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Technology-driven roadmaps for identifying new product/market opportunities: Use of text mining and quality function deployment

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ABSTRACT

A technology roadmap (TRM), an approach that is applied to the development of an emerging technology to meet business goals, is one of the most frequently adopted tools to support the process of technology innovation. Although many studies have dealt with TRMs that are designed primarily for a market-driven technology planning process, a technology-driven TRM is far less researched than a market-driven one. Furthermore, approaches to a technology-driven roadmap using quantitative technological information have rarely been studied. Thus, the aim of this research is to propose a new methodological framework to identify both profitable markets and promising product concepts based on technology information. This study suggests two quality function deployment (QFD) matrices to draw up the TRM in order to find new business opportunities. A case study is presented to illustrate the proposed approach using patents on the solar-lighting devices, which is catching on as a high-tech way to prevent environmental pollution and reduce fuel costs.

1. Introduction

To compete with a market leader or to secure their positions, firms develop new technology and launch new products in the market. From a corporate standpoint, careful technology and product planning have been considered a continuing challenge in building profitable businesses. Several tools have been suggested to support the process of technology innovation by academic researchers as well as practitioners. The technology roadmap (TRM) is one of the most widely used methods to support the strategic management of technology [1–3]. The TRM method helps organizations plan their technologies by describing the path of technologies, products and markets.

When organizations plan their technologies, two basic strategies can be distinguished, which are often referred to as "technology-push" versus "market-pull" strategies [4,5]. The technology-push strategy is a strategy containing activities that focus on invention without concern for market attractiveness and applications of technologies to products, following capabilities that exist within firms or even the intuition of top managers [6]. In contrast, the market-pull strategy is oriented toward the marketing concept emphasizing the requirements of a targeted market. In both strategies, new products and services have to be accurately responsive to consumer demands [7]. Thus, the market-pull strategy, which reflects the needs of customers, has been considered the general strategy in product development.

Recently, the life cycle of technology has become shorter, and the level of technical complexity and difficulty has been increasing. As the length of time spent replacing existing technology with another technology is shortened, the market-pull strategy to develop products based on consumer reaction causes a delay of the product launch to the market. Moreover, an increase in technical complexity makes consumers ignorant, rendering most consumers unaware of what technologies can be realized. In addition, consumers have requirements that are only associated with existing products, rather than requirements on a latent product. The development of a new product through a market-driven strategy usually means product enhancements, making us overlook promising disruptive technology to meet the latent customer needs that did not exist before. Therefore, it is important to assess whether new technology can provide some benefits to customers as a product. Because the consumers themselves are often unaware of their needs, it has emerged as an important issue for companies to launch new products reflecting the consumers' hidden needs through the technology-push strategy.

As the market-pull strategy holds a dominant position in product development, a technology-driven TRM has been far less

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studied than the market-driven one. Because TRM has evolved as a management practice, rather than management theory, most early research on TRM has dealt with case examples [8–10], and only a few studies have suggested practical methodologies for TRM [11,12]. From the perspective of a corporate strategy, previous studies have concentrated on technology roadmapping by applying a market-pull strategy [13–15], rather than a technology-driven one [16,17]. From the viewpoint of analysis, the roadmaps depend on qualitative analysis, such as workshop with domain experts and TRM experts [12]. Qualitative analysis is a methodology to prove an existing hypothesis or to configure a new theory based on field observations, conversations and questions. This method requires a lot of time and high costs to investigate the current situation, and it is highly dependent on the judgment of experts. As quantitative analysis involves analyzing the data indicated in the figures, it is easy to ensure objectivity because of the numerical criteria for judgment. In addition, most of the studies on technology-driven roadmaps investigate indirect relationships, such as technology-industry maps, actor-similarity maps and portfolio-affinity maps [17]. Recently, there are attempts to develop the technology roadmap by using QFD [14], the Bayesian network [18], text mining and patent analysis [17,19].

Therefore, the aim of this study is to offer a new methodological framework to identify both profitable markets and promising product concepts with existing technology using quantitative analysis. The concept of technology-driven TRM is addressed on the basis of the assumption that a specific technology has been developed. Patent information is used for analysis by text mining that uncovers the wealth of information from the literature to compensate for the fact that the early studies used qualitative analysis. While patents are used to analyze technologies, product manuals are collected to investigate the products, and market reports are applied to scrutinize markets. This study suggests two quality function deployment (QFD) matrices to link between each layer to draw up a technology-driven TRM that starts with a given technology that has been developed as a method to find new business opportunities. When a new technology is developed in the firm, it is placed in the technology layer. Next, a product layer is created by the technology layer based on technological information, and then a market layer is drawn up by the derived product layer. Through the results of an interpretation of the identified product opportunities, a promising market can be found in which the firm has the possibility to earn money. Although the proposed approach serves as a new, valuable method for exploring new opportunities for new products and markets by systematically analyzing current technology and their relationship in advance, it is not regarded as a panacea for all issues related to business strategies. Because this method will depend on the relationship among existing technologies, products and markets, the scope of relevant technologies to which it can be applied is restricted to technological areas where past information is sufficient to anticipate future trends of technology/product/market development. In addition, the suggested process is not an expert-free approach because it includes semi-automatic techniques, such as text mining and QFD. Although many users want to utilize an automatic system that produces useful outputs without domain knowledge of experts, the involvement of experts is mandatory for valuable information to draw roadmaps.

The basics of TRM and patent analysis are briefly reviewed in Section 2. Section 3 presents the method for TRM by using reversed QFD targeted at obtaining the relationship between technologies and products, and between products and markets, as well as the method for mapping on the TRM. An illustration is presented in Section 4, and Section 5 summarizes the contributions of this study and discusses their implications. The limitations of this study and the directions for future research are also discussed in this section.

2. Background

2.1. Technology roadmap

Along with the rapid development of technology, the role of technology planning is becoming increasingly important. The appropriate use of these techniques and methodologies significantly contributes to improving the productivity of a company. The technology roadmap, Delphi, scenario, analytic hierarchy process (AHP) and quality function deployment (QFD) are known as techniques and methodologies for technology planning [20]. The technology roadmap is broadly used for planning technology, products and markets because it gives action plans for achieving the goals. It also serves as a tool for technology forecasting in that the technology roadmap provides ample information related to diverse technology alternatives, competitors and timing for entering a market in the future through analyzing current technological specification and customer requirements, comparing their advances to the current status of technology development.

The technology roadmap is defined as a medium- and long-term technology planning methodology to derive products and technologies that need to be developed to meet the future demand and to select the best alternative technologies based on the future market forecasts. In other words, the technology roadmap is one of the methods to support the strategic management of technology, exploring the relationships among organizational goals, technical resources held by the organization and changing market opportunities. With these technology roadmaps, technology planning is promoted to establish details of the related project. The technology roadmap can support a process to understand the core technology and technology gap with the performance target and provide a means to reconcile R&D investment decisions by coordinating research activities among the relevant members [21]. In particular, because in the manufacturing sector, equipment supplier selection can influence technology planning, a new technology roadmap was proposed to reflect the cooperation with suppliers [22].

