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Original Research

Determining Technology Life Cycle Prediction based on Patent Bibliometric Data

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Abstract

The primary purpose of the present study is to determine the life cycle and technology prediction based on patent bibliometric data using Markov hidden model. The study population included 50,915 patent licenses in medical equipment extracted from the US Patent and Trademark Office database from 1976 to 2015. The study findings revealed technology life cycle patterns in 21 medical equipment sub-areas. The status of medical device patent license indicators at different stages of the technology life cycle, alongside the likelihood of state transfer at different stages of the medical technology life cycle, were investigated. Ultimately, the results showed that "Drug delivery equipment, Disposable medical equipment, Oximeters, and Sharps (Medical instruments)" have more suitable areas for investment and commercialization. The current research results can also provide a good insight into technologies and can be used as a guide alongside experts and other decision-making methods.

Keywords: Technology Forecasting, Technology Life Cycle, Patents, Hidden Markov Model, Medical Equipment.

Introduction

The result of R&D activities in companies is often manifested as innovations. Among these, different ways are used to protect these innovations and patents as a mechanism to protect them (Wu & Lee, 2007). Through this, patent licenses are useful information sources for analyzing technology development trends and are being explored in research and development management projects to assess the potential competitors' position (Daim, Rueda, Martin & Gerdsri, 2006). Patent applications are full of bulky technical information that requires a great deal of manpower to analyze them. Therefore, the need to employ automated and semi-automatic tools in the content analysis process of patent applications to assist decision-makers in various fields of technology and foresight is strongly felt (Tseng, Lin & Lin, 2007) .Thus, timely recognition of the future status of technologies in an industry will help managers to invest in emerging technologies. Among the benefits of this outlook are the creation of sustainable competitive advantage and a superior market position in the future industry for firms, since technological changes have been so rapid, in recent decades, many countries and companies have been out of competition) Chesbrough, Vanhaverbeke & West, 2008; Gao et al., 2013) On the other hand, the technology gap between developed and developing countries is widespread. All of this has led to planning for the future, requiring a deep understanding and scrutiny of the emergence of new technologies. In addition to being aware of the future of technology, the first step in planning to start a business and produce a new product in new technologies is forecasting.

Technology forecasting is the systematic study of the future state of a technology that provides an accurate and practical insight into the trend of future technologies, so it can play an important role in research and development management, including strategy formulation (Jun, Park & Jang, 2012). To estimate the future development of one technology and make decisions to invest in it or not, one needs to know the current stage of its technology life cycle (Gao et al., 2013), therefore, by using the analysis of patents, it is possible to determine the status of the technology in the life cycle of the technology and what technologies have reached the end of their life, what technologies may appear in the future, and which of the technologies are the most important.

With technology forecasting, we can provide a vision of the future of technology to corporate executives, industry planners, researchers, and experts, and gather information on the process of technology development and the evolution of new technologies (Ashton, Kinzey & Gunn, 1991; Joung & Kim, 2017; Lee, Kim, Noh, Woo & Gang, 2017). The purpose of technology forecasting is to predict the features, capacities, and parameters of technology that may emerge in the future. In fact, in light of the concept of world trade, the business environment is expanding as countries' trade interactions with the world increase, and organizations are trying to play a useful role in the world market and experience a competitive environment. They are facing new challenges every day, and it is becoming increasingly difficult to retain existing customers and attract new customers. Given the limited budgets for R&D departments in organizations and the fiercely competitive environment among them, it is necessary to focus on the production and development of technologies that are more likely to succeed and shorter in commercializing, and ultimately, you could move toward economic development.

In addition to the previous, nowadays, technology development is a crucial and essential factor in economic development. For that reason, forecasting technologies are a must for many industrial, financial, and service companies. This is all because these companies are deeply influenced by emerging innovations (Gao et al., 2013). On the other hand, technological change has been so rapid in recent decades that it has left many countries and organizations out of the competition and has widened the technology gap between developed and developing countries (Suryadi, Salimridwan, Dou & Purnama, 1999). This is why, in today's world, planning for the future requires a deep understanding of why new technologies are emerging (Khalil, 2000) that Parts of this information are obtained through patent data.

From engineering to medicine and sciences, and even humanities, social sciences, and psychology, they pursue the above objectives through the information of patent licenses. Medicine is one of the fields that has received the most impact from innovations, and the progress of this field is influenced by the development of technologies and innovations. Considering the importance of this field, the review of the research history regarding patents, confirms that the publication of articles has been focused on and They have neglected the importance of patents in decision-making processes, predicting the future of technology, and planning and applying information. For this reason, it becomes necessary to conduct researches that examine the life cycle of technology and predicts the future of technology to respond to the needs of various companies and industries that operate in the field of innovations and the production of competitive goods.

In this study, the technology forecasting and Technology Life Cycle (TLC) examination of medical equipment has been done after analyzing medical equipment patent information using Markov hidden model (HMM). As a significant study in the technology lifecycle; the present research, unlike others, has used seven indicators, including the number of patents, patent assignees, patent classes, backward citations, forward citations, and duration of examination that can be used in examining this lifecycle and its future. Conducting research that examines the life cycle of technology and forecasting the future of technology becomes necessary because it responds to the needs of various companies and industries that are active in the field of innovations and the production of competitive goods. For this reason, the results of this study will help product designers and manufacturers to make decisions about new product design and technology commercialization. They will guide investors and managers in the decision-making process in investment planning and technology research and development. It will also assist in macro-level policy-making to inform the current state of technology and to decide and plan for it.

The remainder of the study is organized as follows: Section II Research Literature, Section III Research Method, Section IV Data Analysis, Section V Technology Life Cycle Patterns of 21 Medical Equipment Sub-fields, Section VI Clustering Technology Life Cycle Patterns, Section VII predicts the future for the advancement of medical device technology and section VIII includes studying and conclusion.

Literature review

Conducting research that examines the technology life cycle and forecasting its future is therefore needed to meet the needs of different companies and industries active in the field of innovation and production of competitive goods. In this regard, the research into the technology life cycle can be examined in several respects. Most studies have emphasized the importance of patent data in determining the life cycle of technology and have investigated this issue using various methods.

There are various methods for technology forecasting. Some of these methods include Delphi (Rowe & Wright, 1999), Scenario (Daim, Rueda, Martin & Gerdsri, 2006), Environmental Scanning (Fahey, King & Narayanan, 1981), Brainstorming (Popper, 2008), Patents Analysis (Daim, Rueda, Martin & Gerdsri, 2006), Relevance Tree (Glenn & Gordon, 2003), Morphological Analysis (Yoon & Park 2004), Cross Impact Analysis (Choi, Kim & Park, 2007) CB-SEM (Dash & Paul 2021), Time Series (Adamuthe & Thampi, 2019), mixed methods approach (Kucharavy, Damand & Barth 2022), and Future Cycle (Lee, Kim, Kwon, & Woo, 2016). The choice of any of these methods for technology forecasting depends on the time and resources available and the goals of technology forecasting implementation.

