Exploring Promising Technology in ICT Sector Using Patent Network and Promising Index Based on Patent Information

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This research proposes the use of a patent analysis methodology that can suggest promising technology in the ICT sector at the micro-level. This approach identifies core patents from the technology field, groups them as research frontiers (RFs), and develops a visualized network based on the citing relationships to monitor the relationship among RFs. In addition, it calculates a "promising index" based on the growth potential, impact, and marketability of patents to ultimately derive promising RFs. To illustrate the proposed approach, this research presents analysis results for a chosen area, which is the user interface and user experience (UI/UX) technology field. By proposing promising technological fields at the micro-level, the proposed methodology will serve as a useful decision-making support tool in selecting R&D projects, technology planning, and determining technology policy direction.

Keywords: Promising technology, promising index, patent analysis, patent network.

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I. Introduction

As business environments rapidly transform and become increasingly complex, a key issue is how to monitor and respond to rapid technological change. A lack of sustained and regular monitoring and responses to technology changes makes it difficult for a company to identify promising technology fields and to secure competitive advantages in the market. As such, the identification of promising technologies and the selection of the optimal targets among them for further development is a critical matter.

Technology prediction methodologies can be largely categorized into qualitative methodologies and quantitative methodologies.

Qualitative analysis, with reference to the relevance-tree and Delphi methods, is where technological trends based on expert discussions and opinion coordination is observed. Quantitative analysis includes trend impact analysis, bibliometrics, and patent analysis. Patent analysis is a form of quantitative analysis used in technology foresight; patents are a source of information on technologies and have commercial value [1]. Qualitative analysis has the advantage of easy validation but the disadvantages of being time-consuming and expensive. Hence, organizations often use quantitative analysis for technology prediction or employ a combination of qualitative and quantitative analysis methodologies [2].

Despite the fact that the information and communication technology (ICT) sector's rapid technology advancements and broad range of technology forecasting present many uncertainties in identifying promising fields, considerable research on promising-field identification methods has focused on qualitative rather than quantitative analysis. To address the changing ICT industry paradigm, an applicable logic must be developed, and a system should be built to facilitate the identification of promising fields in accordance with the characteristics of technology particular to the field of ICT. Furthermore, the results from various existing prediction methods are macro-level technology suggestions. It is necessary to derive a methodology to identify promising fields at the micro-level.

The present research aims to propose a quantitative methodology identifying promising technologies in the ICT sector at the micro-level. Since there have been few attempts at identifying promising technologies reflecting the ICT sector's characteristics that the speed of technological advancement is considerably rapid in the sector, this study is critical in the research field of technology intelligence.

This paper is organized as follows. Section II introduces relevant precedent research. Section III provides a detailed description of the process involved in the suggested methodology for identifying promising ICT fields. Section IV presents the analysis results of the case study using the suggested methodology, which considers the user interface and user experience (UI/UX) technology field. Section V discusses the implications of the findings. Lastly, Section VI presents the contribution, limitations, and applications of this research.

II. Literature Review

The term "promising technology" is used interchangeably with other terms such as "future technology," "emerging technology," "new technology," "breakthrough technology," and "key technology," depending on the perspective.

The term "emerging technology," which is commonly used as a synonym in a variety of literatures, embodies four major concepts [3]: The first such concept refers to a technology that has grown rapidly in recent years [4], [5]. The second concept defines it as a transition or change to something new, to include incremental and radical innovations [6], [7]. The third defines it in terms of market or economic potential, to describe how the emerging technology can be a form of incremental changes within existing industries or radical innovations that lead to the creation of new technology industries [4], [6], [7]. The fourth concept defines it as one that increases science-based innovation [6].

Other phrases that allude to a promising technology include "research front," "research frontier," and "hot field." These are often presented in technological document groupings, such as patent and scientific papers, based on bibliometric techniques and proposed by bibliometric citation analysis.

The concept of the research front was introduced by [8] and refers to those research domains that are densely cited by other papers. The research in [9] and [10] described those scientific papers that were most frequently cited as "research frontiers," and [11] defined the cluster that had the highest number of citations within three years of publication as the "hot field."

The major precedent researches that have attempted to identify promising technology using bibliometric analysis on patents and publication type of data can be categorized by their selection criteria and methodology. The first and most frequently applied method uses the number of times a technology is cited [9]–[16]. The second such method is research reflecting growth trends [5], [16]–[18]. The third such method is identifying promising fields by using citation networks to suggest clusters or topological measures [19]–[23]. The fourth such method is proposing promising fields by analyzing each co-word or co-classification for mapping or clustering [24]–[27]. Other research includes using a combination of bibliometric analysis and a qualitative method of scenario planning; growth curves and analogies; and system dynamics to predict promising fields [28].