The technology roadmap approach is very flexible in terms of the different organizational aims that roadmaps intend to address and the range of graphical forms that roadmaps can take. In terms of the intended purpose, eight types of roadmaps have been identified: product planning [23], service/capability planning [24], strategic planning, long-range planning [25,26], knowledge asset planning [27], program planning, process planning and integration planning [28]. Furthermore, eight types of roadmaps have been identified relating to graphical format: multiple layers [29], bars [30], tables [31], graphs [31], pictorial representations [32], flow charts [33], single layer [30] and text [34]. The most frequently used technology roadmap is basically a time-based graphical chart that has several layers, such as the technology layer, product layer and market layer. Recently, a bibliometric analysis is applied to enhance the role of the technology roadmap by mapping the knowledge evolution and expert networks [35,36].

2.2. Patent analysis

Patent documents contain important research results that are valuable to the industry, business, law and policy-making communities. If carefully analyzed, they can show technological details and relations, reveal business trends, inspire novel industrial solutions or help make investment policies [37–39]. In addition, patents are used to search and assess external technical knowledge, accumulating technological knowledge. Recently, numerous studies of patents focus on patent information analyses to determine the value of patents [40,41].

In general, patent information comprehensively covers all information arising from the moment when an applicant submits a patent application to the patent office. The patent information includes information about who develops the technology and the problems caused by the duplication of the technological development or technology theft can be solved through patent information [42,43]. The resource of each nation concerning patent information is unified as the patent and trademark office, and each country has a well-established patent database that is easily accessible via the Internet to collect and obtain patent information. Furthermore, a unified classification scheme, International Patent Classification (IPC), is used to identify a specific technology area. A patent document contains dozens of items for analysis; some are structured, meaning that they are uniform in semantics and in format across patents, such as the patent number, filing date or assignees, and some are unstructured, meaning that they are free texts of various lengths and contents, such as claims, abstracts or descriptions of the invention [44]. Patent information was simply meaningful as a literature reference. Recently, the development of a high-volume data system and search features has caused the value of the information to increase. This information is one of the sources of the technical information that provides a demonstration of economic and industry trends.

There are several ways to analyze a number of patent information. Text mining is often regarded as a process to find implicit, previously unknown and potentially useful patterns from a large text repository. These patterns can become important intelligence for decision-making [44]. In this study, a large number of patent documents will be analyzed by using data mining.

3. Research methodology

3.1. Basic concepts and overall process

The suggested approach aims to generate a methodology creating the technology-driven technology roadmap to find new business opportunities based on technology invention. Thus, there is an assumption that a firm has new technology which is not yet applied to products and markets and codified documents explaining technology while seeking to find new business opportunities through roadmapping. Basically, the technology roadmap is constructed on the basis of existing technology, product and market by text mining, thereby showing the current status of corporations. After roadmapping for existing things, new opportunities for technology, products and markets are identified through QFD and brainstorming.

This methodology is able to efficiently provide objective and reasonable information in planning new technology, products and businesses by a systematic research framework. That is because it takes a semi-automatic technique such as extracting keywords from text data and analyzing the similarities between technology, products and markets, as well as among them. In particular, it will be effective for firms that adopt technology-driven strategies more frequently than market-pull strategies.

This methodology is largely divided into two modules. The objective of the first module is to make a technology-driven TRM of existing technologies, products and markets. The second module aims at finding new technology opportunities, mapping the result of the earlier steps. The first step in the initial module for mapping technologies, products and markets that the company already has on the technology-driven TRM is to collect relevant data, such as patents, product manuals and market reports. After the main keywords are extracted from the searched documents, the document vectors are generated depending on the occurrence frequency of each main keyword that appears in each document. Those document vectors are used to calculate the values of the similarity between the documents.

Then, technologies, products and market nodes are properly defined, and the connections of those nodes are defined using similarity values calculated in the previous step. Each node is placed on the past and present parts of the technology-driven TRM, which has a technology, product and market layer and is connected with other nodes within the same layer or within an upper layer by lines. Through these processes, the past information about existing technologies, products and markets is presented in the technology-driven TRM. In the second module, in order to apply a new technology to the technology-driven TRM, keyword vectors are generated by utilizing the keywords from existing technologies and products, and the keywords represented in the new technology are extracted from new patents. The technology–product (T–P) QFD representing the relationships between existing technologies and products is built for extracting product keywords related to the new technology by applying new technology keywords into the QFD. To convert these product keywords to product names, product keyword matrix is generated. Then, a product–market (P–M) QFD is constructed to link product names and market keywords. Because the final result of the second module is potential opportunities of new products and markets where newly developed technology can be applied, new links between technology nodes and product nodes and between product nodes and market nodes are generated by using the T–P QFD and P–M QFD. These identified nodes are placed on the technology-driven TRM, considering the timing of the occurrence. Fig. 1 presents the process of developing the technology-driven TRM.

3.2. Components of technology-driven TRM

The component of the technology-driven roadmap can be largely categorized into layers, nodes and connections. Layers are divided into a technology layer, a product layer located above the technology layer and a market layer located above the product layer. These layers have a timeline. The left-hand side of the layers represents the oldest point, and the right-hand side of the layer means the most recent or future time.

Each node that is placed on each layer is a unit of concepts. Technology nodes that are placed in the technology layer represent a technology or a group of technologies. In other words, the technology node is placed in the technology layer by binding similar techniques and naming to a single node. Similarly, each product node which is placed in the product layer means a product or a family of products. Like the technology node, one product can be a node, or it may be considered as one node in a tightened series of products or product family. Market nodes placed in the market layer show the markets where its products have influence. Market nodes can be defined differently depending on the type of product. Products are largely divided into consumer goods and industrial goods. Consumer goods are products that customers purchase for the purpose of consumption, and industrial goods are used for producing other products. In the case of consumer goods, market nodes can be defined as consumer utilities. Otherwise, in the case of industrial materials, market nodes can be defined as products produced by using industrial goods.

Linkages mean relationships between nodes, and there are two types of linkages. The first one is a linkage between two nodes in the same layer; the other is a linkage between two nodes in different layers. Through linkages between technology nodes, the direction of the developed technology can be known, and degrees of technology's similarities can be also determined. Moreover, through a connection between the product nodes, it can be known that how the products have changed and how similar the products are. On the other hand, through a connection between the market nodes, it shows the trend of how changes concerning information about the market where products are launched and the market are influenced