Co-Word Mapping has been used repeatedly to identify technology’s emerging areas. The results of this research identify patent subject areas (by classifying similar topics and identifying new ones) and the evolution of technologies. Along with the syntactic analysis of patents, some researchers have identified technology trends and lifecycles using text mining (Dehghani

Madvar, Ahmadi, Shirmohammadi & Aslani, 2019; Uhm, Ryu & Jun, 2017; Yoon & Park, 2007).

Another way to study the technology life cycle is the S-Curve method, which illustrates how technology matures in 1721. In other studies, the Hidden Markov Model (HMM) and Patent Indicators are also used to estimate and forecast the latest technology (Lee, Lee & Yoon, 2011; Lee, Kim, Kwon, & Woo, 2016). In addition to various statistical methods, the use of expert opinions is common in technology life cycle forecasting despite the biased probability (Shibata, Kajikawa, Takeda, & Matsushima, 2008).

Another group of studies dealing with patent license data relates to research explicitly examining the stages of technological maturity. These researches are based on clustering (Trappey, Wu, Taghaboni-Dutta & Trappey, 2011), logical growth curves (Milanez, de Faria, do Amaral, Leiva & Gregolin, 2014), and examining the patent’s class (Dubarić, Giannoccaro, Bengtsson & Ackermann, 2011) and deep learning (Krestel, Chikkamath, Hewel, & Risch, 2021). The results of research by Trappey, Wu, Taghaboni-Dutta and Trappey (2011) using RFID patent applications in RFID technology indicated that this technology had reached maturity. Also Milanez, de Faria, do Amaral, Leiva and Gregolin (2014) using the patents listed in the DII Derwent innovations index in the field of nanotechnology concluded that the stages of nanotechnology development began in their adolescence Dubarić, Giannoccaro, Bengtsson and Ackermann (2011) obtained wind energy technology in seven years using patent applications from the Swedish patent and registration office (PRV) in the field of wind energy, which was European patent classification (ECLA). The past has grown tremendously, and the maturity of this technology will happen in the future.

In addition to the above research, some studies have investigated the technology life cycle and technology forecasting using research papers. Rezaeian, Montazeri and Loonen (2017) have studied the prediction of science in natural ventilation using research papers on wind receivers using life cycle analysis, data mining, and clustering. The results show that the number of publications in this field will grow by 54% by 2020, and if innovations emerge in this area, the growth length will also increase.

Another group of studies has investigated this subject using bibliographic and citation data (Chen, Chen & Lee, 2011; Kim, 2003; Kim, Suh & Park, 2008; Tsai, Che & Bai, 2021; Mao, Han, Liu, Crittenden, Huang & Ahmad, 2022). In these methods, citations are usually divided into two groups: Backward citation and Forward citation (Haupt, Kloyer & Lange, 2007; Jee, Kwon, Ha & Sohn, 2019). In this group of research, the use of matrix and clustering of patents (Jun, Park & Jang, 2012), K-means algorithm (Dubarić, Giannoccaro, Bengtsson & Ackermann, 2011), keyword-based patent maps (Geum, Lee, Yoon & Park, 2013; Yoon & Park, 2004), patent co-word map analysis (Wu & Leu, 2014), data mining and the combination of statistical methods and neural networks patent (Jun & Lee, 2012; Hosseini Bamakan, Babaei Bondarti, Babaei Bondarti & Qu, 2021; Fadavi Hoseini & Mansouri, 2022) and Markov Model and patent indicators (Lee, Kim, Kwon, & Woo, 2016; Wu, Wei, Chen, Long, Huang, & Mei, 2021) predicted technology life cycle. Jun and Lee (2012) research showed that the matrix map shows wider occupied spaces, whereas the clustering method based on the backing vector shows more specific vacancies. In their study, Kim, Suh and Park (2008) outlined the semantic network and patent license mapping according to the frequency of the words, and using patent mapping provided an overview of emerging technologies and provided an insight into technology.

Patent applications were another type of patent information that was used in research to predict technology. In their study, Jun and Lee (2012) developed the IPC cod Matrix (PICM) using data mining techniques used in Emerging Technology Forecasting (ETF) modeling. Using the results of numerical P Regression and correlation analysis, significant IPC codes were extracted from PICM and constructed the ETF model. This model showed the relationship between IPC codes using multiple regression and neural network models. The proposed model of this research can be used to predict different emerging technologies.

In addition to methods and tools such as citation analysis, bibliometrics, machine learning, data mining, and text mining for forecasting technology, the Hidden Markov model has been used in various studies to analyze the technology life cycle and other fields concerning technology. Due to these characteristics, the Hidden Markov model has been used in multiple research fields such as speech and personality recognition (Azar & Seyedarabi, 2020; Milanez, de Faria, do Amaral, Leiva & Gregolin, 2014; Woodland & Povey, 2002), DNA diagnosis (Churchill, 1989), technology growth analysis (Lee, Lee & Yoon 2012; Rezaeian, Montazeri & Loonen, 2017) and energy forecasting (Lee, Lee & Yoon, 2011).

A review of the records showed that patent applications had attracted the attention of researchers due to their valuable information on studying technologies and identifying new technologies. It is examining the technology life cycle, which is a good way to determine the technology life cycle and predict the future of technology. However, in most studies, the evolutionary stages of technology have not been studied, which is addressed in this research using the hidden Markov model. also, no related research has been found in lifecycle medical technology research, and given its importance in the health and diagnosis of diseases and the likelihood of investor interest, this study examines the life cycle of technology and medical equipment using seven indicators.

Forecasting is the art of imagining a range of possible futures in a way that informed choices could be made about actions that affect the future (Ernst, 1997). Awareness of the future is one of the integral aspects of planning for future activities and events. People know that technology is changing and evolving, but they don't see the location and details of that development. However, it is not appropriate to state that technological changes cannot be recognized. Our actions influence and even shape the future. So, you have to ask yourself what the effect will be. If new technology is to be introduced, how much will it be successful in the market?

Medical Equipment

According to the World Health Organization (2016), medical equipment is any instrument, apparatus, implement, machine, appliance, implant, reagent for in vitro use, software, material, or another similar or related article, intended by the manufacturer to be used, alone or in combination, for human beings, for at least one or more of the following medical purposes:

- Diagnosis, prevention, monitoring, treatment, or alleviation of disease;
- Diagnosis, monitoring, treatment, alleviation of, or compensation for an injury;
- Investigation, replacement, modification, or support of the anatomy or a physiological process;
- Supporting or sustaining life;
- Control of conception;

- Disinfection of medical devices;
- Providing information on in vitro examination of specimens derived from the human body.