Other hybrid methodologies include research to define an index that measures the prospects for identifying promising fields. Reference [18] derived a promising fusion technology by defining both a promising index and a fusion index, and factored patent application numbers and rates of increase to calculate a promising index. Reference [16] used the promising index proposed by [18] and additionally defined a diffusion index based on the diffusion rate of a specific technology observed in a number of citations, and incorporated it into measurement of a prospect. Reference [29] conducted empirical patent analysis using both a fusion index and a promising index to identify promising fusion technology in geoscience and mineral resources engineering.

III. Research Framework

1. Research Process

The analysis process for identifying promising ICT technology areas was conducted as shown in Fig. 1. First, an appropriate patent search string was created to collect patents in the relevant ICT sector from the United States Patent and Trademark Office database. Second, complete patent data in that field was extracted from the database of the National Bureau of Economic Research and a patent citation lag distribution was created. Third, the derived patent citation lag distribution was utilized to predict the future expected citation number of patents collected, based on the citation number at the time of patent collection. This step is to reflect the fast-

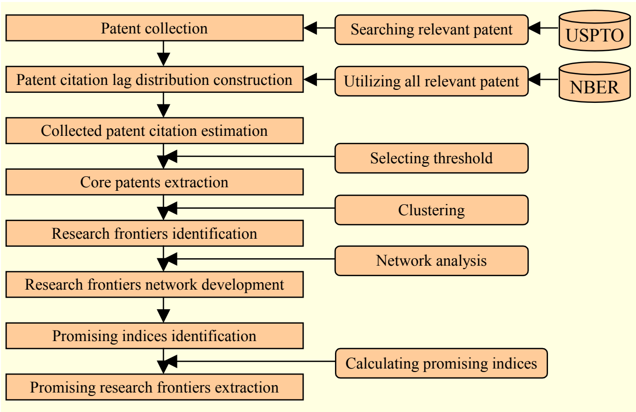

Fig. 1. Research process.

changing characteristics of the ICT sector, since it makes it possible to compare patents with low citation frequency at the time of data collection. Fourth, an appropriate threshold was chosen to identify patents with highly expected citation numbers as core patents. Fifth, core patents were clustered, based on the bibliographic coupling relations, to derive research frontiers (RFs). Sixth, a similarity relationship of identified RFs was visualized based on the bibliographic coupling, to enable understanding of the current status of the RFs. Seventh, a promising index (PI) was proposed to evaluate the RFs' prospects. Lastly, the PI was used to calculate the RFs' prospect scores and eventually identify the leading promising research areas of the relevant ICT sector.

2. Data Collection

An appropriate patent search string was developed to collect patents from authoritative sources such as the United States Patent and Trademark Office database.

To ensure that all patents in the relevant technology field are searched, search strings have to be created based on keywords derived from relevant technology classifications. Involving experts in the development of a search string can further enhance its credibility. Noise must be removed from the data; the patents identified using the search string may include noise.

3. Patent Citation Lag Distribution

Though the patent citation number is an index frequently used to represent the qualitative value of a patent, there are difficulties associated with it when comparing the qualitative values of patents by using the patent citation number at the time of data collection, because patent citation numbers vary depending on the age of the patent.

Therefore, this research employs a correction method. The citation number at the time of data collection is revised to reflect the expected citation number for the same future time period, to make a fairer comparison between patents' qualitative values, and so identify core patents.

The method used to revise the citation number for this research is the concept of patent citation lag distribution from [30], derived to solve the truncation problem, in which an observed citation number is truncated over a period of time.

Patent citation lag distribution is comprised of distributions of values calculated by dividing the citation frequency of a patent in a relevant technology field that was registered in year t received in time lag l by the aggregate citation frequency for all registered patents in the relevant technology field in year t.

$$\Pr_t\{L = l\} = \frac{f_{tl}}{N_t}, \tag{1}$$

where N_t denotes the aggregate citation frequency of the patents in the relevant technology field in year t, and f_{tl} denotes the citation of all registered patents in the relevant technology field in year t (with l denoting citation time lag, which is the year of data collection minus the year of patent application). This research limits the citation lag to 20 years based on the maximum patent maintenance period and under the assumption that the patent citation lag distribution is dynamically stable. We use five years of patent citation data to create a patent citation lag distribution (t = 1982–1986).

