns of technology evolution from the patent database (Shibata et al., 2008), where the number of patent documents related to a technology and the interactions (such as patent citations) among them are low at the technology introduction stage, growing at the growth stage, and declining at the maturity stage.

Telehealth is referred to as “the use of telecommunications by a home care provider to link patients or customers to one or more out-of-home sources of care information, education, or service by means of telephones, computers, interactive television, or some combination of each’’ (Koch 2006). It creates a new paradigm in healthcare, providing a new communication channel between patients and healthcare providers to deliver better quality care at a lower cost than with traditional healthcare relying on face-to-face visits. The telehealth market is expected to reach USD 349.8 Billion by 2020 from USD 227.5 Billion in 2015, growing at a CAGR of 9.0% from 2015 to 2020 (MarketsandMarkets 2015). Major factors driving the growth of this market include rising aging population, increasing incidences of chronic diseases, increasing adoption of telecommunication technologies, growing demand for affordable healthcare delivery systems from traditional clinical settings to home care, technological advancements, and government initiatives to promote home healthcare (Lai and Wang 2015).

However, compared to other industries that have readily transformed their business models with ICT technologies, the health care industry has progressed slowly, because the complexity of health organizations and their fragmented internal structure (England, Stewart et al. 2000, Agarwal, Gao et al. 2010). Barriers to widespread adoption of telehealth services are technological, financial, and legal and have also involved business strategy and human resources (LeRouge and Garfield 2013). For example, many telehealth services fail beyond the pilot phase, because they do not provide successful technology-supported business models that can deliver values to all involved actors such as patients, health providers, vendors, payers, and government agencies (Acheampong and Vimarlund 2015). Additionally, this industry has a moderate degree of patent protection and new companies must develop telehealth services systems that are not in violation of existing patents. In June 2015, the first legal battle between two of the largest telehealth providers in the US (Wicklund 2015) signaled the importance of legal issues for growing this market. Therefore, it is important to monitor the progress of telehealth technologies to avoid the patent infringement risk. There has been much research on technological opportunity analysis based on patent information. However, till now, there is no dominant approach to discover technological opportunities in the literature.

This research aims to develop a dynamic patent citation analysis methodology based on the theory of social network evolution to analyze patent documents for emerging technological opportunity discovery. The proposed methodology assumes that the pattern of technology development is similar to the evolution of social network, where social groups in the network experience the dynamics of community formation, growth, stagnation, and shrinking over time. Therefore the social network evolution analysis can be applied to discover the patterns of technological changes. The patent citation network is used to capture the influence of one patent on another patents and the Girvan-Newman algorithm (Girvan and Newman 2002) for detection of technology communities along successive time frames. Then the Group Evolution Discovery (GED) algorithm that considers both quantity and quality of group members is applied to analyze the evolution patterns of technology communities in the consecutive time frames. Based on the results obtained, emerging technology communities are identified and the text mining techniques are used to analyze their potential opportunities. The proposed methodology is illustrated with the telehealth industry, because its rising global market value and importance to Taiwan's healthcare industrial development.

The rest of the paper is organized as follows. The literature review of technological opportunity analysis is presented in section 2. The proposed patent mining approach is introduced in section 3. The patent analysis and results for the telehealth industry are discussed in section 4. Finally, section 5 provides concluding remarks.

2 Literature Review

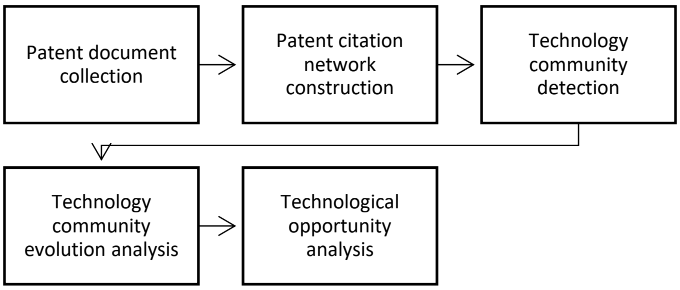
The most common approaches to identifying technological opportunities are qualitative and expert based, which utilizes the explicit knowledge of domain experts (Cozzens, Gatchair et al. 2010). However, it is often time-consuming and is also subjective in the current information-flooded era. Another is the computer-based approach, which is compatible with the scale of information, and it is therefore expected to complement the expert-based approach. One of the well-known approach is technological opportunity analysis (TOA) which has been under development at Georgia Tech since 1990 and aims at systematizing the process that prioritizes R&D investment in the emerging technology areas (Porter and Detampel 1995, Ma, Porter et al. 2013). TOA performs value-added data analysis, collecting bibliographic and/or patent information and processing it to a form that is useful to technology managers for decisions making in technology investment. Traditional patent analysis is mainly focus on the structured information of patent document because it has a standard structure and is easier to be processed and analyzed (Daim, Rueda et al. 2006). With the rapid progress of information technologies such as data/text mining (Han and Kamber 2006, Miner, Elder et al. 2012), several studies have developed methodologies for automatically analyzing the unstructured information which contains more useful information about the technology and its applications (Yoon and Park 2005, Tseng, Lin et al. 2007, Lee, Yoon et al. 2009, Wang, Chang et al. 2010, Noh, Jo et al. 2015).