Medical equipment is produced to diagnose, direct and treat medical conditions. The demand for medical equipment has increased in recent years, and its global market is constantly growing. Medical equipment is a very dynamic industry, in which significant developments and innovations are taking place every day. Over time, the demand has increased in foreign markets, and companies are looking for more global profits. With the increasing globalization of medical equipment, it is necessary to understand its global market.

Forecasting Technology

forecasting Technology provided the direction and pace of technological changes and early detection of emerging technologies (Jee, Kwon, Ha & Sohn, 2019; Pérez, 2003). Emerging technologies stimulate technological development and innovation in various fields of technology. The development of technology is dependent on the emergence of related technologies (Bengisu & Nekhili, 2006; Daim, Rueda, Martin & Gerdsri, 2006). Therefore, extracting the relationship between target technology and related technologies is important for technology development.

Technology Forecasting is the prediction of the future of technology that provides precise and practical insight into future technology trends. It can, therefore play an important role in R&D management, including strategy formulation. Using technology forecasting results, it is possible to plan R&D policies and develop new products. Also, a technology prediction model can shape a company's technology life cycle by making strategic decisions about technology licensing and patent management (Jun, Park & Jang, 2012).

Technology Life cycle

The concept of the technology life cycle includes measuring technological changes that involve two dimensions of integrating technologies into products and processes and their competitive impact, among other technologies (Geum, Lee, Yoon & Park, 2013). If a technology has a low competitive impact and integration for forming new technology in products and processes, it is at the emerging stage. High-impact technologies that have not yet been integrated into products and processes are called "pacing technologies", which are in the growth stage and have the potential to affect other technologies. If a technology integrates into products and processes and maintains its competitive stand, a key technology has entered maturity. At this stage, the time required to become a key technology can vary for various technologies. If a technology loses its impact in a short time, it becomes a basic technology, enters the saturated phase, and should be replaced by new technology. As a recommendation, the R & D investment should be focused on pacing technologies, so identifying these types of technologies is critical (Lee, Lee & Yoon, 2011).

Identifying the life cycle stages of a technology area requires identifying the indicators extracted from the patent information. Changes in any of the patent indicators can signify progress or even backwardness in the technology life cycle; it represents a movement from one stage to the following or the previous one.

Hidden Markov Model (HMM)

Because technology forecasting could have a direct and positive effect on the decisions of companies and investors (Popper, 2008), it is necessary to use a method that has accuracy and reliability. According to this, the Hidden Markov model is one of the methods used for technology forecasting, and hence, its validity has been confirmed in various studies.

Markov model, named after a Russian mathematician, Andrey Markov, receives transition from one state to another with countable states. The hidden Markov model is a machine learning technique, based on a doubly stochastic process. The stochastic process is not observable but can be observed by a secondary set of stochastic processes (Geum, Lee, Yoon & Park, 2013).

Most of the studies that have used the Hidden Markov model for technology forecasting stated that this model is more accurate than many other models, and that is because it provides a valuable perspective (An, Han & Park 2017) and facilitates technology life analysis (Lee, Kim, Kwon & Woo, 2016). Usually, researchers who use the Hidden Markov model to forecast and analyze the technology life cycle have also used patents bibliographic and citation information to achieve research goals (An, Han & Park, 2017; Lee, Go, Park & Yoon, 2017; Lee, Kim, Noh, Woo & Gang, 2017; Lee, Kim, Kwon & Woo, 2016; Lee, Yoon & Park, 2009; Momeni & Rost, 2016), because Patent information is a valuable data that makes it possible to provide models related to technology forecasting (Jun & Lee, 2012).

The main difference between the conventional Markov chain and the HMM is that the state sequence of the HMM cannot be observed, while the observation sequence that these hidden states generate can be. Considering this characteristic, the Hidden Markov model is exploited in some research fields, such as speech recognition (Agarwal, 1998), DNA recognition (Gort, & Klepper, 1982), and technology growth analysis (Gort, & Klepper, 1982; Jee, Kwon, Ha & Sohn, 2019). HMM presents three results in the study of the technology life cycle (Lee, Kim, Kwon & Woo, 2016):

1. An unconventional learning machine technique that demonstrates the most likely stages of a technology's progression associated with patent indicators without the need for additional information (such as the growth patterns of the previous similar technologies or pre-determined growth curves). Thus, they provide more practical use.

2. Based on the theory of stochastic processes, the HMM provides objective evidence for the results that allow the researchers to conduct further analysis of them.

3. It is an effective tool for supporting experts' decision-making. When automated, it will enable faster analysis of a huge number of technologies.

As mentioned before, one of the most important issues in the Hidden Markov model is its training and evaluation. Besides this, one of the most popular and common evaluation algorithms is the Baum–Welch algorithm that has been used in this study. To evaluate this model, a 10-step rotational validation analysis method has been used. In this method, firstly, the data were randomly divided into 10 categories. Then nine of them have been used as data training categories, and the one that was left has been used as validation data.

Materials and Methods

In terms of purpose and type, this research is an applied and exploratory one, respectively. It is also deemed as a technological study. The community of this research comprised all of the patents of the medical equipment that have been indexed in the US Patent and Trademarks Office (USPTO) from 1976 to 2015. For the following reasons, patents were used by our research community:

1. Almost eighty percent of the technical information is available in patent publications, which can be valuable as they are published under international standards (Jee, Kwon, Ha & Sohn, 2019; Lee, Kim, Kwon, & Woo, 2016);

2. Patents include technological as well as managerial information, such as countries, assignees, and inventors (Ernst, 1997);

3. Patents provide information on the life cycle of technology before the start of the product (Agarwal, 1998; Geum, Lee, Yoon & Park, 2013); or industry life cycles (Debackere, Verbeek, Luwel & Zimmermann, 2002; Gort & Klepper, 1982). Thus, it helps the firms decide when to start a new business;

4. Finally, the information of patents is global and applicable to a wide range of technologies (McGahan & Silverman, 2001).