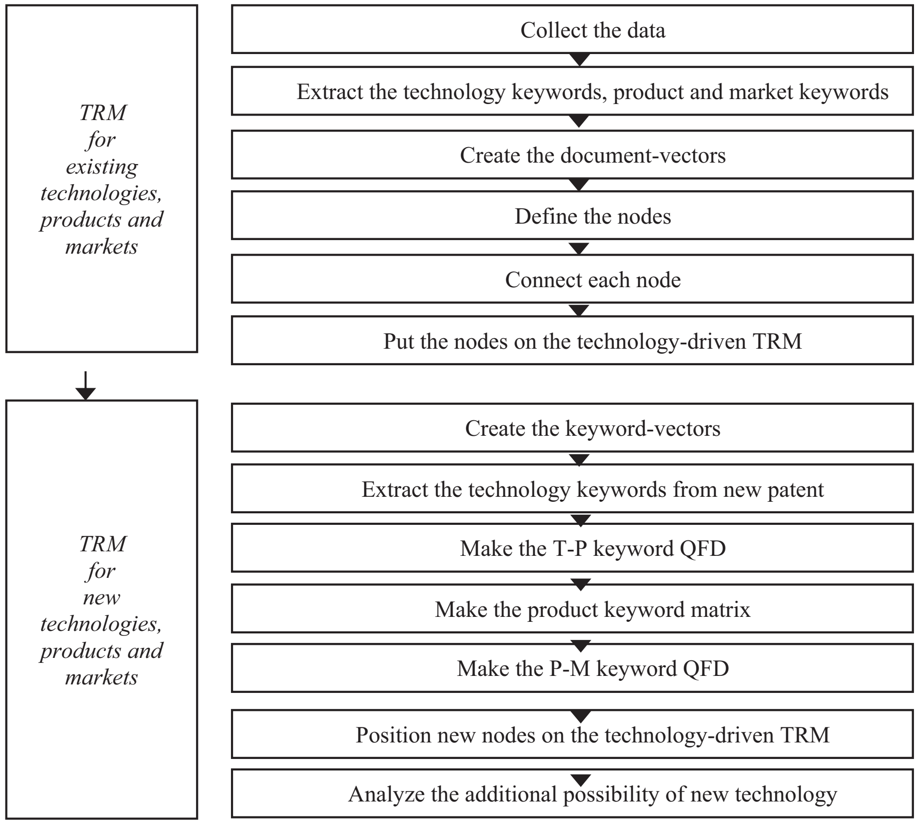

Fig. 1. Technology-driven TRM process.

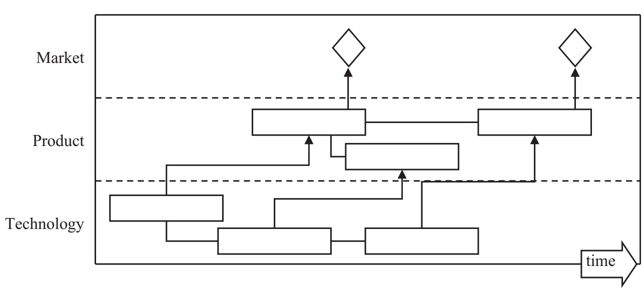

Fig. 2. Example of technology-driven TRM.

by products. The linkage between two nodes in different layers means the link between technology nodes and product nodes or between product nodes and market nodes. Through the former linkages between the technology node and product node, it is possible to identify which technology is related with either the products or the product-related technologies. Otherwise, through the latter connection between the product node and the market node, information on which market is influenced by the product can be identified. Fig. 2 presents the basic form of the technology-driven TRM.

3.3. Technology-driven TRM for existing technology

3.3.1. Data collection

The development of the technology-driven TRM that is suggested in this study has three layers: the technology layer, product layer and market layer. The proposed methodology is based on quantitative analysis. In order to analyze documents to extract important keywords, the text-mining method is typically used for quantitative analysis. Patents are treated as a technology document because patents are regarded as a vital element for analyzing technology, and they also referred to as output of all kinds of science and technological development. Product manuals or technical handbooks of products can be used as product documents. These kinds of documents involve information related to the operation of the product, technological contents for the product and the value gained from using the product. In the market document, there are market reports about the product, articles about the product and additional information. These documents are described by the consumer's view. As shown in Fig. 3, the technology document involves ample information about technology and some information about the product. The product document usually deals with contents about the product itself and some part of the market and technology. The market document describes the product from the market's view.

3.3.2. Extracting keywords and creating document vectors

In order to analyze and extract keywords from technology, product and market documents, the text-mining technique is applied in this research. It aims to solve the chaos of information overload by combining data mining, machine learning, natural language processing, information retrieval and knowledge management [45]. Text mining aims to automatically acquire meaningful and novel information from written resources through stemming, pruning and counting the occurrence of frequency. This technique has been widely utilized for extracting implications through analyzing patent documents [17,19,44–46]. Most of the studies extracted the keyword from the patent that has a significant amount of technology information and then utilized it, developing a patent map [17,48], a technology roadmap [17,19] with a combination of network analysis [47,48] in generative topographic mapping [49,50]. This research also derives keywords representing the characteristics of technology, products and markets and then develops a technology roadmap by considering keywords as the

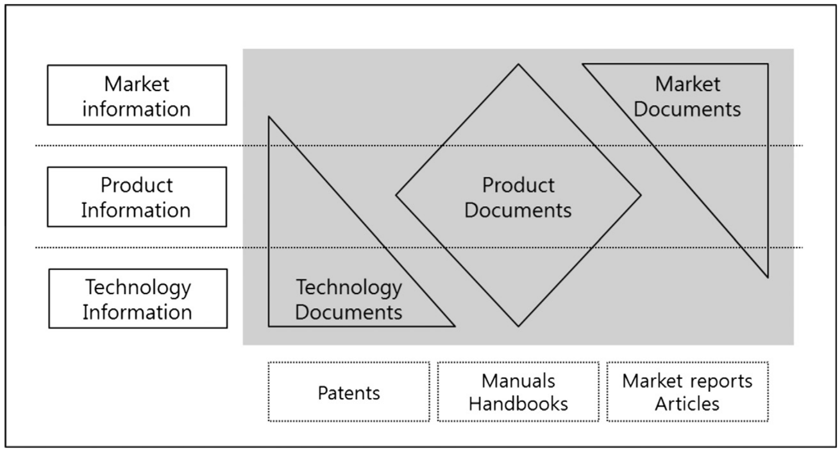

Fig. 3. Relationship among technology, product and market documents.

	Keyword 1	Keyword 2	Keyword 3	....	Keyword n-1	Keyword n
Technology doc. 1	(12	4	0		5	0)
Technology doc. 2	(3	2	0		2	1)
....						
Product doc. 1	(2	0	12		4	9
Product doc. 2	(43	5	0		24	27)
....						

Fig. 4. Example of document vectors.

contents of nodes. Furthermore, the list of keywords will serve as a critical source when analyzing the relationship among documents and planning new technology, products and markets.

The process of extracting important keywords through text mining consists of several steps. First, the particular technical area from the targeted company is selected, and technology, product and market documents are collected. Next, collected documents will be converted to structured data, and keywords will be extracted from each part of technology, product and market documents by the text mining. Because the text mining produces a lot of keywords based on the frequency of their occurrence in documents, useless words such as stop words (for example, "the", "of" and "to"), and irrelevant technology/product/market keywords should be removed in the list of keywords to improve the efficiency of analysis. At this step, domain experts who are able to identify the relevancy of keywords may participate in filtering out unnecessary keywords. After deriving keywords, document vectors are generated to explore the similarity between documents. The document vector means how many times each keyword appears in a document as shown in Fig. 4. The occurrence frequency of keyword *n* in the technology document *l* and product document *m* is presented in the each row of Fig. 4. For example, keyword 1 appears twelve times, and keyword 2 occurs four times in technology document 1. The similarity between each document can be obtained by using those document vectors. Similarity that reveals how much each document is related with other documents is utilized to connect the nodes on the TRM.