A number of approaches have been developed in the TOA literature to identify technological opportunities based on patent information (Ernst 2003, Bonino, Ciaramella et al. 2010, Abbas, Zhang et al. 2014). Based on their innovation potentials, this research categorizes the TOA literature into two types: exploitation approaches and exploration approaches. Most exploitation approaches applied patent vacuum map (2009, Son, Suh et al. 2012), bibliographical analysis (Daim, Rueda et al. 2006, Ma, Porter et al. 2013, Shin and Lee 2013), and morphology analysis (Zwicky 1969, Yoon, Park et al. 2014) for technological opportunity discovery. The exploration approaches include: outlier analysis (2012, 2013, 2015), trend analysis (2008, 2010, Shibata, Kajikawa et al. 2011, 2013), analogy reasoning (2013, 2014), and gap analysis between science and technology (Shibata, Kajikawa et al. 2011, 2015).

3 Methodology

This paper aims to develop a dynamic patent citation analysis methodology based on the theory of social network evolution (Palla, Barabasi et al. 2007) to analyze patent documents for emerging technological opportunity discovery. Social networks, which is defined as social relationships connecting human entities, have become a more and more popular research domain, mainly due to the growing trend of Internet social media, such as Facebook (Scott 2012). Social communities are evolving together with the changes of the entire network. A community may appear, disappear, merge, split as well as new members join or leave existing groups (Palla, Barabasi et al. 2007). This research assumes that the evolution of patent citation network is similar to the evolution of social network. The reason is that a technology will be expanded, enhanced, or enriched as new patents are issued to technology researchers or developers, whose knowledge is built on original patents. So the patent citation network analysis over time may capture useful information about the evolution of a technology as it follows its evolution pattern. The social network perspective provides a set of methods from the theory of complex network (Boccaletti, Latora et al. 2006) for analyzing the evolutionary structure of patent citation network as well as a variety of theories explaining the patterns observed in these structures, which may provide a new perspective to study the landscape of technological innovation (Pyka and Scharnhorst 2009). The methodology of patent citation network evolution analysis consists of the following six steps (see Figure 1).

Figure 1. The proposed patent mining methodology



Step 1: Patent document collection

This research uses patent information to identify technological opportunities because patent documents provide a standardization representation of knowledge on technological advances and innovative activity for a certain technological domain (Ernst 2003). The USPTO (US Patent and Trade Office) patent database will be used as the source of telehealth patent documents because US is one of the leading and fast growing countries in the telehealth market. Since patents related to telehealth are across different technological categories, the broad query strategy is used to retrieve a wide coverage of citation data in this research. The following keywords will be used for different time frames

(t_1, t_2, …, t_{n-1}, t_n) over a reasonable long time to capture technological evolution in the telehealth industry: "telehealth"、"mhealth"、"ehealth"、 "remote patient monitoring"、"mobile patient monitoring"、"telecare"、 "connected health"、"tele home care"、"mobile health"、"telemedicine"、 "telehealthcare". The time frames used in this case study are: 1976-2005, 1976-2008, 1976-2011, 1976-2014, and 1976-2017.6.

Step 2: Patent citation network construction

Citation analysis has been the most frequently adopted tool in patent analysis (Daim, Rueda et al. 2006). Patent citations are defined as the count of citations of a patent in subsequent patents, and citations per patent represent the relative importance of the patent. Citation of one patent by another represents a technological connection between them. Several citation measures can be used to construct a patent citation network, namely, direct citation, co-citation, and bibliographic coupling. This research applies direct citation measure for network construction, because it is not only more efficient and straightforward than other two measures, but also allow us to group patents that are only rarely cited, which is a significant benefit for emerging opportunity identification (Shibata, Kajikawa et al. 2008).