4. Collected Patent Citation Estimation

The citation rate of collected patents is revised by dividing the citation frequency of the patent by the cumulative probability value of the patent citation lag distribution, which factors in the relevant patent's exposure time of citation. Given a patent, A, its estimated patent citation number, EPCN_A, is defined to be

$$\text{EPCN}_A = \frac{O_A}{\text{CPV}_T}, \tag{2}$$

where O_A denotes the observed citation number of patent A at the time of patent collection, CPV_T denotes the patent citation lag distribution's cumulative probability value of the technology field that patent A belongs to till exposure time of citation until time T, and $T = \min(2013 - t, 20)$ denotes time lag l, which is the year of data collection minus the year of patent application. Patents that exceeded the maximum maintenance period of 20 years were excluded, and 2013 represents the year of data collection.

For example, if patent A that was registered in 2004 and had been cited three times by 2013, and the cumulative probability value of the technology area's patent citation lag distribution is 0.38, then the citation number of three over a nine-year period is calculated as 3/0.38, giving an estimated citation number of 7.89 over a twenty-year period.

5. Core Patent Extraction

A threshold of the estimated citation number is selected to use the estimated citation number to identify highly cited patents and derive the core patents of the relevant ICT sector. The existing research on "SCIENCE MAP" (refer to [14]) defines core scientific papers as those appearing in the top 1% of citation rates.

However, patents involve diverse business relationships compared with academic papers, which results in a relatively low citation rate. Hence, using only the top 1% of patents would present difficulties as only very limited data would be available for analysis. To limit the core patent data to two hundred in number, this research identified those patents appearing in the top 10% (based on the estimated citation number) as being core patents qualifying for continued analysis.

6. RFs Identification

Core patents with high estimated citation numbers are grouped by a clustering method. Resulting clusters can then be viewed as potential RFs. An RF is a lower-level concept compared with technology classification, and it can be interpreted as a core research theme derived from core-patent grouping.

Clustering is performed based on bibliographic coupling relationships. Bibliographic coupling conveys the degree of commonality among the references cited by patents. Further, patents with many common references have strong bibliographic coupling relationships and can be determined to possess a high degree of similarity.

Bibliographic coupling represents the coupling strength by the number of shared references, but as each patent has different numbers of cited reference material, it is necessary to use a normalized value. The normalized coupling strength between patents A and B, N_{norm}, can be calculated as follows [31]:

$$N_{\text{norm}} = N_{AB} / \sqrt{N_A N_B}, \tag{3}$$

where N_A and N_B represent the number of references for patents A and B, respectively, and N_{AB} represents the number of references cited by both patents A and B.

The RF is derived by conducting k-means clustering. The clustering process continues using different k-values until similar patents are clustered. Once an appropriate k-value is finally determined, RFs are identified based on expert opinion reviewing patent titles and abstracts.

7. RFs Visualization

A normalized coupling strength matrix among RFs is constructed using (3), similar to calculating a normalized coupling strength among patents in the previous step. Furthermore, to visually present the relationship among RFs, a threshold is selected using sensitivity analysis. The relationship is then visualized using network analysis and intuitively determined using visualized networks; a centrality index provides additional information.

Degree centrality [32] represents the actual number of connected nodes, and given a high degree of centrality, a node can be seen as playing a central role in relation to many other nodes within the network. It can be used to determine an RF that performs a key function within an RF network. *Betweenness centrality* [32] is related to the shortest distance through a particular node. As higher betweenness centrality has a direct correlation with the extent to which a node can be perceived to provide an intermediary role by networking with other nodes within the network, RFs that currently perform this intermediary role in the RF network can be identified.

8. Promising RFs Identification

The prospects of RFs identified using the major concepts of emerging technology are evaluated by the PI based on the technology's growth, impact, and marketability. RFs are evaluated with the understanding that the rapidly evolved technology is promising; this is based on the weighted value of the number of applications and the rate of increase at the time of data collection. *Technical impact* is measured based on the perspective that technology that can achieve science-based innovation is promising. *Marketability* is measured based on the perspective that technology with market or economic potential is promising.

A. Growth Index

The growth index (GI) is defined as the growth potential of an RF and is evaluated using a number of patent applications and their growth rates. This research evaluates the growth potential of an RF based on the PI, which is suggested in [18] for predicting promising fusion technologies. The equation for the GI is as follows:

$$\text{GI}_{ij} = A_i\lambda_j + B_i(1-\lambda_j) = (A_i - B_i)\lambda_j + B_i \quad \text{for } 0 \le \lambda \le 1, \tag{4}$$

where GI_{ij} is the growth index of RF i having weight value j; A_i is the normalized number of patents for RF i; B_i is the normalized growth rate of the number of patents for RF i; and λ_j is a weight value of order j. The number of patent applications (A_i) and patent application growth rate (B_i) both use normalized values, which are calculated using the following equations:

Table 1. Weight extraction of GI.