3.3.3. Defining nodes

The technology layer of the technology-driven TRM is filled by the aid of a patent document. There are two different methods of identifying a technology node. If the number of patents are small enough to fit into the one layer or if there are a few similarities among the patents, one patent is treated as one node. If there are many patents and high similarity among them, some patents could be treated as one node.

To hold some patents together, it depends on the experts, but technology keywords from patents that are intermediate outcomes of the technology-driven TRM can be used. In other words, similarities between patents can be compared by means of the keywords in the patent document and group patents with high similarity to one technology based on the similarity value. In the process of comparing similarities, the similarity value among the documents is calculated using the same method that will be illustrated in the following step.

3.3.4. Linking and placing the nodes on the technology-driven TRM

To define the linkage among the nodes, similarities among each document should be identified. The cosine coefficient, Euclidean distance and inner product are practical methods for the computation of similarities. The cosine coefficient is used in this research because cosine similarity is a measure of similarity between two vectors by measuring the cosine of the angle between them. The cosine of the angle between two vectors, thus, determines whether two vectors are pointing in roughly the same direction. This is often used to compare documents in text mining. In addition, it is used to measure cohesion within clusters in the field of data mining [51]. The cosine value of two vectors can be derived by using the Euclidean dot product formula:

$$\text{Similarity} = \cos\theta = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n}(A_i \times B_i)}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}}, \tag{1}$$

where *A* and *B* represent document vectors, respectively. The placement of each node is determined by the time concept of the layer. Specifically, technology nodes are placed in technology layers considering the application year of the patents. If a technology node includes multiple patents, the average of the application date is

	Document 1	Document 2	Document 3	....	Document n-1	Document n
Keyword 1	(12	3	0		2	43)
Keyword 2	(4	2	1		0	5)
Keyword 3	(0	0	3		12	0)
...						
Keyword m-1	(5	2	1		4	24)
Keyword m	(0	1	2		9	27)

Fig. 5. Example of keyword vectors.

used as a reference. In the case of products, these are placed in the product layer based on when the prototypes are released. Market nodes are applied when the product is actively launched.

3.4. Technology-driven TRM for new technology

3.4.1. Creating keyword vectors

In order to express a new technology on the technology-driven TRM, the degree as to how the new technology is similar to existing technologies is firstly calculated, and then similar products are found. It is assumed that the product associated with a similar technology would be similar to new products that the new technology can be applied to. In order to analyze which technologies are similar to the new technology, keyword vectors should be generated by the occurrence of keywords in documents in advance. A keyword vector measures how many times a keyword appears in each document as shown in Fig. 5, unlike the document vector, which represents how many times each keyword appears in a document. The occurrence frequency of keyword *m* in all documents, respectively, is presented in the row of Fig. 5. For example, keyword 1 appears twelve times in document 1 and three times in document 2. Two words that are closely associated should appear frequently in a document. In terms of the relationships between keywords and documents, the set of keyword vectors is a transposed matrix of the set of document vectors. The keyword vector should be made only for the technology documents and product documents. Because market documents are collected in regard to each product, one market node is matched with one product node.

3.4.2. Extracting technology keywords from new patents

As mentioned above, this methodology assumes that the firm has a new technology and relevant documents, which are not applied to any products and markets yet in order to create a technology-driven TRM. The technology keywords from a new patent are also extracted by the text-mining technique. If there are no patent documents, it has difficulty in deriving information with regard to technology. To solve this problem, technical manuals and reports, which include technological specifications in detail, can be utilized instead of patent documents. On the basis of them, technology keywords are extracted as reflecting the representative features of technology.

3.4.3. Technology–product QFD

Based on the keyword vector, which is the result of a prior step, the technology–product QFD can be constructed. The QFD represents the relationships between technology keywords and product keywords. If the technology keywords related to new technology are selected, the product keywords related to new technology are extracted.

In the technology–product QFD, technology keywords represented in existing patents are placed on the left wall of the QFD where, in the traditional QFD method, a set of customer requirements is filled in. The product keywords representing the existing products are placed on the roof of the QFD where, in the traditional QFD, a number of engineering design requirements is filled in. In the conventional QFD method, relationship degrees are scored by 1, 3 and 9. If a customer requirement and a engineering design requirement have a strong relationship, the degree of relationship receives 9 points. But if the relationship between them is weak, the degree of relationship receives 1 point. In this paper, however, such relationships are calculated by the cosine similarity between the keyword vectors. Although in the conventional QFD process, analyzers score the degree of the relationship between the two factors, the proposed approach utilizes the cosine similarity between keyword vectors of two factors as a systematic process without any involvement of experts. To accomplish this, keywords are first converted into structured data using keyword vectors resulting from text mining, according to their frequency of occurrence. To calculate the cosine similarity between two keyword vectors, this paper uses the same method for the computation of cosine similarity between document vectors. Finally, the degree of relationships among keyword vectors (for example, technology keyword vectors and product keyword vectors in a technology–product QFD) ranges from 0 to 1.

To draw up the technology–product QFD, first, the new technology keywords are scanned for duplicate keywords with the technology keywords from the existing patents. Second, the duplicated keyword frequency from the new patent is placed in the right-hand column of the technology keyword list in the technology–product QFD. Third, the product keywords are prioritized in a high order of the value of product keywords in terms of a new product. It is calculated by multiplying the keyword's frequency and the cosine similarity in each cell and finally aggregating those multiplied values. A higher value means that a keyword is closer to the new product than the other keywords. The keywords that are not identical with the current keywords from the existing patents and can be considered as new things are used for checking the additional possibility of new technology. It will be discussed in the section that includes the *additional possibility of technology* in detail. Table 1 presents the example of the technology–product QFD. PK_n indicates the *n*th product keyword, and TK_k means the *k*th technology keyword. In addition, R_{kn} indicates the degree of the relationship between the *n*th product keyword and the *k*th technology keyword. Finally, p_n and t_k are the degrees of importance of the *n*th product keyword and the *k*th technology keyword, respectively.

Table 1
Technology–product QFD example.

		Degree of importance	Product keywords				
			PK_1	PK_2	PK_3	...	PK_n
			p_1	p_2	p_3	...	p_n
Technology keywords	TK_1	t_1	R_{11}	R_{12}	R_{13}	...	R_{1n}
	TK_2	t_2	R_{21}				
	TK_3	t_3	R_{31}				
	...	...	...				
	TK_K	t_k	R_{k1}				R_{kn}

3.4.4. Product keyword matrix

To obtain the connection between product keywords and products, the product keyword matrix is created. The values of the product keywords should be mapped to the values of the existing products using the product-keywords matrix because the product nodes are put on the TRM; in comparison, the output of the technology–product QFD is the product keywords. In addition, the existing products (or product categories) are used for the product components in the product–market QFD. The product keyword matrix has two dimensions: the product keyword list and the existing products (or product categories). Each cell of the matrix is filled by its frequency in each product instruction manual. By multiplying the values of the product keywords and the figure in each cell, the values of the product keywords transform the values of the existing product because the sum of a row indicates how the existing product is related to the new product.