Therefore, this research describe the set of patents and their citations as a weighted patent citation network $G = (V, E, W)$, where nodes $v_i \in V$ represent individual patents, directed links $(v_i, v_j) \in E$ represent citations from patent v_i to v_j, and weights $w(v_i, v_j) \in W$ indicate relative importance of patent v_j to v_i. Since a citation in a patent document usually has different contribution to the invention of the citing patent, a weight will be assigned for each citation with respect to total number of citations made by the citing patent. In other words, for a cited patent, more weight is given to the citing patent which refers to fewer citations.

In addition, this research aims to identify evolution patterns of patent citation network, we will construct patent citation networks along successive time frames: t_1, t_2, …, t_{n-1}, t_n, where t_1 is the starting investigation time and t_n is the end investigation time period. The appropriate time interval between successive time frames (e.g., t_1 and t_2) is fixed and will be determined in the project based on the tradeoff between time and accuracy.

Step 3: Technology community detection

Having the networks, technology communities are discovered by means of any clustering analysis or community detection methods. A community is defined as a group of nodes that are more densely connected to each other than to other nodes in the network. This research applied the Girvan-Newman algorithm (Girvan and Newman 2002), a hierarchical method, for detection of technology clusters, because of its popularity and computational efficiency to avoid shortcomings of the traditional hierarchical clustering method. The Girvan–Newman algorithm detects communities by progressively removing edges with a high “edge betweenness”, which is most likely "between" communities, from the original network. The "edge betweenness" of an edge is defined as the number of shortest paths between pairs of nodes that pass through it. By removing these edges, the underlying community structure of the network can be identified.

Step 4: Technology community evolution analysis

After technology communities have been identified in every time frames, the next step is to identify evolution patterns of individual technology communities along successive time frames: t_1, t_2, …, t_{n-1}, t_n. Previous studies manually identified how a group of patents grows into a larger group, merges with another group, or splits into more than two different subgroups in the next time frame (Shibata, Kajikawa et al. 2008, Shibata, Kajikawa et al. 2011, Chen, Huang et al. 2012, Érdi, Makovi et al. 2013).

This research will apply the Group Evolution Discovery (GED) method (Bródka, Saganowski et al. 2013) that was developed for the dynamic social network literature to identify evolution patterns of technology communities along the successive time frame. The major advantage of GED is that it uses not only the group size and equivalence of groups' members, but also considers their social position within a social group. Similar to the social network, we also need to consider the position and relative importance of different individual patents that may have impacts on the invention of a patents developed in the succeeding years for the technology community evolution analysis. The revised GED method for the patent citation network is briefed as follows.

Technology community evolution is a sequence of events succeeding each other in the successive time frame within the entire patent citation network. It is assumed that only one event may occur for two communities (g_1, g_2) in the successive time frames t_i and t_{i+1}. The following classification rules are defined for community evolution discovery:

- Continuing: $I(g_1, g_2) \geq \alpha$ and $I(g_2, g_1) \geq \beta$ and $|g_1| = |g_2|$ (|.| means group size)
- Growing: $I(g_1, g_2) \geq \alpha$ and $I(g_2, g_1) \geq \beta$ and $|g_1| < |g_2|$ or $I(g_1, g_2) \geq \alpha$ and $I(g_2, g_1) < \beta$ and $|g_1| \leq |g_2|$ and there is only one match event between g_1 and all groups in the next time frame t_{i+1}
- Splitting: $I(g_1, g_2) < \alpha$ and $I(g_2, g_1) \geq \beta$ and $|g_1| \geq |g_2|$ and there is more than one match events between g_2 and all groups in the previous time frame t_i
- Merging: $I(g_1, g_2) \geq \alpha$ and $I(g_2, g_1) < \beta$ and $|g_1| \leq |g_2|$ and there is more than one match events between g_1 and all groups in the next time frame t_{i+1}
- Shrinking: $I(g_1, g_2) \geq \alpha$ and $I(g_2, g_1) \geq \beta$ and $|g_1|>|g_2|$ or $I(g_1, g_2) < \alpha$ and $I(g_2, g_1) \geq \beta$ and $|g_1| \geq |g_2|$ and there is only one match (matching event) between g_2 and all groups in the previous time window t_i
- Dissolving for g_1 in t_i and each group g_2 in t_{i+1} $I(g_1,g_2) < 10\%$ and $I(g_2, g_1) < 10\%$
- Birth: g_2 is formed if for all g_1, $I(g_1, g_2) < 10\%$ and $I(g_2, g_1) < 10\%$

Note that the values of α, β are to be within the range [50%, 100%] (Bródka, Saganowski et al. 2013) and are also dependent on application domain. Therefore computational experiments will be conducted to determine their appropriate values.