GI_{ij}	$\lambda_{j=1}$	$\lambda_{j=2}$	…	$\lambda_{j=m}$
$i = 1$	GI_{11}	GI_{12}	…	GI_{1m}
$i = 2$	GI_{21}	GI_{22}	…	GI_{2m}
…	…	…	…	…
$i = n$	GI_{n1}	GI_{n2}	…	GI_{nm}
minGI_j	minGI_1	minGI_2	…	minGI_m

$$\text{Normalized } A_i = \frac{A_i - \min(A_i)}{\max(A_i) - \min(A_i)}, \quad (5)$$

$$\text{Normalized } B_i = \frac{B_i - \min(B_i)}{\max(B_i) - \min(B_i)}, \quad (6)$$

where A_i and B_i are the number of patent applications and the growth rate of applications, respectively; $\max(A_i)$ and $\max(B_i)$ are the maximum values of RF i's number of patent applications and the growth rate of the number of applications, respectively; and $\min(A_i)$ and $\min(B_i)$ are the minimum values of RF i's number of patent applications and the growth rate of the number of applications, respectively.

Weight (λ) is calculated using each core technology's number of patent applications (A) and the application number's growth rate (B) to calculate the GI and the minimum value for order j (minGI_j) to select the maximum of minimum GI (momGI). A derivation of the growth weights can be represented in sequence (see Table 1), where minGI_j represents the minimum growth index by weight j, momGI_j is the maximum of the minimum growth index, i represents the core technology, and j is a weight (λ) defined as ($0 \leq \lambda \leq 1$).

Therefore, the growth index of each technology is calculated using a weight between 0 and 1; minGI is calculated per each weight j to identify momGI for determining the associated weight. To determine an appropriate weight, it is assumed that identified core patents have high possibility to be promising technologies. Thus, the weight reflects the future prospects well when the technology fields that most involve the core patents rank highly in the calculated GIs of all data.

B. Impact Index

The impact index (II) of a technology is defined as the extent to which a technology can also be applied to other technologies, and is evaluated using the diffusion index proposed by [16]. As a significant number of patent citations in the technology field can be considered as high impact, the II is calculated using (7) and is normalized through calculation in (8).

$$\text{II}_i = C_i / P_i, \quad (7)$$

$$\text{Normalized II}_i = \frac{\text{II}_i - \min(\text{II}_i)}{\max(\text{II}_i) - \min(\text{II}_i)}, \quad (8)$$

where II_i denotes the II of RF i, C_i denotes the number of times RF i was cited, P_i denotes the number of patents in RF i, $\max(\text{II}_i)$ denotes the maximum value of RF i's II, and $\min(\text{II}_i)$ denotes the minimum value of RF i's II.

C. Marketability Index

Marketability index (MI) is defined as the applicability of the products and services that utilize a technology, and is evaluated using the number of patent families.

Generally, one must apply and register a patent in all countries in which one seeks rights, but since patent rights take effect only within each country's national territory, the number of family patents can signal the business development of the potential of products and services using the related technology of qualifying patents, and can be perceived as the qualifying technology's potential market size.

MI is calculated using (9) and is normalized using (10).

$$\text{MI}_i = F_i / P_i, \quad (9)$$

$$\text{Normalized MI}_i = \frac{\text{MI}_i - \min(\text{MI}_i)}{\max(\text{MI}_i) - \min(\text{MI}_i)}, \quad (10)$$

where MI_i denotes RF i's MI, F_i denotes the number of family patents in RF i, P_i denotes the number of patents in RF i, $\max(\text{MI}_i)$ denotes the maximum MI value of RF i, and $\min(\text{MI}_i)$ denotes the minimum MI value of RF i.

D. Promising RFs

An RF's prospects can be evaluated using the PI, which is the summed value of the normalized GI, II, and MI, as follows:

$$\text{PI} = \text{GI} \times \lambda_1 + \text{II} \times \lambda_2 + \text{MI} \times \lambda_3, \quad (11)$$

where GI_i represents the growth index of RF i, II_i represents the impact index of RF i, MI_i represents the marketability index of RF i, and λ represents a weight variable. A weight variable is selected using an analytic hierarchy process [33], and using this weight variable, a weighted sum is calculated to evaluate the prospect of the RF. The evaluator conducts pairwise comparison using the criteria of growth, impact, and marketability. Then, an arithmetic mean is applied to the identified weights, λ_1, λ_2, λ_3, to derive a final weight, which is then used for evaluating the prospect of the RF. Derived weights are used to calculate PIs of RFs, and then high-ranking RFs are identified as promising RFs.