3.4.5. Product–market QFD

To obtain the connection between market keywords and product nodes on the product layer, the product–market QFD is constructed based on the result of the product keywords matrix. Through the result of the product keyword matrix in the previous stage, the product–market QFD is generated to link the product nodes in the product layer to the market nodes in the market layer on the TRM. Using this product–market QFD, links are found between the product nodes for the existing product and the market nodes for the existing market. Based on these links, market keywords that may be better for the new technology are found. Ultimately, the market that the new patent affects through the product is abstracted. Table 2 shows the example of the product–market QFD. PN_k and MK_n, respectively, indicate the product names and market keywords, which have degrees of importance such as p_k and m_n.

3.4.6. Linking and placing new nodes on the technology-driven TRM

New patents represent the emergence of new technologies on the technology-driven TRM. This patent is treated as a single technology node and placed in the technology layer on the TRM based on the patent application date, as well as other technology nodes. The new product node is for new virtual products, and its name refers to technology keywords from new technology and product keywords related to new technology. Market nodes are made by market keywords from market documents.

The product node should be placed in the product layer based on the average of the time interval between the recent technology and the recent product applying that technology or the average time to apply the most similar technology to the new product. As with the product node, the market node should be placed considering the average time that the prototype product takes to launch to the market. The existing technology nodes and the new ones are connected by using a document vector of the new one. The new technology and the existing technologies could be linked by the cosine similarities between them in the same way as between existing technologies. Connections between an existing product node and a new one are linked with the values of the product keywords on the product keyword matrix.

Table 2
Product–market QFD example.

		Degree of importance	Market keywords				
			MK_1 m_1	MK_2 m_2	MK_3 m_3	… …	MK_n m_n
Product names	PN_1	p_1	R_{11}	R_{12}	R_{13}	…	R_{1n}
	PN_2	p_2	R_{21}				
	PN_3	p_3	R_{31}				
	…	…	…				
	PN_K	p_k	R_{k1}				R_{kn}

3.4.7. Additional potential of new technology

The additional business opportunities of new technology can be explored from the market report embracing a variety of products. To analyze the market, the market reports about products of a company were used. However, to find new business opportunities, not only the market reports of the company but also those of other companies have to be analyzed. Through this exclusive market report analysis, the company can find new areas to advance and identify a position of new technology on industry development flow. Furthermore, an additional possibility of new technology can be explored through searching for the latest patent using a particular keyword as the core keyword. Through patent analysis, new products and new fields for new technology to be applied can be found, and new technology to apply to the product can be searched. After mining using this broaden market report and text-mining method, a possibility can be found through the expert's brainstorming based on the rest of the keywords, except related keywords of the company's holding product.

If a cosine similarity between the new patent and an existing patent is too low, it is impossible to connect technology nodes. A new patent without linkages with other nodes needs to apply a distinct procedure when finding a promising product and market because there is no information about existing technology, products and markets. For the purpose of exploring the additional possibility of new technology, keywords are extracted from the new patent, and they are utilized to search product and market reports across the industry, as this helps to discover new products and markets.

4. Case study

4.1. Data

An analysis of organizations that adopt the technology-push strategy indicates that these organizations share some common features, such as their personnel's high level of initiative and creativity, their need to always be ready to solve problems within their specificities, their enduring efforts in basic and applied research and their complex scientific and technical expertise acquired over a long period of time [52]. This research selected the field on solar light-emitting diode (LED) lighting as an illustrative example because it coincides with features of companies adopting the technology-push strategy. Most consumers may be ignorant about laser medical devices because the specifications of the relevant technology embodied in products are difficult to understand, such as principles and components. Because it is challenging to acquire customer requirements, new product development is led not by customer needs but, rather, by advances in technology and inventors. Although the proposed approach is based on technology and consumers are not familiar with technology, they will be associated with technology more and more because potential and possible concepts of products and markets are extracted from technological specification. Thus, firms in the solar LED lighting field easily choose a technology-driven strategy more than a market-pull strategy for their R&D planning.

Due to high fuel prices and environmental problems, green growth and sustainability have become hot topics on the lips of people all over the world. The study on new renewable energy, such as solar photovoltaic energy, and the effective usage of this energy are being extensively researched. A solar cell (also called a photovoltaic cell) is an electrical device that converts the energy of light directly into electricity by the photovoltaic effect. Once

Table 3
Product information.

Product line	Product name	Description
Solar brick	SB150B	• Mounting hardware for the SB100 types • Stainless steel
	SB200F	• Whole surface lighting • Suitable for leading light and decoration tile
	SB200	• Suitable for leading light and decoration tile
	SB500	• 5 zones lighting • Suitable for leading light and decoration tile
	SB300	• Suitable for leading light and decoration tile
	SB100	• Whole surface lighting • Suitable for leading light and decoration tile
	SB80R	• Round type solar light • Suitable for leading light and decoration tile
Solar garden light	SG-S900	• Combination of solar brick and LED lighting
	SG-C900	
	SG-S450	• Suitable for guard & decoration light such as a walk, a crossing and a public square
	SG-C450	
Solar street light	SL-1000S	• Safety maximization and clean-energy source without environmental pollution, radiation leakage
	SL-2000S	
	SL-3000S	• It is available to extend the battery life by PWM constant current charge
	SL-5FTL	

Table 4
Cosine similarity among the documents.

	200F	200	500	300	100	80R	S900	...	Patent 1	Patent 2	Patent 3	Patent 4	Patent 5	...	New P.1	New P.2
200F	–	0.887	0.896	0.946	0.989	0.929	0.581		0.101	0.106	0.114	0.156	0.378		0.407	0.009
200		–	0.969	0.925	0.886	0.898	0.596		0.096	0.103	0.101	0.162	0.307		0.287	0.008
500			–	0.925	0.891	0.898	0.606		0.098	0.106	0.103	0.166	0.318		0.309	0.008
300				–	0.941	0.968	0.565		0.110	0.115	0.124	0.17	0.387		0.245	0.009
100					–	0.924	0.574		0.101	0.105	0.113	0.155	0.377		0.413	0.009
80R						–	0.563		0.108	0.113	0.121	0.166	0.379		0.245	0.012
S900							–		0.003	0.015	0.034	0.067	0.105		0.371	0.033
...																
Patent 1									–	0.113	0.153	0.091	0.087		0.011	0.066
Patent 2										–	0.21	0.267	0.259		0.037	0.007
Patent 3											–	0.559	0.204		0.027	0.168
Patent 4												–	0.743		0.093	0.119
Patent 5													–		0.173	0.07
...																
New P.1															–	0.008
New P.2																–

exposed to light, it can generate and support an electric current without being attached to any external voltage source. Its high efficiency, long life and controllability by digital signal make LED lighting the next generation of lighting, as it would be substituted for incandescent bulbs and fluorescent lamps [53]. As a result, the LED lamp is adopted as a light source of the solar-lighting device. A specific firm producing a solar LED lighting device is chosen for the illustration. 14 patents were retrieved from the database of the Korea Intellectual Property Rights Information Service (KIPRIS) [54], and 15 products were targeted for analysis as shown in Table 3.