The patent database of the United States is the largest patent market worldwide, and most patents that are accepted on this site are accepted in other countries as well. This database is suitable for analyzing global technology, and the data are well organized on this site. Also, the full patent file is available in the patent database from 1976 to 2015, which is why the website was used as a source of data collection. The reason for addressing the field of medical equipment is the high impact of this area of technology on innovations. In general, medical technology is a vast field, in which innovations play a vital role. Medical equipment includes several sub-fields. To determine these sub-fields, the divisions of the Library of Congress subject headings were used:

Medical instruments and apparatus
Narrower Terms

- Audiology--Instruments
- Biosensors
- Colloids in medicine
- Contraceptives
- Dental instruments and apparatus
- Dermatology--Apparatus and instruments
- Diagnostic ultrasonic imaging--Instruments
- Disposable medical equipment
- Drug delivery equipment
- Electroconvulsive therapy--Equipment and supplies
- Endoscopes
- Extremity pumps
- Holography in medicine
- Imaging Systems in Medicine
- Lasers in medicine
- Linear accelerators in medicine
- Medical radiology--Instruments
- Medical thermometers
- Metals in medicine
- Obstetrics--Apparatus and instruments

- Oximeters
- Polymers in medicine
- Sharps (Medical instruments)
- Speculum (Medicine)
- Speech therapy--Instruments
- Stethoscopes
- Stomach-pump
- Surgical instruments and apparatus
- Tourniquets

Narrower terms were considered as subdivisions in medical equipment. On this basis, this field includes 29 sub-fields and the search for patent licenses based on the keywords of each sub-field.

Table 3 lists the search formulas for each of them. Of the 29 sub-fields of medical equipment, 3 sub-fields were not considered as separate ones in this study, because they were subsets of other sub-fields in the Library of Congress Classification. These areas marked in the star chart include Holography in medicine, Linear accelerators in medicine, and Speculum (Medicine). Holography in medicine was a sub-field of Lasers in medicine, Linear accelerators in medicine were a sub-field of Medical Radiology - Instruments, and Speculum (Medicine) was a subset of surgical instruments and apparatus.

The short form “ttl” used in the search term is abbreviated for Title, Ab stands for Abstract, and Icl stands for International Classification. Considering that this research field of study is medical equipment and “equipment” is equivalent to the words “medical instrument”, “medical apparatus”, “medical device” and “medical equipment”, in the search term of the fields in which the word “equipment” was in the title, these four words with the logical operator “or” were combined.

In addition to keywords, the search term "a61" was used internationally to provide a more accurate search, and the International Classification of Indexes for Patent A61 has been published as follows:

MEDICAL OR VETERINARY SCIENCE; HYGIENE (Medical or Veterinary Sciences; Health)

Because the US Patent and Trademark Office has not classified applicable patent licenses since June 2015, the international category of patent licenses has been used instead. To recover all a61 subclasses, this category was used along with the $ sign in the search term. For example, the search term “Diagnostic ultrasonic imaging - Instruments” is as follows:

(ttl/ (Diagnostic and ultrasonic and imaging and (instrument or equipment or device or apparatus)) or abst/ (Diagnostic and ultrasonic and imaging and (instrument or equipment or device or apparatus))) and icl/a61$

With this search term, patent licenses are recovered with Diagnostic ultrasonic imaging in the title or abstract, along with at least one of the “medical Instrument”, “medical apparatus”, “medical device”, or “medical equipment” keywords, and where in their international categories a61 exists. Through Patent Licenses International Classification, category a61d belongs to veterinary medicine. And only a 61d category was removed from the search results. Finally, 50,973 patent licenses were recovered.

Table 3-2 shows the number of patent licenses for each sub-field:

According to the present study, for the study of the technology life cycle and forecasting forty-year, the sub-fields that had less than 30 patents during this period were not examined due to the low number of cases. These areas included Dermatology - Apparatus and instruments, Electroconvulsive therapy - Equipment and supplies, Extremity pumps, Obstetrics - Apparatus and instruments, and Speech therapy - Instruments, which are marked with an asterisk in the table.

Given that the low number of patent licenses could be due to the new nature of that field, the patent licenses of these five areas were examined. it was determined that the patent licenses in Dermatology-- Apparatus and instruments from 1979 to 2012, Electroconvulsive Therapy Patent Licenses - Equipment and supplies from 1988 to 2001, Extremity pumps from 1977 to 2012 Obstetrics and Apparatus and instruments patents from 1981 to 2015, and Speech Therapy and Instruments patents from 1986 to 2015. Due to this, it was confirmed that these areas were not new and consequently, were excluded from the research.

Data Analysis

The operational definition of the patent indicators used in this study is shown in Table 1.

Table 1
The Operational Definition of the Patent Indicators

Indicator	Operational definition
Number of patents	The number of patents issued in the medical equipment technology from 1976-2015
Patent assignees	The number of different assignees in the medical equipment technology from 1976-2015
Patent classes	The number of different classes of the relevant patents in the medical equipment technology from 1976-2015
Backward citations	The average number of backward citations of the relevant patents in the medical equipment technology from 1976-2015
Forward citations	The number of forward citations of the relevant patents in the medical equipment technology from 1976-2015
Duration of examination processes	The average time between the filing date and granting date of The related patents in the medical equipment technology from 1976-2015
Claims	The average number of the claims of the relevant patents in the medical equipment technology from 1976-2015

These indicators were extracted from 1976 to 2015 for 21 sub-fields of medical equipment and saved in an Excel file, the results of which were stored in a 7*840 matrix. Part of this matrix is shown in Table 2. Concerning two indicators of the number of assignees and classes of the patents in medical equipment from 1976 to 2015, the similar assignees and classes in each sub-field of the medical equipment were only counted once. For example, if several patents were assigned by one particular assigner in 2015, it was only counted once for 2015. For the patent classes, if multiple patents were similar in 2015, then that class was only counted once for 2015.

Table 2
Part of the Patent Indicator Matrix

Sub-field	Year	Number of Patents	Patent assigners	Patent classes	Backward citations	Forward citations	Duration of examination Processes (month)	Claims
Audiology--Instruments	1976	2	2	12	3.00	95	21.5	١١.00
Audiology--Instruments	1977	4	2	14	2.25	101	18.1	7.50
…	…	…	…	…	…	…	…	…
Contraceptives	1990	19	15	69	11.53	388	25.8	16.74
Contraceptives	1991	18	8	62	11.00	240	22.2	11.44
…	…	…	…	…	…	…	…	…
Sharps (Medical instruments)	2014	39	30	14	109.51	42	47.8	18.41
Sharps (Medical instruments)	2015	44	37	20	113.34	16	46.82	18.91

After obtaining the indicators of the patents (Table 2), the HMM was implemented in R Software with four stages introduction, growth, maturity, and saturation. The first stage is the introduction of technology, which begins with new ideas in products or processes. In the second stage, growth, companies make new products and compete with other companies to make the product. At the end of this stage, the product's technology is well-known in the marketplace. At the maturity stage, the companies that have consolidated their position in the market during the growth of technology will benefit greatly. At this stage, the technical idea of the product will not be altered, and the changes will be applied more to its appearance and side features than its essence. In the fourth stage, saturation, the previous technology will be replaced by a new one soon. Companies are inclined to build new technology, the previous technology will be removed from the market, and the people will move to buy a product with new technology. If the technology is in this state of its life cycle, any investment in that technology will not be profitable. Using the HMM, the table of the average of the patents indicators vectors was obtained at each stage of the life cycle of the medical equipment technology according to the numbers in the patent's indicators matrix of 21 sub-fields of the medical equipment (Table 3). Since the differences were determined by subject and the number of patents in each subject was used as an effective indicator in the analysis, the patents of each subject were also analyzed independently and were not accordingly normalized. On the other hand, since the Hidden Markov model is non-observational, it is used in situations where observer data is not available (Lee, Kim, Kwon & Woo, 2016). Accordingly, for the reason that the present study did not have any observer data available, Markov hidden model which did not require any training was used.