Table 2. Results of patent data collection.

Upper classification	Lower classification	Collected patent # (%)	Core patent # (%)
User intent-aware interface	Human motion interface	120 (6.53)	18 (9.89)
	Speech recognition interface	43 (2.34)	10 (5.49)
	Bio-signal interface	79 (4.30)	7 (3.85)
Pointing device type interface	Tabletop-type interface	466 (25.37)	19 (10.44)
	Handheld-type interface	229 (12.47)	51 (28.02)
	Screen-type interface	138 (7.51)	17 (9.34)
Realistic interface	Tactile interface	202 (11.00)	21 (11.54)
	Auditory interface	11 (0.60)	0 (0)
	Olfactory interface	216 (11.76)	14 (7.69)
	Taste interface	95 (5.17)	1 (0.55)
	Movement by experience interface	30 (1.63)	2 (1.10)
	Visual interface	55 (2.99)	2 (1.10)
	Neural stimulation interface	27 (1.47)	3 (1.65)
Hybrid interface	Wearable interface	63 (3.43)	6 (3.30)
	Multimodal interface	63 (3.43)	11 (6.04)
Total		1,837 (100)	182 (100)

IV. Results

1. Data

This research selected the UI/UX field from among the ICT sectors to conduct analysis on the suggested methodology. Accordingly, a relevant classification of UI/UX technology was identified by reviewing it from a relevant research institute. To search and collect the relevant patents well, we developed a search string by referring to the predefined aforementioned UI/UX technology classification. The search period was limited to the past ten years, and public and registered patents between 2004 and 2013 were collected from the US Patent Office's database. Table 2 classifies the 1,837 patents that remained after noise was removed from the data collected.

2. Patent Citation Lag Distribution and Patent Citation Estimation

Analyzing the distribution of the classes that make up the United States Patent Classification (USPC), which contains 1,837 UI/UX technology–related patents collected over the past ten years, the top ten USPC classes (in terms of volume of patents) accounted for approximately 51% of the total number of patents. The patent citation lag distribution table of the UI/UX technology field is constructed on the basis of the patent data extracted from National Bureau of Economic Research that were registered between 1982 and 1986 and included in the top ten USPCs as the main classes. The number of citations of the 1,837 patents is estimated based on the patent citation lag distribution. As indicated in the distribution of the estimated citation number, approximately 68% of the patents have not been cited, and patents in the top 5% are expected to be at approximately 60 or higher in terms of estimated citation number.

Table 3. RFs.

RF no.	RF	Patent #
RF1	3D graphic user interface	2
RF2	3D pointing device	13
RF3	3D pointing selective input system	4
RF4	Adjusting 3D pointing position	6
RF5	Adjusting method for tactile feedback interface	6
RF6	Aroma-diffusing apparatus	13
RF7	Artificial intelligence based processing	1
RF8	Digital image capturing and processing system	12
RF9	Elastomeric wave tactile interface	2
RF10	Filtering noise	1

3. Core Patent Extraction and RFs Identification

The distribution of the estimated citation number, from which 182 core patents with estimated citation numbers of more than 30 and ranked in the top 10%, was extracted. Comparing the ratio of total patents and core patents for each of the technology categories in Table 2, human motion interface, speech recognition interface, handheld-type interface, and multimodal interface make up a larger distribution ratio in core patents than in all patents, while tabletop-type interface and taste interface have a lower distribution ratio in core patents than in all patents.

Extracted core patents are clustered into RFs using *k*-means clustering. Through sensitivity analysis, an appropriate *k*-value of 40 was derived. Upon further review by domain experts, 40 RF titles were defined, and a number of them is representatively presented in Table 3.