4.2. Analysis

The technology keywords that represent existing technology are extracted using a text-mining tool named TextAnalyzer from the 14 collected patents related to solar-lighting devices. TextAnalyzer reveals how many words, including stop words, appear in the articles. It splits all sentences into words, and then, the occurrence frequency of keywords in the documents is calculated. Among them, some meaningless keywords, such as stop-words, were eliminated, and 571 major technology keywords were found by frequency of occurrence. The product keywords were extracted through investigating corporate product instruction manuals relevant to the solar-lighting devices. After scanning the results, 227 major product keywords representing the characteristics of the product were selected.

The cosine similarity values between documents are found with document vectors as shown in Table 4. Whether the nodes on the TRM are linked or not depends on that similarity value. In addition, patents and product documents whose similarities are too high can be assembled into one node in the linkage between two nodes.

In this illustration, a similarity value over 0.3 is presented as a dotted line, and a similarity value over 0.5 is presented as a line. Because all pairs between nodes have a similarity value, strong relationships should be chosen and linked for visualization among them. Thus, sensitivity analysis is conducted to define the connection types between nodes in order to derive an intelligent roadmap that can show the evolutionary paths within and among layers and provide meaningful information. At first, the value of 0.5 was decided as the cut-off value for identifying whether the linkage between nodes was established. Next, the value of 0.3 was defined as a criterion for dividing the degree of connection into strong and weak relationships. It is conducted to determine the cut-off value by adjusting the value until the roadmapping result is able to show high visibility. In particular, all nodes can be connected with other

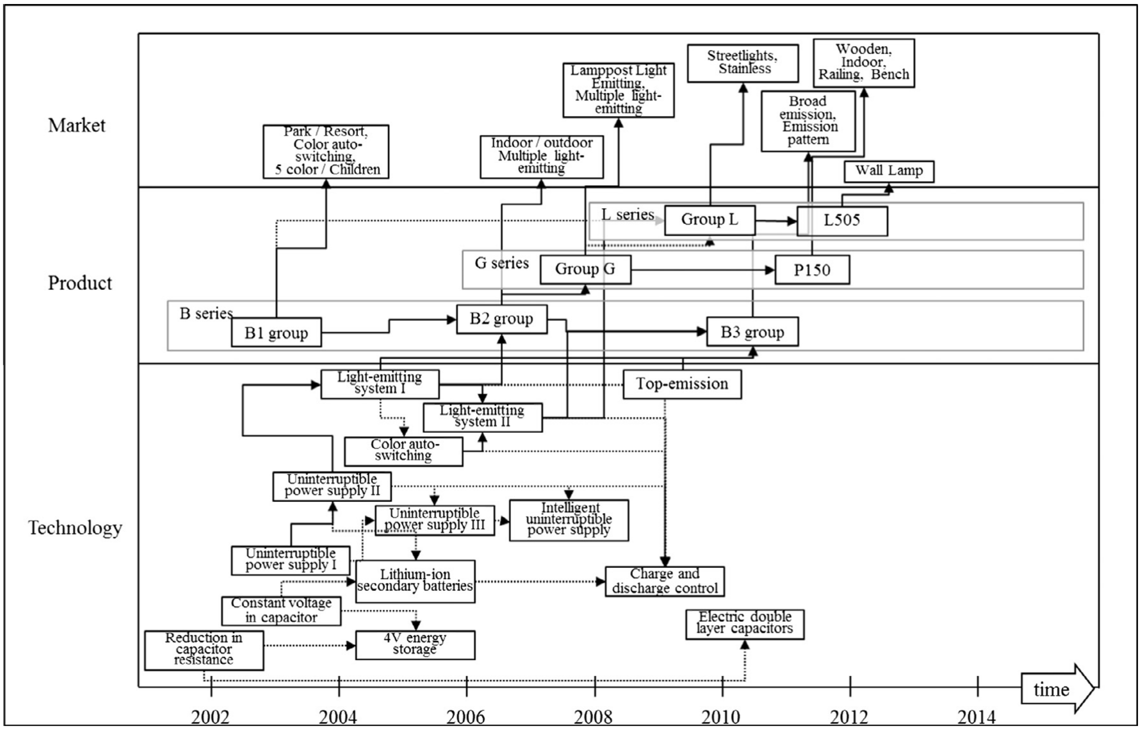

Fig. 6. Technology-driven TRM for existing technology.

nodes, which is important in the concept of roadmaps. In addition, two documents with a connection value greater than 0.95 were treated as a single node. Using the same text-mining software, market keywords are extracted and market nodes are made by main market keywords. The technology-driven TRM presented the existing technology, products and markets as shown in Fig. 6.

The following diagram is a process to apply new technology to the technology-driven TRM. To investigate the correlation between the technology keyword and the product keyword through the technology–product QFD, the keyword vector is created as a frequency of the keyword through the result of text mining from the existing and new patent and product document. In addition, to define the connection between the technology nodes, the document vector should be created, and the cosine similarity value with the existing patents should be produced. The technology–product QFD is composed of the same elements shown in Table 5, and by putting the keyword from the new technology into the QFD, the value of the product keyword is computed.

The product keyword matrix was constructed by converting the value of the product keyword to the value of the product name. The value of the product name is calculated by multiplying the value of the product keyword extracted from the technology–product QFD in Table 5 and the occurrence frequency of the keyword in the relevant product manuals and finally aggregating those values as shown in Table 6.

Also, drawing a product–market QFD representing the relation between the product name and the market keyword as in Table 7, new technology and related market keywords are extracted. Using the result, market nodes are organized. Through the result from these two QFDs, the technology-driven TRM is completed.

4.3. Results

The technology-driven TRM is finally completed as shown in Fig. 7. Each node is placed on the technology, product and market layers, and the nodes for new technologies are placed on the lower right side. Product nodes and market nodes with a dotted outline suggest that the product and market have not yet emerged.

One of the recent technologies called side-emitting has a much greater affinity with the technology named front-emitting than the others. An application of this new technology is similar with the products in the B3 group. It also implied that the products in the B3 group can be improved by grafting the new technology.

Market keywords associated with new technology, such as trails, parks and bike lanes, were extracted, and the keywords considering important keywords that have an impact on the market, such as remote identification and keyword edge emitting, are additionally extracted from technology keywords to make a market node.

Because an electrothermal glove which is regarded as new technology has low similarity with other technology nodes, there are no linkages between other technology nodes; thus, it is difficult to determine the concept of the product through existing technology information. In this case, the company needs to consider establishing a strategy that expands the product line or business areas. Thus, the representative keywords of the patent are utilized to collect the market documents relevant to the electrothermal glove firstly; then, the market keywords are extracted from the collected documents. Consequently, market nodes derived by market keywords are placed on the market layer, linking to the new product node simultaneously.