The social position of a node v_j for the technology community $g \in G(V, E, W)$ of the patent citation network is calculated in the iterative manner:

$$SP(v_j) = (1-\varepsilon) + \varepsilon \sum_{(v_i,v_j)\in E} SP(v_i)w(v_i,v_j), \quad (1)$$

where parameter $\varepsilon \in [0, 1]$ is used to weigh the importance of social positions of predecessor nodes (citing patents) and $SP(v_0) = 1$, where v_0 is the node without any predecessor node in a technology community. Note that the function of *SP* can be replaced with other patent indicators or statistical measures to reflect the patent quality, such as patent scopes, family sizes, forward citations, backward citations, number of claims, grant lags, generality, originality, and technology life cycle, which are positively correlated with the value of patents (Lanjouw and Schankerman 2004). Then the following group inclusion measure, which takes the quantity and quality of community members into consideration, is defined to evaluate the inclusion of one community in another:

$$I(g_1, g_2) = \frac{|g_1 \cap g_2|}{|g_1|} \cdot \frac{\sum_{v_i\in V(g_1\cap g_2)} SP_{g_1}(v_i)}{\sum_{v_i\in V(g_1)} SP_{g_1}(v_i)}, \quad (2)$$

where the first part determines what portion of members from community g_1 is in g_2, and the second part measures what contribution of important members from community g_1 is in g_2.

Step 5: Technological opportunity analysis

After identifying the evolution patterns of technology communities over the consecutive time frames, the text mining technique (Miner, Elder IV et al. 2012) is used to analyze the unstructured data in the patent document which might contain more useful information about the technology and its applications. Key features or Keywords were extracted from parts of patent documents including title, abstract, and claims, where key contributions of patents are usually summarized in these fields. Each patent document in a community was preprocessed by tokenization, stemming, and stop word filtering, in order to retrieve keywords from the unstructured data of collected patent documents. Then patent documents in a community can be transformed into a term-document matrix, where each entry is the term frequency–inverse document frequency (TF-IDF), which is a numerical statistic, to reflect how important a word is to a patent document in the set of patent documents in a community. Next, the latent Dirichlet allocation (LDA) method (Blei, Ng et al. 2003), which is a generative statistical topic model, is applied to discover underlying topics from patent documents involved in a patent community. According to the LDA results, potential technological opportunities may be discovered.

4 Experimental Results

This research applies the developed patent mining approach to analyze patent documents for the telehealth industry. The USPTO (US Patent and Trade Office) patent database was used as the source of patent documents because the US is one of the leading and fastest growing countries in the telehealth market. After stage 1, a number of patent documents were collected in different time frames as shown in Table 1. We can observe that the telehealth related patent documents were growing along the timeline. Then, we constructed a patent citation network for each time fame in stage 2 and applied the Girvan-Newman algorithm to detect corresponding patent communities in stage 3 (Table 1). Due to the characteristics of the Girvan-Newman algorithm, there are many small patent communities. Therefore, to simplify the analytical complexity, we removed the communities with its size less than the average size of all communities. From Table 1, the number of patent communities were also growing for the four time frames (1976-2014). However, the number of communities dropped from sixty-seven to twenty-three in the last time frame (1976-2017.6), because several communities that were distinct from each other in the previous time frame were merged into larger communities. This may be explained that, due to recent advancement of information and communication technologies (ICT), telehealth technologies has become mature and many technology silos have been gradually integrated (Martin-Khan, Freeman et al. 2017).