4. RF Network

Derived RFs are visualized using network analysis based on bibliographic coupling strength. A threshold of 0.03 is selected to visualize the relationship among RFs as in Fig. 2, using the free, open-source network visualization template NodeXL [34]

http://dx.doi.org/10.4218/etrij.16.0115.0613

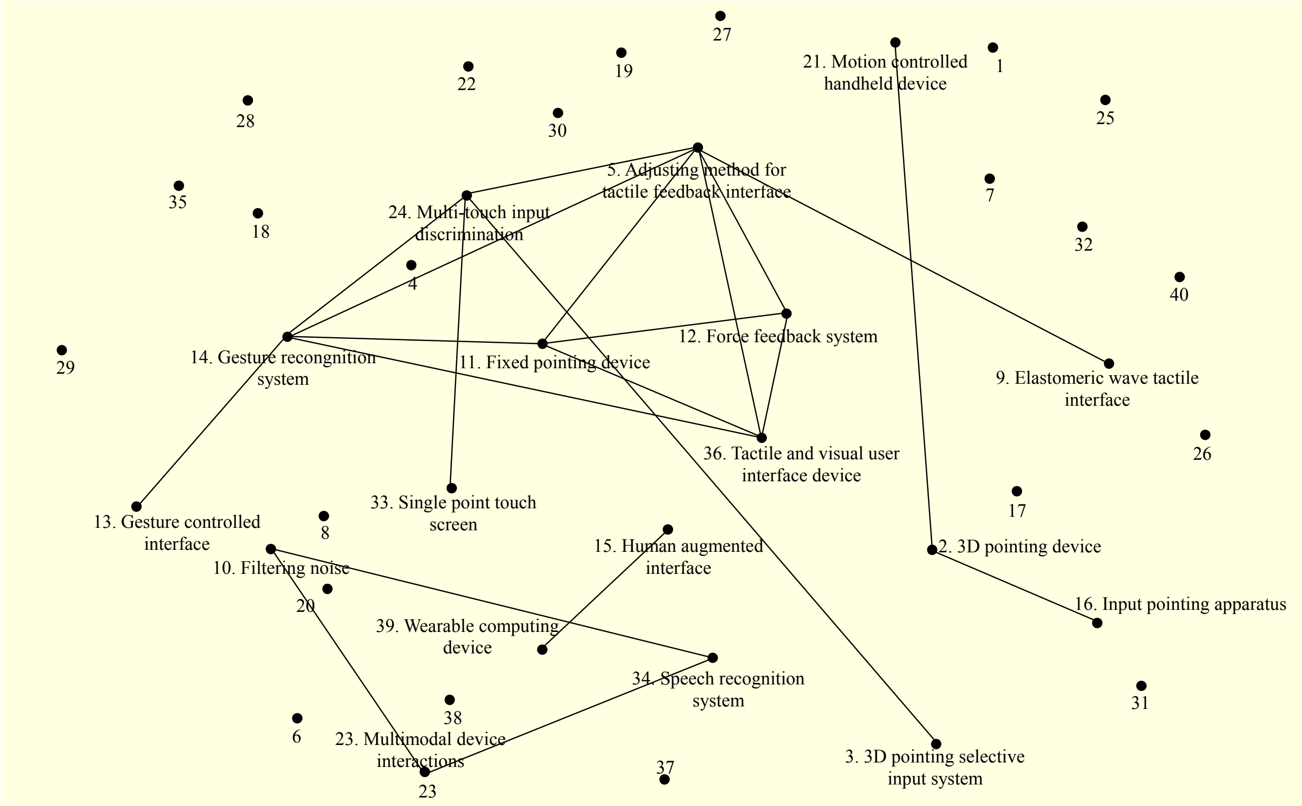

Fig. 2. RF network (threshold = 0.03).

Table 4. Top ten RFs of degree centrality.

RF no.	RF	Degree centrality
RF5	Adjusting method for tactile feedback interface	6
RF14	Gesture recognition system	5
RF24	Multi-touch input discrimination	4
RF36	Tactile and visual user interface device	4
RF11	Fixed pointing device	4
RF12	Force feedback system	3
RF2	3D pointing device	2
RF10	Filtering noise	2
RF23	Multimodal device interactions	2
RF34	Speech recognition system	2

Table 5. Top six RFs of betweenness centrality.

RF no.	RF	Betweenness centrality
RF24	Multi-touch input discrimination	15
RF5	Adjusting method for tactile feedback interface	14.667
RF14	Gesture recognition system	11
RF2	3D pointing device	1
RF11	Fixed pointing device	0.667
RF36	Tactile and visual user interface device	0.667

made for MS Office.

The top ten RFs of degree centrality and top six RFs of betweenness centrality can be seen in Tables 4 and 5, respectively. RFs with high network degree centrality perform a central role in the entire network of RFs.