Table 3

The Average of the Patents Indicators Vectors at Each Stage of the Life Cycle

Indicators	Stage 1	Stage 2	Stage 3	Stage 4
Number of patents	3.8	62.3	127.9	333.9
Patent assigners	2.6	33.5	71.6	3269.2
Patent classes	10.7	137.7	118.3	586.2
backward citations	12.9	14.8	78.5	8.4
Forward Citations	97.6	3258.5	1083.8	19723.6
The average duration of examination processes	25.5	25.3	48.6	30
Claims	12.4	16.2	18.7	17.5

For example, according to Table 3, 3.8 represents the average number of patents that are in the first stage of the technology life cycle; 82.3 represents the average number of patents that are in the second stage of the technology life cycle; 127.9 represents the average number of the patents that are in the third stage of the technology life cycle; and 333.9 represents the average number of the patents that are in the fourth stage of the technology life cycle.

As it is clear in Table 3, some indicators of the patents for medical equipment vary widely between the stages of the technology life cycle. For example, the number of patent assigners, the number of patent classes, and the average number of backward and forward citations of the patents showed a significant difference between the third and fourth stages. This can be considered useful in determining the transition between specific stages of the technology life cycle. The high number of changes in the average forward citation at stage 4, 19723.6, is since the patents form the initial steps of a new technology's establishment and must be cited for further patent requests.

Given the implementation of the HMM, the probability of being at any stage of the technology life cycle at the onset is known as the first stage of the technology life cycle (Table 4). No. 1 in Table 4 means the probability of the initial state. That is to say that the technology of medical equipment, according to the HMM, starts with the introduction stage, which is the first stage of the technology life cycle.

Table 4

The Probability of the Initial State

Stage 1	Stage 2	Stage 3	Stage 4
1	0	0	0

Technology Life cycle patterns in Medical Equipment

Using the data obtained in the previous steps, the HMM was implemented and the patterns of the technology life cycle were mapped for 21 sub-fields of the medical equipment (Figure. 2). As the different life cycle patterns of the medical equipment technology show, sub-technologies are in various stages of the technology life cycle and show different development. As the various patterns of medical equipment technology life cycle elaborate, the sub-technologies in this field are in different stages and show different progress behaviors, but most of these patterns are in their growth phase. Finally, it can be concluded that medical equipment technology in many areas is still in the early stages of the technology life cycle.

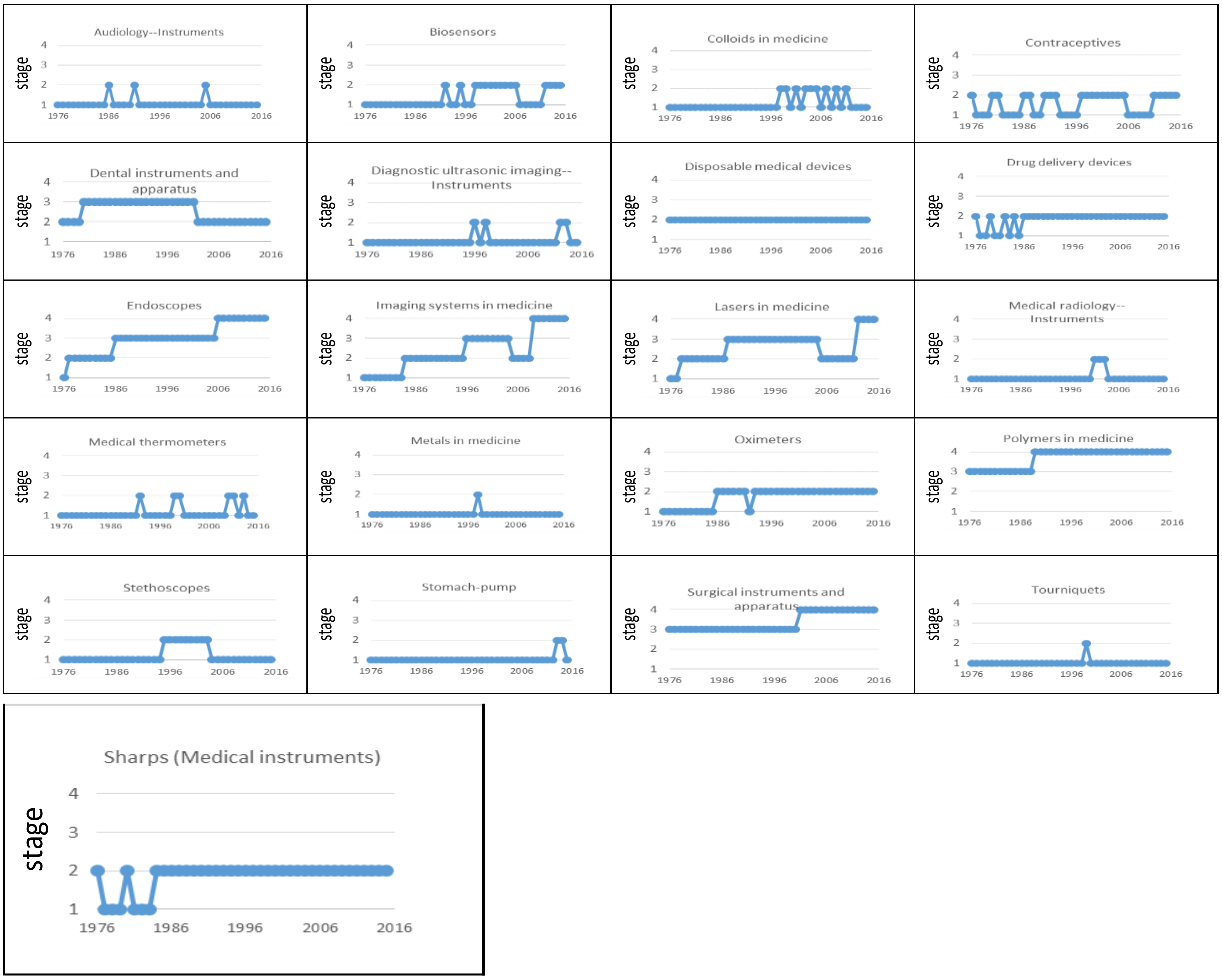

*Figure 2: Life cycles of medical equipment technology**Technology lifecycle patterns***

Clustering

The Technology life cycle patterns vary in terms of factors, such as the number of ups and downs of the technology life cycle and the duration of each stage of the technology life cycle (Table 5).