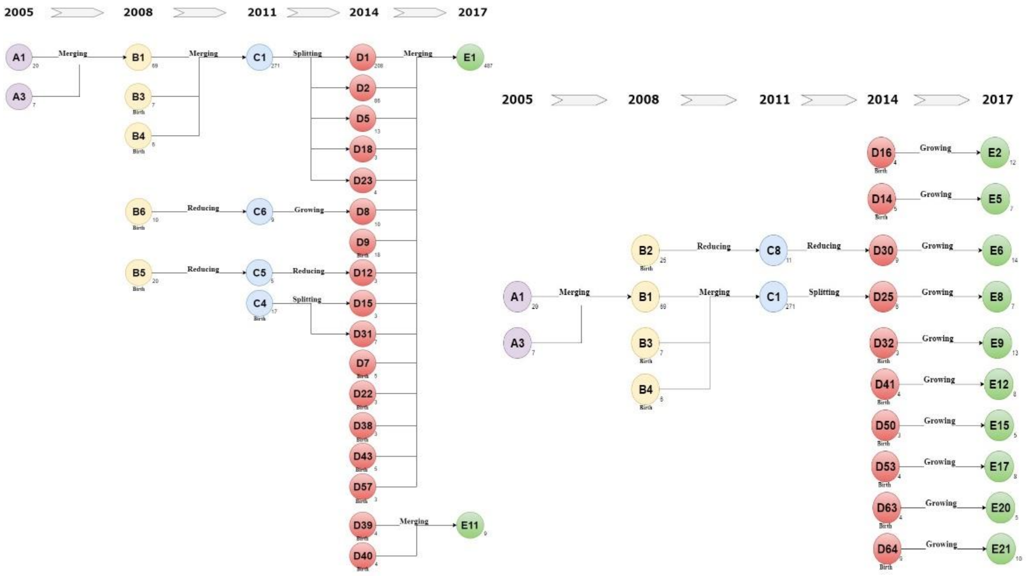
Table 1. The numbers of patent documents and corresponding patent communities in different time frames

Time frame	Number of patents	Number of communities	Community no.
1976-2005	313	3	A1~A3
1976-2008	735	6	B1~B6
1976-2011	1564	12	C1~C12
1976-2014	2641	67	D1~D67
1976-2017.6	3816	23	E1~E23

In stage 4, the Group Evolution Discovery (GED) method (Bródka et al. 2013) was applied to identify evolution patterns of patent communities along the successive time frame. Figure 2 shows two examples of evolution pattern that community E1 merged with other communities from 2005 to 2017 and E11 merged with newly birth communities D39 and D40. Since the evolution patterns of patent communities are large and complex, this paper only discusses the evolving patent communities that have might have potential technological opportunities, such as growing and birth. We found that the growing community from 1976 to 2017included E1, E2, E5、E6, E8、E9, E12, E15, E17, E20, and

E21, whereas the birth community only involved E3 and E23. In addition, the second screening criteria is the average patent publication year of a community was after 2014. Therefore, growing communities E1 and birth communities E3, E23 were selected for technological opportunity analysis using text mining tools.

Figure 2. Examples of community evolution from 2015 to 2017



(a) (b)

Next, text mining was used to preprocess patent documents of each community and then LDA was used to examine the underlying topics for each of five communities. Community E1 involved patent documents related to remote patient monitoring, roughly including the following areas: patient data collection (topics 1, 3, 8, 10), data transmission (topic 2), patient condition evaluation and notification (topics 4, 6, 7), and patient care intervention (topics 5, 9, 10). For example, for patient data collection, new opportunities might include new material can reduce product costs, weight and increase durability for patients, while new monitoring methods on sensors, devices, and robotics bring the benefits such as saving staff resources, improving accuracy and performance, improving patient compliance with health care regimens, and encouraging device usages for patients. For data transmission, the opportunities are related with the unified transmission “hub” concept that could receiving and delivering multiple biological parameters from different devices or sensors that may have different transmission protocols used by distinct incumbent firms, enhancing inter-operability between individual devices using different communication protocols and minimizing over-the-air (OTA) usage charges. For evaluation and notification, the opportunities is to develop new indicators and programs for more sensitive detection of genuine deviations at a lower false alert rate. Finally, for patient intervention, a real-time knowledge-sharing mechanism can be provided for facilitating coordination among responders and care team members, such as physician, the nurse, and the family members, who can provide timely assistance for patients. In addition, video conference and robotics can be used to enhance telepresence for more user-friendly care services.