This Illustration is about how to draw a technology-driven TRM for companies. Using the proposed methodology, the technology-driven TRM can be written for the industry level as well as the corporate level. This methodology covered not only short-term forecasting for new technology but also middle- and long-term technology forecasting. Because the basic concept of the proposed approach is based on linkages between technology and product established by keywords, this methodology can be utilized to new technology of which relevant patents are not applied yet if there are technical documents.

Table 5
Technology–product QFD.

			Product keywords															
			Monsoon	Decoration	Lamp	Bus stop	Garden lights	Landscape	Lighting	Battery	Li–Fe	Gas	Drying	Season	Overcharge	Lead-acid batteries	Day time	...
			17.584	0.736	15.246	23.837	3.576	30.537	24.741	84.940	59.977	26.316	33.402	63.401	39.465	63.184	69.787	
Technology keywords	Pseudo capacitors	0	0	0	0	0	0	0	0	0	0	0.162	0.447	0	0	0	0	
	Acetylene	0	0.191	0	0.135	0	0	0	0	0.322	0	0.685	0.764	0	0.522	0.294	0.241	
	Aluminium	0	0.083	0	0.0587	0	0	0	0	0.2807	0	0.533	0.548	0	0.493	0.356	0.105	
	External control	0	0	0	0	0	0	0	0	0.267	0	0	0	0	0	0.217	0	
	Secondary battery	1	0.493	0	0.349	0	0	0.006	0.002	0.451	0.039	0.198	0.325	0.008	0.194	0.593	0.507	
	Resistance	2	0	0	0	0	0	0	0	0.022	0	0.005	0.021	0	0	0.036	0.006	
	Electric bulb	0	0	0	0	0	0	0.632	0.163	0	0	0	0	0.832	0	0	0.400	
	Electrode	1	0.109	0	0.077	0	0	0	0	0.154	0	0.266	0.593	0	0.346	0.089	0.143	
	Current limiting circuit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	Isolation	1	0	0	0	0	0	0	0	0.267	0	0.973	0.596	0	0.866	0	0	
	Light source	0	0	0	0	0	0	0.632	0.163	0	0	0	0	0.832	0	0	0.400	
	Control module	16	0	0	0	0	0	0	0	0.267	0	0	0	0	0	0.217	0	
	Control signal	5	0.355	0	0.251	0	0	0.395	0.102	0.383	0	0.121	0.158	0.519	0.108	0.142	0.736	
	Controller	17	0	0	0	0	0	0	0	0.267	0.640	0	0	0	0.289	0	0.2	
	Pulse	8	0	0	0	0	0	0.632	0.163	0	0	0	0	0.832	0	0	0.4	
	Phenol based activated	0	0	0	0	0	0	0	0	0	0	0.162	0.447	0	0	0	0	

4.4. Validation of the proposed approach

In general, the validity of a new approach can be evaluated by comparing the results of the traditional and the newly proposed approach. Because the traditional approach to developing a roadmap takes an expert-oriented method in a workshop, the suggested process to utilize a systematic, data-oriented method can be validated by investigating two developed roadmaps. In this paper, six domain experts of solar-lighting technology participate to draw a roadmap with the same data used in the proposed process. Then, in order to evaluate the performance of technology-driven roadmapping, the degree to which the results of two roadmaps are identical is examined by a confusion matrix in a binary classification handled in Tables 7 and 8, identifying whether links are properly classified. If all of the links between the nodes in an expert-oriented roadmap also exist in a roadmap through the proposed approach, this method can be perfectly utilized as a preliminary supporting tool.

The performance of a classification can be evaluated by calculating the number of correctly recognized class cases, the number of correctly recognized cases that do not belong to the class and the number of cases that are either incorrectly assigned to the class or not recognized as class cases. The four types of classification form a confusion matrix shown in Table 8 for the binary classification. Although many measures can be considered to investigate the correctness of a classification, the most frequently used measures for the binary classification, such as accuracy, error rate, precision and recall, have been presented on the basis of the values of the confusion matrix explained in Table 9.

The notion of a confusion matrix is modified to be applied to validate the links between nodes in the developed roadmap. All of the possible links between nodes are composed of elements in the data set, and the classes are separated into 1 or 0 by investigating whether two nodes are connected (1) or not (0). In addition, while the actual class in the original confusion matrix is changed into the link between the nodes by experts, the expected class is modified to link the nodes by the proposed approach. For example, if the proposed approach does not connect the relationship of the two nodes which are connected by experts, this instance is classified into f_{10}. In the illustration of this paper, all possible links from the identified 31 nodes (16 technology nodes and 15 product nodes) become 465 by combining the nodes. Among the 465 links, the number of links in the technology–technology, product–product and technology–product relationship becomes, respectively, 120, 105 and 240. Table 10 shows the confusion matrix of 465 links for the validation of links in roadmaps. Four cells of f_{11}, f_{10}, f_{01} and f_{00} in the confusion matrix have 54, 57, 33 and 321 in sequence. In order to analyze the performance evaluation of roadmapping, four indices (accuracy, error rate, precision and recall) are measured. The accuracy and error rate of the roadmap by the proposed approach are 80.64% and 19.35%, respectively, when compared with the expert-oriented roadmap. Moreover, the precision and recall are 62.07% and 48.65%, respectively. Thus, this approach shows high accuracy and a low error rate, indicating that the data-oriented process can provide useful information for roadmapping. In addition, while the precision is relatively high, the recall is not high, implying that the proposed approach misses considerable links identified by experts. Because domain experts have profound knowledge to overview and scrutinize technology and products, they can find latent links of nodes that might not be trawled in the data-oriented approach. In terms of precision, it can provide many links that experts could not identify because a link can have a hidden, complex and unrevealed relationship. Thus, after the suggested approach offers basic information for roadmapping, experts can add and check the links among the nodes. However, four indices for the performance evaluation explain that this systematic

Table 6
Product keyword matrix.

			Product names					
			200F 7387.085	200 4699.149	500 4955.689	300 5317.647	...	5F5L 8889.498
Product keywords	Overcharge	12.17633						1
	Light source	35.78531	1			1		
	Light guide Plate	225.9652	3					
	Road	17.19022	1			1		
	...	...	...	...	...	...	...	...
	Patterns	214.4519	1					
	Permanent	66.93534						
	Light-emitting	101.6648	4	1	2	1		5
	Emitting member	166.9973	1	1	1	1		
	Emission system	73.26738	4	2	2	4		
	Discharge	52.6703						2
	Battery	16.89914						3
	Light energy	9.984084						
	Light energy\	202.4195	1	1	3	1		
	Spread	214.5004	2					

Table 7
Product–market QFD.