Table 5

Factors Extracted from Sub-Technology Life Cycles

Factor	Operational definition
Number of ups and downs	The number of ups and downs in the technology life cycle
Duration at stage 1	The number of time units at stage 1
Duration at stage 2	Duration at stage 2 The number of time units at stage 2
Duration at stage 3	Duration at stage 3 The number of time units at stage 3
Duration at stage 4	The number of time units at stage 4

Using Agglomerative Hierarchical Clustering (AHC), which is a clustering method designed to build a hierarchy of clusters, the medical equipment sub-technologies were identified with a similar life cycle, the results of which are given as a dendrogram diagram in Figure. 3. As the dendrogram diagram shows, the life cycles of 21 sub-fields of medical equipment are divided into 4 clusters according to the factors in Table 5. In these four clusters, the maximum similarity within each cluster and the maximum difference between distinct clusters are maintained at an appropriate level. Table 6 identifies the number of the medical equipment sub-technologies in each cluster and their titles along with the characteristics of each cluster.

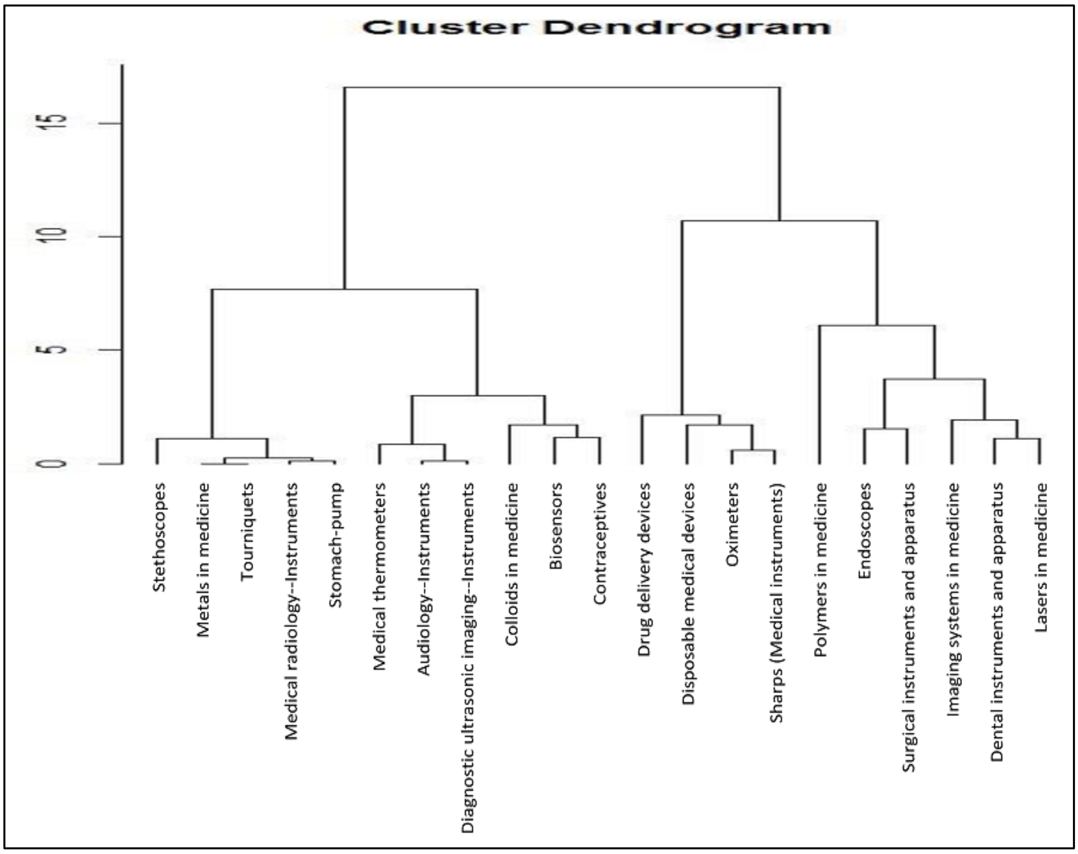

Figure 3: Dendrogram generated by the AHC algorithm.

As shown in Table 6, the technologies of Stomach-pump, Medical Radiology-Instruments, Tourniquets, Metals in Medicine, and Stethoscopes are in the first cluster. These technologies are in the first stage of the life cycle. As they stayed longer in the first stage and just moved to the second one from 1976 to 2015, they were moved back to the first stage.

Table 6
Clustering Life Cycle Patterns

Cluster	Size	Sub-Technologies	characteristics
1	5	- Stomach-pump - Medical radiology—Instruments - Tourniquets - Metals in medicine - Stethoscopes	1. In the first stage 2. they have just moved to the second stage and were moved back to the first one 3. Their staying duration is longer in the first stage.
2	6	- Medical thermometers - Audiology—Instruments - Diagnostic ultrasonic imaging--Instruments - Colloids in medicine - Biosensors - Contraceptives	1. In the introduction or growth stages 2. they have moved between the first and the second stages 3. their staying duration in the second stage is longer than the first cluster
3	4	- Drug delivery devices - Disposable medical devices - Oximeters - Sharps (Medical instruments)	1. In the growth stage. 2. they have moved between the first and second stages once or more 3. The duration of their staying in the second stage is longer than the first and second clusters.
4	6	- Polymers in medicine - Endoscopes - Surgical instruments and apparatus - Imaging systems in medicine - Dental instruments and apparatus - Lasers in medicine	1. Most of them are at the stage of maturity or saturation 2. Passed all the stages of the life cycle

The technologies of medical thermometers, Audiology-Instruments, Diagnostic ultrasonic imaging-Instruments; Colloids in Medicine, Biosensors, and Contraceptives are in the second cluster. These technologies are in the introduction or growth stages of the life cycle. From 1976 to 2015, they were moved between the first and the second stages and stayed longer in the second stage than in the first cluster.

The technologies of Drug Delivery Devices, Disposable Medical Equipment, Oximeters, and Sharps (Medical Equipment) are in the third cluster. These technologies are in the growth stage of technology, and, from 1976 to 2015, they were moved between the first and second stages and have stayed longer in the second stage than the first and second clusters.

Polymers in medicine, Endoscopes, Surgical Instruments and apparatuses, Imaging Systems in Medicine, Dental instruments and Apparatus, and Lasers in Medicine are the technologies in the fourth cluster. Most of these technologies are at the stage of maturity or saturation of the life cycle, and they have almost passed all the stages of the life cycle.