Birth community E3 was related to telemedicine, such as providing renal care through video-as-a-service delivered to patients, remote medical consultation and diagnostic systems, and virtual clinics. In addition birth community E23 was associated with Internet of Things (IOT) communication technologies to enhance medical device interoperability, security, reliability, and faster scalability, especially for 5G.

Table 2. The numbers of patent documents and corresponding patent communities in different time frames

Topic	Meaning	Terms
1	Wearable devices	Devic, communic, network, mobil, wireless, connect, interface, processor, modul, implant, softwar, memori, instruct, portabl, unit
2	Medical data transmission technologies	Data, medic, method, devic, server, receiv, transmit, invent, present, system, automat, person, transmiss
3	Remote patient health condition monitoring	Patient, health, provid, care, apparatus, monitor, remot, inform, system, program, condit, network, individu, programm, oper
4	Video-based telehealth services	user, servic, inform, provid, imag, video, electron, access, databas, applic, function, telemedicin, record, audio, interfac
5	Medical record management	patient, system, medic, manag, diseas, base, record, treatment, store, health, autom, perform, method, therapi, state
6	Vital sign alarm management	measur, physiolog, paramet, subject, indic, detect, monitor, relat, determin, individu, event, captur, condit, method
7	Patient condition assessment	patient, data, associ, display, select, collect, clinic, system, analysi, test, diagnost, central, center, support, examin
8	Vital sign detection	system, sensor, configur, signal, receiv, process, compris, plural, input, includ, comp, vital, exampl, client, digit
9	Patient care planning	method, comput, inform, healthcar, provid, physician, identifi, generat, determin, embodi, profession, request, plan, storag, file
10	Medical tele-robotic system	remot, monitor, system, control, locat, includ, station, robot, camera, coupl, allow, oper, platform, view, internet

The following recommendations are provided for Taiwan's telehealth industry. Firstly, most of Taiwan's telehealth device manufacturers mainly develop various monitoring devices and sensors for chronical diseases (MOEA 2015). However, Taiwan's firms usually focus on fulfilling functional performance needs, rather than patient experience (Kohler, Fueller et al. 2011) to enhance their purchasing intention and willingness to use. Therefore, Taiwan's device firms may design and develop monitoring devices integrating with artificial intelligence (AI) technologies for enhancing user experience for the entire remote patient monitoring process. Secondly, since the usage behaviors of telehealth services for the elder people or patients with chronical diseases are not well understood, device manufacturers need to pay more attentions on latent user needs for value creation. Thirdly, it appears that Taiwan's telehealth firms build devices and systems by their own without considering interoperability across different platform players (Chang 2010). Firms should consider how to improve interoperability and scalability with advanced IOT technologies based on a 4G, or even 5G, communication infrastructure among various systems and platforms. However, as the telehealth industry enters the fast growing stage, firms should carefully monitor and evaluate which technology will be the proprietary standard in the future.

5 Conclusions

Early identification of emerging technological opportunities is crucial for companies to formulate technology strategies that can provide a core competitive advantage over competitors in the future. It is required to have an effective approach to support industrial practitioners to identify and analyze technological opportunities in the emerging telehealth market. This research developed a dynamic patent citation analysis methodology based on the theory of social network evolution to analyze patent documents for emerging technological opportunity discovery. The Newman's community detection method and the Group Evolution Discovery (GED) algorithm were applied to analyze the evolution patterns of technology communities in the consecutive time frames. Then, the text mining approach was used to analyze patent documents of patent communities that might have potential opportunities for the telehealth industry. Based on the results obtained, We found several technological opportunities, including healthcare administration, vital sign detection methods, transaction-based healthcare network management, movement disorder therapeutic system, health related services for IOT devices, alarm management for vital signs, and teleconference among medical practitioners.

The potential contributions are as follows. Firstly, the methodology based on the social network evolution analysis may provide different network perspective to identify emerging technological opportunities, locate influential entities, and examine network dynamics, which can classify and even predict the evolution pattern of a particular technology in the future. The research findings will be useful for Taiwan's telehealth firms to understand the technological trend and explore potential technological opportunities, while formulating technology strategies to provide a core competitive advantage over competitors in the future.

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References

Abbas, A., L. Zhang and S. U. Khan (2014). "A literature review on the state-of-the-art in patent analysis." World Patent Information **37**: 3-13.

Acheampong, F. and V. Vimarlund (2015). "Business models for telemedicine services: a literature review." Health Systems **4**(3): 189-203.