			Market keywords								
			Streetlights 350151.52	Boundary stone 5410.19	Park 44013.56	Play ground 3308.04	Road 39835.40	Luminaires 254655.65	... ...	Separator 9924.12	Trails 51340.68
Product names	200F	7387.085		2	1		4				
	200	4699.149					1				
	500	4955.689			1						
	300	5317.647									
	...	...					1				
	5F5L	8889.498	11		2		1	8			2

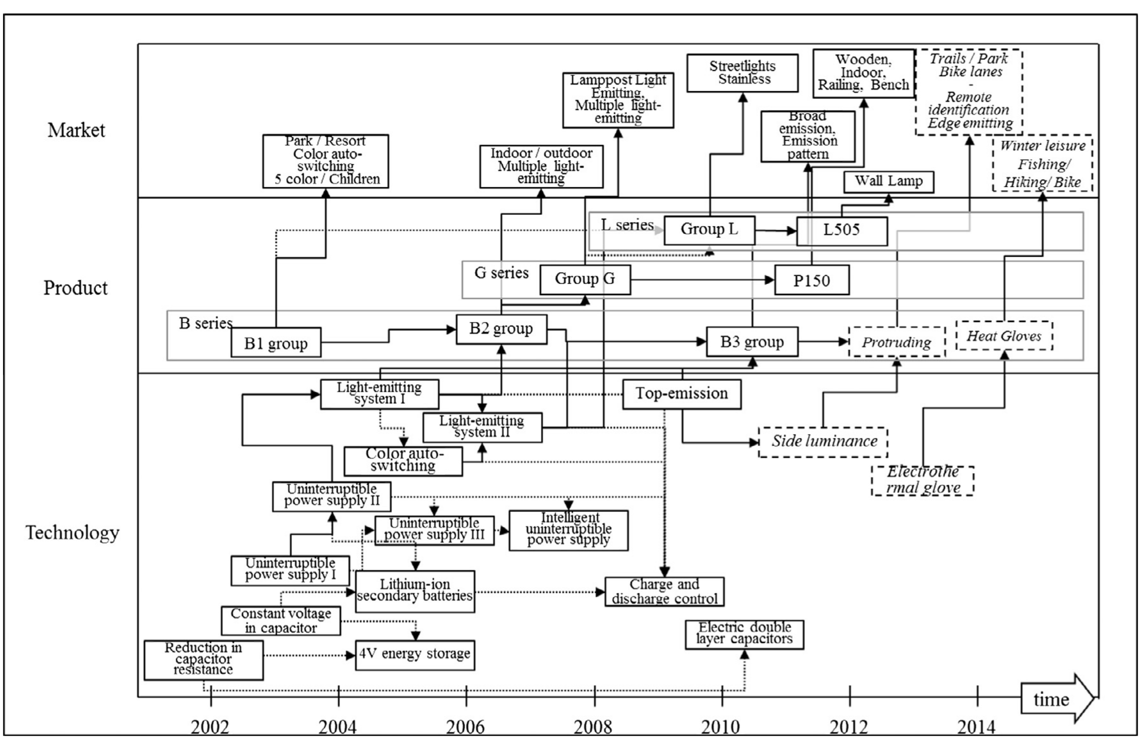

Fig. 7. Technology-driven TRM of solar lighting technology.

Table 8
A confusion matrix in a binary classification.

Data class		Predicted class	
		Class = 1	Class = 0
Actual class	Class = 1	f_{11}	f_{10}
	Class = 0	f_{01}	f_{00}

Table 9
Measures for the binary classification.

Measure	Formula	Definition
Accuracy	$\frac{f_{11}+f_{00}}{f_{11}+f_{10}+f_{01}+f_{00}}$	Overall effectiveness of a classifier
Error rate	$\frac{f_{10}+f_{01}}{f_{11}+f_{10}+f_{01}+f_{00}}$	Proportion of instances misclassified over the whole set of instances
Precision	$\frac{f_{11}}{f_{11}+f_{01}}$	Class agreement of the data labels with the positive labels given by the classifier
Recall	$\frac{f_{11}}{f_{11}+f_{10}}$	Effectiveness of a classifier to identify positive labels

Table 10
Confusion matrix of solar lighting technology roadmapping.

Data class		Links of nodes by the proposed approach	
		Link = 1	Link = 0
Links of nodes by experts	Link = 1	54(f_{11})	57(f_{10})
	Link = 0	33(f_{01})	321(f_{00})

approach shows high performance in roadmapping on the whole. Although the type I error (false positive) and type II error (false negative) slightly exist in the identification of links, this approach has a high level of accuracy, meaning that it correctly connects most of the relationships among the nodes.

5. Conclusions

This research presents a method to build a technology-driven TRM to seek new business opportunities. Two major challenges have emerged in earlier studies, one of which is that the TRM focuses on the market-driven approach, and there are a few methods to build a TRM: the other one is that the methods for building a TRM mostly draw on experts' perceptions. In an attempt to solve these challenges, this paper presents a new methodological framework to identify both profitable markets and promising product concepts based on technology information. Two QFDs are suggested in drawing up a TRM that starts with a given technology that has been developed as a method. Keywords from patents, product instruction manuals and advertisements are used for data analysis. This method can be applied at firms that select a technology-driven strategy, as well as in the solar-lighting device industry. The proposed approach has several advantages in terms of data, methodology and applications. A large amount of documents including patents, products and markets is utilized to develop a roadmap, which does not depend on the domain knowledge of experts. Furthermore, while traditional processes to draw a roadmap apply expert-oriented techniques such as workshops, the systematically proposed process to explore new business opportunities based on a technology-oriented roadmap uses a structured framework with which analysts can derive standardized outputs. Finally, new opportunities for potential products and markets that cannot be identified in the traditional approaches of roadmapping can be explored in the proposed approach. In general, the domain knowledge of experts is inclined to focus on the constrained scope of existing opportunities. Thus, a lot of valuable information for latent opportunities that are drawn from the suggested approach can improve the quality of roadmapping.

Despite these contributions, however, the research is subject to some limitations. Firstly, it cannot be applied to all new technology, as some technology does not have similar technology. Secondly, this methodology generally focuses on qualitative analysis, but the help of experts is needed in the process to screen core keywords among text-mining results. The experts' intervention problem of this screening process will reduce the efficiency of applying the text-mining method. Thirdly, this research only presents an illustrative case study, rather than a real case study. Though the feasibility of analysis can be verified by the example, an application to a real case will be required to confirm its validity. Expert opinion on the approach is needed to judge the effectiveness of this research. Finally, automated supporting systems need to be developed to save time and costs associated with drawing the TRM manually, thereby increasing the efficiency of the suggested approach.

Therefore, future research can be conducted to elaborate keyword extraction and screening through the other techniques, such as term frequency and inverse document frequency (TF-IDF), without depending on the frequency of occurrence, semantic analysis and subject–action–object (SAO) analysis to overcome the aforementioned limitations. These techniques attract the researchers' attention because it makes possible to extract more meaningful as well as specific information from unstructured data. Moreover, real cases can be investigated to validate the feasibility of analysis on the future work. With the addition of cases and methodologies, bibliometric tools and approaches could be enhanced quantitatively and qualitatively. In addition, TRM-supporting systems need to be developed to assist researchers in analyzing and utilizing the bibliometric information in the roadmapping.

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