Forecasting for medical equipment technology development

The Future forecasting for the development of the medical equipment is based on the current stage position of the technology life cycle and the transition matrix. This matrix determines that the technologies can 1. Be returned to the previous stage, 2. Stay at the same stage, 3. Go to the next stage. This section examines the future of the technology for the next one, three, and five years.

Transition probability matrix

The transition probability matrix at different stages of the technology life cycle in the next one, three, and five years is given in Tables 7, 8, and 9.

Table 7
N-Stage Transition Probability Matrix, n=1

	Stage 1	Stage 2	Stage 3	Stage 4
Stage 1	0.922	0.056	0.020	0.002
Stage 2	0.060	0.9	0.036	0.004
Stage 3	0.134	0.022	0.834	0.010
Stage 4	0.034	0.000	0.017	0.949

Table 8
N-Stage Transition Probability Matrix, n=3

	Stage 1	Stage 2	Stage 3	Stage 4
Stage 1	0.801	0.141	0.052	0.006
Stage 2	0.163	0.741	0.085	0.012
Stage 3	0.316	0.070	0.590	0.025
Stage 4	0.096	0.006	0.043	0.855

Table 9
N-Stage Transition Probability Matrix, n=5

	Stage 1	Stage 2	Stage 3	Stage 4
Stage 1	0.714	0.199	0.075	0.011
Stage 2	0.245	0.624	0.113	0.019
Stage 3	0.420	0.116	0.429	0.035
Stage 4	0.149	0.019	0.060	0.772

According to Table 7, if the medical equipment technology is in the first stage of its life cycle, it remains at the same stage with a 92.2% probability and moves to the second, third, and fourth stages with a probability of 6.5%, 2%, and 0.2%, respectively, in the following year. If the medical equipment technology is in the second stage of its life cycle, it will remain at the same stage with a 90% probability, will be transferred to the third and fourth stages with the probabilities of 3.6% and 0.4% will get back to the first stage in the following year with a probability of 6%. If the technology of the medical equipment is in the third stage of its life cycle, it remains at the same stage with an 83.4% probability, will be transmitted to the fourth stage with a 1% probability, will go back to the second, and first stages in the following year with the probabilities of 2.2% and 13.4%, respectively. If a technology is in the fourth stage of its technology life cycle, it stays at the same stage with a 94.9% probability. It will get back to the third, second, and first stages in the following year with probabilities of 1.7 %, 0 %, and 3.4 %, respectively.

According to Table 8, if the technology of the medical equipment is at the first stage of the technology life cycle, it remains at the same stage with an 80.1% probability and will be transited to the second, third, and fourth stages in the following year with the probabilities of 14.1%, 5.2%, and 0.6%, respectively. If the technology of the medical equipment is in the second stage of its technological life cycle, it remains at the same stage with a 74.1% probability, will be transmitted to the third and fourth stages after three years with a probability of 8.5% and 1.2% and will get back to the first stage in the following three years with a probability of 16,3%. If the medical equipment technology is in the third stage of the technology life cycle, it will remain at the same stage with a 59% probability and will pass to the fourth stage with a probability of 2.5%, and will get back to the second and first stages in the following three years with probabilities of 7% and 31.6%, respectively. If the medical equipment technology is at the fourth stage of the technology life cycle, it remains at the same stage with an 85.5% probability and will return to the third, second, and first stages with the probabilities of 4.3%, 0.6%, and 9.6%.

According to Table 9, if the medical equipment's technology is in the first stage of the technology life cycle, it remains at the same stage with a 71.4% probability and will be transmitted to the second, third, and fourth stages in the following five years with the probabilities of 19.9%, 7.5%, and 1.1%, respectively. If the medical equipment technology is at the second stage of its life cycle, it will remain at the same stage with a 71.4% probability, will be transmitted to the third and fourth stages after five years with the probabilities of 11.3% and 1.9%, respectively, and will get back to the first stage in the following three years with a probability of 24.5%. If the medical equipment technology is at the third stage of the technology life cycle, it will stay in the same stage with a 42.9% probability, will be transmitted to stage 4 with a probability of 3.5%, and will get back to the second and first stages in the following three years with the probabilities of 11.6% and 42%, respectively. If the technology of the medical equipment is at the fourth stage of the technology life cycle, it remains in the same stage with a probability of 77.2% and will return to the third, second, and first stages with a probability of 6%, 1.9%, and 14.9%, respectively.

Technological changes in the field of medical equipment based on the integration of this area of technology into products and processes and its competitive impact using the life cycle of this technology

After depicting the life cycle patterns of technology in 21 sub-fields of medical equipment using the Hidden Markov model, the review of the technological changes in the field of medical equipment based on the integration of this area of technology into the products and processes and its competitive impact by the technology life cycle was based on a definition proposed by Arthur D. Little (Little, 1981) for the technology life cycle.

The study of the life cycle patterns of technology in 21 sub-fields of medical equipment showed that the technologies of Audiology-Instruments, Colloids in Medicine, Diagnostic Ultrasonic Imaging-Instruments, Medical Radiology-Instruments, Medical Thermometers, Metals in Medicine, Stethoscopes, Stomach- pump and Tourniquets, as shown in Fig. 2, are at the beginning of the technology life cycle. These technologies have little competitive impact and have not had much influence on the products and processes. These technologies were transferred to the growth stage once or more during the years 1976 to 2015 and returned to the introduction stage. This indicates that the competition for these technologies, over the course of forty years, has risen, still, they have not matured because they could not penetrate the products and processes, and have returned to the introduction stage since they have lost their competitive edge.

Technologies of Biosensors, Contraceptives, Dental Instruments and Devices, Disposable Medical Equipment, Drug Delivery Devices, Oximeters, and Sharps (Medical Equipment), as shown in Fig. 2, are at the growth stage of the technology life cycle. These are technologies with more competitive impact, but they have not yet fully penetrated the processes and products, and have been imported to a small extent in them. Biosensors, Contraceptives, Drug Delivery Devices, Oximeters, and Sharps (Medical Equipment), during the years between 1976 and 2015, have returned to the introduction stage of the technology life cycle several times. This shows that these technologies have lost their competitive edge over the course of these forty years. However, as the competition has grown up for these technologies, they re-emerged at the growth stage. The Technology of Dental Instruments and Apparatus, although at its growth stage, entered the maturation stage once in 1980 in the period of 1976 to 2015 and has been at this stage for 21 years. This technology has been a key one over the past 21 years. The competition for this technology has been high and has had a huge influence on the products and processes. However, the transition from the maturation stage to the growth stage can indicate an innovation in this technology. By making certain changes, this technology has been prevented from reaching the stage of saturation and technological degradation before it is turned into a basic one and replaced by new technology. The technology of disposable medical Equipment has been at the growth stage from 1976 to 2015. During these forty years, there has been no shift in the stages of the technology life cycle. It means that it has developed over the past 40 years as a pacing technology. Also, since it has not been integrated into the products and processes, it has remained at this stage. Moreover, as this technology has not lost its competitive edge over the years, it has not returned to the introduction stage.