Agarwal, R., G. Gao, C. DesRoches and A. K. Jha (2010). "Research commentary—The digital transformation of healthcare: Current status and the road ahead." Information Systems Research **21**(4): 796-809.

Blei, D. M., A. Y. Ng and M. I. Jordan (2003). "Latent dirichlet allocation." Journal of machine Learning research **3**(Jan): 993-1022.

Boccaletti, S., V. Latora, Y. Moreno, M. Chavez and D.-U. Hwang (2006). "Complex networks: Structure and dynamics." Physics reports **424**(4): 175-308.

Bonino, D., A. Ciaramella and F. Corno (2010). "Review of the state-of-the-art in patent information and forthcoming evolutions in intelligent patent informatics." World Patent Information **32**(1): 30-38.

Bródka, P., S. Saganowski and P. Kazienko (2013). "GED: the method for group evolution discovery in social networks." Social Network Analysis and Mining **3**(1): 1-14.

Chang, T. Y. (2010). Taiwan's tele-healthcare industry overview, Industrial Economics and Knowledge Center (IEK), Industrial Technology Research Institute.

Chen, S.-H., M.-H. Huang and D.-Z. Chen (2012). "Identifying and visualizing technology evolution: A case study of smart grid technology." Technological Forecasting and Social Change **79**(6): 1099-1110.

Chesbrough, H. (2003). Open Innovation: The New Imperative for Creating and Profiting from Technology. Cambridge, MA, Harvard Business School Press.

Cozzens, S., S. Gatchair, J. Kang, K.-S. Kim, H. J. Lee, G. Ordóñez and A. Porter (2010). "Emerging technologies: quantitative identification and measurement." Technology Analysis & Strategic Management **22**(3): 361-376.

Daim, T. U., G. Rueda, H. Martin and P. Gerdsri (2006). "Forecasting emerging technologies: Use of bibliometrics and patent analysis." Technological Forecasting and Social Change **73**(8): 981-1012.

England, I., D. Stewart and S. Walker (2000). "Information technology adoption in health care: when organisations and technology collide." Australian Health Review **23**(3): 176-185.

Érdi, P., K. Makovi, Z. Somogyvári, K. Strandburg, J. Tobochnik, P. Volf and L. Zalányi (2013). "Prediction of emerging technologies based on analysis of the US patent citation network." Scientometrics **95**(1): 225-242.

Ernst, H. (2003). "Patent information for strategic technology management." World Patent Information **25**(3): 233-242.

Geum, Y., J. Jeon and H. Seol (2013). "Identifying technological opportunities using the novelty detection technique: a case of laser technology in semiconductor manufacturing." Technology Analysis & Strategic Management **25**(1): 1-22.

Girvan, M. and M. E. J. Newman (2002). "Community structure in social and biological networks." Proceedings of the National Academy of Sciences **99**(12): 7821-7826.

Han, J. and M. Kamber (2006). Data Mining: Concepts and Techniques, Morgan Kaufmann.

Jeong, C. and K. Kim (2014). "Creating patents on the new technology using analogy-based patent mining." Expert Systems with Applications **41**(8): 3605-3614.

Koch, S. (2006). "Home telehealth—Current state and future trends." International Journal of Medical Informatics **75**(8): 565-576.

Kohler, T., J. Fueller, K. Matzler, D. Stieger and J. Füller (2011). "Co-creation in virtual worlds: The design of the user experience." MIS quarterly: 773-788.

Lai, J.-Y. and J. Wang (2015). "Switching attitudes of Taiwanese middle-aged and elderly patients toward cloud healthcare services: An exploratory study." Technological Forecasting and Social Change **92**: 155-167.

Lanjouw, J. O. and M. Schankerman (2004). "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators*." The Economic Journal **114**(495): 441-465.

Lee, C., B. Kang and J. Shin (2015). "Novelty-focused patent mapping for technology opportunity analysis." Technological Forecasting and Social Change **90, Part B**: 355-365.

Lee, S., B. Yoon and Y. Park (2009). "An approach to discovering new technology opportunities: Keyword-based patent map approach." Technovation **29**(6–7): 481-497.

LeRouge, C. and M. Garfield (2013). "Crossing the Telemedicine Chasm: Have the U.S. Barriers to Widespread Adoption of Telemedicine Been Significantly Reduced?" International Journal of Environmental Research and Public Health **10**(12): 6472.