Furthermore, it is consistent with the next generation of UI/UX technology and its evolutionary direction, which is realism, emotional fulfillment, and increased convenience. RF 24 with its high betweenness centrality falls under "touch technology," which is deemed to be one of the most innovative interfaces since the mouse and keyboard. It is one of the most widely used fields among UI/UX's diverse technology fields, and acts as an intermediary among RFs. RF5, which has the highest degree centrality in the network, is noted as a tactile interface. It has relationships with other similar tactile interfaces (RF9, RF12, RF36), and pointing device (RF11) and multi-touch (RF24) are also linked to sense of touch and exhibit a relationship in the network. RF34, which ranks 10th in degree centrality, is in a technology area that qualifies as a speech recognition interface, linked to similar technology areas RF10 and RF23. Here, RF23, which is a hybrid interface that can be related to a variety of devices, including touch and sound, is indirectly linked.

5. Promising RFs

A. Growth Index

The top five technologies in upper classifications that have the most core patents were considered to be the promising future core technology areas. The top ten RFs determined from the GI and calculated using the weight value (λ) of 0.38 are presented in Table 6. RFs including touch and pointing touch devices (RF3, RF2, RF24, RF8), gesture recognition interface (RF21, RF14), tactile interface (RF20), olfactory interface (RF6), human enhancement interface (RF15), and wearable computing device (RF39), all had a high-ranking GI.

B. Impact Index

The top ten RFs on the II are set out in Table 7. The gesture recognition interface (RF13, RF21, RF14); touch and pointing device (RF2, RF24); speech recognition and natural language processing interface (RF10, RF7, RF34); tactile interface (RF20); and visual interface (RF1) were the RFs with the highest-ranking II.

C. Marketability Index

The top ten RFs on the MI are set out in Table 8. The touch and pointing device (RF8, RF25, RF17, RF3, RF11, RF24, RF2); tactile interface (RF12, RF20); and speech recognition and natural language processing interface (RF34) were the RFs with the highest-ranking MI.

D. Promising Index

The PI was calculated using weights (λ) of 0.330, 0.504, and 0.164 for growth potential, impact, and marketability, respectively, by using an analytic hierarchy process and taking the arithmetic mean of evaluations conducted by six experts. The expert group comprises experts, two UI/UX relevant domain experts, and four experts who have worked in the field related to future technology strategy or technology analysis and planning with more than five years of experience in each field. The CR was 0.0427, and as per the standard criteria, a CR of less than 0.1 is determined to have sufficient consistency.

Table 9 presents the top ten promising RFs, derived by calculating the PI using the determined weights. Tactile interface (RF20); speech recognition and natural language processing (RF10); motion recognition interface (RF13, RF21, RF14); touch and pointing device (RF2, RF24, RF8, RF3); and olfactory interface (RF6) were identified as promising RFs.

Table 6. Top ten RFs of GI score.

RF no.	RF	GI
RF3	3D pointing selective input system	0.696
RF20	Marking apparatus	0.671
RF21	Motion controlled handheld device	0.587
RF15	Human augmented interface	0.464
RF6	Aroma-diffusing apparatus	0.305
RF2	3D pointing device	0.304
RF24	Multi-touch input discrimination	0.279
RF14	Gesture recognition system	0.279
RF8	Digital image capturing and processing system	0.279
RF39	Wearable computing device	0.254

Table 7. Top ten RFs of II score.

RF no.	RF	II
RF20	Marking apparatus	1.000
RF10	Filtering noise	0.843
RF13	Gesture controlled interface	0.604
RF2	3D pointing device	0.373
RF24	Multi-touch input discrimination	0.359
RF7	Artificial intelligence based processing	0.273
RF21	Motion controlled handheld device	0.245
RF14	Gesture recognition system	0.231
RF1	3D graphic user interface	0.210
RF34	Speech recognition system	0.179

Table 8. Top ten RFs of MI score.

RF no.	RF	MI
RF8	Digital image capturing and processing system	1.000
RF12	Force feedback system	0.344
RF20	Marking apparatus	0.190
RF25	Multiuser input systems	0.176
RF17	Interactive touch screen	0.124
RF3	3D pointing selective input system	0.112
RF11	Fixed pointing device	0.102
RF24	Multi-touch input discrimination	0.090
RF34	Speech recognition system	0.059
RF2	3D pointing device	0.052

Overall, RFs related to touch and pointing devices and motion recognition interfaces rank the highest. On the growth front, technology related to touch and pointing devices appear

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Table 9. Top ten promising RFs.