Technologies of Endoscopes, Imaging Systems in Medicine, Lasers in Medicine, Polymers in Medicine, and Surgical Instruments and Devices, as shown in Figure. 2, are at the saturation stage of the technology life cycle. These are the technologies that have lost their competitive impact have been largely integrated into the products and processes, and have become basic technologies so that shortly they will probably be replaced by the new ones and thus, become the old technologies. Among these technologies, Imaging Systems in Medicine and Lasers in Medicine, within the years between 1976 to 2015, have returned from the maturation stage to the growth stage, which probably represents an innovation in these technologies. Before any of these technologies become basic technologies and be replaced with new ones, the saturation stage was precluded beforehand by making a new change in the technology. However, this new change, after a while, reached the saturation stage without reaching the maturation stage. It means that it suddenly lost its competitive impact and penetrated the products and processes, and became a basic technology without becoming a key one

Discussion

The production and designing of a new product, the commercialization of technology, and the investment and planning for the research and development of the technology in medical equipment require sufficient information about that technology. The lack of knowledge about the process and speed of the advancement of various fields in medical equipment technology and the state of the new technologies in this area would lead to wrong investments, lack of profitability, and financial losses. Therefore, according to the results of the present study, it was found that there are 9 subfields of medical equipment at the introduction stage, 7 subfields at the growth stage, and 5 subfields at the saturation stage of the life cycle. That is to say, more than fifty percent of this technology is in the first and second stages. It shows that medical equipment technology is one of the technologies that are in the introduction and growth stages in its life cycle. Hence, it can be concluded that there are many innovations in medical equipment. This technology, among some technologies like Audiology-Instruments, Colloids in Medicine, Diagnostic Ultrasonic Imaging-Instruments, Medical Radiology-Instruments, Medical Thermometers, Metals in Medicine, Stethoscopes, Stomach-pump, and Tourniquets, is among the new technologies that have not yet been integrated into processes and products and have a little competitive impact. These technologies start with a new idea in products or processes and indicate the birth of a new product. In These technologies, if to be invested in, costs would outweigh the revenue as they are in the early stages of the technology life cycle (Ernst, 1997; Khalil, 2000). This Subject has been emphasized in various studies (Jun, Park, & Jang, 2012). The technologies of Biosensors, Contraceptives, Dental Instruments and Devices, Disposable Medical Equipment, Drug Delivery Devices, Oximeters, and Sharps (Medical Equipment) are considered to be pacing technologies, which have a lot of competitive impacts, are integrated into processes and products, and are in the growth stage. These technologies are welcomed by companies, and there is competition among the companies for their mass production, they are well-known in the market and have great potential for commercialization and revenue generation. In the case of investment in these technologies, the investment costs will be restored and the revenue would ensue. The technologies of Endoscopes, Imaging Systems in Medicine, lasers in Medicine, Polymers in Medicine, and Surgical Instruments and apparatuses are basic technologies that have lost their competitive impact and have greatly penetrated processes and products. Companies that are active in the field of technology tend to develop new technologies because these technologies will probably be removed from the market or to be replaced by other technologies, and the customers will tend to buy a product with newer technologies. In this case, the companies can compete in the market if they make changes to the product and add innovation. These technologies are not the correct options for investing as they have excessive influences on products and processes.

The results of the present research showed that the medical equipment technology at the second stage is more liable to return to the first stage after one, three, and five years than to progress to the following one. t. If the technology is at the third stage, the likelihood of staying at that stage after five years is less than 50%, and the technology will return to the previous stages with a probability of 53.6%. Hence, returning to the previous stages after 5 years is more probable than staying in the third stage, and if the technology is in the fourth stage of its life cycle, the probability of staying in the fourth stage after one, three, and five years is much greater than the probability of returning to the previous ones.

Conclusion

The main advantage of this kind of research is that it facilitates business decision-making concerning a technology life cycle (Ernst, 1997; Khalil, 2000). Integrating patent indicators into the HMM provides a comprehensive and balanced view of the technology life cycle. Although this research focuses on the life cycle of a technology, the proposed approach can be used to analyze the life cycle of industry and production as well. From the practical point of view, the results of this research provide information on the current stage position and the future forecasting of technology, providing faster analysis of a wide range of technologies and supporting decision-making with reasonable time and cost. Therefore, the proposed approach is more practical than the previous approaches, given that there is no need for additional information on the patterns of growth of similar technologies or predetermined growth curves. Unlike some of the studies that used a single indicator in the life cycle of technology (Wu & Leu, 2014; Milanez et.al., 2014; Jun & Lee, 2012), the present study used seven indicators to examine the technology life cycle and its future forecasting. However, it should be stated that investment and commercialization should not solely be based on the results obtained from these methods. These methods can provide a proper view of the technology, and act as a guide along with the opinions of the experts and their experiences. Moreover, when technology in a developed country is deteriorating, it might not have reached its deterioration in a developing country and more years for it may remain yet.

Regarding the use of the Hidden Markov model, the results of the present study showed that this model is suitable for forecasting and analyzing the technology life cycle. Figure 1 shows that medical technologies are in different conditions according to their patents data and condition, and based on the results, it can be analyzed and illustrated by using this model. To confirm each technology condition, it is recommended that the subject be finalized by examining the market and interviewing the experts.

Limitations and future research directions

Limitations

In terms of the applicability of the proposed approach, this study also has certain limitations:

- The relationship between technologies in this research is not considered, and this can be effective in analyzing the life cycle of the technology. Some technologies are substitutes for others, or some are dependent on other technologies, so additional supplemental indicators are needed to increase the accuracy and reliability of the results of this model.
- Reviewing the life cycle of a technology based on patents may provide limited information about the market and the basic science of the technology. Therefore, using other databases, such as databases of articles or market reports in this model, can provide far better results.
- The proposed approach is not likely to be very effective for the emerging technologies due to the limited amount of data in the early stages of the advent of a technology. Therefore, there should be other ways to provide the possibility of examining emerging technologies with greater reliability and accuracy.
- This study was limited to examining the field of the medical equipment. Using this model in various other technologies could elucidate the merits of the proposed approach.

Research suggestions

- The suggested approach in the present study might be used in other areas of the technology.
- Reviewing the technology life cycle through other databases can provide more complete

and accurate information in the field of technology.

- Utilizing other complementary indicators, such as the novelty of a technology and market share can be effective in the technology life cycle.
- The indicators used in this study are not constant and can change in different technologies. More research is needed to be conducted in a wider range of other technologies, to identify the value of this model.

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