Ma, T., A. L. Porter, Y. Guo, J. Ready, C. Xu and L. Gao (2013). "A technology opportunities analysis model: applied to dye-sensitised solar cells for China." Technology Analysis & Strategic Management **26**(1): 87-104.

MarketsandMarkets (2015). Home Healthcare Market by Product & Telehealth - Global Forecasts to 2020, MarketandMarket Co.

Martin-Khan, M., S. Freeman, K. Adam and G. Betkus (2017). The Evolution of Telehealth. Mobile e-Health, Springer**:** 173-198.

Miner, G., J. Elder IV and T. Hill (2012). Practical text mining and statistical analysis for non-structured text data applications, Academic Press.

Miner, G., J. Elder, A. Fast, T. Hill, R. Nisbet and D. Delen (2012). Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications.

MOEA (2015). White paper of industrial technology, Ministry of Economic Affairs.

Noh, H., Y. Jo and S. Lee (2015). "Keyword selection and processing strategy for applying text mining to patent analysis." Expert Systems with Applications **42**(9): 4348-4360.

Palla, G., A.-L. Barabasi and T. Vicsek (2007). "Quantifying social group evolution." Nature **446**(7136): 664-667.

Park, H., J. Yoon and K. Kim (2013). "Using function-based patent analysis to identify potential application areas of technology for technology transfer." Expert Systems with Applications **40**(13): 5260-5265.

Porter, A. L. and S. W. Cunningham (2004). Tech mining: exploiting new technologies for competitive advantage, John Wiley & Sons.

Porter, A. L. and M. J. Detampel (1995). "Technology opportunities analysis." Technological Forecasting and Social Change **49**(3): 237-255.

Pyka, A. and A. Scharnhorst (2009). "Innovation networks." Innovation Networks: New Approaches in Modelling and Analyzing, Understanding Complex Systems, ISBN 978-3-540-92266-7. Springer-Verlag Berlin Heidelberg, 2009 **1**.

Scott, J. (2012). Social Network Analysis, SAGE Publications Ltd.

Shibata, N., Y. Kajikawa and I. Sakata (2011). "Detecting potential technological fronts by comparing scientific papers and patents." Foresight **13**(5): 51-60.

Shibata, N., Y. Kajikawa, Y. Takeda and K. Matsushima (2008). "Detecting emerging research fronts based on topological measures in citation networks of scientific publications." Technovation **28**(11): 758-775.

Shibata, N., Y. Kajikawa, Y. Takeda, I. Sakata and K. Matsushima (2011). "Detecting emerging research fronts in regenerative medicine by the citation network analysis of scientific publications." Technological Forecasting and Social Change **78**(2): 274-282.

Shin, J. and H. Lee (2013). "Low-risk opportunity recognition from mature technologies for SMEs." Journal of Engineering and Technology Management **30**(4): 402-418.

Son, C., Y. Suh, J. Jeon and Y. Park (2012). "Development of a GTM-based patent map for identifying patent vacuums." Expert Systems with Applications **39**(3): 2489-2500.

Tseng, Y.-H., C.-J. Lin and Y.-I. Lin (2007). "Text mining techniques for patent analysis." Information Processing & Management **43**(5): 1216-1247.

Wang, M.-Y., D.-S. Chang and C.-H. Kao (2010). "Identifying technology trends for R&D planning using TRIZ and text mining." R&D Management **40**(5): 491-509.

Wang, M.-Y., S.-C. Fang and Y.-H. Chang (2015). "Exploring technological opportunities by mining the gaps between science and technology: Microalgal biofuels." Technological Forecasting and Social Change **92**: 182-195.

Wicklund, E. (2015). Can telehealth be protected by a patent? mHealth News.

Yoon, B., I. Park and B.-y. Coh (2014). "Exploring technological opportunities by linking technology and products: Application of morphology analysis and text mining." Technological Forecasting and Social Change **86**: 287-303.

Yoon, B. and Y. Park (2005). "A systematic approach for identifying technology opportunities: Keyword-based morphology analysis." Technological Forecasting and Social Change **72**(2): 145-160.

Yoon, J. and K. Kim (2012). "Detecting signals of new technological opportunities using semantic patent analysis and outlier detection." Scientometrics **90**(2): 445-461.

Zwicky, F. (1969). Discovery, Invention, Research - Through the Morphological Approach. Toronto, The Macmillan Company.