RF no.	RF	Lower classification	Mean
RF20	Marking apparatus	Tactile interface	0.720
RF10	Filtering noise	Speech recognition interface	0.481
RF13	Gesture controlled interface	Human motion interface	0.368
RF21	Motion controlled handheld device	Handheld-type interface	0.352
RF2	3D pointing device	Handheld-type interface	0.332
RF24	Multi-touch input discrimination	Screen-type interface	0.320
RF8	Digital image capturing and processing system	Handheld-type interface	0.299
RF3	3D pointing selective input system	Handheld-type interface	0.287
RF14	Gesture recognition system	Human motion interface	0.243
RF6	Aroma-diffusing apparatus	Olfactory interface	0.195

to be promising based on patent volume and rate of increase. On the impact front, which represents a patent's qualitative value, technologies related to motion and speech recognition will be promising. On the marketability front, which indicates potential market size, touch and pointing devices are dominantly distributed.

V. Discussion

Previous research [30] proposed two approaches to measure the amount of technological knowledge, citation-based patent stock (CPS) and valuation-based patent stock (VPS). VPS reflects monetary value at the macro level, while citation-based considers the quality of an individual patent. The utilization of CPS is appropriate in this research in that we conduct a micro-level analysis and do not consider monetary value. This research follows the assumption of proportionality in previous research [30], meaning that the distribution on the number of citations over time is independent of the total number of citations received. With the proportionality, the observed total number of citations at a given point in time for any patent can be corrected to solve the truncation issue by scaling up the observed citation total, dividing it by the fraction of the lifetime citations. Thus, we can verify that estimated citation frequency is a means of comparing patents with low citation frequency for a given time of data collection. However, the problem of citation inflation still exists, and a modified method that addresses this issue needs to be considered in future research.

The comparison among RFs derived using the PI and those derived comparing degree and betweenness centrality can be summarized as follows.

Among the identified promising RFs, RF14, RF24, RF2, and RF10 displayed a high degree centrality value, whereas RF14, RF24, and RF2 displayed a high degree betweenness centrality value. Therefore, the aforementioned RFs presently play a central, intermediary role among the RF relationship network, and are determined to be promising fields in their future roles too.

RF5, RF36, and RF12, which are related to tactile interface technology, did not feature in the list of top ten promising RFs, and among the tactile interface–related technologies, only RF20 was selected as number 1. RF20 is, however, an input device using tactile senses and is a realistic interface that utilizes environmental and operational information from the device to enhance determination of location, and is distant from tactile technology with a high degree centrality value.

RF11 is a field that has high values for both degree centrality and betweenness centrality, but it was not included in the top ten promising RFs, and RF3 was added as a pointing-related field. This can be interpreted to mean that devices with 3-D pointing technology will be more promising in the future than fixed pointing devices.

Besides RF14 among the motion-related interfaces that have high degree and betweenness centrality values, RF13, and RF21 are included in the top ten promising RFs. This can be interpreted to mean that in addition to current technology related to motion recognition, technology related to motion control interface will also be promising.

There are several RFs that include only one patent, such as RF7, RF10, RF18, and so on. These clusters also are meaningful in that they represent a specific research subject since the clusters are generated among core patents. Furthermore, the RFs are relatively long-term promising research themes compared to those RFs that include more than two patents.

VI. Conclusion

This research makes several contributions to overcoming the dependency that promising-field identification has on policy makers and on the consultation and qualitative judgments of field experts. First, the research utilized public patent data to develop a network that presents the current status of RFs and to propose a systematic way of defining promising RFs at the micro-level. Second, it reflected the fast-changing characteristics of the ICT sector and used estimated citation frequency to make it possible to compare patents with low citation frequency at the time of data collection, and on a similar level. Third, the research identified promising RFs by developing a *promising index*. Such an approach enhances the objectivity of the promising-field identification process and provides evidence that could increase the validity of the identified promising areas.

Despite these contributions, the research faces limitations to becoming a completely automated system because of the required expert participation during some parts of the process. Nevertheless, the analysis of large volumes of patent data and collaboration with technical experts and thorough technical review was able to produce highly valid results that propose details that may escape an expert's intuition. Furthermore, the use of patent data may produce results where future promising technologies are short term and in technical aspects that are suitable for commercialization, rather than identifying future promising technology such as proprietary technology and technology that is promising in the long term. This implies that future research should consider exploring ways to overcome this limitation by combining technical information with foundational, core technology, such as data on scientific papers.

The proposed approach is able to initiate organizations' technology intelligence by assessing a series of emerging technology candidates. Although the proposed approach in this research was applied to the ICT sector, the coverage of application can be easily extended to other fields; furthermore, the citation lag distribution can be changed since the speed of technology change differs across technologies.

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